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THE IMPACT OF THE RUSSIA-UKRAINE WAR ON THE COMPETITIVENESS OF EUROPEAN AIRLINES

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Abstract. *Purpose* – The research identifies the impact of the Russia-Ukraine war on the stock prices of six publicly traded European airlines and evaluates their ability to adapt to this situation.

Research methodology – The dependence of the development of airline stock prices on the level of public and institutional stress due to the war was measured using GoogleTrends and is analysed on the basis of a Vector Autoregression model (VAR).

Findings – A short-term negative relationship was confirmed between the development of stock prices and GoogleTrends; the impact of the stress related to the war was negligible about 5 months after the outbreak thereof. Those companies that were the fastest to adapt to the shock of the war in terms of share prices are identified.

Research limitations – The link between GoogleTrends, as an input variable reflecting market sentiment, and the stock prices of European airlines, is considered a limitation.

Practical implications – The impact of investor sentiment on the returns on the stocks of airlines is a thing of the past; which is an important finding for financial market participants and airlines alike.

Originality/value – The ability of the specific airlines to adapt to the shock of war creates a competitive advantage.

Keywords: air transport, share price, GoogleTrends, VAR model, war.

JEL Classification: D53, G15, C32.

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1. Introduction

The outbreak of the Russia-Ukraine war in February 2022 was primarily a shock to the European and Russian economies. The ensuing sanctions and restrictions have limited trade relations, reduced the volume of service flows and led to increased energy and food prices, as a result of which the war has affected almost all industrial sectors. However, as quantitative and structural general equilibrium trade models indicate, some producers and providers have been hit hard, while for others, the war has presented business opportunities (Feng et al., 2023). According to Le et al. (2023), this war has had a significant negative impact on the airline industry and a positive impact on the defence industry.

The war has undoubtedly had a negative impact on trade, even in non-combat areas. This is because, among other things, intergroup trust has been eroded, with all the consequences thereof (Korovkin & Makarin, 2023), as confirmed by Estrada and Koutronas (2022) on the basis of an intraregional war simulator. The authors also see the serious disruption of trade relations and opportunities being limited to the European-Russian area, thereby arguing that the extent of the impacts thereof is asymmetric. They believe that the conflict will reshape international trade and lead to a reconsideration of the importance of global value chains, whereby the goal for companies will be to create competitive advantage by catching trends on time and applying them to increase efficiency. This is compounded by the fact that some sectors are more sensitive to macroeconomic changes than others (Valaskova & Nagy, 2023).

This is clearly reflected in the results of the capital markets. Boungou and Yatié (2022) confirmed a negative relationship between the Russia-Ukraine war and global stock market returns on the basis of stock returns in 94 countries for the period 22 January – 24 March 2022. In the first two weeks of the war, there was a significant overall drop, which was notably larger (by 7.78%) for those countries geographically located close to the two countries. This was followed by a significant easing of the decline in subsequent weeks, and even a return to asymmetric growth in the individual countries and for those companies that started to take advantage of the opportunities brought about by the introduction of sanctions and restrictions.

As stated, one of the industries most affected by the war is the aviation industry (Bartoš et al., 2022). With airspace closed and airlines grappling with higher fuel prices, it is no wonder that the sector is finding it difficult to recover from the problems caused by the COVID-19 pandemic. The Russia-Ukraine war resulted in a jump in oil prices and significantly increased the costs associated with the assessment of airspace risks at a time when the demand for travel was still low due to the pandemic.

The air transport sector can be considered a highly cyclical one featuring sharp fluctuations in turnover and profit, which are strongly dependent on the economic cycle. The aviation industry is also characterised by intense competition, rapid changes brought about by deregulation, rapid technological developments, industrial consolidation and innovation (Tamošiūnas & Kitkovskij, 2022). Airlines that are able to adapt more quickly therefore gain a competitive advantage.

The presented paper seeks to analyse the impact of the war between Russia and Ukraine based on the development of the stock prices of six publicly traded European airlines and to evaluate the competitiveness of these companies from the perspective of the speed with which they have adapted to this unprecedented situation.

2. Background

The war in Ukraine, exacerbated by the waning COVID-19 pandemic, significantly influenced the expectations of the European economy, including the fulfilment of Agenda 2030, the key policy on sustainable development (Bin-Nashwan et al., 2022). This was confirmed by Balli et al. (2022), who analysed the situation in 26 European countries, identifying the significant impact on the tourism sector in the period when transport companies and companies operating in the hospitality sector expected an increase in interest after the relaxation and removal of quarantine measures (Gavurova et al., 2023). According to the global economic model of Liadze et al. (2022), Europe was the most affected region, with an expected decrease in GDP growth of more than 1% compared to predictions at the beginning of 2022, whereby the energy, food and transport sectors were the most affected industries. A study conducted by the Vienna Institute for International Economic Studies (Astrov et al., 2022) points to the direct impact of inflation growth, as well as the opportunities for the arms industry, green transformation, or other industries that can respond quickly to a sudden change in circumstances.

Macroeconomic impacts are directly reflected in share prices, as both recent and past news have a significant impact on current volatility (Trivedi et al., 2021). Specifically, there was a sharp increase in volatility shortly after February 24, which had not been predicted by models. However, Fiszeder and Małecka (2022) used the Range-GARCH model to choose those stock listings that were able to respond most effectively to the changes in variables under conditions of extreme volatility.

2.1. Exogenous shocks and airline stocks

Financial markets have been affected both by sanctions and extremely volatile commodity prices (Najaf et al., 2023). Nevertheless, as Alam et al. (2022) state based on vector autoregression, some regions and fields are more threatened by risk spill-overs than others. These include air transport, which is affected both by the administrative interventions (sanctions) related to changes in flight routes (Neto, 2022) and oil prices, which are directly reflected in costs (Horobet et al., 2022). This fact is also confirmed by Güntner and Öhlinger (2022) using the Bayesian SVAR model and by Fasanya et al. (2021) and Naeem et al. (2023) through linear and non-linear regression. However, it is still necessary to take into account that the effects of oil price changes on stock returns are dynamic and show high asymmetry and heterogeneity (Khalfaoui et al., 2022).

According to Alici and Sevil (2022) and Choi and Choi (2023), the price of airline stocks is also significantly influenced by aircraft load, which is related to flight times, slots and routes, which are factors that are affected by the war. However, these are not the only variables. According to Carter et al. (2022), during periods of volatility, market players take into account the size of the company and cash reserves in the prices of transport and accommodation services, as in such periods, the shock hits those companies with a higher level of indebtedness the most.

