Investigating Extreme Linkage Topology in the Aerospace and Defence Industry

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Abstract

This paper analyses return and volatility spillovers among 21 global aerospace and defence (A&D) companies from six countries and three continents using quantile-based models and daily data from August 23, 2010, to July 1, 2022. The results show that both return and volatility spillovers vary over time, and those estimated at normal market conditions, intensify during COVID-19 and Russia-Ukraine war periods. Spillovers of returns estimated at lower and upper quantiles exceed those estimated at the middle quantile. Volatility spillover is extremely high at the upper quantile and exhibits low variability. Chinese defence stocks are segmented from the rest under normal return conditions and a moderate volatility state. In contrast, they are somewhat integrated under extreme return conditions and volatility states. Hence, Chinese defence stocks entail more diversification benefits under normal conditions than in bear or bull markets. Further analysis shows that geopolitical risk consistently plays a significant role in driving both returns and volatility spillovers, especially during the pandemic and war periods, without ignoring the role of macroeconomic and financial variables. These results have implications for investors concerned with stock portfolio management under various return and volatility conditions and for policymakers preoccupied with policy design under unstable periods

keywords: Aerospace and defence companies; Ukrainian war; Russia; quantile vector-autoregression; COVID-19.

Introduction

On 24 February 2022, the mounting tension between Russia and Ukraine peaked, instigating a brutal war that has led to wide-scale devastation, especially in Europe, the consequences of which will be felt far into the future. While the humanitarian effects are almost incomprehensible, this destructive war has substantially affected the commodity markets, notably energy and grain prices, the global economy, the financial markets, and the fortunes of defence companies. There appears to be no end to the war, and the spending on defence has experienced a notable increase globally. In 2022, global military expenditure surpassed $US2.2 trillion for the first time. Large increases in military spending are noticed in Europe in response to the Russia Ukraine war. To top the chart, the United States (US) spent the most on military spending$ (US 877 billion), followed by China ($US292 billion), Russia$ (US 86.0 billion), India ($US81.0 billion), Saudi Arabia$ (US 75.0 billion), the United Kingdom (UK) ($US69.0 billion), Germany$ (US 56.0 billion), and France (($US 54.0 billion)

On 24 February 2022, Russia attacked Ukraine, initiating a war that has led to wide scale devastation, especially in Europe, the consequences of which will be felt far into the future. While the humanitarian effects are almost incomprehensible, this destructive event has also substantially affected financial markets, the global economy, energy and grain prices, and the fortunes of defense companies. There unfortunately appears to be no end in sight for the war and increases in spending on defense continued to increase globally. In 2022 global military expenditure surpassed $US 2 trillion for the first time (World military expenditure passes $2 trillion for first time according to SIPRI). During the same year, the United States (US) spent the most on military spending ($US 750 billion), followed by China ($US 237 billion), Saudi Arabia ($US 67.6 billion), India ($US 61 billion) and the United Kingdom (UK) ($US 55.1 billion).[1]

This defence spending has seen the global aerospace and defence (A&D) industry outperforms the equity markets. According to Refinitiv Eikon, for the year ending 31/12/2022, the total return of the A&D industry equated to 13.89%, compared to -3.45% for the global equity markets. This is even though the average total market capitalisation of A&D companies represents only 1% of the global equity markets. Total revenues of the year ending 31/12/2022 were $US 665 billion[2], with the top 21 largest companies by revenue capturing 75% of this total revenue (See Appendix Table A1 for detailed Market Analysis). Merger and acquisition activity in the A&D industry was also high, with 361 deals with a total value, including Net Debt, of $US 36 billion. Given the Russia and Ukraine war and the outsize recent market performance of many A&D companies, our study investigates the network topology of the return and volatility spillovers among major companies from the global A&D industry and the factors that drive these spillovers. Using a quantile-based approach to spillovers, we explicitly consider the transmission pathway of return and volatility from one company to another under various market return conditions and volatility states. Furthermore, we conduct various regressions to understand the role of geopolitical risk in driving return and volatility spillovers while considering various macroeconomic and financial variables.

[1] Data are according to Stockholm International Peace Research Institute (https://sipri.org/)

[2] All market analysis was conducted using Refinitiv Eikon on 22/02/2023. The A&D sample consisted of 351 publicly listed securities with a total market capitalisation of $1.37 trillion dollars. The global equity market capitalisation at this time was 118 trillion dollars.

Surprisingly, the related literature could be more extensive in this regard. Studies on the A&D industry date back at least as far as the 1960s, mainly focusing on the investment quality of companies in this industry (Butler Jr, 1966b, 1966a, 1967) and their profits and market performance (Agapos and Gallaway, 1970; Suarez, 1976; Bohi, 1973). McDonald and Kendall (2011) studied the effects of war on the U.S. defence industry, focusing on 16 firms that provided military equipment to the Department of Defence. Applying a cumulative prediction error (CPE) technique, they find that stock prices of defence firms tend to increase because of military actions. Capelle-Blancard and Couderc (2008) analyse the effect of media information on defence companies only, showing that news relating to earnings announcements and analyst recommendations are significant in explaining abnormal returns for these companies. Recently, Federle et al. (2022) analysed stock market responses to the war in Ukraine, finding that firms closer to Ukraine suffered from a relative proximity penalty, experiencing negative equity returns during the four weeks surrounding the beginning of the war. Le et al. (2023) use war-related news articles to investigate the market response of some companies to the war in Ukraine, showing a negative impact on airline stocks and a positive impact on defence stocks. Zhang et al. (2022) consider the co-movements between geopolitical risk and the returns and volatility of global aerospace and defence companies, indicating significant co-movements around the onset of the war in Ukraine. This is labelled a 'flight-to-arms' phenomenon, with co-movement found to be significant for many European and US companies in the sample. This paper contributes to the above body of literature by analysing the network of returns and volatility spillovers across major A&D companies, using a quantile-based connectedness, and covering the drivers of spillovers. First, the flexibility of this connectedness approach allows for accounting for various market return conditions and volatility states. This is an important feature as previous findings highlight the importance of considering the sign of return shocks and size of volatility shocks when studying the spillover effects in the financial markets (see, Bouri et al., 2020; Chatziantoniou et al., 2021; Saeed et al., 2021; Iqbal et al., 2022). This should add to Zhang et al. (2022) and Le et al. (2023), who consider only mean-based models. Second, our sample of 21 A&D companies incorporates eight out of the ten largest in the world by revenue and covers six countries, namely US, UK, France, Germany, China and Singapore, across three continents (North America, Europe, and Asia) over the period August 23, 2010 to July 1, 2022. The period under study covers important events such as the Russian invasion of Crimea in 2014, the COVID-19 pandemic of 2020, and the Russia-Ukraine in 2022, thus enabling the identification of significant spillovers across a varying set of global turbulent market conditions and geopolitical events. Third, analysing the factors driving the return and volatility spillovers across various market conditions constitutes another contribution to the literature on A&D companies (Federle et al., 2022; Le et al., 2023; Zhang et al., 2022). Specifically, it shows the importance of geopolitical risk in driving up the spillover effect of both returns and volatility while accounting for the significance of macroeconomic and financial variables. The main results on the spillover effects across various quantiles show intensified spillover effects for both stock returns and volatility under extreme market conditions and evidence of time evolution in the spillovers, especially for lower and upper tails returns. This suggests that the system of spillovers under extreme market conditions, irrespective of whether it is bull or bear market, is unstable. Thus, it should be carefully monitored, given its potential consequences on portfolio and risk management in the A&D industry. An additional analysis involving the drivers of spillovers shows the impact of heightened geopolitical risk around the Russian-Ukraine war period on the return and volatility spillovers across A&D companies in most of the quantiles considered. Furthermore, the level of returns and volatility spillovers is also driven by macroeconomic and financial variables such as corporate credit conditions, stock market volatility, short-term liquidity risk, and real business condition. Therefore, participants in the A&D industry, especially in the US and Europe, should closely examine the global geopolitical environment given its significant impact on the dynamics of information transmission in the A&D industry and, thus, the integration of A&D stocks and the possibilities of diversification. The findings also highlight the tail risk propagation within the network system of aerospace and defence stocks, which should concern risk managers and policymakers. The paper proceeds as follows. Section 2 describes the dataset. Section 3 provides a quantile-based spillover approach. Section 4 presents and discusses the results. Section 5 concludes.

Data

Our dataset comprises the daily closing prices of 21 global aerospace and defence companies in six countries (US, UK, France, Germany, China, Singapore) and three continents (North America, Europe, and Asia). The selected companies are chosen to be large and liquid, with an individual market capitalisation exceeding e billion USD. The list of 21 companies is provided in Appendix Table A1. Appendix Figure A1 shows the share our sample captures of the total market capitalisation of the global A&D industry, which represents 72 %. The sample period (August 23, 2010 - July 1, 2022) is selected according to the availability of A&D stock price data from Refinitiv DataStream, especially for the Chinese Aecc Aviation Power 'A' because it exhibited many zero price fluctuations at the daily basis before the start of the sample period on 23 August 2010.

Appendix Figure A2 plots the price series levels and highlights the country of incorporation. Furthermore, Appendix Figure A3 and Figure A4 display the log-return and volatility series, respectively. The price series levels reveal several distinct groupings in their movements. For many cases, price series levels in Figure A2 show common movement with a regime shift towards higher prices and larger volatility around 2020. Notably, Chinese stocks experienced a shock in 2016 of a similar magnitude to that of 2020. In July 2016, it was reported that China had performed a week of military drills in the South China Sea amid legal debates regarding its territorial claims to regional areas, which could account for this increase in volatility. In Figure A3, we notice a large variability in the returns around the peak of COVID-19 in 2020 and the Russia-Ukraine war in early 2022, especially for most US-European A&D stocks. Based on Figure A4, we observe that the volatility of some A&D companies such as Boeing, Transdigm, Safran, and Rolls-Royce Holdings experienced a spike around the pandemic outbreak and the Russia-Ukraine war.

Appendix A2 and Table A3 present summary statistics for daily returns and volatility series, respectively. Notably, Table A2 shows that the distributions of the daily returns series are mostly skewed to the left and exhibit fat "tailedness", with Airbus, Boeing, Rolls-Royce Holdings, Safran, and Transdigm experiencing the highest daily standard deviation. These companies are either directly in the aviation industry or supply to it, as Rolls-Royce supplies the Trent engine to Airbus. In this regard, airlines were hit particularly hard during the COVID-19 pandemic, with an estimated economic loss of US$168 billion in 2020 (COVID-19's impact on the global aviation sector | McKinsey)*LISA add ref please*, which may be a factor in the observed volatility. All return series are stationary, as shown by the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) test statistics. The same is true for the volatility series, as reported in Appendix Table A3.

