J. Int. Financ. Markets Inst. Money 93 (2024) 102004

Contents lists available at ScienceDirect

Journal of International Financial Markets, Institutions & Money

journal homepage: www.elsevier.com/locate/intfin

Clustering asset markets based on volatility connectedness to political news

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ARTICLE INFO

JEL Classification:
G14
G41
E32

Keywords:
Markets and media
Volatility connectedness
Market clustering
Political news
Large language model

ABSTRACT

To assess similarities in international asset markets' responses to political news, we construct a political news index using advanced natural language processing. We then examine how the volatility across international asset markets is connected to the development of our political news index by measuring the daily directional connectedness using a VAR-based framework. Finally, we apply an unsupervised algorithm to cluster markets based on their volatility connectedness to political news. Our analysis reveals eight distinct clusters that reflect the markets' sensitivities to political dynamics. This data-driven analysis offers insights into the influence of political developments on market volatility.

1. Introduction

The connection between politics (political news, events, and environment) and financial and other asset markets has been the subject of numerous studies in the literature, see among others Bilson et al. (2002), Białkowski et al. (2008), Lehkonen and Heimonen (2015), Wisniewski (2016), Gholipour (2019), Al-Maadid et al. (2020), Abolghasemi and Dimitrov (2021), Apostolakis et al. (2021), Ding et al. (2022), Yang et al. (2023), Pandey et al. (2023) and Gala et al. (2023). Scholars have explored how political events and announcements impact markets with varying results. While there is a consensus that political news affects markets, much still needs to be learned about how these effects are transmitted across global market segments and over time. Specifically, it is an open question how similarly different markets react to the spread of political news. This study aims to illuminate this aspect by focusing on the directional time connectedness from political news to asset markets' volatility. First, we uncover patterns of connectedness that illustrate how political news influences volatility across global markets. Second, we cluster markets based on their sensitivity to political news to examine how similarly they behave in response to this type of news.

To conduct this study, we collect daily price data from 40 international asset market segments, including various stock and commodity indices, from 14 November 2014 to 9 April 2022. We particularly concentrate on various global market segments because their connectedness has been extensively studied in the literature (e. g. Rejeb and Arfaoui, 2016; Maghyereh et al., 2016; Prasad et al., 2018; Chen et al., 2020; Liao et al., 2021; Benlagha et al., 2022; Kangogo and Volkov, 2022; Jiang et al., 2022a,b), but what distinguishes our examination is that we investigate their connectedness to political news. Lucey and Ren (2021) highlight that news

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https://doi.org/10.1016/j.intfin.2024.102004

Available online 13 May 2024

stories convey crucial tone and sentiment that can influence market dynamics. Moreover, Yarovaya et al. (2022) emphasize the importance of incorporating behavioral facets, like the analysis of media and news, in examining information transmission mechanisms. To achieve this, we use news headlines from the politics section of the investing.com website. We opt for the news headlines because they can be easily retrieved and succinctly convey the essence of full articles (Li et al., 2019). This approach boosts the accuracy of the textual analysis because headlines are the most important part and summary of a news article (Bonyadi and Samuel, 2013). They typically contain fewer repetitive or irrelevant phrases and are to the point (Nassirtoussi et al., 2015). Finally, we extract the sentiment of the news sample using a large language model and construct an index as the final outcome from this step.

To extract the sentiment of our news sample, we use the Bidirectional Encoder Representations from Transformers (BERT) model (Devlin et al., 2018). BERT is a novel and powerful language model that can understand the meaning of ambiguous language and quantify the sentiment based on the meaning of text. The sentiment score ranges from $+1$ (indicating the most positive) to -1 (indicating the most negative). Using the BERT, we build a political news index (PNI) based on the semantic sentiment of our political news sample. Next, we employ the connectedness framework, proposed by Diebold and Yilmaz (2012) (DY henceforth), to measure how much of the volatility seen in the analyzed international markets is connected to the PNI. Our particular focus is on market volatility due to its potential for rapid growth and its tendency to increase over real-time events. During times when many individuals simultaneously seek to exit or enter the market, there can be complex interconnections. Using a rolling-window analysis within the DY framework, we generate daily data on the directional connectedness from political news to market volatility. This dataset shows the percentage of daily volatility in international markets that can be attributed to the spreading of the PNI. Finally, we use these data to cluster the markets. For this purpose, we employ the K-means clustering algorithm, which aims to cluster n inputs into k clusters, where each data item belongs to a cluster with the nearest cluster centroid (mean) (MacQueen, 1967). We optimize the K-means parameters using a genetic algorithm to tackle its inherent shortcomings and improve the results (Krishna and Murty, 1999). Clustering is a type of unsupervised learning algorithm whose core idea is to find similarities between various data items by categorizing them within the same cluster. Data items in the same cluster are more similar to each other than those in the other clusters.

Clustering markets based on their sensitivity to political news assists in asset allocation and risk management. For instance, financial institutions and investors can utilize these insights to diversify portfolios and reduce risk exposure. Understanding the formation of market clusters that share similar reactions to political news enables investors to allocate assets more optimally, taking into consideration the influence of political events on their investment decisions.

Our findings indicate that volatility in international markets is connected to political news, although the extent of this connectedness varies over time for each market segment. Typically, the dynamic connectedness across daily intervals is below 10 %, but it can spike to as high as 50 % at specific times.[1] One reason can be the nature and scope of the news. Some news events may be seen as having a direct and significant impact on the underlying fundamentals of the economy or a particular industry, while others may have a more limited impact. For instance, trade conflicts between the U.S. and China enhanced the market volatility connectedness to political news to 50 % and 32 % in the U.S. and China, respectively. This increase was primarily due to uncertainties about corporate profits and concerns regarding a slowdown in the Chinese economy. However, when China retaliated by imposing tariffs on U.S. goods, the connectedness was negligible. This aligns with He et al. (2021), who note that the U.S. plays a dominant role in the trading conflict, with China acting more as a passive recipient responding to relevant U.S. policies. In addition, market reactions are not only shaped by the events themselves but also by the anticipations leading up to them. Around the events described, market participants possibly had already factored in or anticipated the imposition of tariffs by China. Such preemptive pricing could result in a dampened response once the policy was formally implemented. Our results also show that during the analyzed period, there were subperiods when political news had trivial informational value for the markets, leading to negligible connectedness. For example, from early September to late December 2019, the daily spillover from the PNI to U.S. market volatility was less than 2 %. The overall sentiment and psychology of investors can also play a role. This can be traced to the nature of the PNI, which is based on the meaning of the news and can serve as a proxy for its psychological significance.

In the second step of our analysis, we find that the markets are optimally clustered into eight groups based on the estimated daily connectedness data. These clusters unveil a complex web of relationships and dependencies in response to political news, underpinned by global risk and international investment behaviors. For instance, we identify clusters mostly consisting of geographically dispersed markets, e.g., the cluster consisting of Brazil, China, Czech, Gold, Greece, Mexico, South Africa, South Korea, and Switzerland, where we discern the compelling influence of trade agreements and investment ties. This aligns with Karolyi and Stulz's (2003), who indicate that international equity flows and trade agreements contribute to market co-movements. They argue that these flows are not merely responses to local market conditions but also to global risks, which explains the cohesive response to international political news observed within such clusters.

Geographical positioning is another key element in our clustering results. We find groups comprising regional markets, such as a cluster including Middle Eastern countries. The coherence of this grouping is largely due to regional affiliations and cultural ties. This is consistent with the findings of Balli et al. (2015), who document the role of cultural factors in economic integration and shock transmission. Previous literature also emphasizes the role that culture plays in market reactions across nations (e.g. Hofstede, 2001; Nguyen and Truong, 2013; Ashraf, 2021). This suggests that markets with shared cultural backgrounds tend to exhibit similar responses to global events, as investors in these markets process information in comparable ways. We also observe the significant role of

[1] The connectedness percentage reflects the proportion of forecast error variance in a market's volatility attributed to shocks in the PNI. For instance, a 50% connectedness does not imply a 0.5 correlation with the PNI but rather that half of the forecast variance in the market's volatility is due to innovations in the PNI.

shared economic mechanisms as another primary factor. This is even more pronounced in another cluster formed by European countries. This finding is consistent with Bae et al. (2003), who provide a basis for this discussion by presenting the concept of cross-regional contagion, showing that events in one region can influence the probability of similar market responses in another. This sheds light on a complex pattern of interdependencies and reactions to political events, suggesting that market clustering can be influenced by both regional and inter-regional dynamics, as seen in other clusters.

While our analysis is primarily based on a data-driven approach, the clustering patterns observed resonate with economically viable explanations. These patterns are presumably shaped by a combination of political events, trade interdependencies, economic policies, and regional and cultural ties, all of which contribute to a co-movement in responses to international political news. This observation is consistent with literature suggesting that equity market integration reflects increased interdependencies and signals a trend towards a cohesive approach for cross-border financial asset pricing (Chowdhury, 2005; Aggarwal et al., 2010; Patel et al., 2022).

A crucial aspect of interpreting our clustering results is the nuances within each cluster, as highlighted by the Euclidean distance metric. Upon closer observation, we notice distinctive characteristics in markets such as the U.S. and China. Despite being in different clusters, their unique Euclidean distances with other cluster constituents underscore their dominant and distinct roles in the global economy. Additionally, within another cluster containing the Brent and WTI oil markets, a noticeable distance between them reflects the complex interplay of geopolitics, transportation logistics, and market efficiencies that shape their respective responses to political news. In essence, our study reveals a multifaceted landscape where varying factors lead to a dynamic interplay in market reactions to political news, underscoring the complexity and depth of global market behaviors.

This study adds notable contributions to the literature. First, our political news index differs fundamentally from previously used indices. We construct the PNI based on the semantic meaning of the text using the BERT and fine-tune this machine learning model on financial language. This approach estimates news sentiment based on the perceived impact that a given political news might have on market prices and not necessarily the political polarity. This distinguishes our index from established indices like the Geopolitical Risk Index (GPR) (Caldara and Iacoviello, 2022), which is based on counting the number of news articles on adverse geopolitical events, and Global Economic Policy Uncertainty (Baker et al., 2016), which is based on a word-metric method. In contrast, the PNI represents a market-oriented semantic measure. Shiller (2017) proposes the necessity of using semantic textual analysis instead of the practices of passive word collection because semantic experiments reveal the meaning and psychological significance. Furthermore, unlike established proxies for political news that mainly focus on negative aspects, the PNI differentiates between negative and positive news. This leads to capturing the impact of positive sentiment. For instance, the U.S. Congress passed an unprecedented infrastructure bill in August 2021, and this news had the potential to positively affect the U.S. stock market, specifically on companies in the technology, energy, and infrastructure sectors. This matter is neglected in the established indices as they basically focus on adverse news. By capturing positive sentiment, the PNI provides a more refined and comprehensive index of news sentiment.

Second, our research delves deeper than just analyzing the volatility transmission from the PNI to global markets. We innovatively cluster these markets based on their sensitivity to global political news. Unlike prior studies that group financial markets by firm-level volatility connectedness (Cerqueti et al., 2023) or market-level historical returns (Bastos and Caiado, 2014; León et al., 2017), our study employs daily directional connectedness to political news for clustering, offering a novel perspective on global political impacts. This study not only corroborates development (Bastos and Caiado, 2014) and geographical (León et al., 2017) factors but also reveals a wider array of clustering determinants such as international trade, economic ties, and political trends. These comprehensive findings provide insights into the complex relationship between political events and international market behaviors, which are essential for policymakers, financial institutions, and investors.

The research is organized as follows. We describe our data in Section 2. Section 3 presents the methods. Section 4 reports the empirical results, and Section 5 concludes.

Table 1

List of the selected markets. This table presents the markets included in the study, specifying the indices representing each market. The data comprise aggregated stock market indices at the country level, with the exception of Brent, Gold, and WTI, which are indices for spot price quotations in the respective commodity markets.

Market	Index	Market	Index	Market	Index
Belgium	BEL 20	India	Nifty 100	Singapore	MSCI
Brazil	Bovespa	Indonesia	JKSE	Slovakia	SAX
Brent	_	Ireland	ISEQ	South Africa	JTOPI
Canada	TSX	Italy	Italy 40	South Korea	KOSPI 100
China	CSI 1000	Japan	N 225	Spain	IBEX 35
Colombia	COLCAP	Mexico	MXX	Sweden	OMXS 30
Czech	OETOB	Morocco	Moroccan	Switzerland	SMI
Denmark	OMX	Netherlands	AEX	Tunisia	Tunindex 20
Finland	OMX 25	New Zealand	NZ 50	U.K.	UK 100
France	CAC 40	Norway	OSEAX	U.S.	S&P 500
Germany	DAX 30	Oman	MSM 30	UAE	DFMG
Gold	_	Peru	S&P Lima General	WTI	_
Greece	ATG	Portugal	PSI 20		
Hungary	Budapest SE	Qatar	QSI		

2. Data

We collect daily prices for 40 financial and commodity (asset) markets around the world, as presented in Table 1. The data were sourced from investing.com from 14 November 2014 to 9 April 2022. Volatility is unobserved directly but can be calculated from the price data in various ways depending on the analysis goals. In this paper, we calculate it using the range-based measure developed by Parkinson (1980) as:

$$\sigma_t^2 = \frac{1}{4ln2}[ln(H_t) - ln(L_t)]^2 \tag{1}$$

where H_t is the maximum price on day t, and L_t represents the minimum price on the same day. The Parkinson's range-based measure incorporates the full spectrum of intraday price fluctuations, allowing for a nuanced estimate of volatility by using both intraday high and low prices. This feature makes this measure a better choice for our study compared to the standard measures of volatility. For instance, the rolling-window variance method, as an alternative measure, predominantly relies on closing prices and may miss the information that intraday highs and lows can offer. Moreover, in long time series, the rolling-window variance method could over-emphasize older observations, which may not be as pertinent to the contemporary volatility calculations. This is critical for our study as we aim to delve into intraday dynamics. Empirical evidence from the literature also underlines the superiority of volatility estimators derived from high-low prices over traditional estimators (Beckers, 1983; Bali and Weinbaum, 2005; Smales, 2022). Therefore, our choice of Parkinson's range-based volatility measure is arguably more appropriate for our research objective.