Borochin (2020) provides a long-term view concerning airline stocks, stating that the level of systemic risk is more of a liability rather than a risk factor. The author recommends focusing primarily on return on sales as a key indicator.

Research into the impact of shocks on airline valuation is nothing new. In the last two decades, even before the outbreak of the war in Ukraine, the Boeing 737 Max fleet was grounded, which, in addition to the quarantine measures in place, also had a major impact on operators and contributed significantly to the reduction in air transport (Janić, 2022). Collings et al. (2022), using the DCC-GARCH model, showed that in the former case, there were significant interactions between Boeing's stock prices and the airlines tied to this supplier (Choudhury et al., 2022). According to the same model, financial markets were able to quickly identify real risks and opportunities, with the recovery of stocks of less affected companies occurring within one month. In the case of air crashes involving Boeing aircraft, this phenomenon can be partly explained by the theory of Situational Crisis Communication, whereby there is a strong public reaction that is reflected in the market valuation (Butler, 2021). In these cases, there is an increased risk of unintentional and intentional dissemination of misinformation, which has a significant negative impact on the market valuation of air carriers (Akyildirim, 2020). In contrast, more intensive media coverage is associated with a lower tendency for companies to withhold bad news, with regression-discontinuity analysis based on Russell 2000 indicating a negative relationship between media coverage and the risk of a stock price crash for companies subject to higher reputational risk (An et al., 2020).

In the case of airlines, a shock caused by exogenous factors (war, disease, aircraft grounding) has an impact on their competitive position, which is then reflected in their market valuation (Colak et al., 2023). More space on competitive routes and the degree of resistance of the original carriers are analysed by Aryal et al. (2022), who believe that compliance with the form of communicating planned transport capacities is key. Within this context, Liu et al. (2021) developed a unique bidding game model that takes into consideration the speed of price adjustment and the coefficient of price elasticity in the competitive airline market. According to the authors, once the speed of adjustment and the price elasticity coefficient exceed the threshold value, a chaotic state occurs, which would lead to the disruption of competition. However, as pointed out by Klein et al. (2020), at the moment of shock, there also occurs cooperation between competing companies, when the use of the temporary advantage is determined by the complex interplay among the intensities of simultaneous competition and cooperation on the air transport market.

2.2. Exogenous shocks and the VAR model

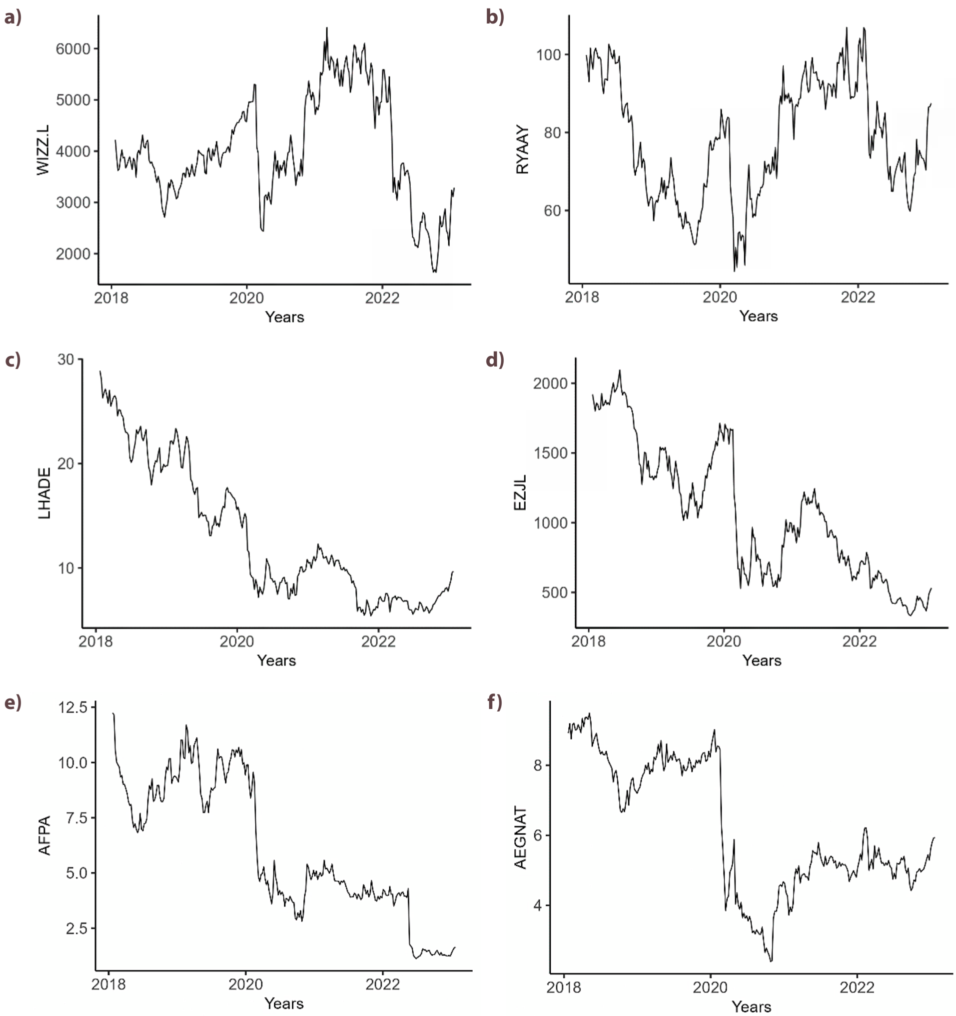
The VAR model is a relatively standard and frequently used tool for assessing the specific impact of an exogenous shock on market capitalisation (Shojaie & Fox, 2022). Bastianin and Manera (2018) use the VAR model to analyse the effects of oil shocks on the volatility of the US stock market, while Ghosh and Kanjilal (2012) use an extended VAR model for the analysis of oil shocks and their effect on inflation and foreign exchange reserves. The VAR model was similarly used by Jiang and Fang (2022) to determine the response of the Chinese shadow banking system to exogenous shocks. Yun and Yoon (2019) used VAR-GARCH-BEKK to analyse the effect of a shock in the form of changed oil prices on the volatility and price of airline stocks. It was found that the stock price of small companies responds more strongly. Pal and Garg (2019) used the VAR model to analyse the effect of macroeconomic surprises and found that stock returns are affected by monetary policy as well as other shocks. Specifically, within the context of assessing the impact of war, regression models suggest that the effects of geopolitical risks on stock valuation are heterogeneous in various countries, despite their global interconnection (Hoque et al., 2021). Lee (2018) deals with selecting the optimal method. Using analysis and comparison of the domestic monetary policies of Korea and the USA, the author selects the most effective model from DSGE, DSGE-VAR and VAR. Based on the marginal data density standard, the DSGE-VAR model was found to be the most effective model; based on the RMSE criterion, the VAR model was found to be the most accurate.