Table 1: Extremely votality events

Date	stock	return	volatility	country
2020-03-18	Airbus	-0.25	0.06	France
2020-03-16	Boeing	-0.27	0.07	US
2020-11-09	Rolls-Royce Holdings	0.36	0.13	UK
2020-03-18	Safran	-0.26	0.07	France
2020-03-18	Transdigm Group	-0.25	0.06	US

Furthermore, we consider extreme volatility events, which coincide with the peak of the COVID-19 outbreak and indicate in Table 1 that the most volatile A&D stock is Rolls Royce Holdings. The company reported a loss of £4 billion for 2020 and was forced to raise £7.3 billion in debt and equity and cut almost one-fifth of its workforce (COVID-19: Rolls-Royce blames the 'severe impact' of the pandemic as it dives to £4bn loss | Business News | Sky News)*LISA add ref please*. Unsurprisingly, Table 1 indicates that the five highest daily volatility scores mainly occur around the end of March 2020 at the height of the uncertainty during the onset of the COVID-19 pandemic.

Methodology

The nature and strength of spillovers across financial markets have traditionally been measured using conventional mean estimators such as the connectedness approach of Diebold and Yılmaz (2014). Interestingly, Ando et al. (2022) argue that systemic shocks are likely to be much larger than average shocks and that extreme negative return (or low volatility) shocks do not necessarily propagate in the same way as extreme positive return (or high volatility) shocks. Therefore, quantile-based estimators allow for identifying whether the spillover effects' topology changes with the shock distribution's size and sign as captured by the various quantiles of the shock distribution (Bouri et al., 2020).

To study the return and volatility connectedness across 21 global aerospace and defence companies, we use the quantile-VAR-based connectedness approach following Ando et al. (2022)[3]. This approach extends the mean-based connectedness approach of Diebold and Yılmaz (2014) and thus allows for capturing the extreme connectedness estimated at the lower, middle, and upper quantiles. For returns, this helps obtain the connectedness of return shocks in bear, normal, and bull markets. For volatility, it helps capture the connectedness of volatility shocks in low, middle, and high volatility states.

We consider a portfolio enivroment, where stocks are indexed i=1,2,...,N, and time periods are indexed t=1,2,...,T. Based on a quantile regression (Koenker, 2005), we consider a quantile-VAR process of p^{th} order for a set of N return (volatility) series for time T, $y_{it} = \{y_{t=1,i=1}, \dots, y_{t=T,i=N}\}$, as given by:

$$y_t = c_{i(\tau)} + \sum_{j=1}^{p} B_{j,(\tau)} y_{t-j} + e_{t(\tau)}, t = 1, \dots, T$$

where, $c_{(\tau)}$ denotes a vector of constant terms at quantile , $B_{j(\tau)}$ represents the matrix of the j^{th} lagged coefficients of the dependent variable at quantile , with i =1,..., p, and $e_{t(\tau)}$ denotes a vector of error terms at quantile . Equation (1) is estimated by assuming that the error terms conform to the population quantile restriction, $Q_t(e_{t(\tau)}|y_{t=1}, \dots, y_{t=p}) = 0$.

We express the th conditional quantile of response y as:

$$Q_t(y_t|y_{t=1}, \dots, y_{t=p}) = c_{(\tau)} + \hat{B_{i(\tau)}} y_{t-i}$$

Following the approach of Diebold and Yılmaz (2014) , we compute return and volatility connectedness measures based on a quantile variance decomposition.

We represent Equation (3) as an infinite order vector moving average process:

$$y_t = \mu_{(\tau)} + \sum_{s=0}^{\infty} A_{s(\tau)} e_{t-s(\tau)}, t = 1, \dots .T$$

where,

[3]The methodology has been used by Bouri et al. (2020), Chatziantoniou et al. (2021) and Saeed et al. (2021).

$$\mu(\tau) = \frac{c_\tau}{\left(I_n - B_{1(\tau)} - \cdots - B_{p(\tau)}\right)}$$

$$A_{s(\tau)} = \begin{cases} 0, s < 0 \\ I_n, s = 0 \\ B_{1(\tau)}A_{s-1(\tau)} + \cdots + B_{p(\tau)}A_{s-p(\tau)}, s > 0 \end{cases}$$

and y_t is given by the sum of $e_{t(\tau)}$

The generalized forecast error variance decomposition (GFEVD),$\theta^h_{i,j}$, is computed as in Diebold and Yılmaz (2014). The GFEVD reflects the contribution of the i^th stock return (volatility) to the variance of the forecast error of the stock return (volatility) i^th at h-steps ahead and is defined as:

$$\theta^{(h)}_{j\leftarrow i,(\tau)} = \frac{\sigma_{ii}^{-1} \sum_{l=0}^{h} (e_j' h_h \Omega_{(\tau)} e_j)^2}{\sum_{h=0}^{H-1} (e_i' h_h \Omega_{(\tau)} e_i)}$$

where, V is the variance matrix of the vector of residuals, σ_{ii} is the j^th diagonal element of the V matrix, and $e_i$denotes a vector with a value of 1 for the i^th element and 0 otherwise.

Its scaled version,$\theta^h_{j\leftarrow i,(\tau)}$, is represented as:

$$\theta^h_{j\leftarrow i,(\tau)} = \frac{\theta^{(h)}_{j\leftarrow i,(\tau)}}{\sum_{j=1}^{N} \theta^{(h)}_{j\leftarrow i,(\tau)}}$$

The scaled version measures the spillover of the idiosyncratic shock affecting variable i onto variable j (Ando, Greenwood-Nimmo, and Shin 2022).

Various spillover measures are estimated at each quantile and are summarised in Table 2. The third column, "Description", describes how these can be interpreted in terms of the system of spillovers. Note that, by construction, own share and FROM sum to one for i=1,2,..,m; however, TO can take values bigger than or less than one.

The lag order of the quantile VARs is selected based on SIC. It equals 1 for the quantile-VAR of the return series and 2 for the quantile-VAR of the volatility series. As for the forecast horizon (H), we use ten days. Furthermore, we conduct a time-varying spillover analysis (Diebold & Yilmaz, 2014) based on a rolling window of 200 days. To assess the robustness of our results, we use a fixed window length of 200 days and a 5-step forecast horizon and show that our spillover results remain almost the same, suggesting their robustness to the window size and forecast horizon. These results are not reported here but are available on request from the authors.

Table 2: Table 2: Description of modelling outputs

Name	Formula	Description
Own share	$\tilde{\theta}^h_{j\leftarrow i,(\tau)}$	The proportion of the h-steps-ahead GFECD of the ith variable that can be attributed to the shocks to variable i
FROM	$F^h_{i\leftarrow\cdot,(\tau)} = \sum_{j=1,i\neq j}^{m} \theta^h_{j\leftarrow i,(\tau)}$	Measures the total spillover from the system to i, capturing external condition effects on i.
TO	$T^h_{\cdot\leftarrow i,(\tau)} = \sum_{j=1,i\neq j}^{m} \theta^h_{j\leftarrow i,(\tau)}$	Measures the total spillover from i to the system, capturing the influence of ith node in the network.
NET	$T^h_{\cdot\leftarrow i,(\tau)} - F^h_{i\leftarrow\cdot,(\tau)}$	Meaures the directional connectedness of variable i.
TOTAL	$S^h_\tau = m^{-1} \sum F^h_{i\leftarrow\cdot,(\tau)}$	Is the sum of the from system estimates.

Results

In the context of global defence stocks, we are primarily interested in the spillover effects due to crisis periods and conflict events, particularly relevant in the current geopolitical climate. Regarding financial risk management, the propagation of idiosyncratic risk contagion is often defined as the difference in how the shock propagates during extreme events relative to normal times (Londono, 2019). Our analysis thus attempts to investigate how much of the uncertainty associated with A&D stocks can be attributed to the idiosyncratic shocks coming from these stocks as the shock size varies.

We present the return and volatility spillovers across the 21 A&D stocks under study. The sample period of August 23, 2010 - July 1, 2022, covers normal and extreme market conditions, including the COVID-19 outbreak and the Russia-Ukraine war.

Network topology of return and volatility spillovers

To understand the aggregate spillover intensity among A&D stocks, we visualise the results of a full-sample analysis for both returns and volatility at the median, 5th and 95th percentile. The network visualisation reflects the strength of the bilateral spillovers by the relative thickness of the edges. At the same time, the size of each node is proportional to the square root of the total spillover (inwards and outwards) (Ando et al., 2022). Finally, the country of origin of the company is represented by colour.

Return spillovers

Figure 4 illustrates the network visualisation of the bilateral spillover effects of the 21 return series, whereas Figure 6 displays the exact visualisation for the 21 volatility series. Some similar patterns emerge, notably the consistent size of the US stock nodes representing the significant aggregate spillover effects in both directions. In all plots, Raytheon Technology experiences the most considerable aggregate spillover effects, indicative of its dominance in the A&D industry. However, there are also some crucial differences. Firstly, the most substantial individual pairwise spillover effects are observed at the median conditional distribution, primarily within countries. Notably, Chinese stocks show the most robust linkages within the country but the weakest linkages outside their country of origin. This corresponds to literature relating to general stock market trends observed in China; for example, Valukonis (2014) finds that following the recovery from the financial crisis of 2008, Chinese and US stock market indices display a weak correlation which is perhaps due to Chinese markets being somewhat isolated from global markets and not as influenced by globalisation as other markets may be.

In contrast, all pairwise spillover effects are weaker at the extremes of the return distribution. This finding is consistent with previous studies, which show that in times of stress, the network is characterised by a more significant number of weaker bilateral linkages increasing the weight completeness of the network (Dungey et al., 2019; Ando et al., 2022). In our context, this would mean that while shock spillovers between individual stock pairs are small, the overall connectedness of the system is increasing in times of stress, meaning that the shock propagation is higher under extreme return conditions ( ).

Volatility spillovers

Moving to the network of volatility spillovers, Figure 6 exhibits a similar pattern to those for the return spillovers. Weak bilateral spillovers characterise the extreme upper quantile, and the strongest pairwise spillovers occur at the median quantile. Again, we observe the most robust volatility linkages between Chinese companies, followed by volatility linkages between US companies. Strong volatility linkages between Chinese companies are also apparent at the extreme lower quantile. Huang et al. (2021) constructed a tail risk spillover network for China's industry sectors. They showed that the national defence sector is defined as a 'downstream' sector due to its position in the industrial chain. It is found that it has relatively high volatility compared to other leading industries. Bu et al. (2019) analysed movement in the Chinese stock market using a causal network method, finding that investors are concerned with risk and return in normal periods but are only concerned about risk in crisis periods.