Table 2 presents the descriptive statistics for the markets under consideration. Standard deviations confirm that WTI and Brent have the highest variations, respectively. Notably, these two benchmark qualities are traded beyond the borders of any specific country. As highlighted by Junttila et al. (2018), over the past two decades, a strong trend of financialization has led to the development of speculative characteristics in these markets. This shift signifies that commodities like Brent and WTI are influenced by a diverse range of international factors, leading to more pronounced and intricate volatility patterns compared to assets that are tied to the economic landscape of a single country. Among the country-level stock markets studied, the Greek market shows the largest variations, whereas the stock markets based in Oman, Slovakia, and Tunisia exhibit the lowest variations, respectively. In addition, all data series are highly skewed. Furthermore, we check the stationarity of the volatility series using the Augmented Dickey-Fuller (ADF) test, whose null hypothesis implies the existence of a unit root. The results, presented in the last column of Table 2, confirm the stationarity for each series at the 5 % significance level.

In our initial analysis, the time series data for range-based volatility from the Swedish and Canadian markets were non-stationary. To address this, we applied the differencing method—a standard technique in time series analysis. By calculating the differences between consecutive observations, we transform a non-stationary series into stationary ones, removing any unit roots from the data generating process. This adjustment was crucial for the Swedish and Canadian markets, ensuring that our analyses across all markets are based on stationary time series observations.

The United Arab Emirates (UAE) market's ADF-test statistic stands out as positive, warranting further examination. We employed the Supremum Augmented Dickey-Fuller (SADF) test (Phillips et al., 2011) to investigate potential explosiveness in the data series. The resulting test statistic is 1.3435, which falls below the 95 % critical threshold of 3.026, indicating no evidence of explosiveness in the series. Additionally, we used the Zivot and Andrews (1992) test to check for a structural break in the UAE series. With a test statistic of −8.4133, which is more negative than the typical critical values, there was evidence of one structural break on 6 March 2017. This break is attributable to substantial governmental regulatory changes.

We also extract political news from investing.com. We choose this website because it is known for its comprehensive and publicly available collection of financial and political news. Not only does this site produce its own content, but it also aggregates news from a plethora of trusted sources. Notably, 97 % of our sample are directly sourced from Reuters, a globally recognized news agency, ensuring the credibility and reliability of our data. The remainder of the news is generated by either investing.com itself or other well-known outlets, such as Seeking Alpha. Our choice to exclusively rely on investing.com is driven by its consistency in reporting, representation of trustworthy news sources, and structured presentation which facilitate efficient data extraction.

A total of 23,986 news headlines were collected for the period from 14 November 2014 to 9 April 2022. We examine this period first because this timeframe corresponds to the availability of our news data. From 14 November 2014, there is a continuous stream of political news on investing.com. Secondly, this period encompasses various subperiods of contemporary relevance, including dates of intense global political conflicts (such as U.S.-China trade conflict and unrest in the Middle East), local conflicts (such as the two U.S. elections and Brexit), and periods of peace and prosperity (such as the U.S.- Iran nuclear deal). These subperiods are crucial for understanding the significance of the full spectrum of political news. Finally, our news sample delivers a coverage of publicly available political news, accessible to a broad investor audience.

Our choice to focus on news headlines rather than entire articles is based on several considerations. Notably, our news sample, sourced from reputable outlets such as Reuters, ensures the absence of misleading or overly sensationalized headlines. Our analytical tool, which employs semantic sentiment analysis, is adept at capturing the main sentiment embedded within headlines. This contrasts with earlier research methodologies that relied on word counts, necessitating a broader content scope. Furthermore, headlines are designed to succinctly convey the essence and primary sentiment of an article (Li et al., 2019). This approach has also been adopted in previous studies such as Chan (2003) and Abdollahi (2023).

Figure 1 illustrates the distribution of news articles over time. Notably, there is not a single day without news coverage. The peak is observed on 9 November 2016, with 50 articles, predominantly centered around Trump's U.S. election victory and the implications for

Table 2
Descriptive statistics. This table shows descriptive statistics for the volatility data from 40 financial markets over the period from 14/11/2014 to 9/4/2022. Values in the first column present the daily mean for each volatility series followed by the minimum and maximum values in the next two columns. SD stands for standard deviations. Numbers in parentheses in the last column show the p-value at the 5% significance level. Swedish and Canadian market observations were made stationary by taking the first difference of the original series.

Market	Mean ($\times10^4$)	Minimum ($\times10^4$)	Maximum ($\times10^4$)	SD ($\times10^4$)	Skewness	ADF
Belgium	0.77	0.02	48.69	1.92	13.474697	−7.98 (0.0)
Brazil	2.10	0.07	170.16	6.39	15.52284	−6.874 (0.0)
Brent	6.58	0.0	619.29	22.83	18.069608	−8.410 (0.0)
Canada	0.49	0.01	31.54	1.76	12.723396	−9.716 (0.0)
China	2.07	0.05	58.48	3.97	5.702178	−4.905 (0.0)
Colombia	1.00	0.01	252.35	6.92	28.850131	−3.45 (0.0094)
Czech	1.17	0.06	56.91	3.16	10.321957	−3.245 (0.0175)
Denmark	0.69	0.02	22.66	1.24	7.410309	−8.301 (0.0)
Finland	0.86	0.01	25.97	1.56	7.701784	−6.807 (0.0)
France	0.87	0.006	29.423	1.81	8.737113	−7.98 (0.0)
Germany	0.93	0.007	33.77	1.81	8.794246	−12.784 (0.0)
Gold	0.78	0.00	25.72	1.56	8.701309	−8.891 (0.0)
Greece	2.28	0.03	243.36	7.86	18.969694	−9.333 (0.0)
Hungary	1.27	0.04	68.74	3.65	12.110297	−12.136 (0.0)
India	0.75	0.00	104.76	2.93	26.186686	−7.961 (0.0)
Indonesia	0.63	0.02	39.59	1.61	12.680361	−6.567 (0.0)
Ireland	1.25	0.00	125.55	4.02	19.646137	−7.602 (0.0)
Italy	1.29	0.04	78.53	3.06	16.028916	−12.768 (0.0)
Japan	0.70	0.00	34.41	1.69	9.937168	−9.714 (0.0)
Mexico	0.77	0.03	30.43	1.36	10.213693	−6.623 (0.0)
Morocco	0.30	0.003	30.73	1.06	17.896038	−6.801 (0.0)
Netherlands	0.76	0.01	31.45	1.64	9.402736	−7.968 (0.0)
New Zealand	0.41	0.00	46.53	1.60	17.564566	−7.980 (0.0)
Norway	0.92	0.03	70.57	2.54	17.068664	−7.590 (0.0)
Oman	0.17	0.00	14.56	0.63	14.110191	−13.531 (0.0)
Peru	0.81	0.01	43.75	2.27	11.682557	−9.167 (0.0)
Portugal	0.78	0.03	23.38	1.35	8.168002	−7.954 (0.0)
Qatar	0.55	0.00	12.15	0.94	5.255814	−14.73 (0.0)
Singapore	0.46	0.00	22.55	0.96	11.203826	−6.545 (0.0)
Slovakia	0.22	0.00	8.37	0.56	5.213452	−5.777 (0.0)
South Africa	1.11	0.01	83.64	3.01	18.268946	−7.454 (0.0)
South Korea	0.67	0.03	48.72	1.69	16.323285	−6.696 (0.0)
Spain	1.06	0.00	42.83	2.13	10.170697	−9.292 (0.0)
Sweden	0.84	0.04	28.89	1.61	9.466635	−13.113 (0.0)
Switzerland	0.67	0.02	88.48	2.78	21.491142	−10.486 (0.0)
Tunisia	0.26	0.00	7.99	0.39	8.745990	−7.708 (0.0)
U.K.	0.66	0.01	21.36	1.45	8.736485	−6.715 (0.0)
U.S.	0.71	0.01	26.48	1.78	8.094311	−7.338 (0.0)
UAE	1.10	0.03	55.13	2.90	8.958275	9.563 (0.0)
WTI	8.41	0.00	748.4	30.87	13.894177	−7.183 (0.0)

his foreign policy. This is closely followed by 4 November 2020, registering 43 articles primarily focused on the U.S. presidential election again. Another spike is seen on 7 November 2018, with 39 articles, emphasizing the U.S. House election and potential shifts in foreign policy under the Democrats.

The majority of the news sample originates from the U.S., which is understandable given that studies indicate that nearly half of the global population follow the U.S. news.[2] However, our news sample also includes regional and national news to some extent, covering topics ranging from ISIS deployment in the Middle East, OPEC oil price conflicts, and conflicts between South Korea and Japan, to the governmental policy to raise house taxes in South Korea, the French presidential election, the Hong Kong protests, and more.

Our news sample comprises exclusively English-language articles, aligning with prevalent practices in text analysis in finance. A primary rationale behind this is the global prevalence and accessibility of English news, which significantly influences investor decisions worldwide. While some articles in our sample do not specify an author, being attributed instead to *staff*, others have named authors. However, the individual identities or cultural backgrounds of these authors remain unspecified. Our analysis prioritizes the sentiment interpretation of news as received by investors, rather than its inherent objectivity. The goal is to capture the sentiment landscape that investors are likely to navigate when making decisions.

An important issue to consider is the time zones of the markets in our dataset. For example, the New Zealand market is closed when European markets operate. Therefore, a news item published during European market hours typically impacts the New Zealand market

[2] https://www.pewresearch.org/global/2018/01/11/publics-around-the-world-follow-national-and-local-news-more-closely-than-international/.

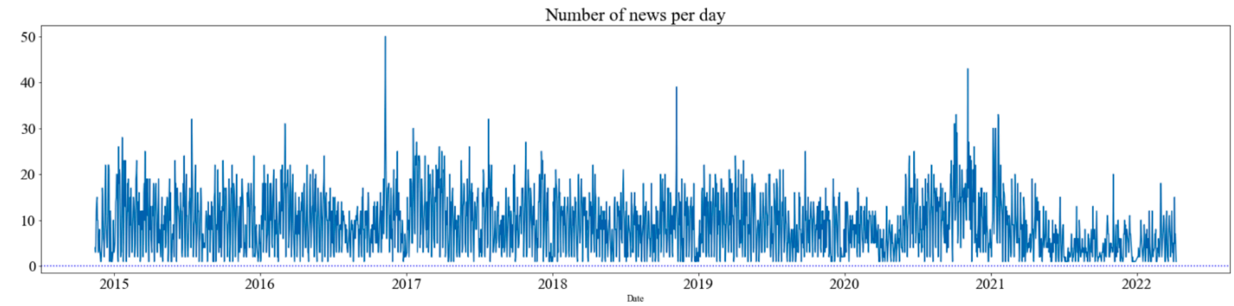


Fig. 1. The number of news articles over the sample. This figure illustrates the daily quantity of news articles from 14/11/2014 to 9/4/2022, scraped from the investing.com.

on the following day. Although we include lags in our calculations, we also partition the markets into four time zones: America, Europe, Central Asia, and Australia. This practice follows the approach of Kia et al. (2018), and we adjust the sentiment index for each market accordingly.

3. Methodology

3.1. Sentiment extraction

We use the BERT model, proposed by Devlin et al. (2018) and developed by Google, which has recently been adopted for textual analysis in the finance domain due to its cutting-edge capabilities (e.g. Jiang et al., 2022a,b; Costola et al., 2023; Abdollahi et al., 2024). As our focus is on applying political news to a finance context, we fine-tune the BERT using financial PhraseBank developed by Malo et al. (2014). The PhraseBank contains news sentences labeled by finance experts based on the potential impact of the news content on market prices: positive, negative, or neutral. The BERT predicts these probabilities for each piece of news, and the sentiment score is calculated by subtracting the probability of negative sentiments from that of positive sentiments. Therefore, the final sentiment score ranges from -1 (most negative) to 1 (most positive). Each day's sentiment score is the average of the scores from all news stories of that day. This approach aligns with common practices in sentiment index construction, as demonstrated in Abdollahi (2023) and Costola et al. (2023). To ensure the consistency of our sentiment analysis, we draw upon the confidence theory by Griffin and Tversky (1992). This theory implies that the strength or saliency of news, as indicated by the number of articles in our context, influences the sentiment index. On days with multiple news articles about a particular event, these articles are likely to have similar sentiment scores, especially if the event is highly salient. By averaging the scores of these articles, we capture the cumulative sentiment impact of this salient event on the market for that day.[3]

3.2. Volatility connectedness

We follow the framework proposed by Diebold and Yilmaz (2012) to calculate the directional connectedness of range-based volatility in the markets to the PNI development. This allows us to capture the percentage of shocks in market volatility that is due to the PNI spreading. In doing so, we first run a $VAR(p)$ model on the vector of PNI and market volatility variables ($x_t = \sum_{i=1}^{p} \theta_i x_{t-i} + \epsilon_t$), where the moving average of this $VAR(p)$ representation is:

$$x_t = \sum_{i=0}^{\infty} \varphi_i \epsilon_{t-1} t = 1, \cdots, T$$

$$\varphi_i = \theta_1 \varphi_{i-1} + \theta_2 \varphi_{i-2} + \cdots + \theta_m \varphi_{i-m} \tag{2}$$

and x_t denotes a $(K \times 1)$ vector for the series, φ_0 is an $n \times n$ identity matrix which equals zero for $i < 0$, θ_i is the $n \times n$ autoregression coefficient matrix, and ϵ_t denotes the vector of error terms ($i.i.d.$). We use the Akaike Information Criterion to determine the optimal lag length in the VAR.

Next, we decompose the forecast error variance of the VAR approximations. The H-step-ahead forecast error variance decomposition of the i^{th} variable coming from the j^{th} variable is given by $\varphi_{ij}^{H} = \frac{\sigma_{ij}^{-1} \sum_{h=0}^{H-1} (e\hat{\text{Å}}_i \varphi_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e\hat{\text{Å}}_i \varphi_h \Sigma \varphi \hat{\text{Å}}_h e_j)}$, where σ_{ij} denotes the standard deviation for the error term in the j^{th} equation, Σ is the covariance matrix of the error term (ϵ_t) vector, and e_i presents a selection vector that equals one

[3] Considering the confidence theory, we recognize that the averaging might not fully capture the sentiment on days with multiple articles and multiple underlying events. To address this, we also examine an aggregate scoring approach as a robustness check, aiming to better represent the cumulative sentiment impact on such days.

for the i^{th} element and zero for the others. Finally, we acquire the directional volatility connectedness by normalizing the input of variance decomposition based on

$$C_{i\leftarrow j} = \frac{\varphi_{ij}^H}{\sum_{ij=1}^N \varphi_{ij}^H} \tag{3}$$

We compute the dynamic volatility connectedness through a 100-day rolling-window analysis, which provides daily directional volatility connectedness. This dataset indicates the extent of markets' volatility resulting from shocks in the PNI on a daily basis. We use these data for clustering.