Based on the above research, and for the purposes of this paper, the VAR model was therefore selected to determine the impact of the Russia-Ukraine war on the stocks of European airlines.

3. Materials and methodology

This paper aims to identify the impact of the outbreak of the war between Russia and Ukraine on 24 February 2022 on the stock prices of six publicly traded European airlines (Wizz Air Holdings Plc (WIZZ.L), Ryanair Holdings plc (RYAAY), Deutsche Lufthansa AG (LHADE), easyJet plc (EZJL), Air France-KLM SA (AFPA) and Aegean Airlines S.A. (AEGNAT)).

The data was sourced from the MarketWatch database (MarketWatch, 2023a, 2023b, 2023c, 2023d, 2023e, 2023f, 2023g). The observation frequency is based on the average weekly price (in EUR). Each variable contains 262 observations.



Note: Period 22 January 2018 – 23 January 2023; RStudio software was used for data processing and visualisation, with the graphs constructed using "ggplot2".

Figure 1. Stock price development: a – WIZZ.L; b – RYAAY; c – LHADE; d – EZJL; e – AFPA and f – AEGNAT

The Russian invasion of Ukraine had a negative impact on the aviation industry. In the first week, the aforementioned airlines lost 0–14.47% of their market capitalisation and wrote off 6.89% of their value on average. In the period from 24 February 2022 to 23 January 2023, the market value of WIZZ.L decreased by 11%, RYAAY by 6.77%, EZJL by 24.65%, and AFPA by 56.91%.

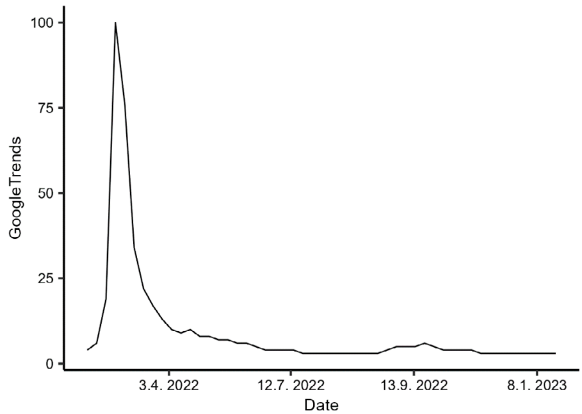
Figure 1a–f shows the development of the stock price (in EUR) of the selected companies during the period 22 January 2018 – 23 January 2023 in monthly intervals. The data series show a decreasing trend throughout the entire monitored period. The development of the stock prices of LHADE, EZJL, AFPA and AEGNAT follow a similar pattern. Common features were recorded also in the case of the WIZZ.L and RYAAY data series. An unprecedented drop in demand for air transport accompanied by a plunge in stock prices was recorded in March 2020 as a result of the spread of the COVID-19 pandemic in Europe. Airlines suspended operations or reduced their capacities by up to 99% compared to the equivalent weeks in the year 2019. This was caused by the state-ordered border closures to foreign nationals. Airports reduced their operations and much of their premises became a parking lot for grounded aircraft (Budd et al., 2020). This was followed by a recovery, which saw airline stock prices pick up until the outbreak of the Russia-Ukraine war.

Table 1 presents the descriptive statistics of the stock prices for the airlines WIZZ.L, RYAAY, LHADE, EZJL, AFPA and AEGNAT for the period 22 January 2018 – 23 January 2023. The variables include 262 observations in total. Within the monitored period, the lowest recorded stock price for RYAAY and AEGNAT occurred during the COVID-19 pandemic, with that of the remaining companies occurring during the war in Ukraine. LHADE, EZJL, AFPA and AEGNAT recorded their maximum stock price before the pandemic, whereas WIZZ.L and RYAAY did so in the period between the COVID-19 pandemic and the war in Ukraine. The most expensive stock is that of WIZZ.L, the price of which is on average 51.37 times higher than that of RYAAY, 307.27 times higher than that of LHADE, 3.79 times higher than that of EZJL, 672.7 times higher than that of AFPA, and 650 times higher than that of AEGNAT. The volatility (Std) of the stock price of WIZZ.L is 70.61 times higher than that of RYAAY, 162.54 times higher than that of LHADE, 2.2 times higher than that of EZJL, 341 times higher than that of AFPA, and 567.15 times higher than that of AEGNAT. A negative asymmetry is evident in the stock price of RYAAY, whereas for all the other companies a positive asymmetry exists. The skewness coefficient confirms a flatter distribution of the stock price for all the companies.

Table 1. Descriptive statistics of stock prices – WIZZ.L, RYAAY, LHADE, EZJL, AFPA and AEGNAT

	n	Mean	Median	Std	Skew	Kurt	Min	Max
WIZZ.L	262	4 016.03	3 863.73	1054.89	0.13	0.59	1 637.10	6 415.64
RYAAY	262	78.18	77.99	14.94	0.06	–1.07	44.37	106.98
LHADE	262	13.07	10.58	6.49	0.68	–0.87	5.42	28.88
EZJL	262	1058.90	1008.05	480.30	0.36	–1.04	333.64	2096.113
AFPA	262	5.97	4.87	3.09	0.16	–1.24	1.12	12.245
AEGNAT	262	6.17	5.42	1.86	0.10	–1.23	2.40	9.49

Note: Period 22 January 2018 – 23 January 2023; (n) number of observations, (Std) standard deviation, (Skew) skewness, (Kurt) kurtosis; the results were generated in RStudio using the "tseries" and "lessR" packages.



Note: RStudio software was used for data processing and visualisation, with the graphs constructed using "ggplot2".

Figure 2. Relative frequency of searches for the phrase "Russia-Ukraine war" in GoogleTrends (2023) converted into the interval <0, 10> % for the period 30 January 2022 – 15 January 2023 in weekly frequencies.

The time series of airline stock prices were correlated with the incidence of the phrase "Russia-Ukraine war" in GoogleTrends (GoogleTrends, 2023) – see Figure 2. The data from GoogleTrends were calculated based on relative frequencies, with respect to the highest value of the phrase, and converted into the interval <0, 100> %.