Time varying spillover results

So far, we have analysed measures of connectedness for the entire sample using the network topology visualisation. However, it is essential to illustrate meaningful time variation in the

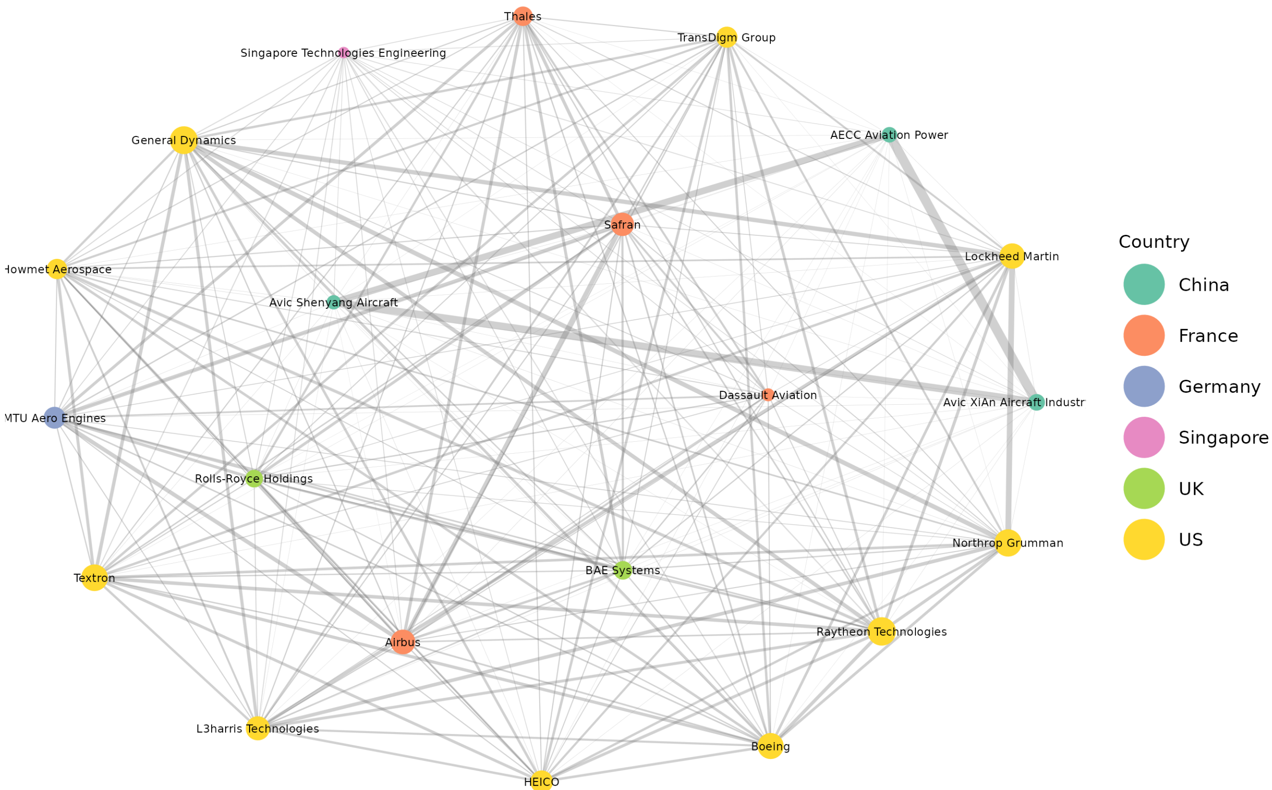
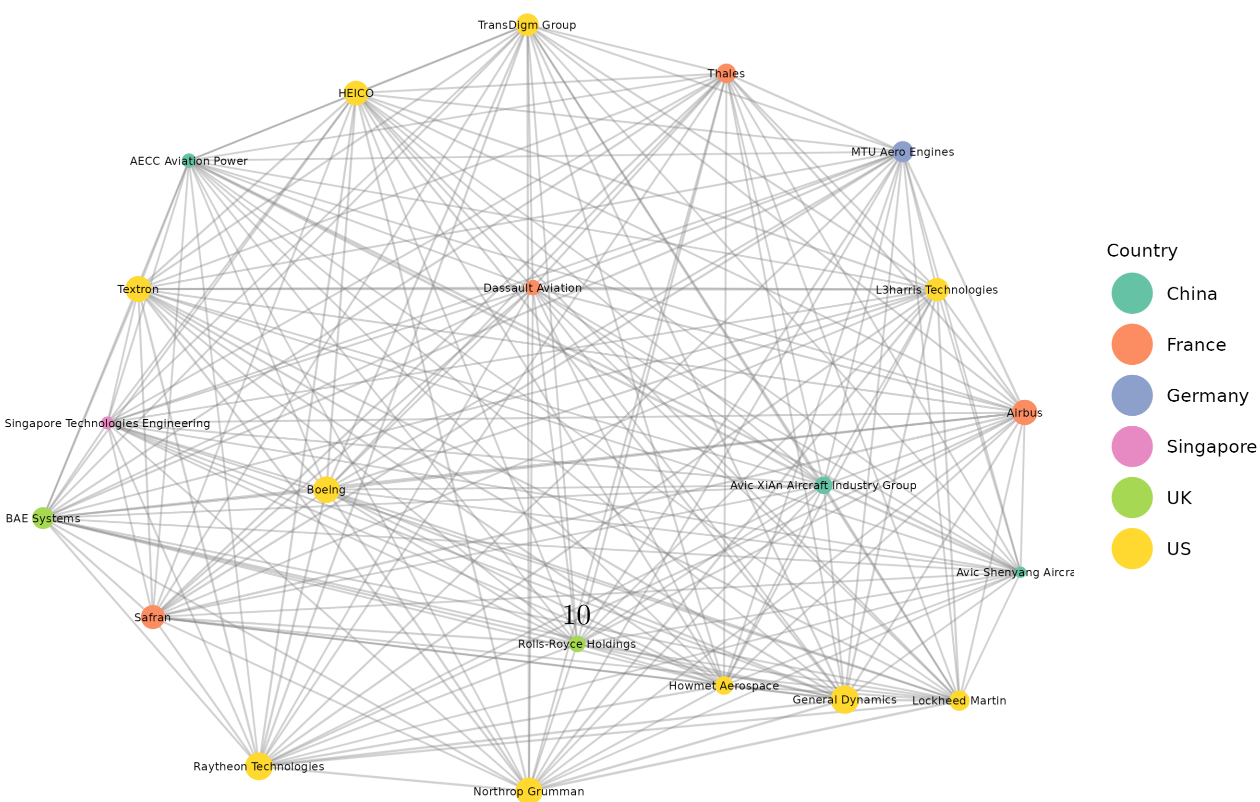


Figure 1: Middle quantile (50th Percentile)



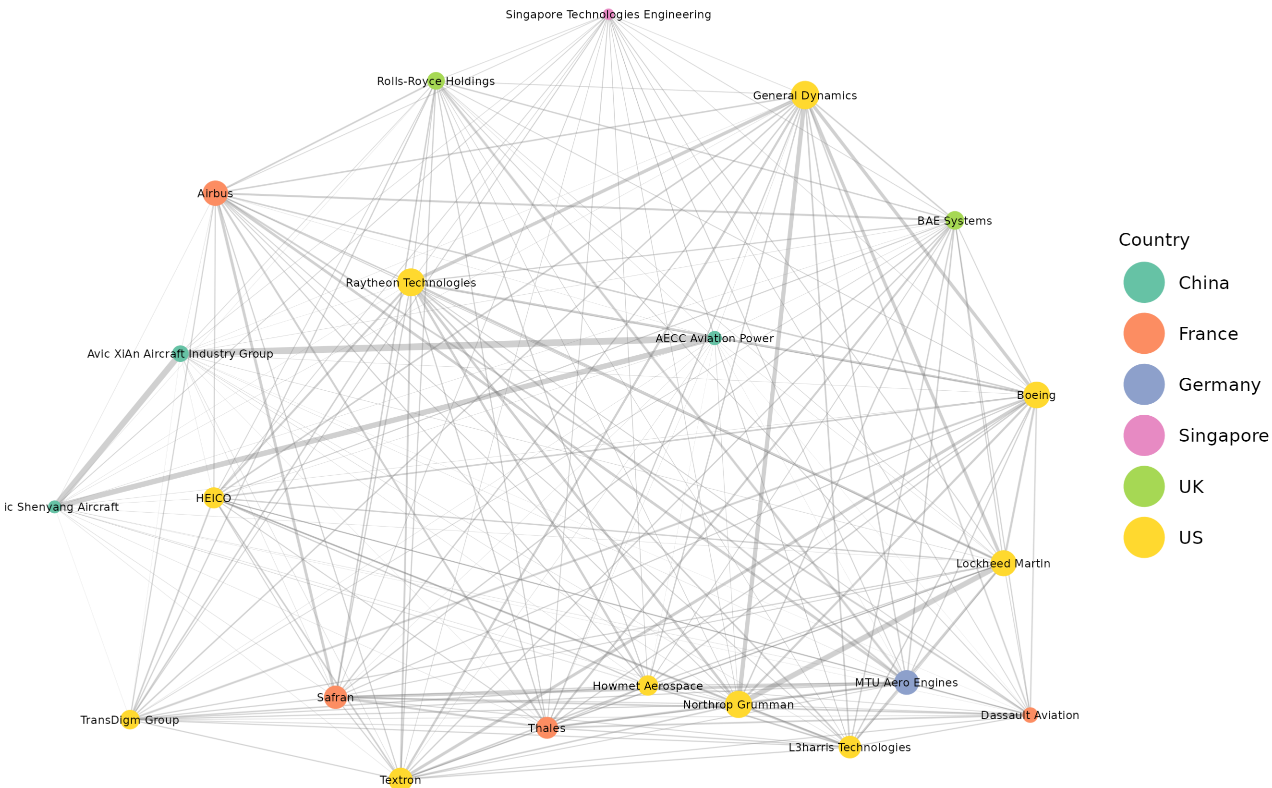
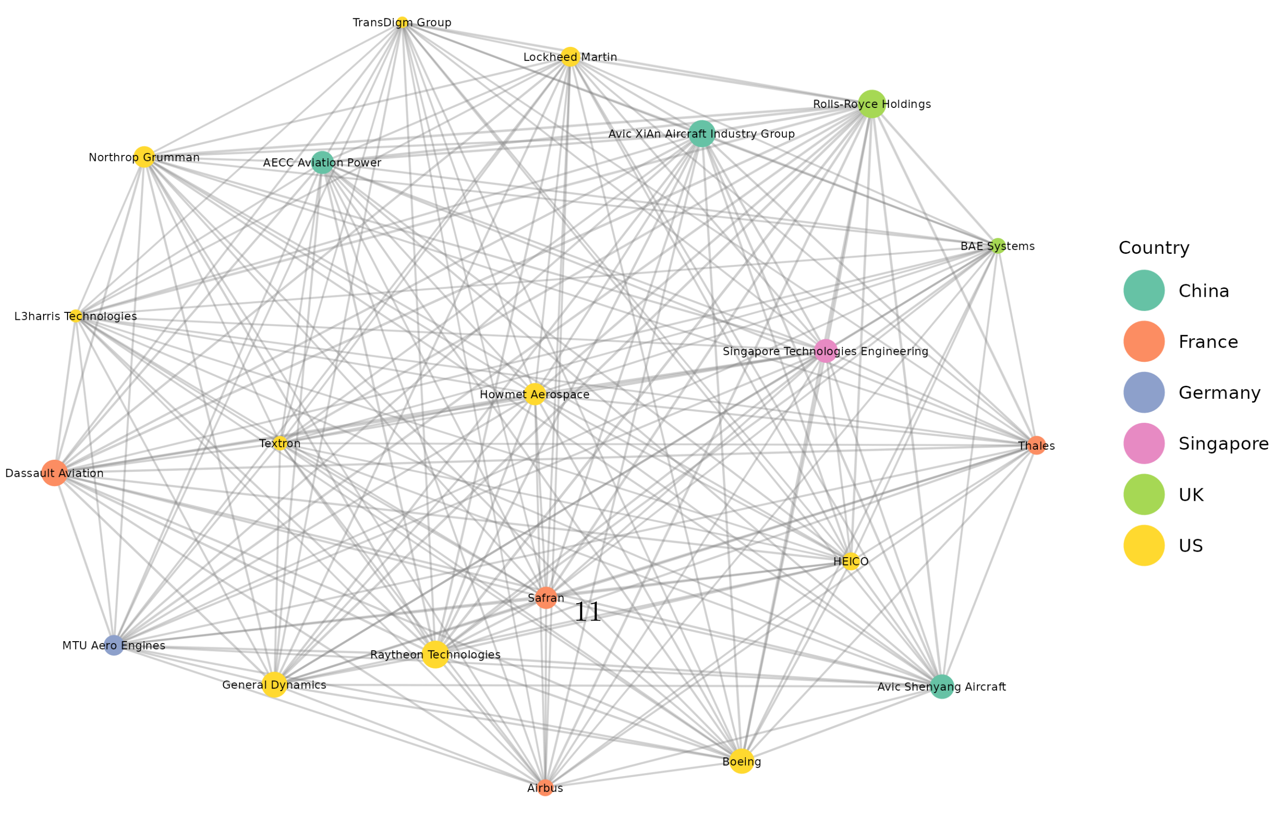