3.3. Markets' clustering

We employ a genetic K-means algorithm (GKA) to cluster the markets based on their connectedness to the PNI. K-means is a widely used clustering algorithm whose aim is to cluster a set of n inputs into k clusters, where each data item belongs to the cluster with the nearest cluster centroid (mean) (MacQueen, 1967). The operation of K-means can be briefly described as follows: (i) take k data points as the initial cluster centroids, (ii) assign the remaining data points to their centroids based on the minimum distance criterion, (iii) offer an initial clustering, and (iv) repeat steps (ii) and (iii) until the centroids of clusters do not change, the data items remain in the same cluster, or an a priori defined maximum number of iterations is met.

Assume $X = \{x_1, x_2, \cdots, x_n\}$ is a dataset (here the daily connectedness series) in a d-dimensional Euclidean space $\mathbb{R}^d$, and $F = \{f_1, f, \cdots, f_m\}$ are the centroids of m clusters. Let $S = [s_{ik}]_{n\times m}$, where s_{ik} represent a binary variable that shows if the data item x_i is assigned to the k^{th} cluster, where $k = 1, 2, \cdots, m$. The objective function of the algorithm is $J(S, F) = \sum_{i=1}^n \sum_{k=1}^m s_{ik} \|x_i - f_k\|^2$. The aim of repeating the operation is to minimize the objective function using updated centroids and memberships as shown in Equations (4) and (5):

$$f_k = \frac{\sum_{i=1}^n s_{ik} x_{ij}}{\sum_{i=1}^n s_{ik}} \tag{4}$$

$$s_{ik} = \begin{cases} 1, if \|x_i - f_k\|^2 = \min\limits_{1\le k\le m} \|x_i - f_k\|^2 \\ 0, otherwise, \end{cases} \tag{5}$$

where $\|x_i - f_k\|$ is the Euclidean distance between the data item x_i and cluster centroid f_k. However, the shortcoming of k-means algorithm is that it gets trapped in the local optima and may fail to reach the globally optimal solution simply because it gets stymied at the first stable centroids and stops improving them for a better solution. Previous research shows that this drawback of k-means is solved using genetic algorithm which is an evolutionary optimization algorithm (Krishna and Murty, 1999). It does not cease at the first solution but continues to improve it, seeking the globally optimal solution through random alterations. The basic procedure in the genetic algorithm includes:

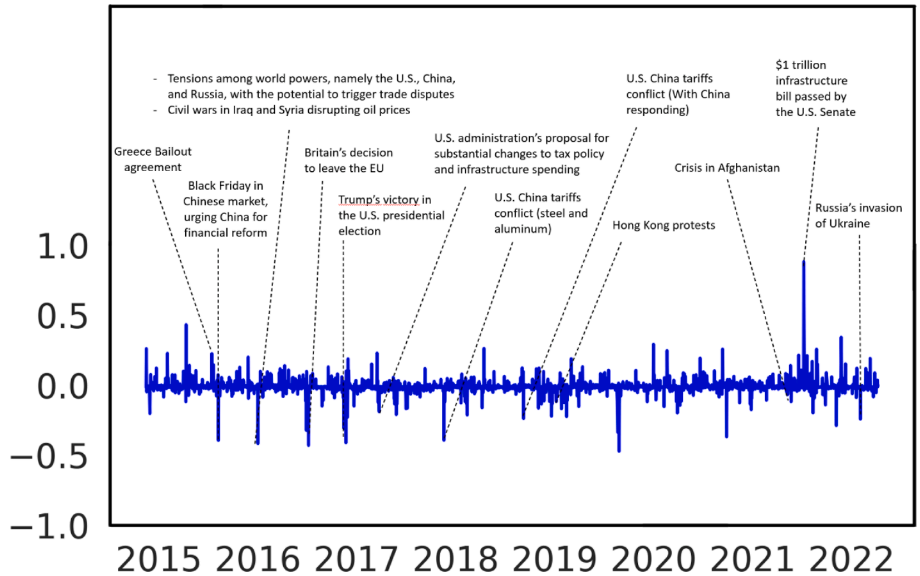


Fig. 2. Political news index (PNI). This figure shows the PNI from 14/11/2014 to 9/4/2022. The PNI was extracted from 23,986 political news headlines from the investing.com website using a financially fine-tuned BERT. Some eminent individual news events were retrieved and marked on the graph. However, certain events continued to occur or kept repeating during a period, e.g., Brexit. To avoid cluttering the figure, we mark such events only once on the graph.

(i) ***Initialization***: Generate a random population of potential k-means configurations
(ii) ***Evaluation:*** Each configuration is assessed using a fitness function, given by the silhouette score. This score, ranging from −1 to 1, measures how similar a market is to its own cluster compared to other clusters. A higher silhouette score indicates a better fit, showing that the clusters are well separated and cohesive.
(iii) ***Selection:*** Configurations with higher silhouette scores are preferentially selected.
(iv) ***Crossover:*** Pair individuals (configurations) undergo genetic crossover to share information.
(v) ***Mutation:*** Introduce subtle, random alterations to maintain diversity.
(vi) ***Repeat:*** Repeat until convergence criteria, like a fixed number of generations, are met. The configuration with the highest silhouette score across generations is chosen.

4. Empirical results

4.1. Textual analysis

We begin the empirical analysis by quantifying news sentiment. For this purpose, we first train the BERT on the financial PhraseBank dataset, using 80 % of the dataset for training and validation, and 20 % for the test set. The model achieves an accuracy of 0.83 on a scale from zero to one, where one represents the highest possible score. The financially fine-tuned BERT is then employed to extract sentiment scores for each news headline. When multiple articles are present for a particular day, we average their sentiment scores to obtain a consolidated measure for that day. This ensures that the PNI represents a holistic sentiment of the day's political events, rather than being swayed by a single article. The presence of multiple articles on a single day may suggest heightened political activity or significant events warranting extensive coverage. Therefore, such an approach aligns with the confidence theory (Griffin and Tversky, 1992), emphasizing not just the weight but also the strength of the evidence presented.

The PNI, illustrated in Figure 2, seems reasonably volatile as the political atmosphere is a dynamic matter that changes day by day. Rather than narrowing our focus to an individual political region, we consolidate various political news from around the world into a unified PNI. In today's interconnected global landscape, amalgamating political news into a single index allows us to account for the multifaceted nature of these impacts. This composite index serves as a representation of global politics, capturing the dynamics of the political milieu at any given time. Our foundation for the PNI rests on the assumption that while specific political events are transient, the underlying sensitivities of countries to a generalized political news index remain relatively consistent over time. Hence, investors should anticipate that both the distribution of political news and the countries' sensitivities to the PNI will generally maintain their relative consistency. The PNI serves as a semantic proxy for news sentiment and can be incorporated into any time series analysis, including the DY connectedness framework.

Before going further, and to provide a tangible representation of the relation between news sentiment and market reactions, Table 3 presents a selection of political news, their sentiment scores, and the subsequent daily change in prices for the pertinent markets. A clear pattern emerges where equity markets tend to exhibit directional shifts consistent with the sentiment of the news. For instance, negative news sentiment regarding Yemen's situation led to a dip in the UAE market prices by 0.21 %. Similarly, optimistic news sentiment in the U.S. corresponded with a slight uptick in market prices. Interestingly, while negative news typically depresses equity prices, it has the opposite effect on commodities like oil. As presented in the table, negative sentiment concerning an attack to oil tankers resulted in a rise of 1.01 % in WTI oil prices. This divergence shows the nuanced nature of market reactions based on asset class and reinforces the alignment between news sentiment and market direction. These data offer empirical evidence to substantiate the premise that markets do, in fact, respond to political news in anticipated manners based on the nature of the asset. Through our subsequent analyses, we aim to unveil discernible patterns in these sensitivities.

4.2. Directional connectedness

We estimate the directional dependence of individual market volatilities on the PNI development. We perform this dynamic analysis by rolling the fit over 100 days, using Equations (2) and (3). The DY framework approximates a VAR model as a vector of volatility and the PNI at time t. It then uses the variance decompositions to identify the fraction of connectedness within H-step-ahead error variance in forecasting VAR, with a forecasting horizon (H) set at 15 days. Figure 3 shows the estimated directional volatility connectedness, indicating what percentage of volatility in markets is due to the development of political news across daily intervals. As observed in Figure 3, the connectedness follows a time-varying pattern in all markets. The magnitude of volatility connectedness can drop to zero at some points among the markets studied. This fact signifies that the impact of political news on market volatility is not consistently present across the markets. We can interpret that political news, on average, contributes a relatively small amount to the market volatility most of the time, but it also sends irregular massive shocks to markets.

We can trace the connectedness to the news for each point on the connectedness graph, but that would be voluminous. Furthermore, we have enumerated some of the major events in Figure 2. However, we retrieve additional major events concerning the U.S. market and provide further evidence in Section 4.4. In November 2017, the then-U.S. President tapped the Fed Governor Jerome Powell to become the chairman of the Federal Reserve board of governors, stating basically that the U.S. economy requires sound monetary policy and prudent oversight. Some analysts criticized this appointment, and the uncertainty surrounding the future of monetary policy contributed to market volatility. During this time period, our calculated connectedness measure peaked at 31 %.

In addition to the tariff clashes between the U.S. and China, in November 2018, the U.S. midterm elections also contributed to market volatility. These elections had the potential to change the balance of power in Congress, which could have affected the Trump

Table 3
Examples of the impact of political news on market prices. This table provides an overview of selected political news articles, detailing their release date and time, sentiment scores, associated markets, and the daily change in prices of those markets.

News	Date and time	Sentiment score	Market	Change in prices (daily)
Yemen's Houthis say 26 killed in coalition airstrikes, UAE media blame Houthis	August 23, 2018 02:20 PM ET	−0.29	UAE	−0.21 %
Putin warns North Korea situation on verge of 'large-scale conflict'	September 01, 2017 11:38 AM ET	−0.61	South Korea	−0.13 %
Saudi Arabia says oil tankers hit off UAE coast, Iran calls for probe	May 13, 2019 06:34 ET AM	−0.39	Oil (WTI)	1.01 %
Trump says thinks Republicans have the votes to pass tax reform: Fox Business interview	October 20, 2017 11:45 PM	0.22	U.S.	0.05 %
Italy on path to rejecting reform referendum, PM Renzi to speak later	December 04, 2016 05:10 PM	−0.12	Italy	−0.18 %
Kerry: Good progress made on Pacific trade deal despite talks failure	August 4, 2015 8:51 AM	0.48	New Zealand	0.08 %
Trump downbeat ahead of trade talks with EU	July 24, 2018 08:57 PM ET	−0.55	Germany	−0.83 %
Trump ready to threaten Mexico with tariffs over immigration: Washington Post	May 30, 2019 05:18 PM ET	−0.56	Mexico	−1.38 %

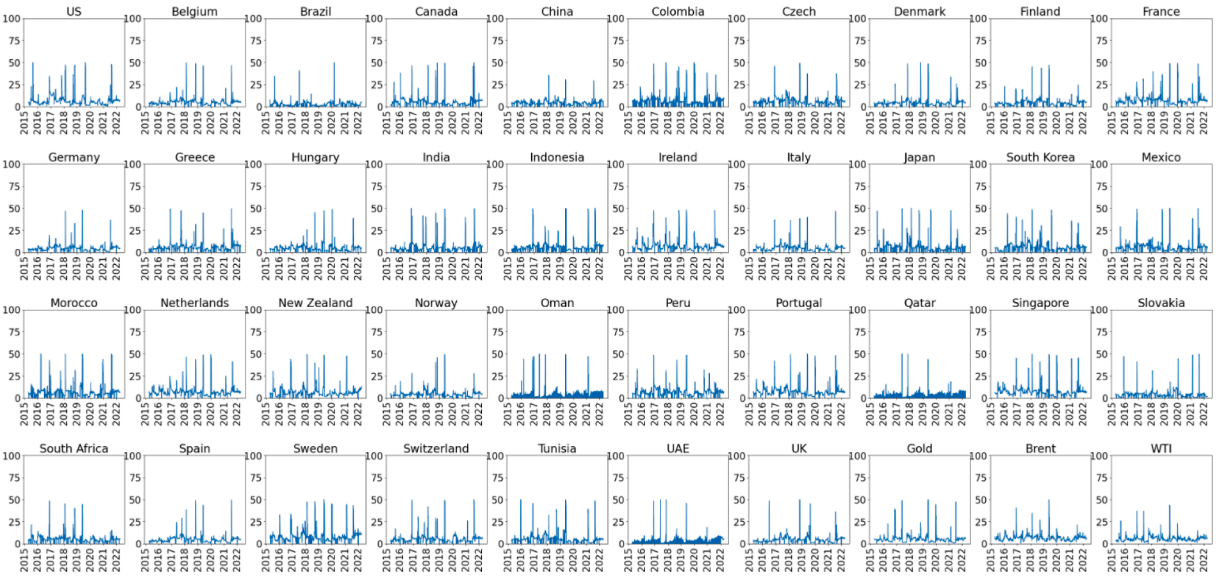


Fig. 3. Directional connectedness from political news to markets' volatility. These figures show the transmission mechanism from the Political News Index (PNI) development to international markets' volatility from 14/11/2014 to 9/4/2022 using a 15-day ahead forecast horizon (H = 15) and 100-day rolling window subsamples.

administration's ability to implement its policy agenda. Therefore, investors were uncertain about the potential impact of the election results on businesses and the market, and this uncertainty increased the connectedness measure to 47 %. In July 2021, the Federal Reserve held a policy meeting, and there was positive sentiment surrounding the U.S. Congress negotiation concerning the Infrastructure Act reflected in the news coverage, which lifted the connectedness to 25 %.

In Figure 3, each spike in the graphs represents a day when a specific market exhibited heightened sensitivity to political news. The presence and characteristics of these spikes offer insights into the interplay between political news and market volatility. It is appropriate to consider the spikes as indicative of moments where the PNI's influence on market volatility was particularly pronounced. Different markets exhibit these moments to varying degrees, and the underlying reasons can be multifaceted. By observing these connectedness patterns, we can infer not only the presence of a reaction to political news but also the relative intensity and duration of the impact across different markets. These data form the empirical foundation for our clustering analysis.

A noteworthy observation in the daily connectedness estimation relates to the importance of event-specific interpretations. While we use the PNI as a comprehensive proxy for the global political news, the connectedness framework primarily focuses on the shocks or fluctuations within the associated indices. This means we might observe simultaneous spikes in the connectedness of multiple markets. However, caution is required in attributing these coinciding spikes to a single political event, as their underlying reasons might vary considerably.