Table 2 presents the descriptive statistics of the relative frequency of searches for the phrase "Russia-Ukraine war" in GoogleTrends during the period 30 January 2020 – 15 January 2023 converted into the interval <0, 100> %. The variable includes 51 observations for the whole monitored period. The minimum was most frequently recorded on 10 July 2022, and the maximum on 20 February 2020. The skewness coefficient indicates that the relative frequency of searches for the phrase "Russia-Ukraine war" in GoogleTrends is positively asymmetric, with the kurtosis coefficient indicating a leptokurtic distribution.

Alternative sources of information for analysis include online search engines such as Social Searcher (2023) and Keyword Tool (2023). The Keyword Tool platform operates on a similar principle to GoogleTrends, scanning the internet to identify trends. It is available in a free version, which is insufficient for research purposes. The Social Searcher (2023) platform shares many characteristics with GoogleTrends, allowing users to search and analyse content from various social networks for free, including the ability to browse historical data and provide statistical evaluations. The GoogleTrends platform was chosen due to its specific capabilities

Table 2. Descriptive statistics of the relative frequency of searches for the phrase "Russia-Ukraine war" in GoogleTrends (2023) converted into the interval <0, 100> %

	n	Mean	Median	Std	Skew	Kurt	Min	Max
GoogleTrends	51	9.47	4	17.18	4.3	19.38	3	100

Note: Period 30 January 2020 – 15 January 2023; (n) number of observations, (Std) standard deviation, (Skew) skewness, (Kurt) kurtosis; the results were generated in RStudio using the "tseries" and "lessR" packages.

useful for analysis, such as the development of term popularity over time, data filtration based on geographic location, relevance to current events, and data visualisation.

In the sub-sections that follow, we discuss the suitability and adjustment of the data for the VAR model (3.1), the determination of the VAR model and its stability (3.2), and analyse the relationships between the variables (3.3–3.5).

3.1. Stationarity

The VAR model is most often used for multivariate time series and the analysis of the dynamic relationships between variables. It is a system of equations in which the endogenous variables are influenced by their lag and the lag of other variables in the system. The model is commonly used to assess financial crises and macroeconomic, as well as monetary, shocks. The creation of a VAR model requires data stationarity (Tran & Nguyen, 2022). The stationarity of the time series was verified using Augmented Dickey-Fuller (ADF), a unit root test, where the p-value must be below 5% to confirm stationarity. The notation of the general equation of the ADF test is as follows:

$$\Delta y_t = \alpha + \beta_t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \ldots + \delta_{p-1} \Delta y_{\{t-(p-1)\}} + \varepsilon_t, \tag{1}$$

where Δy_t is the difference in the value of the time series at time t and the values of the time series at time (t–1), α is a constant, β_t is a trend if existing in the time series, γ is the coefficient of the preceding value of the time series y, Δy_{t-1}, ..., $\Delta y_{\{t-(p-1)\}}$ are differences of the preceding p-values of the time series, ε_t is white noise. Here, the null hypothesis is tested, according to which the coefficient γ equals 0, which indicates the existence of a unit root and the series is not stationary. If the series is not stationary, it needs to be transformed into stationary through differencing (Gelo, 2009).

3.2. Determination of the VAR model

For the creation of a VAR model, it is essential to select the optimal lag length, which can be determined on the basis of Akaike Information Criterion (AIC), Schwarz Information Criterion (SC), Bayesian Information Criterion (BIC), Hannan-Quinn Information Criterion (HQ), and Final Prediction Error (FPE), which is a criterion measuring the prediction error at the last point of a time series based on the number of parameters (Zhao & Qian, 2014). The optimal lag length for each criterion is reached at the point where the criterion value is the lowest, which indicates that the model is the most suitable one in terms of the balance between good data interpretation and model simplicity (Suharsono et al., 2017). If the number of lags is too low, the residual of the regression will not show white noise, which means that the model will not accurately estimate the actual error. When creating the VAR model, all the aforementioned criteria must be taken into consideration and the optimal lag length selected on the basis of the most frequent occurrence. The last step before the implementation of the VAR model involves the mutual cointegration of the data, which occurs if there is a long-term relationship between two or more variables (Gospodinov et al., 2013). The existence of cointegration was verified by applying the Johansen cointegration test. The formula for the Johansen cointegration test is as follows:

$$y_v = A_1 x_{v-1} + e_v; \tag{2}$$

$$\Delta y_v = A_1 x_{v-1} - x_{v-1} + e_v; \tag{3}$$

$$= \left(A_1 - 1\right) x_{v-1} + e_v, \tag{4}$$

where the vectors in the equation are denoted as x_1 and e_v, while matrix A_1 indicates the eigenvalue decomposition matrix.

Upon selecting the optimal lag length and performing the Johansen cointegration test, it is possible to determine the VAR model, the general equation for which has the following form:

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \ldots + A_p y_{t-p} + \varepsilon_t, \tag{5}$$

where y_t is a vector of length k containing the values of the variables at the observed time t, c is a constant, A_1, A_2, ..., A_p are matrices of autoregressive coefficients with the dimensions of $n \times n$, and ε_t is a vector of n errors.

Stability is determined by calculating the roots of the characteristic polynomial of the VAR model, which is a mathematical function derived from the autoregressive model coefficients, including the calculation of the determinant of the matrix of coefficients, whereby the coefficient values are derived from the previous values in the model. If all roots of the characteristic polynomial are inside the unit circle, the model is considered stable, and its behaviour stabilises over time. If the roots are outside the unit circle, the model is not stable and may result in inconsistent predictions. For this reason, stability needs to be verified (Fanelli, 2007). The general equation for calculating the roots of the *n-th* order polynomial is as follows:

$$z^n + a_{n-1} \cdot z^{(n-1)} + \ldots + a_1 \cdot z + a_0 = 0, \tag{6}$$

where a_0, a_1, ..., a_{n-1}, a_n are the polynomial coefficients, and z are its roots. The equation will be solved for an unknown z.

3.3. Granger causality test

The Granger causality test is used to determine the causality between two time series. It verifies whether one time series can be used to improve the accuracy of the prediction of the target time series (Aliu et al., 2023a). The Granger causality test can be generally expressed using the F-statistic as follows:

$$F = \frac{\left(RSSR - RSSUR\right)}{p} / \frac{RSSUR}{\left(n - k - 1\right)}, \tag{7}$$

where *RSSR* is the residual sum of squares (*RSS*) for the autoregressive (AR) model containing the endogenous variable and potential causal variable *RSSUR* is the *RSS* for the AR model containing only the endogenous variable, p is the number of lags included in the model, n is the number of observations, and k is the number of additional variables. The *F*-statistic is compared with the critical value of *F*, which is given by the number of observations and parameters in the model. If the value of *F* is greater than the critical value of *F*, the null hypothesis stating that the additional variable does not Granger-cause the endogenous variable is rejected (Usman & Bashir, 2022).