Figure 5: Middle quantile (50th Percentile)



returns and volatility spillover effects of A&D stocks under various market conditions. Furthermore, bilateral spillover of idiosyncratic risk seems stronger for both returns and volatility series, which reflect the interconnectedness across A&D stocks. However, it is important to note that restricting the network analysis to the middle of the distribution will not capture the full extent of dependence when large negative return and large positive return shocks occur (i.e. under extreme market conditions and events) as well as very low and very high volatility shocks manifest. Therefore, in this section, we conduct a rolling analysis with a quantile VAR to capture the time variability in the return and volatility spillovers in normal times (i.e. at the median of the conditional distribution) and abnormal market conditions (i.e. at the upper and lower tails of the conditional distribution). We use a fixed window length of 200[4] days and a 10-step forecast horizon. This will provide a comprehensive analysis of connectedness at the center and in the left and right tail dependence. This is conducted for both returns and volatility.

Total system connectivity

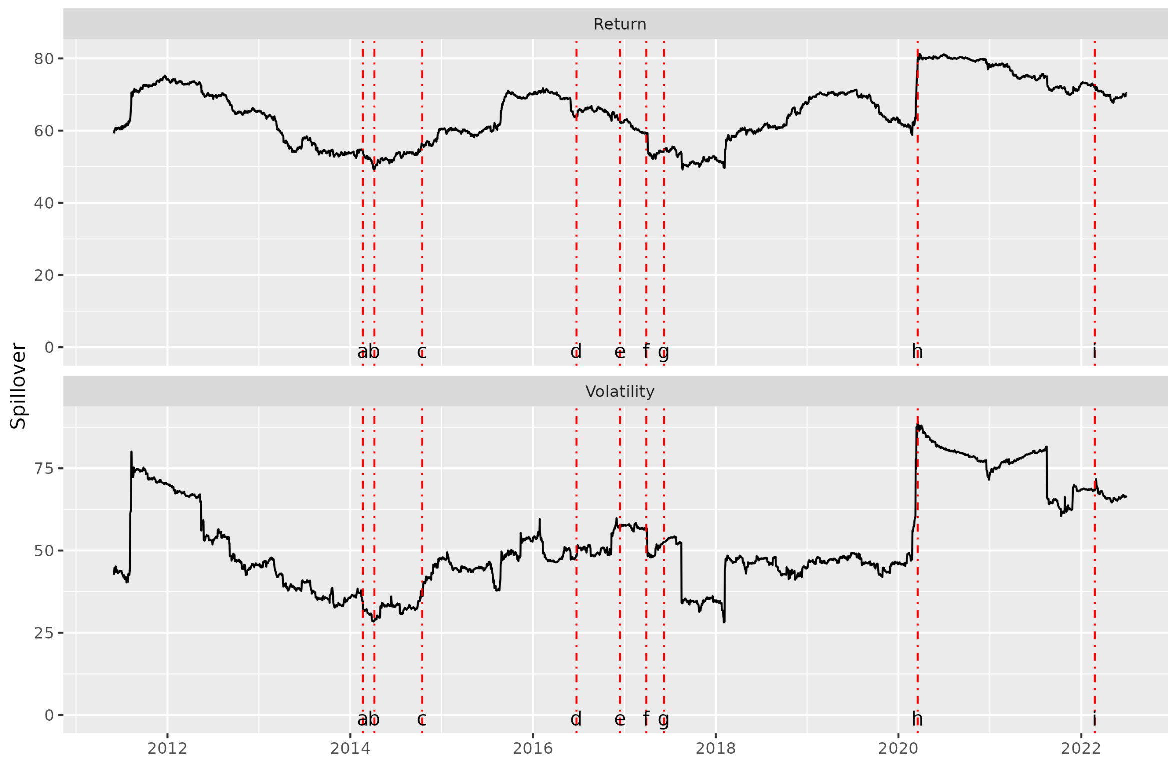


Figure 9: Conditional Median

[4]Existing studies in the Deibold-Yilmaz network literature use windows ranging from 100-250 days. Sensitivity analysis has been done and available upon request.