In April 2017, there was notable heightened connectedness in the French market. This spike can be attributed to the dual factors of uncertainties surrounding the impending French elections and a terrorist attack in Paris, which also had implications for other European markets. Headlines from the period included phrases like "*Islamic State claims Paris shooting, one policeman killed.*" Almost concurrently, geopolitical tensions were rising in the Korean Peninsula due to North Korea's missile tests, affecting the dynamics of Asian markets. Pertinent headlines from the same time frame reflected global concerns, with statements such as "*Fears of World War 3 spike as geopolitical tensions simmer.*"

In June 2017, we observed a pronounced increase in the connectedness of Qatar and other Middle Eastern markets. This heightened activity was in response to the blockade imposed on Qatar by its neighboring countries, evidenced by headlines such as *"Qatar vows no surrender in Gulf crisis as U.S., Kuwait seek solution."* Almost concurrently, the Brazilian market demonstrated a similar spike in connectedness. However, the catalyst here was distinct, driven by political concerns in Brazil, as highlighted by headlines like "*Brazil court opens case that could unseat President Temer."* In essence, the simultaneity of spikes does not necessarily imply a common cause. Analyzing the specific nuances and political developments of each market is essential to decode the true nature and cause of these volatilities.

We examine the sensitivity of the dynamic connectedness to the forecast horizon and the length of the rolling window. The results of these tests are presented in Appendix A1 for brevity. The sensitivity tests show no significant variation among the time-varying results. In other words, the results for volatility connectedness are insensitive to different values for the H-step-ahead forecast horizon and to different values for the rolling window, confirming robustness.

The estimated dynamic connectedness provides unique data on the directional volatility transmitted from political news to international markets. We use this novel dataset to cluster the markets based on their similarity in how they receive volatility from political news. Before that, we split the PNI data into positive and negative sentiments and estimate the static directional connectedness from these sentiments to market volatility. The static results furnish interesting insights, especially when contrasting news types, as they represent the average connectedness over the entire sample period. Table 4 presents the volatility connectedness of markets to positive and negative PNI, employing a 15-day ahead forecast horizon. A consistent observation across several markets is a pronounced connectedness to negative PNI compared to positive PNI. For illustration, the U.S. stock market's connectedness stands at 10.55 % for negative news compared to 8.72 % for positive news. A similar disparity is evident in the German stock market, which shows 6.79 % connectedness to negative news and a considerably lesser 1.31 % to positive news. Such patterns underscore the general sentiment that markets tend to react more profoundly to adverse political events than to favorable ones. However, some markets show results contrary to this trend. Notably, the Chinese stock market's connectedness to positive news, at 5.27 %, slightly surpasses its 4.35 % connectedness to negative news. This divergence might be attributed to China's unique political and economic landscape, which potentially perceives positive global news as more influential or advantageous for its domestic development and growth trajectory.

4.3. Clustering

To better understand the similarities in markets' behavior concerning volatility connectedness to political news, we apply the GKA to the daily directional connectedness data.[4] Initially, we determine the optimal number of clusters based on our dataset and optimize the hyperparameters of the K-means algorithm. For this purpose, we employ a genetic algorithm with specific parameter configurations. The population size is set to 50, and the algorithm is allowed to run for 1,000 generations. The probability for crossover events is calibrated at 0.7, while the mutation probability is kept at 0.2.

The genetic algorithm tests various configurations of K-means parameters—namely, the number of clusters (K), the initialization method, and the number of initializations—through 1,000 iterations (or generations). Each configuration of parameter sets is known as an individual. At the beginning of each generation, 50 different parameter sets (individuals) are evaluated based on their effectiveness in clustering markets. To assess the effectiveness of these parameters, the silhouette score is used as the fitness measure. This score considers both how tightly markets are grouped within a cluster (cohesion) and how well-separated markets are between clusters. The silhouette score provides a quantitative measure of how well the data are clustered; a higher silhouette score indicates better clustering quality. The algorithm then selects the most successful parameter sets of each generation for mating, where they combine features to create new sets. The probability of this mating is set at 0.7, meaning there is a 70 % chance for any two individuals to combine their characteristics and produce new individuals for the next generation. This process allows for the mixing of effective parameter combinations from different individuals, potentially creating even more successful configurations. The algorithm also introduces random changes (or mutations) to explore a wider array of configurations. This mutation probability is set at 0.2, indicating a 20 % chance that an individual's parameters will undergo random changes. This mechanism introduces new variations to prevent the algorithm from becoming stuck in local optima and encourages exploration of the entire parameter space. This cycle of selection, mating, and mutation gradually refines the parameters. The final result is a set of K-means parameters that yield the highest silhouette score. This score indicates the optimal clustering outcome, with the findings presented in Table 5.

Panels A and B in Table 5 present the optimal model configuration using connectedness to the PNI and the GPR, respectively. The differences in these configurations stem from the genetic algorithm's capacity to customize the K-means parameters specifically to the unique characteristics of each dataset. Therefore, employing any alternative parameter sets for these distinct datasets would result in

[4] Our initial dataset included three additional markets: the Bitcoin, Egypt, and Hong Kong. However, upon analysis using the Local Outlier Factor method, these markets were identified as outliers in terms of their characteristics in cluster analysis. The literature highlights the disruptive influence of outliers, and it is a standard practice to exclude such outliers from the dataset. Consequently, we decided to remove these three markets from our sample.

Table 4
Static volatility connectedness to positive and negative PNI. This table shows the estimation results of each market's volatility connectedness to positive and negative Political News Indices (PNIs) from 14/11/2014 to 9/4/2022 using a 15-day ahead forecast horizon.

Market	Negative	Positive	Market	Negative	Positive
Belgium	5.67	1.22	Morrocco	7.49	5.58
Brazil	6.17	0.81	Netherlands	8.30	0.40
Brent	7.07	2.60	New Zealand	1.83	0.67
Canada	4.17	1.66	Norway	4.58	2.16
China	4.35	5.27	Oman	2.01	2.09
Colombia	6.33	0.20	Peru	7.14	0.10
Czech Republic	7.75	0.89	Portugal	8.53	3.86
Denmark	4.56	2.02	Qatar	5.84	4.32
Finland	4.55	1.34	Singapore	7.03	4.45
France	7.73	5.99	Slovakia	2.47	1.52
Germany	6.79	1.31	South Africa	2.94	2.60
Gold	3.67	2.36	South Korea	4.25	4.42
Greece	3.44	2.13	Spain	6.25	2.14
Hungary	3.20	1.29	Sweden	10.98	7.92
India	4.32	0.32	Switzerland	1.82	1.17
Indonesia	3.35	0.40	Tunisia	4.37	2.31
Ireland	8.53	5.27	U.K.	5.72	3.15
Italy	5.16	2.64	U.S.	10.55	8.71
Japan	5.24	3.50	UAE	5.81	5.22
Mexico	3.94	3.03	WTI	8.00	2.66

Table 5
Optimal K-means parameters derived from a genetic algorithm. This table presents the optimal configuration for the K-means clustering algorithm as determined by the genetic algorithm. The table suggests the ideal number of clusters, the initialization method used, and the count of algorithm initializations to achieve the most reliable clustering results. The results in Panel A are based on the connectedness to the Political News Index (PNI), while the results in Panel B are based on the connectedness to the Geopolitical Risk Index (GPR).

	No. clusters	Initialization method	No. initializations	Fitness
Panel A				
PNI	8	Random	9	0.53
Panel B				
GPR	2	k-means++	1	0.46

less optimal clustering outcomes. The clustering based on GPR is examined in Section 4.4. For the PNI, Panel A suggests an optimal cluster count of eight. The initialization method is set to *random*, meaning that initial cluster centroids are chosen randomly from the data points rather than being predetermined. Furthermore, the algorithm undergoes nine initializations. Multiple initializations mean that the K-means algorithm is run several times with different starting centroids, ensuring a more comprehensive search for the best clustering solution.

Figure 4 offers a holistic view of market clustering and the Euclidean distances between markets based on their connectedness to the PNI. These clustering results indicate that markets within each cluster share the highest similarity in how they respond to political news. The closer the markets are to each other (i.e. the shorter the Euclidean distance), the more similar their sensitivity towards political news.

Starting from left to the right in Figure 4, we observe that Sweden and Singapore are combined into one cluster. These countries, representing developed markets, originate from distinct corners of the world: Northern Europe and Southeast Asia, respectively. Their grouping implies shared sensitivities, perhaps rooted in their intertwined trade and economic interactions. Both countries are key players in bilateral trade, with major Swedish corporations having a significant footprint in Singapore. Their shared stature as small, export-driven economies, high ranking in global competitiveness and innovation indices, and mutual emphasis on multilateralism collectively explain this clustering.

Following this, we find a second collection primarily of Western developed markets. This cluster notably combines European nations—Portugal, France, the Netherlands, and Ireland—with the U.S. Such a configuration prompts reflection on the deep-rooted historical, political, and economic ties binding these nations. These countries have been longstanding allies in global affairs and key players in shaping the international economic and political landscape. The U.S. and these European nations maintain extensive trade relationships. For many decades, the transatlantic economy has been the anchor of the global trading system. This robust economic linkage suggests a level of co-movement in their markets in response to global political events. The inclusion of Morocco in this ensemble is interesting. Its geographical proximity to Europe and longstanding economic and political relationships, especially with France, grant it a unique position. Morocco, which can also be considered a neighbor of Portugal's, often acts as a bridge between Africa and Europe, aligning its market reactions closely with its European counterparts. Recognizing the economic interrelations within this cluster is vital. According to the Morocco's foreign trade watchdog Office d'Echange (2022), the U.S., France, and the Netherlands are top investors in the country. Also, Ireland has historically been receptive to trade and capital, especially from the EU

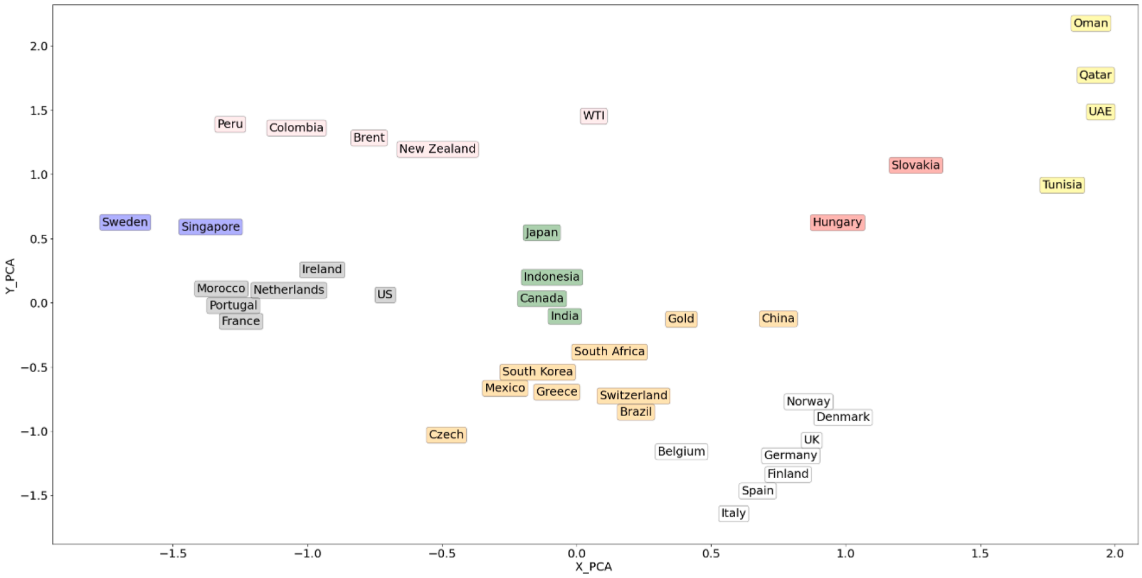


Fig. 4. International markets clustered by GKA based on volatility sensitivity to political news. This figure shows how international markets are clustered in eight groups based on the volatility connectedness to the Political News Index (PNI) from 14/11/2014 to 9/4/2022 using the Genetic K-means Algorithm (GKA). The X-axis represents the first principal component, and the Y-axis illustrates the second principal component. In our analysis, X-axis shows the long-term trend (average connectedness), while Y-axis illustrates the short-term variability in this connectedness. A shorter distance between points indicates greater similarity between markets.

and U.S. Its strong economic interdependence, especially with the U.S., means that structural shifts in the U.S. economy or policy can have impacts on Ireland. This aligns with the report by the Irish National Treasury Management Agency Economics (2018), which underscores the structural risks Ireland faces from the U.S.

Adjacent to this is a cluster heavily influenced by commodities, with Brent and WTI oil markets being particularly noteworthy. Within this group, South American neighbors, Peru and Colombia, have economies swayed by commodity price dynamics. New Zealand's inclusion, despite its geographical distance, hints at certain commodity trade patterns or market influences rendering it similarly responsive to global political news. Such mechanisms across these countries have been studied in the literature (e. g. Jaforullah and King, 2015; Chavez-Rodriguez et al., 2018; Otero, 2020).

Another cluster manifests geographic diversity, encompassing Japan, Canada, India, and Indonesia. Each of these countries has its own significant influence on the global economy, be it through tech innovations, natural resources, or manufacturing prowess. Their collective sensitivity could be traced back to established trade agreements and relations. For instance, Japan has trade pacts with both Canada (CPTPP), India (CEPA), and a significant investment history in Indonesia (the Japan-Indonesia EPA). Canada and India share trade and diasporic ties (Verma, 2023). The India-Japan partnership is significant and encompasses strategic, defense, security, and economic cooperation, impacting regional and global dynamics (Garge, 2016). Meanwhile, India and Indonesia are interlinked through the ASEAN-India Free Trade Area and are reliable partners with respect to the politico-strategic landscape of Asia (Shekhar, 2010). This cluster's cohesiveness could be attributed to their intertwined economic strategies that aim to foster mutual growth and stability.