3.4. IRF

The Impulse Response Function (IRF) is used to determine the response that an impulse of one variable will cause in other variables in the system (Katsampoxakis et al., 2022). Impulse refers to a sudden change. The IRF describes the effect of the impulse on the dependent variable over time, i.e. how the variables in the system change in response to the impulse (Aliu et al., 2023b). In general, the equation for calculating the IRF in the VAR model can be expressed as follows:

$$G_t = H^t \cdot A, \tag{8}$$

where G_t is a vector of length p containing the expected average changes in each variable in the system at time t after the application of the impulse, H is the IRF of the matrix with the dimensions p x kp, which describes how the impulse influences each variable in the system over time, and A is the vector of autoregressive coefficients of length kp, which is gained on the basis of the VAR model estimate.

3.5. Variance decomposition

Variance decomposition is a method used within VAR models to decompose the variance of one or more variables into relevant resources. The method enables the identification of how much of the variability of one variable is explained by the other variables in the system (Li et al., 2011). Variance decomposition is performed using the IRF, based on which coefficients are then calculated, which determine the percentage of each variable's variability that can be explained by other variables in the model (Du et al., 2010).

4. Results

As before, in the sub-sections that follow, we analyse the appropriateness and modification of the data for the VAR model (4.1), deal with the determination of the VAR model and its stability (4.2), and subsequently analyse the relationships between the variables (4.3–4.5).

4.1. Data stationarity

To determine whether the data is stationary, the Augmented Dickey-Fuller (ADF) test was performed – see Table 3.

Table 3. ADF test using p-value on the analysed variables

Variables	In level		In first difference		In second difference	
	Dickey-Fuller	p-Value	Dickey-Fuller	p-Value	Dickey-Fuller	p-Value
WIZZ.L	–0.51115	0.9781	–3.1789	0.1002	–7.6346	0.01
RYAAY	–1.3513	0.8356	–4.3735	0.01		
EZJL	–0.33816	0.9857	–3.626	0.03941		
AFPA	0.20981	0.99	–3.8895	0.0211		
AEGNAT	–1.5139	0.7701	–5.9363	0.01		
LHADE	–2.3107	0.4494	–6.2666	0.01		

Note: Period 30 January 2022 – 15 January 2023; undifferenced variables include 51 values; the values were generated in RStudio using the "tseries" package.

In the first two columns, the test was performed on the original data. It is evident that all the time series are non-stationary. To make them stationary, differencing was therefore performed. The next two columns present the results of the ADF test after the first differencing. The results show that the null hypothesis on the presence of the unit root can be confirmed only for WIZZ.L. For the remaining time series, the null hypothesis is rejected at the 5% confidence level and the data is stationary. The last two columns present the results of the second differencing for the WIZZ.L time series. At the 5% confidence level, it was confirmed that the time series was stationary.

4.2. Determination of the VAR model

For the company WIZZ.L, the selected optimal lag length is 4; for the remaining VAR models, the selected optimal lag length is 5, since these are values where the AIC, BIC and HQIC criteria are the lowest. Based on this, it was possible to select the optimal lag length for the creation of individual VAR models. Table 4 shows that the ideal lag length in the model for the individual variables is 2.

Table 4. Results of optimal lag length calculations for the VAR model for the six analysed variables

	Lag	1	2	3	4	5
WIZZ.L	AIC	11.59926	11.12976	11.21970	11.18482	
	HQ	11.68814	11.27789	11.42709	11.45146	
	SC	11.83545	11.52340	11.77081	11.89339	
	FPE	109055.18679	68280.01287	74919.13517	72721.80797	
RYAAY	AIC	2.892408	2.618497	2.741171	2.850845	2.761270
	HQ	2.981288	2.766629	2.948557	3.117483	3.087162
	SC	3.128597	3.012145	3.292279	3.559412	3.627297
	FPE	18.042965	13.737274	15.574511	17.468832	16.102072
EZJL	AIC	7.017829	6.492697	6.614643	6.755611	6.610883
	HQ	7.106709	6.640830	6.822028	7.022249	6.936775
	SC	7.254018	6.886346	7.165751	7.464178	7.476910
	FPE	1116.748917	661.370056	749.275938	867.126044	756.393137
AFPA	AIC	–1.5562135	–1.8614742	–1.7384901	–1.6454218	–1.5294393
	HQ	–1.4673339	–1.7133417	–1.5311046	–1.3787832	–1.2035477
	SC	–1.3200244	–1.4678258	–1.1873824	–0.9368547	–0.6634128
	FPE	0.2110066	0.1556947	0.1765722	0.1947871	0.2205212
AEGNAT	AIC	–3.46286172	–3.68349941	–3.62341351	–3.61594006	–3.553459
	HQ	–3.37398219	–3.53536687	–3.41602795	–3.34930148	–3.227567
	SC	–3.22667267	–3.28985099	–3.07230572	–2.90737289	–2.687432
	FPE	0.03135084	0.02517552	0.02681084	0.02715032	0.029136
LHADE	AIC	–1.8220500	–1.9860585	–1.878884	–1.7762550	–1.8010338
	HQ	–1.7331705	–1.8379259	–1.671498	–1.5096164	–1.4751422
	SC	–1.5858610	–1.5924101	–1.327776	–1.0676878	–0.9350072
	FPE	0.1617501	0.1374573	0.153444	0.1708992	0.1680732

Note: Period 30 January 2022 – 15 January 2023; recorded on a weekly basis; after the first differencing, the variables RYAAY, EZJL, AFPA, AEGNAT and LHADE contained 50 values; after the second differencing, the variable WIZZ.L contained 49 values; the results were generated in RStudio using the "tseries" package.

The Johansen cointegration test performed in RStudio was analysed using the "vars" and "tidyverse" packages. Table 5 presents the results of the Johansen cointegration test with the trace statistics and the maximum eigenvalues using two lags in the system. The eigenvalues are higher than the confidence levels of 10%, 5%, and 1%, which confirms the existence of the cointegration of airline stock prices with GoogleTrends.