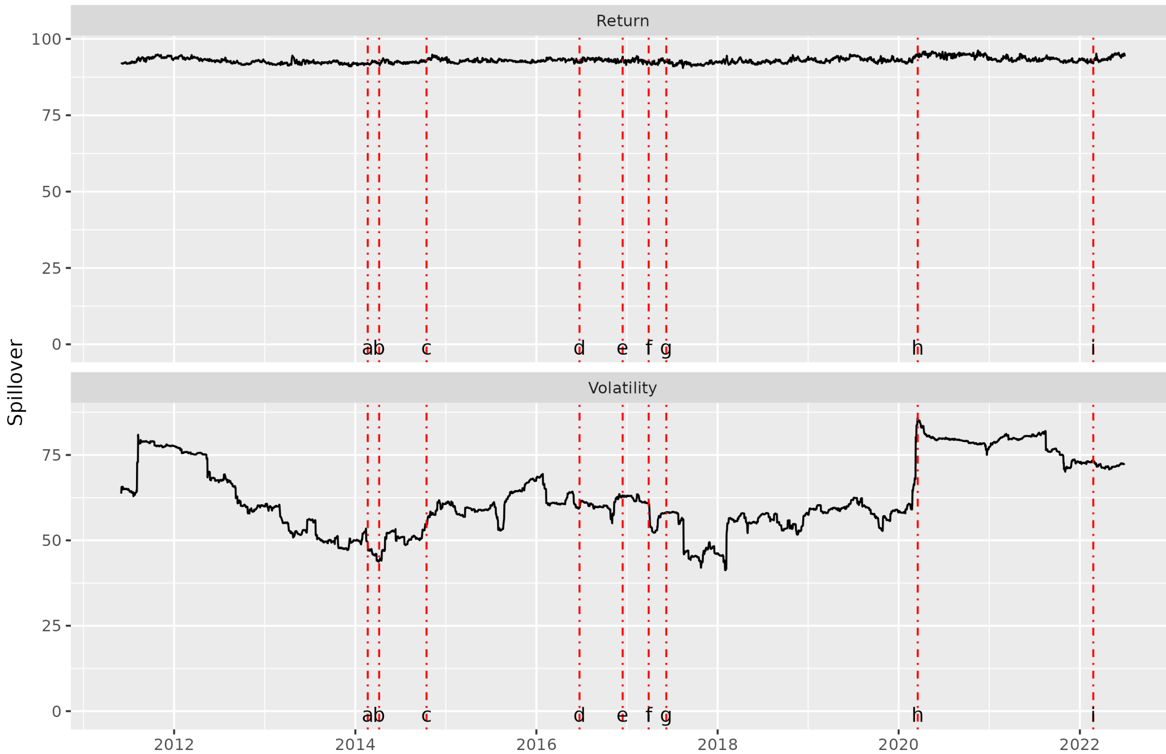


Figure 10: 5th percentile

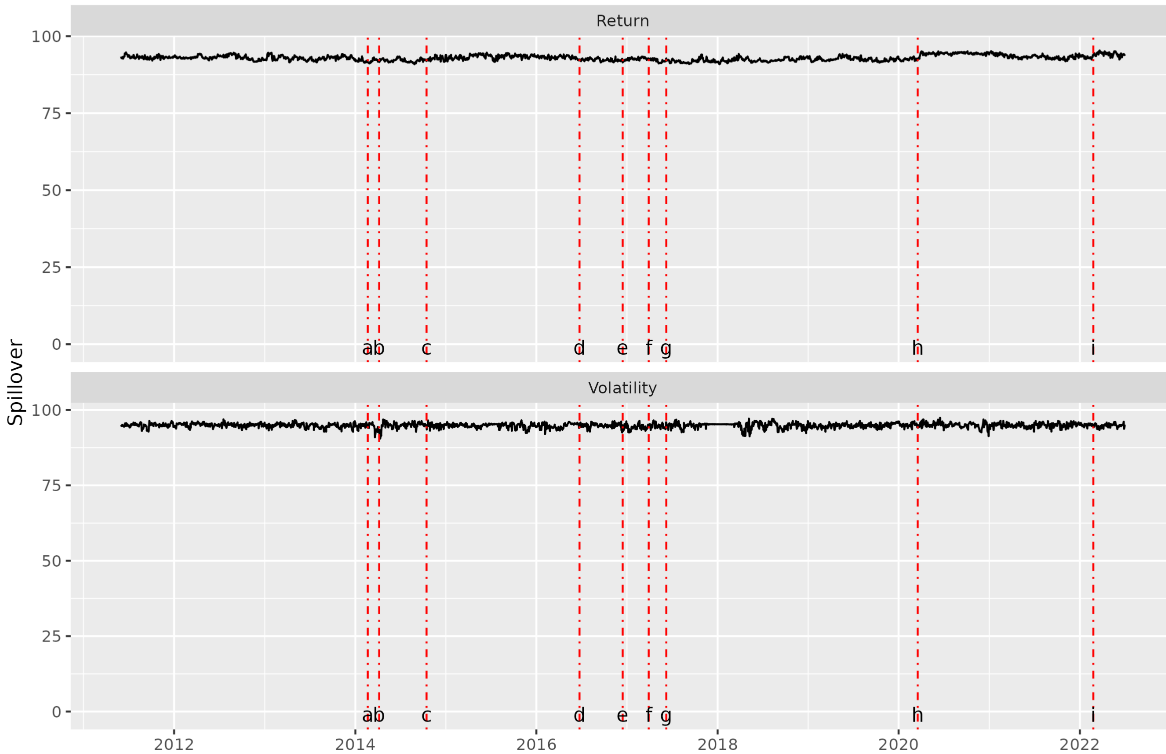


Figure 11: 95~th~ percentile

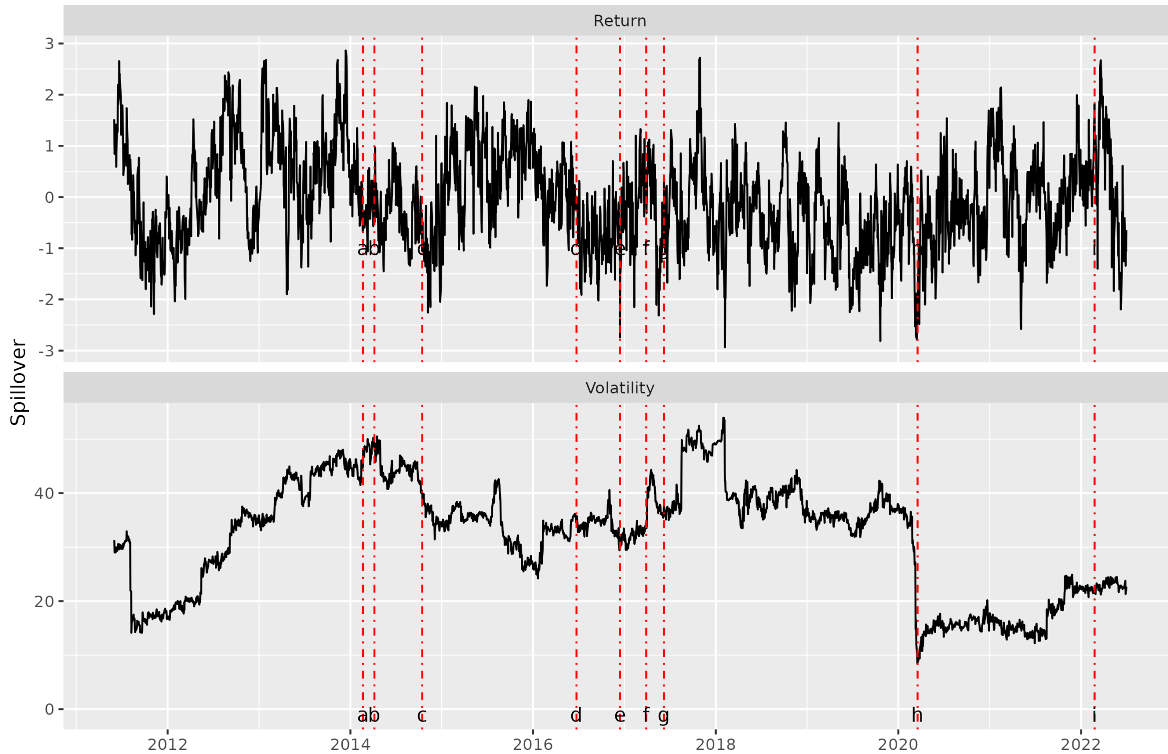


Figure 12: 95th minus 5th percentile

Figure 9, Figure 10, Figure 11, comparing total connectedness of returns and volatility. Vertical red dashed lines denote the dates of some important events, which are described in Table 3.

Table 3: Important Dates

label	date	description
a	2014-02-20	Russia began annexation of Crimea
b	2014-04-07	Start of war in Donbas by pro-Russian activists
c	2014-10-15	October 2014 flash crash
d	2016-06-23	Brexit referendum
e	2016-12-14	Federal Reserve raises interest rates
f	2017-03-29	the United Kingdom invokes article 50 of the Lisbon Treaty
g	2017-06-08	snap election held in the United Kingdom
h	2020-03-18	Dash for cash crisis in bond market peaks
i	2022-02-24	Russia initiated a special military operation in Donbas

The TOTAL connectedness index at the conditional median (a measure of the average connectedness) and extremes for returns and volatility systems are presented in Figure 9. In normal conditions the connectedness in the returns system tends to be larger than that of the volatility system of defense stocks. The connectedness reaches its peak at point h (the 'dash for cash' event) at the beginning of the COVID-19 pandemic. Importantly, while the connectedness levels are greater in the returns system the volatility system connectedness exhibits higher sensitivity to shocks, with the largest regime shift at point h.

Figure 10 and Figure 11 illustrate the time variation of total system connectivity at the 5th and 95th percentiles of the conditional distributions. It is noted that return system connectedness is persistently high (above 90) at both tails of the conditional distribution, while volatility system connectedness in period of extremely low volatility (5th percentile) is more sensitivity temporal events.

In the spirit of Ando et al. (2022), we illustrate in Figure 12 the relative tail dependence (RTD) calculated as the difference between the 95th and 5th percentile for both returns and volatility spillovers. Positive (negative) values of RTD indicate stronger (weaker) dependence in the right tail compared to the left tail. For returns, we interpret increases (decreases) in RTD as evidence of a rising (falling) connectedness of the financial performance of defence stocks. For volatility, we interpret increases (decreases) in RTD as evidence of rising (falling) connectedness of financial uncertainty in defence stocks, or more succinctly, rising (falling) financial fragility as positive (negative) volatility shocks disseminate through the system of defence stocks.

Starting with the illustration of the RTD of the return spillovers, the upper panel of Figure 12 shows a time variation of the RTD for return spillovers and evidence of asymmetric effect over the period, indicative of non-equally spread of positive and negative feedback loops in return spillover effects. Moving to the lower panel of Figure 12, we notice the persistent one-sidedness of the RTD for the volatility series, with the right tail of the condition distribution dominant throughout the period. This asymmetry suggests that the size of that uncertainty amplifies volatility spillovers across the defence. These results suggest that the total connectedness across the shocks of A&D stocks is affected by the sign of returns and the size of the volatility in the system.

Furthermore, we consider the chronological order of prominent global economic and conflict turmoil events in the context of median and extreme spillovers in volatility and return shocks. Some striking patterns emerge in this chronological order. From the beginning of the conflict in Crimea (a + b) to the Brexit referendum (d), the RTD for volatility trends down, which is indicative of an increase in resilience (reduction in fragility) in the system of A&D stocks. This is coupled with the fact that RTD is primarily positive for the return system in this sub-period. This finding suggests that upper tail returns (right tail of the conditional distribution) in this period induce some spillover effects while the financial fragility of the system weakens. There is also a notable regime shift at the dash for cash date (h), where the financial fragility (the volatility system) fell by 50% (TCI = 40 to TCI = 20).

Individual connectivity

To disentangle the total connectedness variation further explore the net spillover effects $T^h_{\cdot\leftarrow i,(\tau)} - F^h_{i\leftarrow\cdot,(\tau)}$. Figure 16 presents the Net spillover of individual stock returns at the median, lower and upper quantiles. Figure 20 presents the same estimates for stock volatilities.

We group these plots by country, and some interesting patterns emerge. Firstly, at the median of distributions, the three Chinese defence stocks are net spillover receivers in both their return performance and volatility. This may indicate the need for global maturity in these stocks compared to the other members of the system belonging to developed markets (e.g., the US and Europe). Secondly, the US A&D stocks dominate the sample and are net transmitters of both volatility and return spillover effects. More precisely, in normal periods (i.e. the median of the conditional distribution), Raytheon Technologies and General Dynamics are dominant net transmitters. This pattern also replicates at the extremes of the conditional distributions. While this is unsurprising given that Raytheon Technologies is the largest global defence stock, it is worth noting that General Dynamics is the sixth largest. For the latter, the result can be driven by some sizeable recent defence contracts signed, for example, the US National Geospatial-Intelligence Agency in March 2022 (US$4.5 billion), the US Navy in August 2022 (US$1.4 billion) and the US Army in 2022 (US$1.2 billion). Compared to the system of returns, the system of volatilities exhibits much more time variation, perhaps indicative of the high sensitivity to market fluctuations of financial risk.

In terms of the prominent dates in Figure 20, there are notable positive spikes at the start of the COVID-19 pandemic with the largest appearing in the median of the conditional distribution of the volatility system. The largest of these are in Raytheon Technologies and Howmet Aerospace, which both spike at over 200 in net transmission terms. Within the US stocks, Raytheon and General Dynamics are the most transmitive in both their median and extreme spillover effects. Finally, in terms of magnitude, Singapore technology engineering, are the largest receiver of spillover effects at both the median and the extremes, which is not surprising given their small market capitalization compared to the others (see Table A1 for details of size of stocks).

Compared to previous studies, our above findings reveal that both return and volatility spillovers are unstable over time, and those estimated at normal market conditions (at the middle quantile), intensify during crisis periods such as the COVID-19 outbreak. There is also evidence of intensified spillover effects for return shocks at both lower and upper quantiles, exceeding the return spillover effects estimated at the middle quantile, thus indicating significantly different behaviour of spillovers across different market conditions. The level of spillovers at the lower quantile in the return system is considerably larger than that in the volatility system. However, the level of volatility spillover is exceptionally high at the upper quantile only and exhibits a low variability. Finally, Chinese defence stocks seem segmented from the rest under normal return conditions and a moderate volatility state. However, they