There is a notably diverse cluster comprising the stock markets from the Czech Republic, Greece, Mexico, Brazil, South Africa, Switzerland, South Korea, and China. Gold, a universally recognized asset, is also included in the cluster. The cohesiveness of this cluster can be traced to a web of ties and agreements. The Czech Republic and Greece are closely tied to Switzerland, not just through their mutual EU membership but also through Switzerland's significant direct investments in their economies, as underscored by the Swiss Federal Department of Foreign Affairs (2019a,b). Swiss companies are instrumental in these countries, creating jobs and stimulating economic activity. Mexico and Brazil, as members of the Latin American Integration Association and the two largest economies in Latin America, promote regional economic collaboration. Brazil connects to South Africa through the IBSA Dialogue Forum, and with China as part of the BRICS economic bloc. Brazil and South Korea deepen trade and investment ties through a bilateral trade and investment promotion framework. The South Korea–China free trade agreement is another testament to the close economic relationship across this cluster in a way that China is the largest export destination of South Korea (Jung, 2023). Furthermore, the intertwining relations and investments, such as China's in Brazil (Santoro, 2022), South Africa (which is China's largest trading partner in Africa; see Sun, 2014), and Mexico (Peters, 2019), Switzerland's in Greece and the Czech Republic, and South Korea's in Brazil, indicate deeper economic meshing. In this notably diverse cluster, we observe a mix of emerging markets and key players in global trade and industry. Countries like Brazil, South Africa, the Czech Republic, Mexico, and China represent some of the most dynamic emerging economies. Their financial markets are particularly responsive to global political news that impacts international trade policies, commodity prices, and economic growth prospects. Switzerland and South Korea, although more developed, play crucial roles in global supply chains, especially in the pharmaceutical, technology, and automotive sectors. Their markets, too, are possibly sensitive to the same global dynamics that impact emerging economies. The inclusion of Gold in this cluster is significant. Gold's market dynamics are closely aligned with those of emerging markets, where it is seen as a hedge against political and economic uncertainties. This cluster, therefore, exemplifies a confluence of markets that, despite their geographic and developmental differences, have shown a common sensitivity to global economic and political shifts. This sensitivity is likely due to their interconnected roles in the global economy, where political events can have cascading effects across these diverse but interconnected markets.

There is also a cluster predominantly of European markets, including both EU members like Belgium, Italy, Spain, Finland, Germany, and Denmark, and non-EU countries such as the UK and Norway. The shared economic dynamics of the euro area influence the clustered EU nations, while the UK, despite Brexit, continues to exert financial influence across Europe. Norway, connected through the European Economic Area, also aligns economically with the EU. Hence, their shared economic mechanics and regional proximity could make them resonate similarly to political events.

As a cluster of their own, we observe Slovakia and Hungary, whose economic strategies during their transition and EU accession have emphasized similar trade openness and competitive tax rates to attract foreign direct investment (Torrisi, 2015). Such shared economic policies likely contribute to their parallel sensitivities to global political narratives due to intertwined political and economic landscapes. Concluding the sequence, a cluster emerges spotlighting Middle Eastern nations: Oman, Qatar, the UAE, and Tunisia. These markets, apart from Tunisia, belong to the Persian Gulf region and share many economic, cultural, and political ties like the Gulf Cooperation Council. These countries, as highlighted by Hanieh (2018), have used their substantial oil and gas resources to establish a recognizable presence in global finance, thereby influencing not only regional dynamics but also the broader geopolitical landscape. Tunisia, while geographically part of North Africa, shares profound Arab ties, which are similarly reflected in their market's dynamics. These shared characteristics and the collective role they play in the global economic order substantiate their clustering, as they respond in tandem to the shifts in political and economic narratives that reverberate through the Gulf's finance capital and its expansive investment strategies in the region.

A notable fact is that these clusters should not be viewed in isolation. Their formation suggests that markets within the same cluster have, on the whole, exhibited similar reactions in terms of their market volatility from the PNI during our study period. However, being part of one cluster does not mean a market lacks similarities with those in another. For instance, based on Euclidean distance, India is closer to South Africa, which is grouped in another cluster together with other BRICS countries (excluding Russia, which is not studied), than to Japan which is in its own cluster. This is characteristic of the clustering process because the method first calculates the Euclidean distance between markets, maps them, and then forms clusters by maximizing the objective function, which minimizes the sum of squared distances between the data points and their respective cluster centroids. Therefore, this specific clustering arrangement offers the optimal value for our objective function. However, it is essential to note that the Euclidean distance between any two markets remains constant, regardless of their cluster assignments.

Digging deeper into the inter-market distances provides even more insights. Both the U.S. and China, despite their placement within clusters, maintain slightly more distance from their respective cluster members. This highlights their unique status as the world's first and second-largest economies. Additionally, an interesting observation is Canada's proximity (based on the Euclidean distance) to the U.S. This closeness refers to the similarity in their market reactions, reinforcing the belief that regional ties can play a role in the market dynamics.

Another interesting fact is the distance between the Brent and WTI oil market volatilities, even though they are grouped in one cluster. This could be due to two inherent distinctions between the markets of these two types of crude oil. One aspect is related to geopolitical events; during times of crises or political upheaval, Brent crude oil prices tend to surge, whereas the WTI oil market is generally less affected because the commodity itself is based in landlocked areas. Additionally, the Brent type is transported by sea, while the WTI type is mainly consumed inland. As a result, the impact of political tensions on sea transportation also affects Brent prices. Another aspect could be attributed to the fact that the Brent market is, on average, more efficient than the WTI market (Okoroafor and Leirvik, 2022). Thus, the impact of political news is incorporated more smoothly into Brent crude oil prices. This factor may also explain why the Brent market reactions are closer to the U.S. market than the WTI reactions. Furthermore, speculative activity and its susceptibility to political news may also play a role in this regard. Overall, these factors contribute to the differences in how the Brent and WTI markets respond to political news.

In Table 6, we present the average volatility connectedness to the PNI for each cluster. Notably, we observe a decreasing trend in average connectedness across clusters. The cluster comprising Sweden and Singapore stands at the forefront, exhibiting the highest

Table 6

Average connectedness to PNI for each cluster. This table presents the clusters identified by the Genetic K-means Algorithm (GKA) and their associated average volatility connectedness to the Political News Index (PNI).

Cluster	Average	[Min, Max]
Sweden, Singapore	8.01 %	[7.67 %, 8.35 %]
US, France, Netherlands, Ireland, Portugal, Morocco	7.28 %	[7.01 %, 7.56]
WTI, Brent, Peru, Colombia, New Zealand	6.70 %	[5.68 %, 7.34 %]
Japan, Canada, India, Indonesia	5.96 %	[5.79 %, 6.03 %]
Brazil, China, Czech, Gold, Greece, Mexico, South Africa, South Korea, Switzerland	5.77 %	[4.31 %, 6.42 %]
Belgium, Denmark, Finland, Germany, Italy, Norway, Spain, UK	4.80 %	[4.55 %, 5.36 %]
Hungary, Slovakia,	4.67 %	[4.32 %, 5.02 %]
Oman, Qatar, Tunisia, UAE	4.12 %	[3.09 %, 3.91 %]

average connectedness at 8.01 %. This is closely followed by the grouping of the U.S., France, the Netherlands, Ireland, Portugal, and Morocco with 7.28 %. On the opposite end of the spectrum, the cluster with Oman, Qatar, Tunisia, and the UAE records the least connectedness at 4.12 %. Overall, as we move from left to right in Figure 4, the average connectedness reduces across clusters. The last column in Table 6 shows the range of average connectedness for each cluster, specified as [Min, Max], indicating the breadth of average connectedness variations within each group.

In Figure 4, the x-axis (X_PCA) represents the first principal component, capturing the greatest variance across the dataset of connectedness to political news. This axis reflects a linear combination of the dataset's features, correlating closely with the average connectedness and representing a long-term trend within the data. Conversely, the y-axis (Y_PCA) identifies an orthogonal dimension, revealing short-term fluctuations in the long-term trend of the connectedness. A progression from the bottom to the top of Figure 4 indicates an increase in the day-to-day variability of this connectedness. Overall, this arrangement not only captures the varying degrees of market reactions to political news across the clusters but also highlights a discernible pattern in how different groups of countries and commodities resonate with global political events.

In our analysis, the connectedness findings highlight the pathways by which political news sends volatility in asset markets. We use this volatility connectedness to group markets into clusters. Recognizing clusters that have similar responses to political news or inter-market distances enables investors to better predict market behavior and devise tailored trading strategies, favoring their market interactions. However, while our clusters might suggest that markets *A* and *B* generally move together in response to political news, a specific event concerning a primary trading partner of market *A* might lead to a temporary divergence in their behaviors. For instance, Japan's decision to remove South Korea from its 'white list' of trusted trade partners caused significant volatility in both countries' stock markets. This occurred almost concurrently with the U.S.-China tariff conflict, underscoring the need to distinguish between specific events driving the connectedness. Such instances highlight the value of event-specific analysis that may sway market responses regardless of their cluster categorization. Our clustering captures average behaviors; however, investors should remain vigilant to temporal deviations from these patterns. To account for this, we conduct additional analyses across separate timeframes and various market volatility regimes. These analyses, presented in Appendix A2 for brevity, reveal some shifts in clustering under different conditions but confirm the general consistency and reliability of our primary findings.

Finally, we check the robustness of our clustering in three ways. First, we employ an alternative approach using Self-Organizing Maps (Vesanto and Alhoniemi, 2000) to cluster the markets. Second, we conduct the same analysis utilizing the net pairwise connectedness. Lastly, we reassess the clusters by aggregating daily sentiment scores to form the PNI, ensuring our findings are robust to different sentiment computation methods. The details are provided in Appendix A3–5. We observe no substantial differences in the results.

4.4. Comparing an alternative to the PNI

Previous literature provides a few indices that serve as quantitative proxies for politics, suitable for econometric analysis. The most analogous measure to the PNI is the GPR. For comparative purposes, we repeat the clustering using the GPR instead of the PNI. The dynamic connectedness shows a similar transmission pattern to that obtained using the PNI. Panel B in Table 5 presents the optimal parameters for the K-means algorithm using GPR-based connectedness derived from the genetic algorithm. It suggests an optimal cluster count of two. The initialization method is set to *k-means++*, which means the centroids are initialized in a manner that spreads them across the dataset, enhancing the likelihood of faster convergence and better cluster quality. This method selects centroids using a probabilistic approach that takes into account the distances between data points and existing centroids. Furthermore, the algorithm undergoes one initialization, meaning that it runs the K-means clustering process just once with a single centroid seed. For brevity, we present only the final clustering results.[5] Figure 5 shows the clustering using the GPR. The first cluster demonstrates an average daily connectedness to political news between 5.03 % and 13.38 %, with a collective average of 7.28 %. The second cluster displays average daily connectedness ranging from 2.77 % to 10.35 %, with a consolidated average of 6.79 %.

In our examination of clustering results derived from PNI and GPR, noteworthy similarities and distinctions emerge. Both analyses yield clusters amalgamating developed and developing markets. However, this is more pronounced for the GPR-based clustering. For instance, some developed markets like Japan and South Korea are grouped with some emerging markets such as the UAE and Colombia. A regional effect is also discernible in the clustering. For example, using the GPR, South Korea, Japan, China, and Indonesia are not only clustered together, but they also share minimal Euclidean distances, highlighting potential regional coherence in the political news impacts. Conversely, there are anomalies as well. Neighboring nations such as Peru and Colombia fall into separate clusters, as do certain Middle Eastern markets. These observations suggest that while geography might play a role in market clustering based on sensitivity to global political news, other influential factors such as political affiliations, trade agreements, and global strategies arguably have profound and time-varying impacts.

The most prominent difference between the two analyses is the number of clusters each dataset produced. The PNI resulted in eight clusters, whereas the GPR led to only two clusters. This implies that the PNI provides a more detailed and nuanced differentiation among countries based on their political news. The clusters are predominantly divided along geographical lines in the GPR results. The first cluster largely consists of markets from Europe, North America, and parts of South America. The second cluster comprises Asian, Middle Eastern, and South American stock markets and commodities.

[5] These results are not reported in the paper for the sake of brevity, but they are available from the authors upon request.

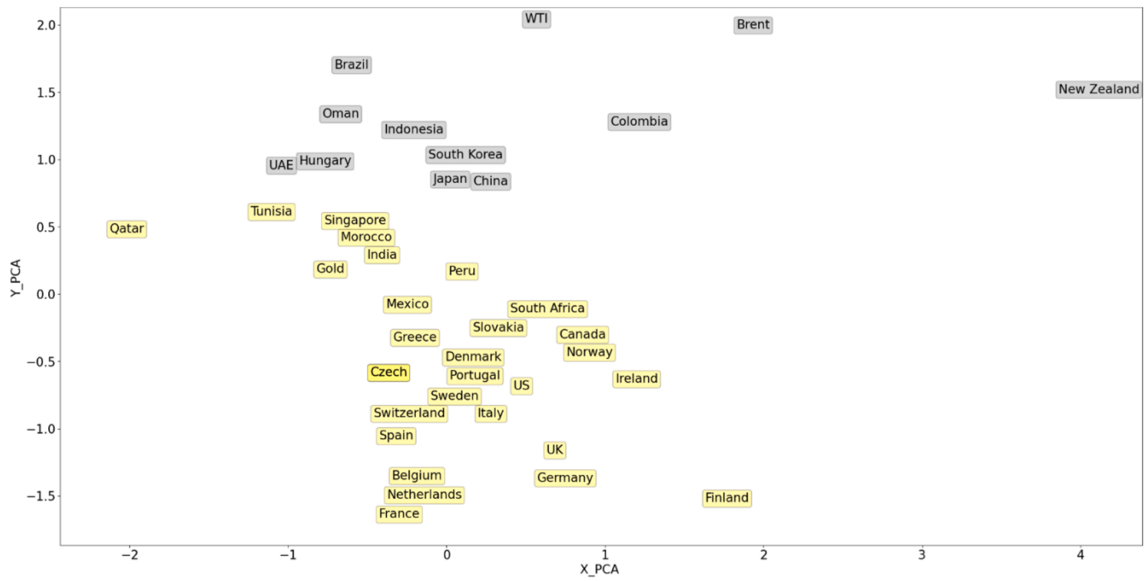


Fig. 5. International markets clustered by GKA based on volatility sensitivity to the GPR. This figure shows how international markets are clustered in two groups based on the volatility connectedness to the Geopolitical Risk Index (GPR) from 14/11/2014 to 9/4/2022 using the Genetic K-means Algorithm (GKA). PCA in each axis describes variations in market connectedness to the GPR. Shorter distance shows more similarity between the markets.