Table 5. Results of Johansen cointegration tests

Test type: maximum eigenvalue statistic (lambda max.), without linear trend and constant in cointegration				
WIZZ.L	(1)	(2)	(3)	
Eigenvalues (lambda):	0.9398359	0.6242179	0	
Values of test statistic and critical values of test:				
	Test	10%	5%	1%
r <= 1	47.96	7.52	9.24	12.97
r = 0	137.72	13.75	15.67	20.20
RYAAY	(1)	(2)	(3)	
Eigenvalues (lambda):	0.3021477	0.2451176	0	
Values of test statistic and critical values of test:				
	Test	10%	5%	1%
r <= 1	14.06	7.52	9.24	12.97
r = 0	17.99	13.75	15.67	20.20
EZJL	(1)	(2)	(3)	
Eigenvalues (lambda):	0.3025013	0.04804499	0	
Values of test statistic and critical values of test:				
	Test	10%	5%	1%
r <= 1	2.46	7.52	9.24	12.97
r = 0	18.01	13.75	15.67	20.20
AFPA	(1)	(2)	(3)	
Eigenvalues (lambda):	0.2634942	0.1711447	0	
Values of test statistic and critical values of test:				
	Test	10%	5%	1%
r <= 1	9.39	7.52	9.24	12.97
r = 0	15.29	13.75	15.67	20.20
AEGNAT	(1)	(2)	(3)	
Eigenvalues (lambda):	0.4452749	0.1716447	0	
Values of test statistic and critical values of test:				
	Test	10%	5%	1%
r <= 1	9.42	7.52	9.24	12.97
r = 0	29.46	13.75	15.67	20.20
LHADE	(1)	(2)	(3)	
Eigenvalues (lambda):	0.5103789	0.1468605	0	
Values of test statistic and critical values of test:				
	Test	10%	5%	1%
r <= 1	7.94	7.52	9.24	12.97
r = 0	35.71	13.75	15.67	20.20

Note: Results with the trace statistic and max eigenvalues in comparison with GoogleTrends (2023); the results were generated in RStudio using the "urca", "tidyverse" and "vars" packages.

The stability of the model was determined using the calculation of the roots of the characteristic polynomial for the VAR model. Table 6 presents the values arranged in the order from the highest to the lowest. From the results in the Table 6 it can be stated that all the created VAR models meet the stability criterion.

Table 6. Results of the calculation of the roots of the characteristic polynomial for the individual VAR models

	1	2	3	4
WIZZ.L	0.6125384	0.6125384	0.5436690	0.2007874
RYAAY	0.61506594	0.61506594	0.35759427	0.06901583
EZJL	0.9100538	0.6460089	0.6460089	0.6411253
AFPA	0.6236729	0.4571041	0.4571041	0.3818195
AEGNAT	0.7459377	0.5511597	0.5033787	0.5033787
LHADE	0.7472587	0.6015389	0.6015389	0.4669510

Note: None of the variables exceeds the critical value of 1, which confirms the stability of the model.

4.3. Granger causality test

For the purpose of determining the causal relationships between the variables, the Granger causality test was performed in order to analyse the relationship between the stock prices of the selected airlines and the incidence of the phrase "Russia-Ukraine war" in GoogleTrends. The results in Table 7 are as expected. With the exception of WIZZ.L, it was found that at the 5% confidence level, the stock prices of the selected airlines do not Granger-cause GoogleTrends, thereby confirming the null hypothesis. This can be due to the fact that the stock price of WIZZ.L grew before the beginning of the Russia-Ukraine war. On the contrary, all stock prices, with the exception of AFPA, are influenced by the development in GoogleTrends at

Table 7. Results of Granger causality test

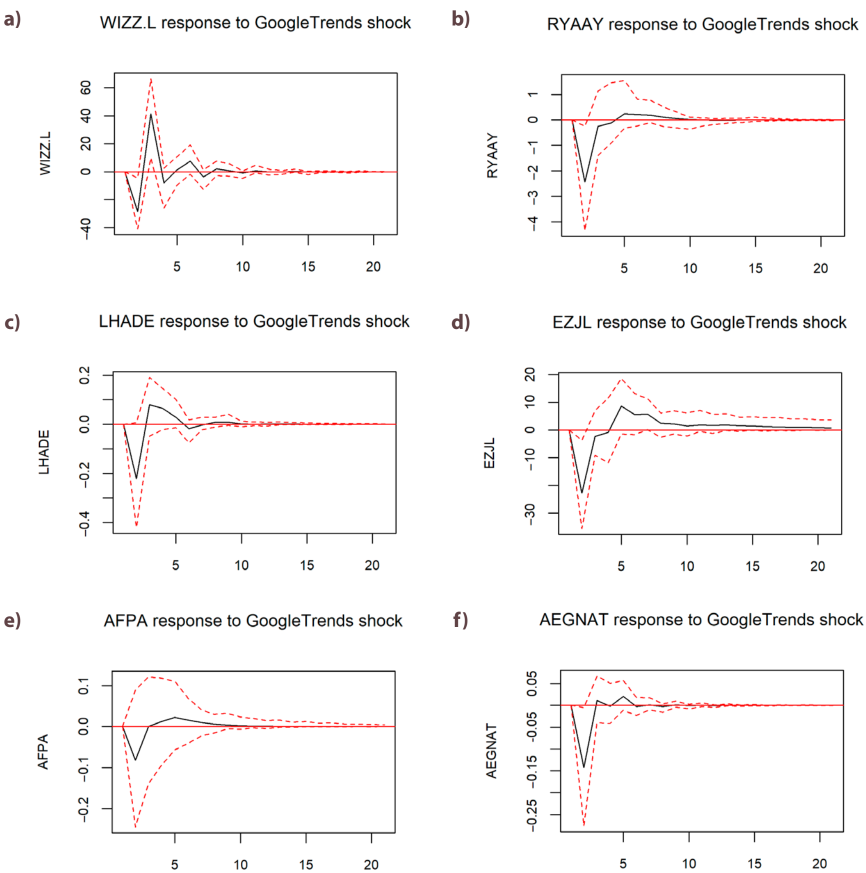
Null hypothesis H0	F-test	p-value
WIZZ.L does not Granger-cause **GoogleTrends**	3.6783	**0.02914**
GoogleTrends does not Granger-cause **WIZZ.L**	6.3166	**0.00271**
RYAAY does not Granger-cause **GoogleTrends**	0.92933	0.3986
GoogleTrends does not Granger-cause **RYAAY**	5.7581	**0.004434**
EZJL does not Granger-cause **GoogleTrends**	2.4466	0.0922
GoogleTrends does not Granger-cause **EZJL**	10.915	**5.579e-05**
AFPA does not Granger-cause **GoogleTrends**	0.48354	0.6182
GoogleTrends does not Granger-cause **AFPA**	0.68068	0.5088
AEGNAT does not Granger-cause **GoogleTrends**	1.3164	0.2731
GoogleTrends does not Granger-cause **AEGNAT**	12.127	**2.116e-05**
LHADE does not Granger-cause **GoogleTrends**	2.1798	0.1189
GoogleTrends does not Granger-cause **LHADE**	5.5787	**0.005167**