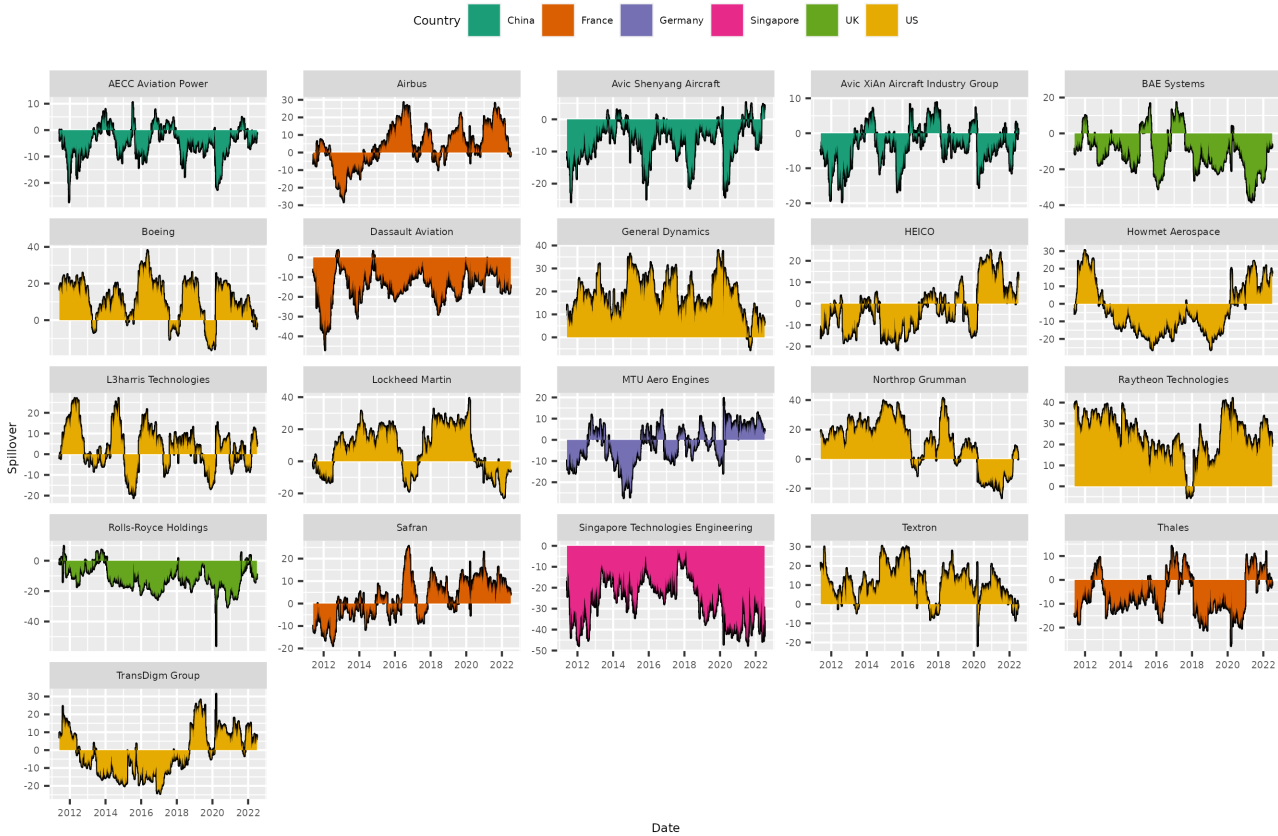
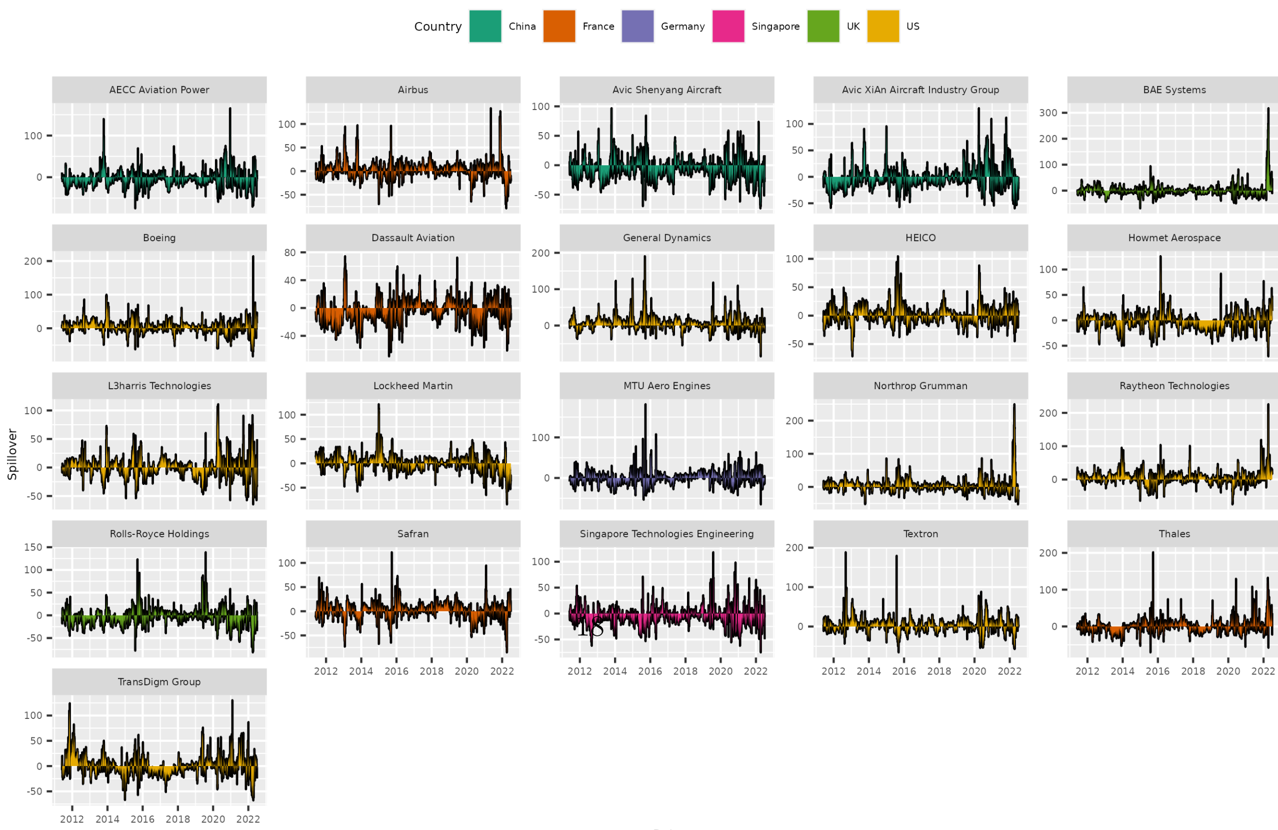


Figure 13: Middle quantile (50th Percentile)



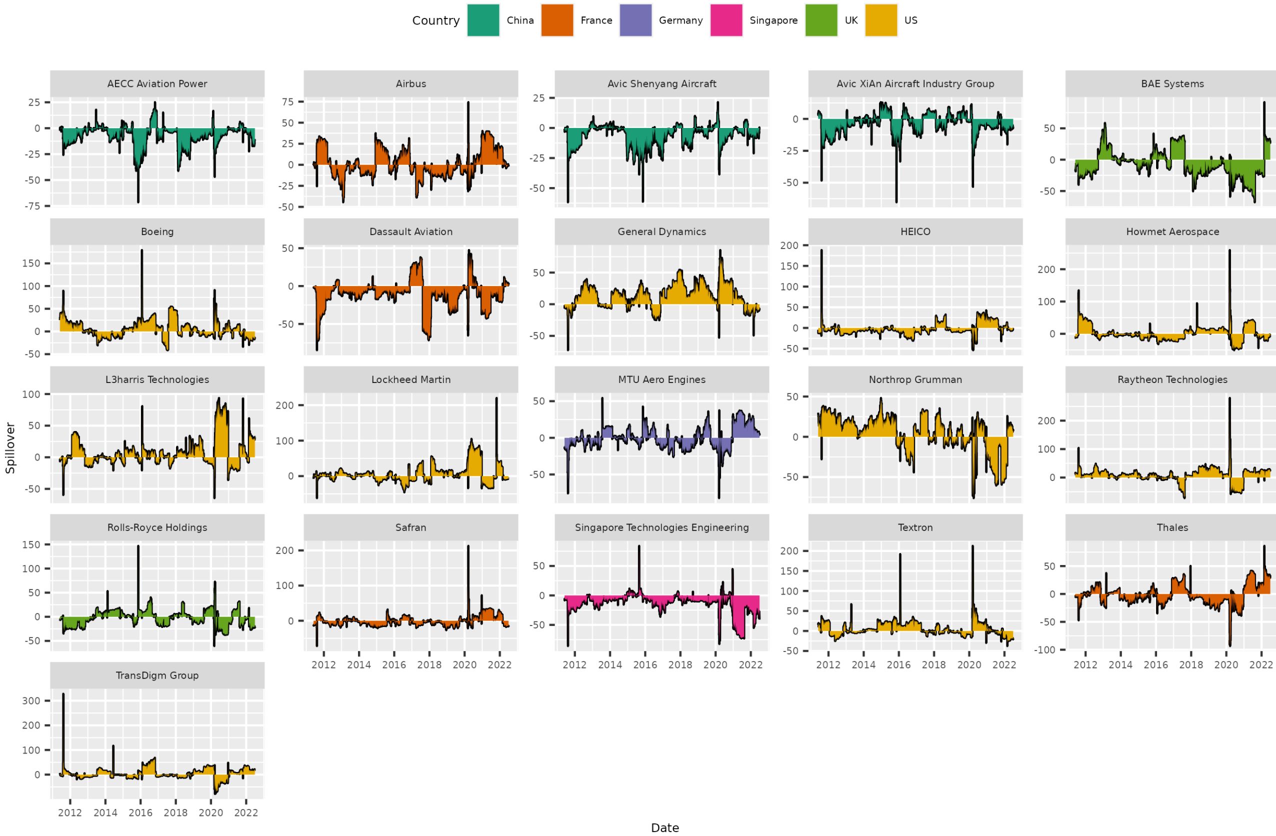


Figure 17: Middle quantile (50th Percentile)

somewhat integrated with global defence stocks under extreme return conditions and volatility states. This implies that Chinese defence stocks entail more diversification benefits under normal conditions than bear or bull markets when returns and volatility are very low or high.

Drivers of return and spillovers – the role of geopolitical risk

In this section, we provide insights into the main drivers of return and volatility spillovers across A&D stocks while paying particular attention to the impact of geopolitical risk. The explanatory variables considered in the analysis, selected based on previous studies, are:

- The geopolitical risk (GPR) index of Caldara and Iacoviello (2022), which is constructed based on press articles covering 11 leading international newspapers, and defined as "the kind of risk related to events such as wars, terrorist acts and political tensions, that can affect the normal and peaceful process of international relations" (Caldara and Iacoviello, 2022)[5];
- An interaction of GPR with the COVID-19 pandemic and Russian-Ukraine war (), where is a dummy variable taking the value of 1 during the COVID-19 outbreak and war period (January 02, 2020– July 01, 2022) and 0 otherwise;
- The US economic policy uncertainty (US EPU) index of Baker et al. (2016), constructed based on US newspaper articles reflecting uncertainties in US economic policies;
- The CBOE VIX index, which captures the 30-day expected volatility of the US stock market and is often used a proxy of fear among investors, not only in the US but across the global stock markets;
- The log returns on the S&P 500 Composite Index, which is used as a proxy for the performance of the global stock markets;
- The US Treasury spread, computed as "10-Year Treasury Constant Maturity Minus 2-Year Treasury Constant Maturity", which reflects the shape of the US yield curve;
- The TED spread, computed as the 3-month LIBOR USD rate minus the 3-month US Treasury Bill rate, which captures short-term liquidity risk;
- Default spread, computed as the yield on Moody's BAA-rated bonds minus the yield on AAA-rated corporate bonds, reflecting corporate credit conditions;
- US business conditions, measured by the Aruoba-Diebold-Scotti (ADS) index of Aruoba et al. (2009), which measures real business conditions on a daily basis;
- The US inflation expectation, as measured by the 5-Year Breakeven Inflation Rate (T5YIE);

We report the estimated coefficients of Equation 1 in Table 4 for return spillovers and in Table 5 for volatility spillovers[6]

[5]GPR indices have been used in various studies (see, Alqahatani et al., 2020; Ma et al., 2022; Mansour-Ichrakieh and Zeaiter, 2019; Wang et al., 2022; Wu et al., 2022).