The differences in clustering, however, call for further scrutiny of the indices employed, which can be primarily investigated from two perspectives: frame of reference and measurement approach.[6] The GPR index focuses solely on the adverse aspect of geopolitical events and associated risks. According to its definition by Caldara and Iacoviello (2022), the GPR uses the term *risk* in its title, following a tradition in media that refers to geopolitical risk as a comprehensive phrase describing the consequences of global crises, tensions, and violence associated with wars, terrorism, and geopolitical struggles. On the other hand, the PNI is free from any presumptions and designed to capture the embedded sentiment in political news irrespective of whether the news is positive or negative. Therefore, the PNI is able to encompass the positive aspect of political news as well. To illustrate this point, we compare the U.S. market volatility connectedness to the evolution of both the PNI and GPR indexes, as shown in Figure 6. We observe similar spiky connectedness patterns, although the magnitude of the spikes may differ. For instance, Trump's victory in the U.S. election in November 2016 is more pronounced in the connectedness captured using the PNI. This outcome mainly stems from Trump's announced policy shifts that could raise trade tensions, increase protectionism, and introduce uncertainty. In March 2020, the World Health Organization declared Covid-19 a global pandemic. There is a spike for this event in the GPR but not in the PNI since the PNI focuses solely on political news, and this specific news was not categorized in politics by the news provider (investing.com). This is reasonable as the topic is more related to health and pandemics.[7] In August 2021, there was positive news about the U.S. Congress passing an Infrastructure Act, whose impact is captured only by the PNI. Lastly, the impact of the Russian invasion of Ukraine in February 2022 is more pronounced in the connectedness captured by the GPR, as 'war' is a fundamental keyword in constructing the GPR index. The rest of the pattern is almost similar. Although we could conduct similar comparisons for other markets, we omit these details for brevity, as they fall outside the primary focus of this study. In summary, the PNI captures both positive and adverse news, considering the entire range of news, while the GPR focuses solely on adverse events.

Another factor that requires consideration is the methods used for measuring and constructing the indices. The GPR utilizes a dictionary-based approach, specifying a list of words associated with geopolitical news and events and measuring their frequency in news articles. In contrast, the PNI employs a large language model, specifically the BERT, capable of producing semantic sentiment from news text. From a natural language processing perspective, using language models outperforms dictionary-based approaches due to several crucial features missing in the latter. For example, the BERT considers surrounding words and their relationships within a sentence, enabling a more accurate understanding of the expressed sentiment. In contrast, dictionary-based methods treat words in isolation, leading to a lack of contextual understanding and potentially inaccurate sentiment analysis. Additionally, the BERT can recognize negation and modifiers (e.g., very, extremely, etc.), which significantly impact sentence sentiment. These nuances are often challenging for dictionary-based methods to capture accurately. Furthermore, the BERT can disambiguate words with multiple

[6] The Pearson correlation between two indices is −0.46. The negative correlation arises from the PNI capturing both positive and negative aspects of political news (it ranges from −1 to 1), while the GPR solely captures adverse aspect (it ranges from 1 to higher positive values). When the GPR increases indicating more adverse political risk, the PNI moves towards its negative end, reflecting negative sentiment in the political news.

[7] GPR documentation also enumerates eight news categories considered for making the index, which are mostly about war and terror. Thus, unless for another reason, that spike can be hardly attributed to geopolitical news.

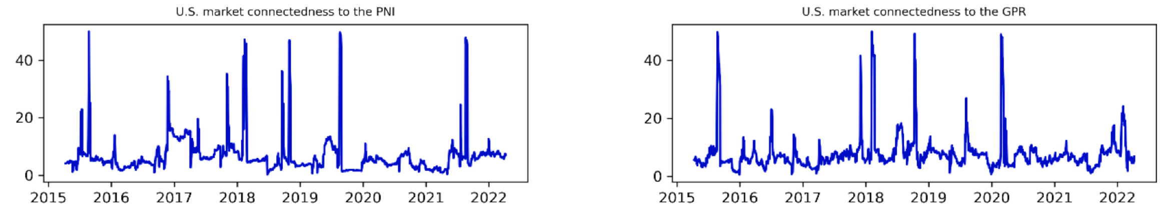


Fig. 6. Directional connectedness from the PNI and GPR to the U.S. market volatility. These figures show the transmission mechanism of political indices development to the U.S. market volatility from 14/11/2014 to 9/4/2022 using a 15-day ahead forecast horizon (H = 15) and 100-day rolling window subsamples.

meanings, ensuring that the correct sentiment is attributed to them, while dictionary-based approaches might struggle with polysemy. Lastly, BERT's domain adaptability is crucial, as it can be fine-tuned on specific datasets to suit particular domains or tasks, making it more adept at performing sentiment analysis on domain-specific texts. In the construction of the PNI, we fine-tune the BERT on financial language, allowing it to produce sentiment based on the perceived impact of news on market prices, an option not available with dictionary-based approaches.

Finally, we compare the quality of clustering obtained through the PNI and GPR using an internal evaluation metric for K-means clustering. For this purpose, we calculate the within-cluster sum of squares (WCSS) for both clusterings. WCSS measures the sum of squared distances between each data point and its assigned cluster center. Lower WCSS values indicate that data points within a cluster are closer to their centroid, suggesting better clustering. The WCSS for the PNI-based clustering is *4.37*, while the GPR clustering yields a higher WCSS of *47.15*. This significant disparity in WCSS can be attributed to the PNI connectedness generating more distinct clusters. However, both measures maintain the same scale of data (connectedness between 0 and 100) and dimensionality (number of markets). Also, the fitness score (silhouette score) values reported for both measures in Table 5 imply that the PNI-based clustering achieves a better fit as the silhouette score is higher. Based on these results, we conclude that the PNI-based clustering offers better-defined and well-separated clusters.

5. Conclusion

We cluster international asset markets based on their connectedness to political news using daily values from 40 international markets and 23,986 news headlines spanning the period from 14 November 2014 to 9 April 2022. We build a semantic sentiment index for political news (PNI) using the BERT model. We then use the PNI to measure the daily directional volatility connectedness from political news to the international asset markets based on the Diebold and Yilmaz (2012) framework. Our findings indicate that while political news often contributes a relatively small degree to market volatility, it can irregularly transmit significant shocks to the market. Furthermore, we observe that negative political news holds higher connectedness to market volatility than positive political news. Using the GKA, we cluster the studied markets into eight groups. Within each cluster, markets show more similar responses to political news compared to those in other clusters.

The empirical findings reveal the clustering of markets based on their responsiveness to political news. Practitioners may take these results into account when making investment diversification decisions across international markets. Given that the market volatility connectedness to political news can occasionally be heightened, future studies should explore the impact of political news on other aspects of the market. Additionally, examining the market volatility connectedness to other categories of news could also be useful for further clustering analysis. Regarding the construction of sentiment indices, future studies could explore metaheuristic methods to more effectively capture dynamic sentiment variability. Such approaches promise to add a better understanding of how sentiments evolve and influence market behavior.

CRediT authorship contribution statement

Hooman Abdollahi: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Juha-Pekka Junttila:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Heikki Lehkonen:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgement

Thanks are extended to the Editors and two anonymous reviewers for their suggestions. Hooman Abdollahi also thanks Espen Sirnes and Sturla Fjesme for their support during the conduct of this research at UiT. The data underlying this article will be made available on dataverse.no in the future.

Appendix 1

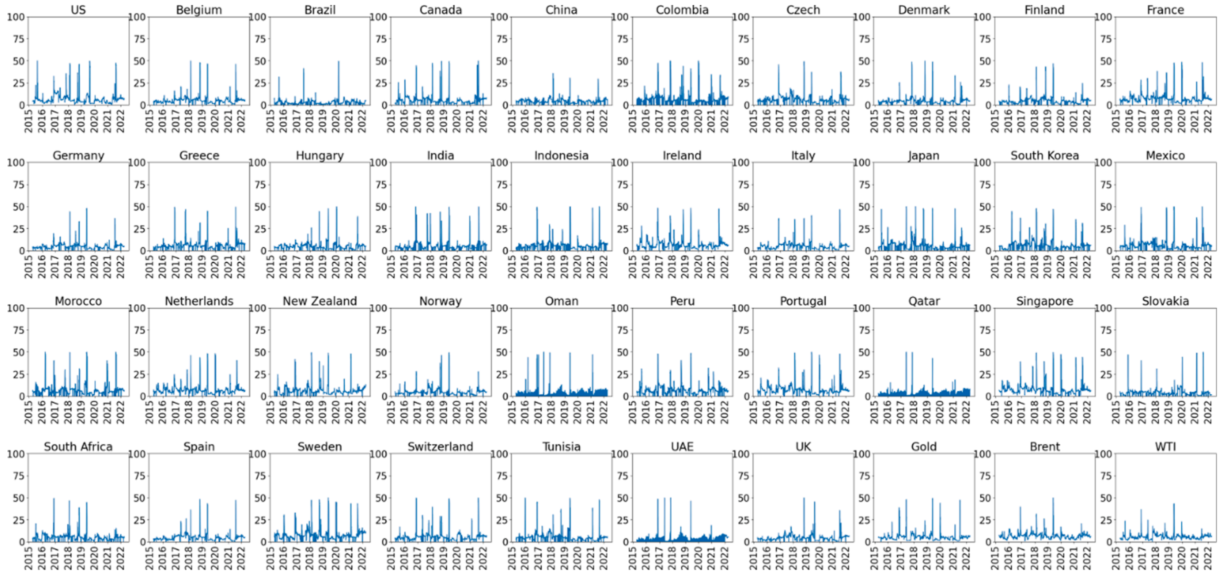


Fig. A1.1. Sensitivity analysis for dynamic connectedness. These figures show the transmission mechanism from the Political News Index (PNI) development to international markets' volatility from 14/11/2014 to 9/4/2022 using a 10-day ahead forecast horizon (H = 10) and 100-day rolling window subsamples.

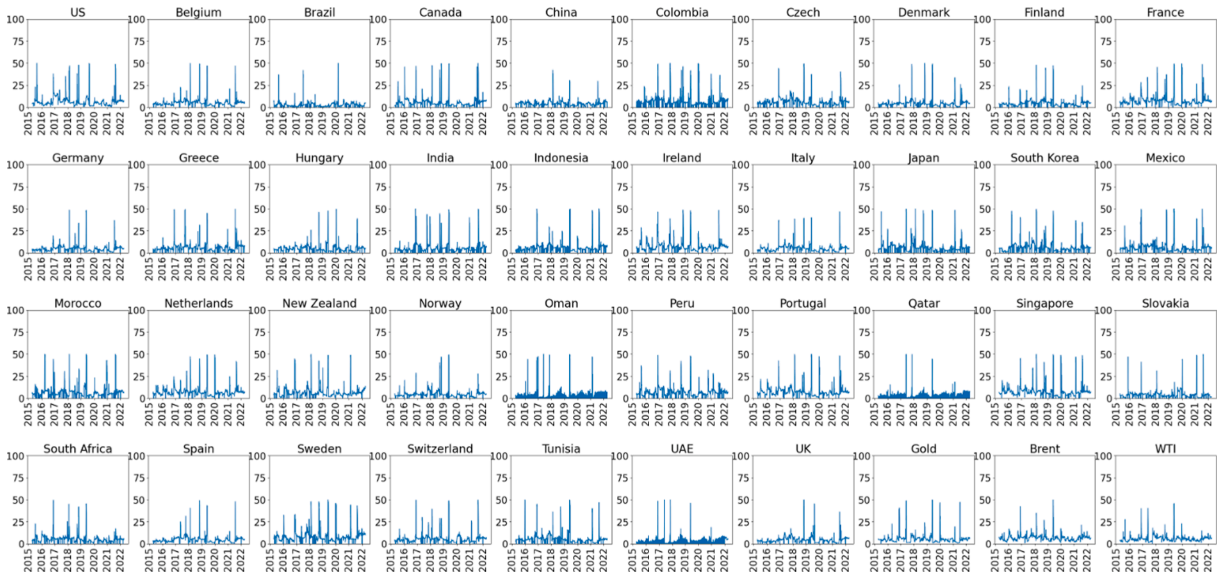


Fig. A1.2. Sensitivity analysis for dynamic connectedness. These figures show the transmission mechanism from the Political News Index (PNI) development to international markets' volatility from 14/11/2014 to 9/4/2022 using a 20-day ahead forecast horizon (H = 20) and 100-day rolling window subsamples.

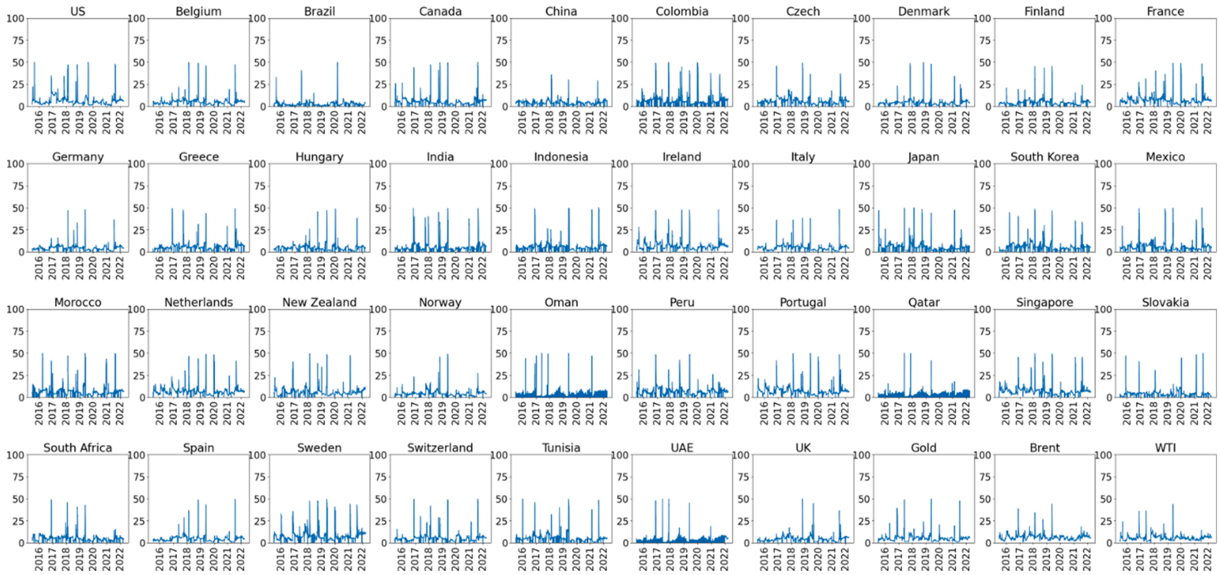


Fig. A1.3. Sensitivity analysis for dynamic connectedness. These figures show the transmission mechanism from the Political News Index (PNI) development to international markets' volatility from 14/11/2014 to 9/4/2022 using a 15-day ahead forecast horizon (H = 15) and 150-day rolling window subsamples.