Note: With exception to the stock price of AFPA, the variable GoogleTrends Granger-causes all the variables.

the 5% confidence level, thereby refuting the null hypothesis. In the case of AFPA, the result was influenced by the issue of 2.26 billion shares in 2022, which led to a sharp decrease in their price. It can therefore be assumed that the result adjusted for this random fluctuation would correspond to the results of the other companies. Given the results of the test and the focus of this paper, further testing of the variable GoogleTrends will not be considered.

4.4. Impulse-response function

The effect of shocks on the VAR system was analysed using the impulse-response function. Figure 3a–f clearly shows that the positive shock of GoogleTrends caused a significant reduction in all the stock prices, followed by growth. The effect of the shock disappeared within twenty days, with exception to the stock price of EZJL. As for AFPA, the effect of the shock on the VAR model is very likely to have been minimal or even zero, since the confidence intervals limit the value to 0. This corresponds with the results of the Granger causality test.



Note: The red line represents the confidence levels; the black line represents the most likely response of the stock price to the shock.

Figure 3. Impulse-response functions to GoogleTrends shock: a – WIZZ.L; b – RYAAY; c – LHADE; d – EZJL; e – AFPA and f – AEGNAT

4.5. Variance decomposition

Table 8 presents the results of variance decomposition. The left column shows the percentage of the stock price attributed to the stock price as such, and the right column, the percentage of the stock price attributed to GoogleTrends. The results suggest that the shocks in searches in GoogleTrends are the source of volatility, especially in the case of LHADE, AEGNAT and RYAAY. In contrast, for WIZZ.L, EZJL and AFPA, the effect is below 5%.

Table 8. Variance decomposition

Weeks	WIZZ.L		RYAAY		EZJL	
	WIZZ.L	GoogleTrends	RYAAY	GoogleTrends	EZJL	GoogleTrends
1	1.0000000	0.000000000	1.0000000	0.0000000	1.0000000	0.0000000
2	0.9966025	0.003397516	0.8056516	0.1943484	0.9948796	0.0051204
3	0.9903318	0.009668218	0.8090697	0.1909303	0.9954831	0.0045169
4	0.9900887	0.009911277	0.8086920	0.1913080	0.9956438	0.0043562
5	0.9902043	0.009976865	0.8072733	0.1927267	0.9957621	0.0042379
6	0.9900653	0.009934678	0.8061514	0.1938486	0.9958105	0.0041895
7	0.9900231	0.009976865	0.8053424	0.1946576	0.9958066	0.0041934
8	0.9900083	0.009991720	0.8050698	0.1949302	0.9957769	0.0042231
9	0.9900097	0.009990319	0.8050003	0.1949997	0.9957445	0.0042555
10	0.9900088	0.009991184	0.8049935	0.1950065	0.9957151	0.0042849
Weeks	AFPA		AEGNAT		LHADE	
	AFPA	GoogleTrends	AEGNAT	GoogleTrends	LHADE	GoogleTrends
1	1.0000000	0.0000000	1.0000000	0.0000000	1.0000000	0.0000000
2	0.9764761	0.0235239	0.6819977	0.3180023	0.8456234	0.1543766
3	0.9767608	0.0232392	0.6808174	0.3191826	0.8308906	0.1691094
4	0.9762463	0.0237537	0.6849821	0.3150179	0.8203725	0.1796275
5	0.974605	0.025395	0.6808206	0.3191794	0.8200792	0.1799208
6	0.9737991	0.0262009	0.6807553	0.3192447	0.8194068	0.1805932
7	0.9734464	0.0265536	0.6808396	0.3191604	0.8194176	0.1805824
8	0.9733421	0.0266579	0.6807683	0.3192317	0.8192568	0.1807432
9	0.97331	0.02669	0.6807634	0.3192366	0.8190818	0.1809182
10	0.9733003	0.0266997	0.6807652	0.3192348	0.8190837	0.1809163

Note: Table 8 is divided into 6 main sections, with each section representing the stock price for one airline. Each variable contains two columns, where the first one shows the percentage of the stock price attributed to the stock price as such and the second one shows the percentage of the stock price attributed to the influence of GoogleTrends.

5. Discussion

This paper assesses the impact of the Russia-Ukraine war on the development of the stock prices of selected European airlines. Although the impact of crises that have occurred in the last few decades, including the COVID-19 pandemic, on capital market performance has been analysed by many researchers, the effects of the Russia-Ukraine war are still under investigation. In the aviation industry, the COVID-19 pandemic accelerated transformational change (Magdalina & Bouzaima, 2021). As a result, many airlines have undergone a process of consolidation and internal changes, with the whole industry also "disrupted" in terms of prices, e.g., by low-cost airlines (Khezrimotlagh et al., 2022). Within this context, many airlines' reassessment of their financial and investment strategies, and in some cases, even reassessment of their business models to avoid bankruptcy and "at least" survive (Kökény et al., 2022), were further disrupted by the Russia-Ukraine war.

As a representative sample, the authors analysed six European airlines of different types. As expected, their stock prices responded with a significant shock to the outbreak of the war, as confirmed by, for example, Alam et al. (2022), with their stock price performance falling dramatically overnight (see Figure 1). However, the question as to what extent the war influenced their stock price performance in the period thereafter, specifically up to 15 January 2023, remained. For this purpose, a number of tests were performed, the results of which supported each other. The tests were based on the premise that time series of airline stock prices correlate with the incidence of the phrase "Russia-Ukraine war" in the GoogleTrends search engine, which, among the available alternatives, was considered the most suitable source of data for the analysis.