[6]We ensure that all variables entered in the regression are stationary, whether in their original levels or transformed (e.g. change) levels.

$$TOTAL_t = c + b_1 GPR_{t-1} + b_2 GPR_{t-1}.DCOVID + b_{it} X_{t-1} + e_t \quad (1)$$

where $TOTAL_t$ is the total spillover index in the system of return or volatility across A&D companies, estimated at the lower, middle, or higher quantiles; GPR_t-1 is the lagged value of the geopolitical risk; $GPR_{t-1}.DCOVID$ is the interaction term between GPR and the COVID-19 and Russian-Ukraine war period; X_{t-1} is the vector of the lagged value of control variables, described above, and is the residual term. Except for GPR index, data on the other explanatory variables are collected from Refinitiv DataStream.

Table 4: Drivers of return spillovers across A&D companies for the full sample period

	Middle quantile		Upper quantile		Lower quantile	
Variable	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
GPRD(-1)	-0.033	0.000	-0.003	0.000	-0.003	0.000
GPRD(-1)*DCOVID	0.069	0.000	0.007	0.000	0.006	0.000
USEPU(-1)	0.008	0.004	0.001	0.040	0.001	0.048
VIX(-1)	0.164	0.004	0.011	0.062	0.028	0.000
SP500(-1)	24.392	0.027	0.075	0.957	6.462	0.000
TERM SPREAD(-1)	-0.733	0.809	0.470	0.269	-0.463	0.300
TED SPREAD (-1)	-0.079	0.000	-0.005	0.002	-0.003	0.122
DEFAULT SPREAD(-1)	19.867	0.000	1.401	0.000	0.683	0.001
ADS BUS CONDITION INDEX(-1)	0.713	0.000	0.071	0.000	0.066	0.000
US INFLATION(-1)	2.478	0.001	0.122	0.134	-0.474	0.000
C	42.044	0.000	91.401	0.000	92.879	0.000
Adjusted R-squared	0.640	8.408	0.392	0.867	0.387	0.901
F-statistic	468.741	0.140	170.260	0.381	166.738	0.360
Prob(F-statistic)	0.000	86.891	0.000	42.132	0.000	38.364

[a] This table presents the estimated coefficients of the regression model in Equation (7) based on a covariance estimator that accounts for the presence of heteroscedasticityand autocorrelation (HAC). The sample period is 23 August 2010 –July 1, 2022.

Table 5: Drivers of volatility spillovers across A&D companies for the full sample period

	Middle quantile		Upper quantile		Lower quantile	
Variable	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
GPRD(-1)	-0.061	0.000	-0.002	0.040	-0.042	0.000
GPRD(-1)*DCOVID	0.115	0.000	0.001	0.194	0.072	0.000
USEPU(-1)	0.035	0.000	0.000	0.257	0.014	0.000
VIX(-1)	0.499	0.000	0.000	0.933	0.416	0.000
SP500(-1)	84.600	0.000	-1.099	0.419	61.075	0.000
TERM SPREAD(-1)	-7.221	0.204	-1.217	0.004	-6.611	0.089
TED SPREAD (-1)	-0.019	0.482	0.000	0.923	-0.055	0.003
CORPORATE CREDIT CONDITIONS(-1)	14.191	0.000	0.060	0.695	16.357	0.000
ADS_BUS_CONDITION_INDEX(-1)	1.001	0.000	0.001	0.884	0.686	0.000
US INFLATION(-1)	3.410	0.017	-0.034	0.602	4.760	0.000
C	23.931	0.000	94.961	0.000	33.540	0.000
Adjusted R-squared	0.584	14.623	0.012	0.792	0.613	10.418
F-statistic	369.986	0.163	4.247	0.858	416.551	0.131
Prob.(F-statistic)	0.000	80.756	0.000	2.233	0.000	85.458

[a] This table presents the estimated coefficients of the regression model in Equation (7) based on a covariance estimator that accounts for the presence of heteroscedasticityand autocorrelation (HAC). The sample period is 23 August 2010 –July 1, 2022.

Starting with the drivers of the TCI of returns, Table 4 shows that many of the estimated coefficients of explanatory variables are not necessarily the same across the middle and upper/lower quantile spillovers. However, the GPR index is a significant driver of return spillovers at all quantiles, and its effect is positive and significant for all cases after controlling for the COVID-19 outbreak period, which includes the Russian-Ukraine war sub-period. This suggests that the heightened level of geopolitical risk around the war period has led to increased return spillovers across A&D stocks. Regarding the control variables, we notice that S&P500 returns, VIX, default spread, and business conditions positively impact return spillovers, irrespective of the quantile, bearing in mind that their magnitude is the largest at the middle quantile. Table 5 considers the results on the drivers of volatility spillovers. The results point to the exact impact of GPR on volatility spillovers, especially when the interaction term is considered, except at the upper quantile. Among the other explanatory variables, we highlight the significant role played by corporate credit conditions, stock market volatility, short-term liquidity risk, and real business conditio

Conclusion

This study analyses the return and volatility connectedness of a sample of major aerospace and defence stocks in normal and extreme market periods using a quantile-based VAR approach of connectedness, which captures the system of connectedness at lower, middle, and upper parts of the conditional distribution of both returns and volatility. Then, the drivers of the connectedness index estimated across various quantiles are revealed, notably the geopolitical risk index. The main results suggest evidence of variation in the quantile structure of the system of connectedness among major aerospace and defence stocks. The network topology analysis shows that shocks propagate more strongly at both lower and upper tails of the conditional distribution than at the conditional median, suggesting that the structure of spillovers at both lower tails is dissimilar to that observed at the conditional median. However, the magnitude of bilateral connections is smaller at the tails relative to those at the median, but they are more apparent. In the latter, connectedness is stronger within countries, but the volatility and return systems are less connected overall. These results suggest that the evolution of the dependence structure at the tails is notable and should not be overlooked. In other words, the system-wide connectedness of shocks in the A&D industry can be masked when connectedness measures are estimated at the conditional median or mean, thus missing a significant portion of the spillover information related to extraordinarily negative and positive shocks and extremely low and high volatility states. Accordingly, applying quantile-based models of connectedness is recommended as a natural extension to the pervasive average-based models. This finding result matters for asset pricing and allocation under various market conditions. The application of a time-varying analysis shows that the degree of tail-dependence varies with time and intensifies during periods of economic and geopolitical-conflict turmoil. Lower-tail dependence is positively correlated with upper-tail dependence, suggesting that extreme adverse events are associated with an increase in stabilising lower-tail connectedness coupled with a concurrent increase in destabilising upper-tail connectedness. Intuitively, the main findings generally concord with the literature on the return and volatility spillovers under various market conditions in the global stock markets, which reflect the nature of A&D stocks despite their price outperformance during periods of intensified geopolitical risk. Furthermore, the relative tail dependence calculation indicates an asymmetry between the behaviour of return (volatility) spillovers in lower and upper quantiles. The findings on the extreme connectedness at upper and lower tails offer a nuanced view of the importance of tail risk propagation within the network system of aerospace and defence stocks, which point to the utility of adopting quantile-based methods of spillovers to differentiate between the networks of spillovers under various market conditions. This might concern the supervision of risk under extreme market conditions. In fact, by extending our knowledge regarding the effects of the size and sign of the spillovers on the system of connectedness among significant aerospace and defence stocks, policymakers can use appropriate policy tools and surveillance mechanisms to manage potential adversative impacts occurring from extreme risk spillovers in the aerospace and defence industry. Otherwise, focusing only on the average shocks within the system of connectedness will likely lead to formulating and applying inappropriate and insufficient stabilising policies during extreme events.

Additional analysis reveals the importance of geopolitical risk at the end of the sample period in driving the spillovers of both returns and volatility without underestimating the significant role played by some macroeconomic and financial variables. Therefore, market participants should closely examine the geopolitical risk levels for making inferences on market integration in the aerospace and defence industry and the diversification possibilities across various market conditions.

Appendix

Table 6: Table A1: Size information for our study's sample

Company Name	Market Capitalistation	Total Revenue 2022	Total Revenue 2021
Raytheon Technologies Corp	147,447,678,880	64,388,000,000	67,074,000,000
Boeing Co	122,950,199,509	62,286,000,000	66,608,000,000
Lockheed Martin Corp	122,335,912,229	67,044,000,000	65,984,000,000
Airbus SE	103,410,072,192	59,283,132,119	62,888,484,589
Northrop Grumman Corp	72,539,645,185	35,667,000,000	36,602,000,000
General Dynamics Corp	64,084,906,210	38,469,000,000	39,407,000,000
Safran SA	61,320,053,976	17,203,237,615	20,893,621,575
L3Harris Technologies Inc	40,447,265,742	17,814,000,000	17,062,000,000
TransDigm Group Inc	40,249,692,781	4,798,000,000	5,429,000,000
BAE Systems PLC	33,378,358,649	26,357,384,087	26,410,065,616
Thales SA	30,091,644,275	18,772,594,040	18,407,111,839
HEICO Corp	20,909,217,802	1,865,682,000	2,208,322,000
AECC Aviation Power Co Ltd	17,702,958,771	4,388,141,416	5,368,648,696
Howmet Aerospace Inc	17,352,985,409	4,972,000,000	5,663,000,000
Avic Shenyang Aircraft Co Ltd	16,570,124,199	4,186,345,594	5,366,470,728
Textron Inc	15,054,696,965	12,382,000,000	12,869,000,000
Dassault Aviation SA	14,937,859,878	6,706,878,359	8,237,497,442
MTU Aero Engines AG	13,157,580,767	4,760,930,359	5,704,195,205
Rolls-Royce Holdings PLC	11,078,227,000	15,711,609,719	15,176,892,376
Avic XiAn Aircraft Industry Group Co Ltd	10,596,757,161	5,131,690,866	5,147,867,743
Singapore Technologies Engineering Ltd	8,369,671,163	5,419,248,997	5,702,642,698

Note:

This data is source from Refinitiv Eikon and all values are in US Dollars. The Market Capitalisation is a weight average of the 2022 daily values