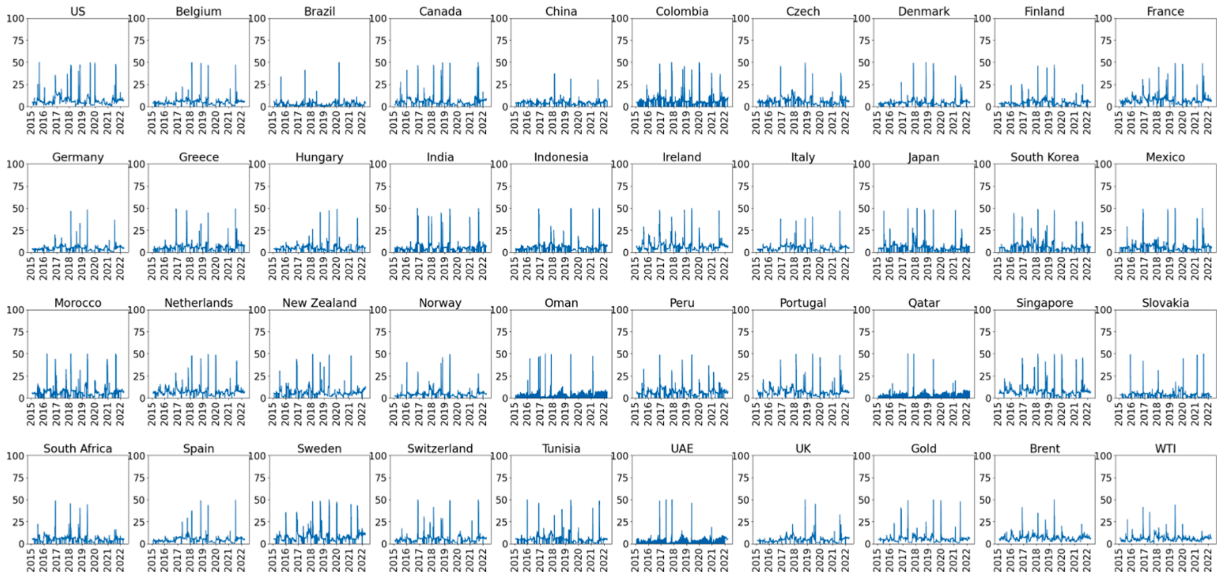


Fig. A1.4. Sensitivity analysis for dynamic connectedness. These figures show the transmission mechanism from the Political News Index (PNI) development to international markets' volatility from 14/11/2014 to 9/4/2022 using a 15-day ahead forecast horizon (H = 15) and 50-day rolling window subsamples.

Appendix 2

We divide the sample into two almost equal subperiods. This practice allows us to assess whether the clustering patterns observed in the overall sample persist or significantly change over time, shedding light on the dynamic nature of market behaviors. Each subperiod is analyzed using the same clustering methodology as in the main study.

Fig. A2.1 shows the clusters for each of the subperiods. In the first subperiod, spanning from April 2015 to December 2018, the clusters largely mirror those of the full sample, with a notable exception where the group of Canada, Japan, India, and Indonesia merges with another cluster. In the second subperiod, from January 2019 to April 2022, we observe some variations, but the majority of the clusters remain consistent. A significant shift is observed with Peru and Colombia forming a cluster of their own and Canada and Japan aligning with the U.S. cluster.

Fig. A2.2 presents a market co-occurrence matrix. Each matrix cell indicates the frequency of two markets being in the same cluster across the two subperiods and the entire sample. We find that the rate of co-occurrence (defined as appearing together in a cluster in at least two out of three analyzed periods) is approximately 65 %. This rate of co-occurrence suggests that, over time, the underlying clustering pattern demonstrates a good degree of stability. However, occasional deviations reflect the dynamic and evolving nature of global markets and their responses to political events. These deviations, while not predominant, are indicative of the subtle shifts in market dynamics and the impact of temporal factors. Thus, while our clustering analysis reveals a consistent trend, it also captures the fluidity and adaptability of markets in a changing global politics.

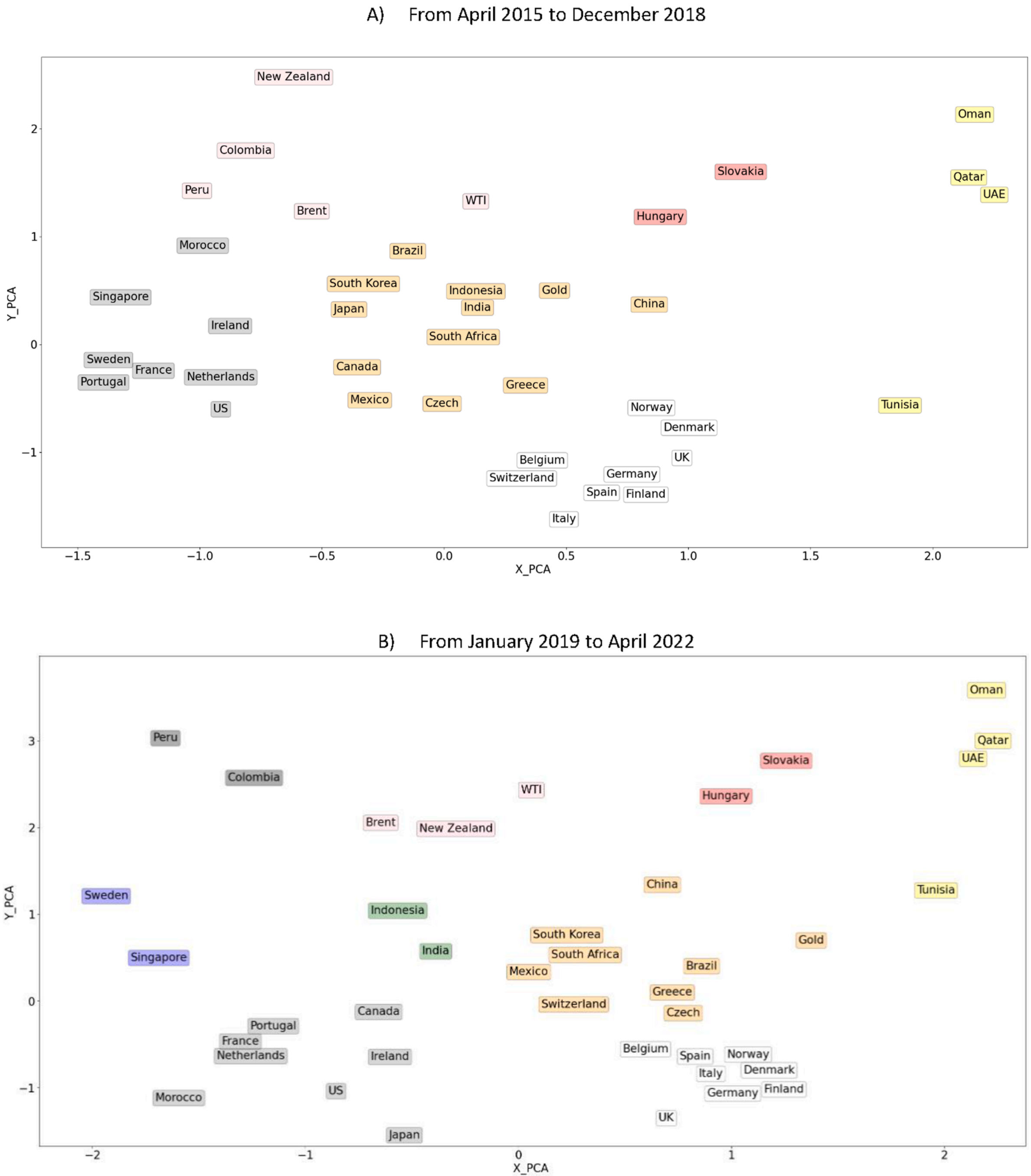


Fig. A2.1. Clustering international markets based on volatility sensitivity to political news across two subsamples. These figures show clustering across different subsamples using the same algorithm. Panel A shows clustering for the period from April 2015 to December 2018. Panel B displays clusters using data from January 2019 to April 2022. Note: As our connectedness analysis is based on a rolling window, the first 100 days of the sample are used for data generation.

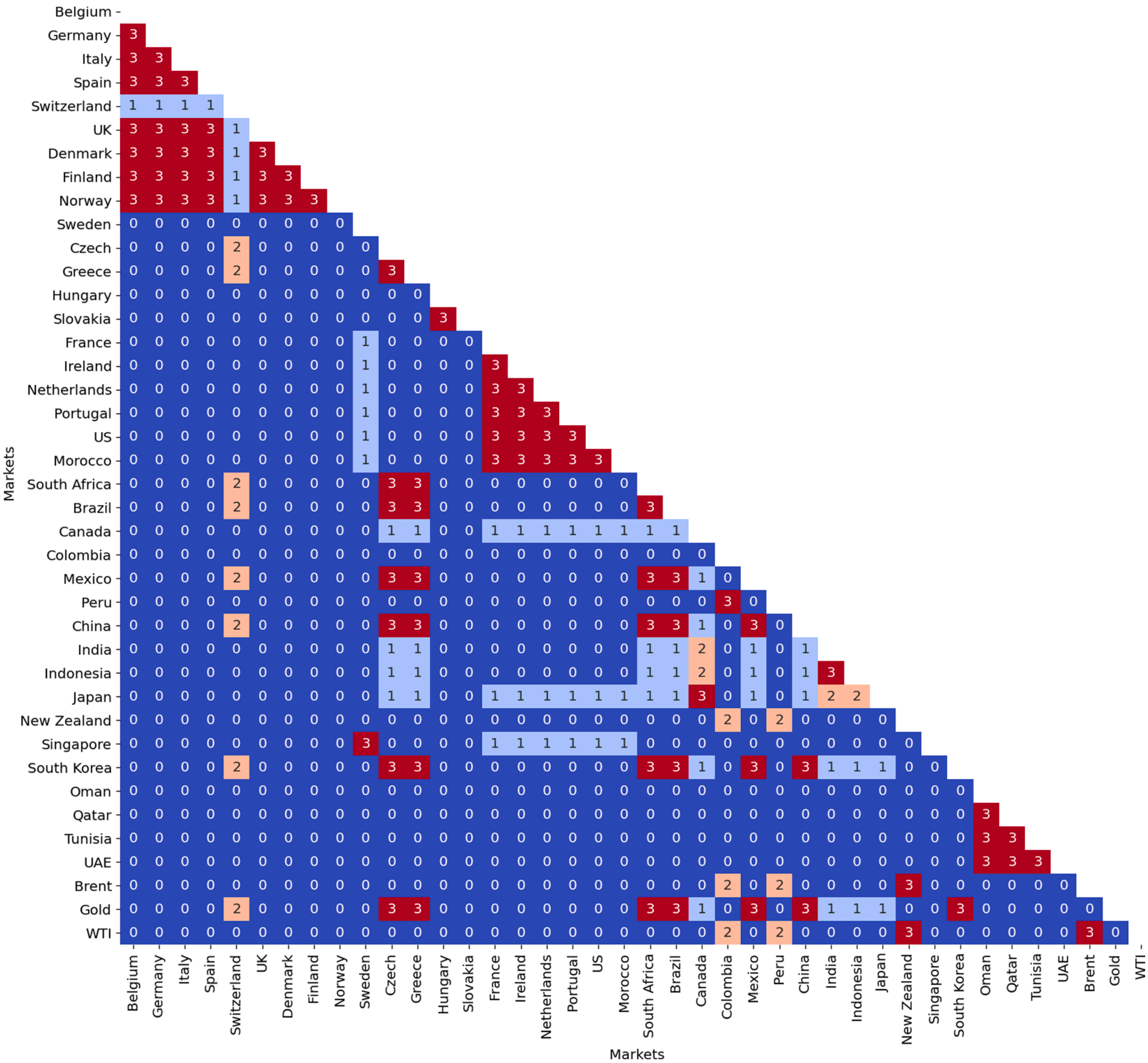


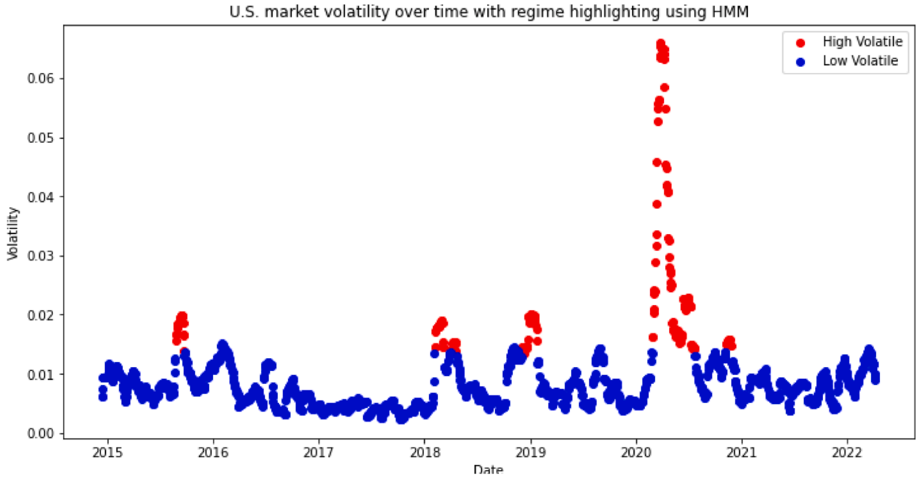
Fig. A2.2. Co-occurrence frequency matrix. This matrix visualizes the number of times each pair of markets has been clustered together across the two subperiods and the entire sample. The values within the cells indicate the frequency of co-occurrence, with higher numbers (highlighted in red) representing more frequent clustering together, suggesting stronger similarity in response to the Political News Index (PNI).

We also delve into the dynamics of clusters during distinct market volatility regimes. To differentiate these periods, we divide the sample into high and normal volatility phases, using the volatility patterns of the U.S. market as our benchmark. This regime detection is facilitated by our application of the Hidden Markov Model (HMM) to the volatility data of the U.S. market. Panel A of Fig. A2.3 depicts the volatility regimes as determined by the HMM, categorizing market conditions into normal and high volatility states.