The Granger causality test at the confidence level of 5% confirmed the causality between the stock prices and the incidence of the phrase "Russia-Ukraine war" in GoogleTrends, which was assumed to reflect the levels of stress and concern of the public. The effect of the shock on the Vector Autoregression model (VAR) was tested using the impulse-response function. As can be seen in Figure 3, the positive shock from GoogleTrends caused a significant decrease in the stock prices of all the analysed companies. However, with exception to EZJL, the effect of the shock almost disappeared within twenty weeks. Variance decomposition supplemented the results with the percentage determination of the variability of the stock price, which is caused both by the change in the stock price and the influence of GoogleTrends. This model clusters the companies according to the intensity of shocks relative to the searches in GoogleTrends, which reflects the price volatility in stocks sensitive to shocks (LHADE, AEGNAT, and RYAAY) and stocks less sensitive to shocks (WIZZL, EZJL, and AFPA).

Due to the fact that the causality between the variables "price" and "war" is weak, and given the fact that most price changes occurred when there was little interest in the phrase "Russia-Ukraine war" in GoogleTrends and the historical development of stock prices, it can be concluded that the changes in stock prices that followed shortly after the outbreak of the war were caused mostly by factors other than the externality of the Russia-Ukraine war in the monitored period (Basdekis et al., 2022). The current development of stock prices is influenced by external factors such as the political climate, inflation, interest rates, tax burden, economic cycles, social trust, etc. (Li et al., 2017), as well as management decisions that have an impact on the amount of dividend, profit, or development investment (Enow & Brijlal, 2016). Specific factors affecting the current prices of stocks in the aviation industry include the development of oil prices (Asadi et al., 2023), interest rates (Amanda et al., 2023), the competitive environment (Memon et al., 2019) and the stability of operating earnings (Assefa et al., 2017). It is worth noting that the behaviour of airline stock prices has been largely in line with the behaviour of European stock indices. After a dramatic but short-term decline, abnormal stock returns were realised. The behaviour of individual stocks within an index was influenced by the geographic proximity of the war zone, market efficiency and macroeconomic factors (Kumari et al., 2023).

Based on the above, it was confirmed that the Russia-Ukraine war had a strong negative but short-term effect on the stock prices of the selected European airlines, which was almost negligible approximately five months after the outbreak thereof. The companies that coped with the shock of the Russia-Ukraine war the quickest in terms of stock prices, were the low-cost airlines WIZZ.L (Wizz Air Holdings Plc) and RYAAY (Ryanair Holdings plc); in terms of profit, the strongest company turned out to be LHADE (Deutsche Lufthansa AG). The ability of these companies to respond promptly to the current situation and set up an appropriate business model can be considered a significant competitive advantage.

The analysis shows that the impact of investor sentiment on the returns of the stocks of the analysed companies resulting from the Russia-Ukraine war is a thing of the past, which is an important finding for financial market participants and airlines. The further development of the stock prices of the selected companies in the monitored period was influenced by external and internal factors not related to the Russia-Ukraine war.

6. Conclusions

The Russia-Ukraine war that started in February 2022 was primarily a shock for European and Russian companies. Due to the COVID-19 pandemic (2020–2021) and the sanctions and subsequent restrictions introduced as a result of military actions, trade relations have been limited, the volume of service flows has fallen and global energy and food prices have risen. From the macroeconomic point of view, the war has had an impact on macroeconomic conditions, financial markets and the financial stability of countries. Economies responded with a significant short-term decline in gross domestic product, while inflation expectations and commodity prices sharply rose. This contractionary supply shock has left many companies facing an existential crisis.

The review of published papers showed that the aviation industry is particularly sensitive to this type of shock. The war has had a particularly harsh impact on air transportation in terms of operational costs, as the transport of passengers and goods becomes more expensive; due to sanctions and airspace closures, airlines were forced to cancel or redirect flights. The immediate response of the stock market to the actual situation was a sharp decline in the stock prices of airline companies. To prevent their financial collapse and support European airlines, strategic measures were applied, which had already proved effective in mitigating the consequences caused by the COVID-19 pandemic. This included financial support in the form of government loans or government-guaranteed loans. An alternative and one-off solution for overindebted companies is a non-refundable state subsidy. However, this is a socially expensive step because it directly increases public debt (Scheelhaase et al., 2022). In addition, when applying state support, the issue of fair competition raises its head.

The aim of this paper was to analyse the impact of the war between Russia and Ukraine based on the development of the stock prices of six publicly traded European airlines and to evaluate the competitiveness of these companies from the perspective of the speed with which they have adapted to this unprecedented situation.

To achieve the set aim, a Vector Autoregression model (VAR) was used to determine the dependence of the development of the stock prices of the selected airlines on the level of stress and concerns of the public and institutions, as represented by the incidence of the phrase "Russia-Ukraine war" in GoogleTrends. The dependent variable (average weekly stock price) and independent variable (the incidence of the phrase indicating the level of stress in GoogleTrends) were analysed for the period 30 January 2022 – 15 January 2023. The application of the VAR model was preceded by the adjustment of the data and processes in order to verify the suitability of the model, to determine the appropriate VAR model, and to test its stability.

The model confirmed a negative and short-term relationship between the development of stock prices and the incidence in GoogleTrends at the 5% confidence level. However, the effect of the stress related to the war on the stock prices was negligible approximately 5 months after the outbreak of the war.

Given that the causality between the variables "stock price" and "war" was weak, and taking into account the fact that most changes in stock prices occurred at the moment when the interest in the conflict represented by the incidence of the phrase "Russia-Ukraine war" in searches in GoogleTrends was low, it can be concluded that the price movements that followed shortly after the outbreak of the war in the monitored period were mostly caused by other factors. The companies that were the quickest to cope with the situation in terms of stock price were Wizz Air Holdings plc, Ryanair Holdings plc and Deutsche Lufthansa AG. The ability of these companies to withstand external shocks and adapt to the situation was reflected in the stabilisation of their stock price, which can be considered a competitive advantage.

The insights gained by the airlines from the shock caused by the Russia-Ukraine war can be applied to understand the consequences of this kind of external shock on the operational, financial and investment level of an air transport business. As a result, the managers of those companies affected by this shock could develop proactive strategies for future crisis management. Through a set of functional measures, airline managers can mitigate potential negative impacts on their company even in the long term. However, several factors associated with an armed conflict need to be considered. In this case, the most significant among them is the economic warfare and sanctions against the Russian economy, which has impacted European airlines and aircraft manufacturers. The question arises as to what extent stringent sanctions may affect their medium-term and long-term plans.

Further research should focus on comprehensively examining the impact of the Russia-Ukraine conflict from the perspective of the European stock market and an analysis of the impact of sanctions against the Russian economy on this market.

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Author contributions

P. Šuleř – conceptualization, resources, review writing, investigation; S. Hašková – original draft preparation, methodology, writing, supervision; L. Divoká – data curation, formal analyses, editing, visualization.

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