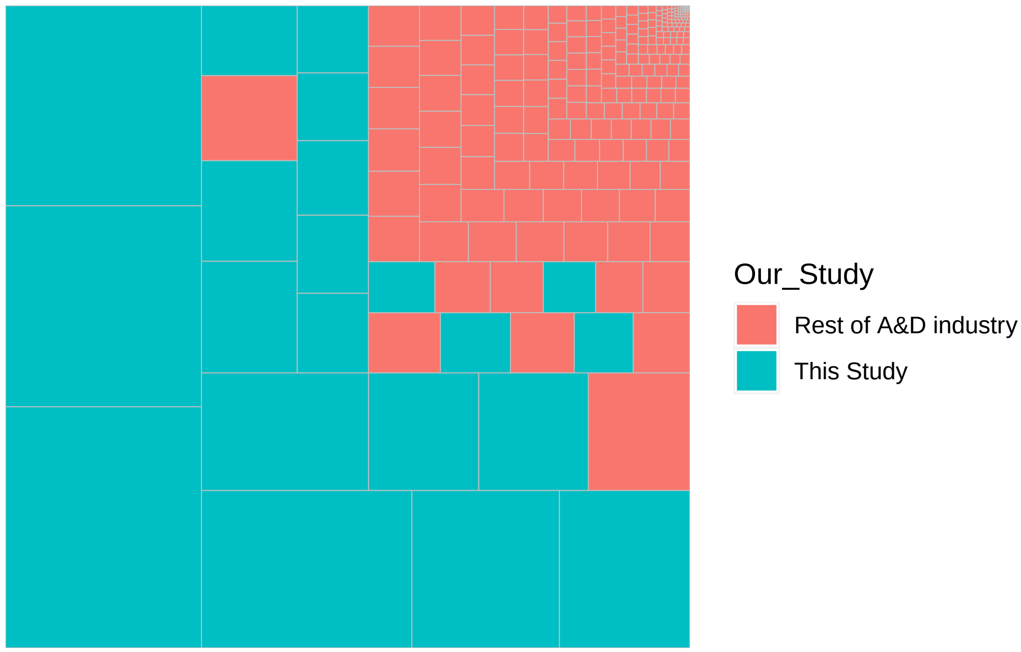


Figure 21: Treemap of market capitalisation of our study's sample

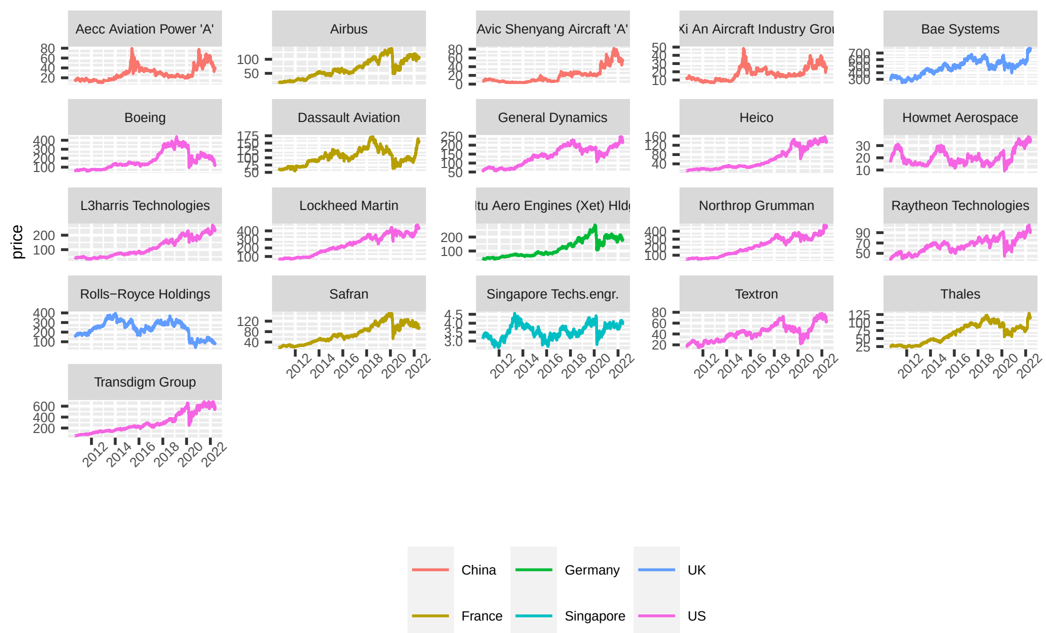


Figure 22: Figure A3: Price series levels

Figure 23: Figure A3: Daily log returns

Figure 24: Figure A4: Daily Volatilities

Table 7: Table A2: Summary statistics of daily returns

A&D Stock	Mean	Median	Std..Dev.	Skewness	Kurtosis	Jarque.Bera	ADF	PP
RAYTHEON_TECHNOLOGIES	0.0003	0.0000	0.0157	-0.3658	18.8916	32636.5***	-21.2901***	-56.4338***
LOCKHEED_MARTIN	0.0006	0.0005	0.0132	-0.7847	18.2347	30248.2***	-56.5766***	-56.7477***
BOEING	0.0003	0.0000	0.0226	-0.5643	26.2666	69973.9***	-18.1156***	-52.3339***
AIRBUS	0.0005	0.0002	0.0222	-0.3905	16.9639	25224.5***	-41.3354***	-53.1875***
NORTHROP_GRUMMAN	0.0007	0.0005	0.0142	-0.1678	10.8567	7974.9***	-57.6092***	-57.9145***
GENERAL_DYNAMICS	0.0004	0.0003	0.0138	-0.4154	9.2145	5069.4***	-56.0303***	-56.0601***
L3HARRIS_TECHNOLOGIES	0.0006	0.0004	0.0156	-0.3236	13.3721	13927.4***	-37.8971***	-58.3311***
SAFRAN	0.0005	0.0000	0.0208	-0.5873	23.2326	52968.0	-27.1859***	-54.0423***
TRANSDIGM_GROUP	0.0007	0.0006	0.0204	-0.8467	26.8661	73823.1	-27.2219***	-58.6233***
BAE_SYSTEMS	0.0003	0.0000	0.0145	0.0418	7.8111	2985.9	-54.9012***	-54.8972***
THALES	0.0005	0.0000	0.0157	0.3395	10.4513	7219.4	-52.8929***	-52.8478***
AECC_AVIATION_POWER___A_	0.0004	0.0000	0.0283	-0.0139	6.3355	1434.8	-50.3413***	-50.2565***
HEICO	0.0009	0.0004	0.0198	0.2280	11.1453	8582.7	-37.9681***	-57.4079***
AVIC_SHENYANG_AIRCRAFT___A_	0.0007	0.0000	0.0317	-0.1037	5.3171	697.9	-50.4755***	-50.432***
TEXTRON	0.0004	0.0000	0.0215	-0.3143	13.2261	13536.4	-56.7672***	-56.7572***
HOWMET_AEROSPACE	0.0002	0.0000	0.0250	-0.3118	13.7557	14968.7	-55.6534***	-55.6534***
AVIC_XI_AN_AIRCRAFT_INDUSTRY_GROUP___A_	0.0003	0.0000	0.0274	-0.1139	6.1919	1320.5	-51.6737***	-51.6765***
DASSAULT_AVIATION	0.0003	0.0000	0.0177	0.2804	10.4996	7293.6	-59.0881***	-59.3442***
MTU_AERO_ENGINES___XET___HLDG_	0.0004	0.0000	0.0196	-0.2349	14.6874	17643.4	-53.5665***	-53.5378***
ROLLS_ROYCE_HOLDINGS	-0.0002	0.0000	0.0263	0.8073	25.6142	66286.0	-42.2588***	-53.3912***
SINGAPORE_TECHS_ENGR_	0.0001	0.0000	0.0121	-0.2655	9.6055	5663.1	-58.7849***	-58.7819***

Table 8: Table A3: Summary statistics of daily volatilies

A&D Stock	Mean	Median	Std..Dev.	Skewness	Kurtosis	Jarque.Bera	ADF	PP
RAYTHEON_TECHNOLOGIES	0.0002	0.0000	0.0010	14.3977	270.2230	9315605	-8.8644***	-71.0605***
LOCKHEED_MARTIN	0.0002	0.0000	0.0007	16.4325	350.1678	15682053	-10.8166***	-57.4850***
BOEING	0.0005	0.0001	0.0026	16.0817	339.0628	14697726	-9.4739***	-59.9743***
AIRBUS	0.0005	0.0001	0.0020	17.2260	424.2219	23033869	-11.5572***	-65.0529***
NORTHROP_GRUMMAN	0.0002	0.0000	0.0006	11.4526	195.7092	4856762	-10.5620***	-55.0415***
GENERAL_DYNAMICS	0.0002	0.0000	0.0005	10.7424	180.7454	4133764	-9.4617***	-64.1503***
L3HARRIS_TECHNOLOGIES	0.0002	0.0001	0.0009	13.5332	273.2503	9512974	-11.8003***	-53.9115***
SAFRAN	0.0004	0.0001	0.0020	19.3285	499.2195	31946613	-11.6048***	-62.0761***
TRANSDIGM_GROUP	0.0004	0.0001	0.0021	16.7444	377.0165	18184391	-8.6389***	-55.6789***
BAE_SYSTEMS	0.0002	0.0001	0.0006	9.3253	129.7845	2117775	-16.0119***	-50.1728***
THALES	0.0002	0.0001	0.0008	11.6051	190.9520	4625049	-16.3795***	-60.5916***
AECC_AVIATION_POWER___A_	0.0008	0.0001	0.0018	3.8458	18.4539	38428	-9.8441***	-62.2551***
HEICO	0.0004	0.0001	0.0013	11.4285	201.3856	5142764	-9.5040***	-65.6277***
AVIC_SHENYANG_AIRCRAFT___A_	0.0010	0.0002	0.0021	3.2338	13.5866	19848	-10.2645***	-62.4013***
TEXTRON	0.0005	0.0001	0.0016	10.1877	141.4459	2525317	-10.6989***	-55.9341***
HOWMET_AEROSPACE	0.0006	0.0001	0.0022	13.6603	265.6162	8990159	-15.2603***	-62.3260***
AVIC_XI_AN_AIRCRAFT_INDUSTRY_GROUP___A_	0.0007	0.0002	0.0017	4.0915	21.3110	51874	-10.7828***	-60.2592***
DASSAULT_AVIATION	0.0003	0.0001	0.0010	12.8240	286.0500	10416628	-12.8417***	-55.6529***
MTU_AERO_ENGINES___XET___HLDG_	0.0004	0.0001	0.0014	11.7559	179.1791	4074035	-9.3358***	-66.7664***
ROLLS_ROYCE_HOLDINGS	0.0007	0.0001	0.0034	21.7076	718.3667	66237434	-5.3944***	-63.2794***
SINGAPORE_TECHS_ENGR_	0.0001	0.0000	0.0004	13.5671	279.9223	9984241	-12.0964***	-67.2677***

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