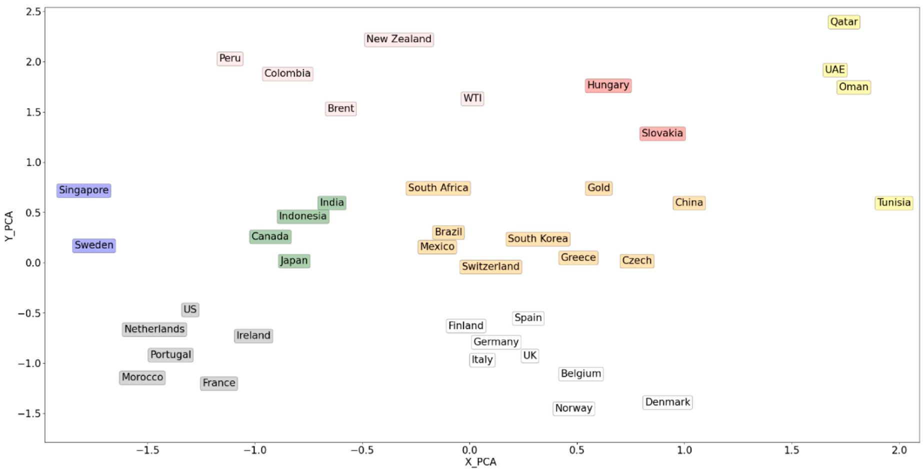
For each state, we re-apply the clustering algorithm to the connectedness data to observe any variations in market groupings due to volatility shifts. As illustrated in Panel B, during periods of normal volatility, the cluster formations largely mirror those identified in the full sample analysis, suggesting a baseline consistency in market behavior under typical conditions. However, in the high volatility regime, we observe notable deviations. Specifically, the U.S. market becomes isolated, forming a cluster by itself, indicating a distinct response to political news during volatile times. Similarly, Gold emerges as a standalone cluster, possibly reflecting its status as a safe-haven asset during market upheavals. Japan shifts away from its original grouping and now aligns with developed European markets, highlighting potential changes in market dynamics under stress. Additionally, Slovakia and Hungary, previously paired together, along with New Zealand and Peru, which were originally from different clusters, now join a predominantly emerging markets cluster. These shifts underscore the fluid nature of the market connectedness in response to elevated volatility. Other markets are grouped as before.

In conclusion, while cluster compositions exhibit sensitivity to the volatility regime, the fundamental patterns of market groupings remain discernible. This persistence reaffirms the robustness of the clustering approach, emphasizing that while the intensity and specifics of market responses may vary at some points, the fundamental clustering remains persistent.

A) Volatility regimes in the U.S market



B) Markets clustering during the normal volatility regime



C) Markets clustering during the high volatility regime

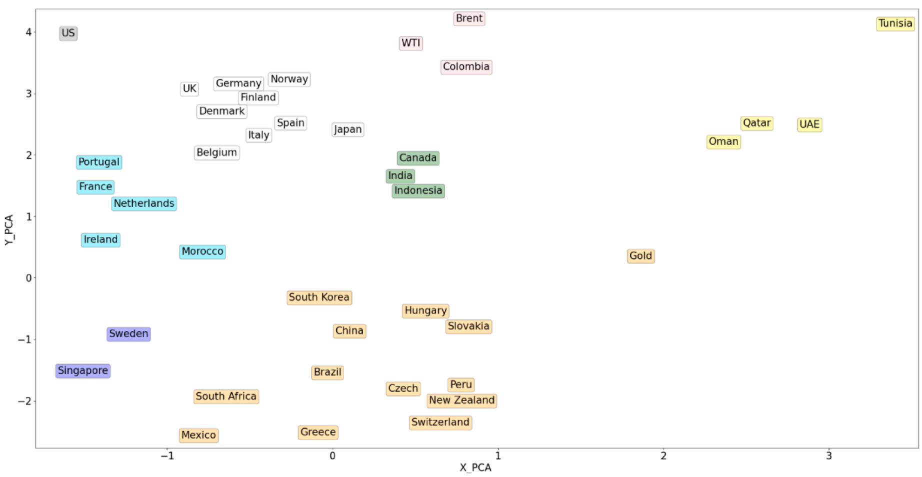


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Fig. A2.3. Clustering international markets based on volatility sensitivity to political news across high and normal market volatility regimes. Panel A shows the volatility regimes in the U.S. market from 14/11/2014 to 9/4/2022 using the Hidden Markov Model. Panel B depicts the clustering over the normal volatility period, while Panel C displays the clustering over the high volatility period.

Appendix 3

We cluster the markets using their volatility connectedness to the PNI using the Self-Organizing Map (SOM) method. The SOM is an unsupervised neural network that is used to produce a low-dimensional representation of high-dimensional data, making it particularly suitable for clustering applications. Table A3 presents the formation of clusters using SOM. This consistency in the clustering, when compared to our primary results, reinforces the robustness of our findings. Thus, we can conclude that the identified market groupings persist across different clustering techniques.

Table A3
Clustering results using Self-Organizing Map (SOM) method.

Cluster	Members
i	Sweden, Singapore
ii	Peru, Colombia, Brent, New Zealand, WTI
iii	Morocco, Portugal, France, Netherlands, Ireland, US
iv	Japan, Canada, India, Indonesia
v	Czech, Mexico, Greece, South Korea, South Africa, Brazil, Switzerland, Gold, China
vi	Slovakia, Hungary
vii	Belgium, Italy, Spain, Finland, Germany, UK, Denmark, Norway
viii	Oman, Qatar, UAE, Tunisia

This table presents the results of market groupings obtained using the SOM clustering method, based on directional volatility connectedness to the Political News Index (PNI) from 14/11/2014 to 9/4/2022.

Appendix 4

We utilize the same clustering settings on net pairwise connectedness data between the PNI and market volatility to verify the robustness of our findings. Figure A4.1 illustrates the cluster formations. While the cluster members remain consistent, the clusters appear more compact, with shorter Euclidean distances for the majority of markets. We can conclude that the clustering results hold consistently across different measures of connectedness.

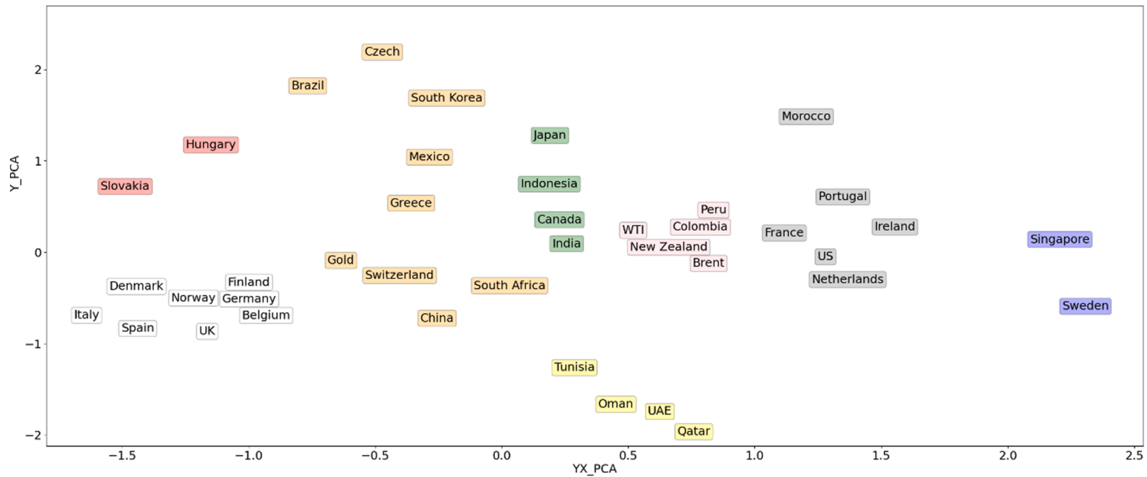

Fig. A4. International markets clustered by GKA based on volatility sensitivity to the PNI. This figure shows how international markets are clustered in eight groups based on net pairwise volatility connectedness to the Political News Index (PNI) from 14/11/2014 to 9/4/2022. The X-axis represents the first principal component and the Y-axis the second, both capturing variations in market connectedness to the PNI.

Appendix 5

We employ an alternative approach by aggregating the daily sentiment scores to construct the PNI. This approach is designed to evaluate whether our findings are consistent when we shift from averaging to aggregating sentiment scores—a method that may better capture the cumulative impact of sentiment on days with multiple news and events.

Fig. A5.1 presents the PNI developed through the aggregation of daily sentiment scores. The aggregation method sums up daily articles' sentiment scores. Fig. A5.2 depicts the cluster analysis of asset markets based on their volatility connectedness to the aggregated PNI. The clusters formed under this alternative approach show a high degree of consistency with our baseline results, although there are noteworthy variations. Specifically, the Japanese market now aligns with its Asian counterparts, such as China and South Korea, suggesting a regional clustering effect. Similarly, Hungary and Slovakia, previously grouped as a unique cluster, now join a cluster predominantly composed of developing countries. While the overall formation of clusters remains largely unchanged, slight shifts in Euclidean distances between markets are observed.

These adjustments in market clustering indicate the stability of market groupings across different methodological approaches, providing rigor in the conclusions drawn from our primary analysis.

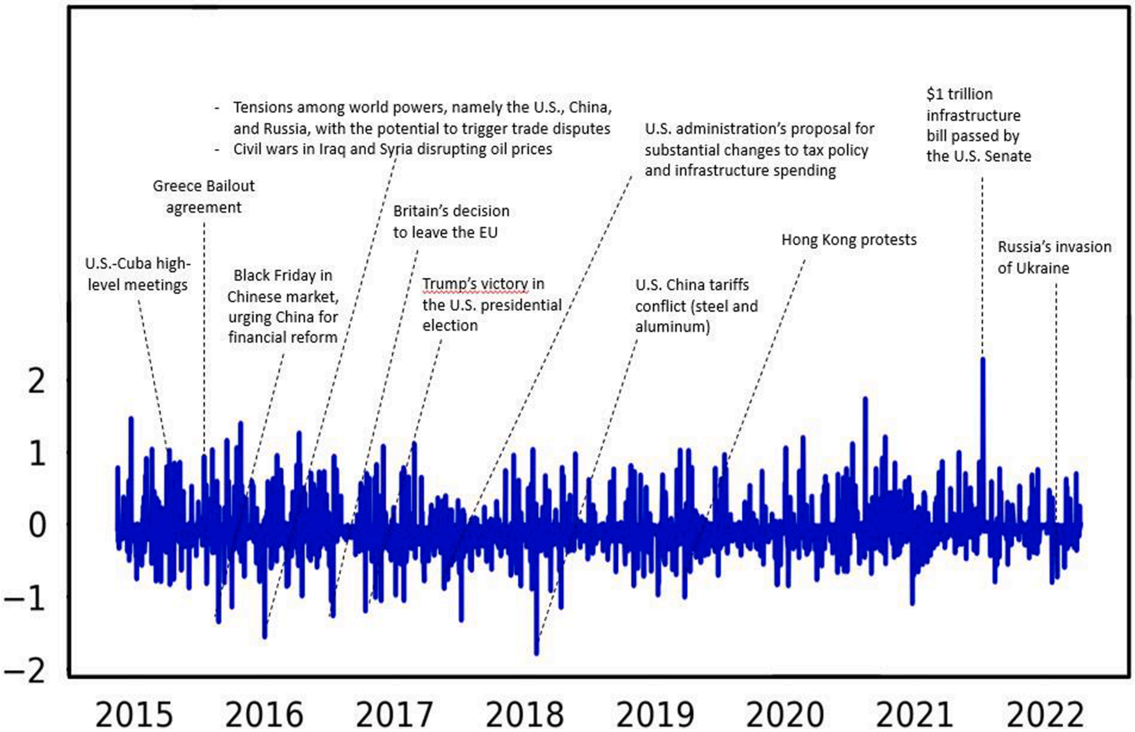

Fig. A5.1. Aggregated political news index (PNI). The PNI covers the period from 14/11/2014 to 9/4/2022, extracted from 23,986 political news headlines from the investing.com website using a financially fine-tuned BERT. The index was obtained by aggregating daily articles' sentiment scores.

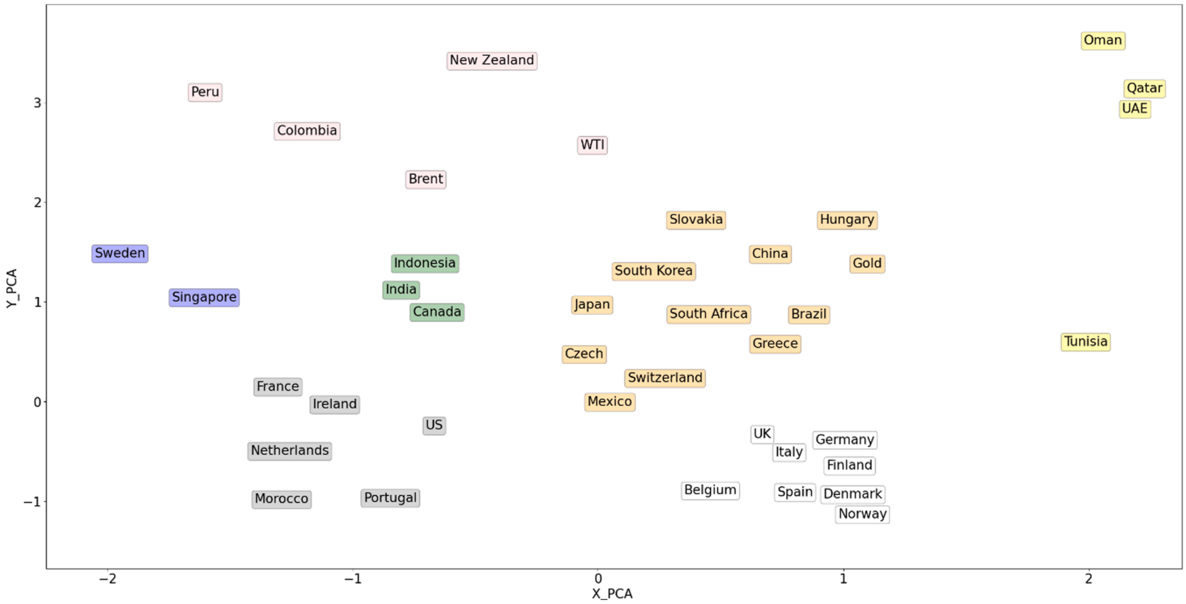

Fig. A5.2. International markets clustered based on volatility connectedness to the aggregated PNI. This figure shows how international markets are clustered based on the volatility connectedness to the aggregated Political News Index (PNI) from 14/11/2014 to 9/4/2022 using the Genetic K-means Algorithm. The X-axis represents the first principal component and the Y-axis the second principal component, both capturing variations in market connectedness to the PNI. A shorter distance between points indicates greater similarity between markets.

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