

A FINANCIAL RETURN ANALYSIS FOR THE UNITED STATES AIR CARRIERS WITH A MONTE CARLO SIMULATION MODEL

Monte Carlo Simülasyon Modeli ile Amerika Birleşik Devletleri Hava Taşıyıcıları için Finansal Getiri Analizi

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ABSTRACT

Air carriers are accustomed to living with financial and economic hardships. Because they are at the crossroads of three important dimensions that are economic, political and technological. Even small changes in these dimensions can be the source of a crisis. The motivations of the US. Air carriers' investors are in a state of continual change. This analysis aims to make a return forecast using the Monte Carlo Simulation method with three scenarios in which the values of standard deviations are 0.01, 0.0001 and 0.000001. According to the findings, as standard deviations increase, the gains or losses increase while the mean is stable. On the other hand, it can be concluded that the states should utilise more stable politics regarding the dynamics of air carriers. Volatility is an enemy of air carriers in financial management, as witnessed in COVID-19 and similar crises. Air carriers and governments should be ready for volatility shocks because airlines are designed as part of state strategies and politics. Therefore, hedging strategies should always continue. This research shows the behaviours of the stock returns and possible results under experimental conditions and changing shocks from small to large.

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ÖZ

Hava taşıyıcıları, ekonomik, politik ve teknolojik olmak üzere üç önemli boyutun kavşağında oldukları için finansal ve ekonomik olarak zor zamanlara alışkındır. Bu boyutlardaki küçük değişiklikler bile bir krizin kaynağıdır. ABD Hava yolu şirketlerinin yatırımcılarının motivasyonları sürekli bir değişim halindedir. Bu analiz, standart sapma değerlerinin 0,01, 0,0001 ve 0,000001 olduğu üç senaryo ile Monte Carlo Simülasyonu yöntemini kullanarak bir getiri tahmini yapmayı amaçlamaktadır. Bulgulara göre, standart sapmalar arttıkça kazançlar veya kayıplar artarken ortalama sabittir. Öte yandan, devletlerin hava taşıyıcılarının dinamikleri konusunda daha istikrarlı politikalar kullanmaları gerektiği sonucuna varılabilir. Finansal yönetimde oynaklık, COVID-19 ve benzeri krizlerde görüldüğü gibi hava taşıyıcılarının düşmanıdır. Hava taşıyıcıları ve devletler oynaklık şoklarına hazır olmalıdır çünkü havayolları devlet stratejilerinin ve politikalarının bir parçası olarak tasarlanmıştır. Bu nedenle, korunma stratejileri her zaman devam etmelidir. Bu araştırma, deneysel koşullar altında ve küçükten büyüğe değişen şoklar altında hisse senedi getirilerinin davranışlarını ve olası sonuçlarını göstermektedir.

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1. INTRODUCTION

Volatile behaviours and volatilities are often observed in the financial markets. Nevertheless, their interpretation is always a problem in the minds of investors and scientists. Bollerslev et al. (2020: 776) classify the return volatilities as “bad” or “good” depending on their existential core, which is behavioural biases, stemming from overreaction to large sudden price declines or negative “jumps”, hard-to-estimate in small firms, firms with more volatile stock prices and more illiquid firms. These findings are consistent with investors’ overreaction to extreme price movements and limits to arbitrage. According to Stoll and Whaley (1990: 41), the volatility of prices is caused by i) new public information, ii) trading pressures of investors, and iii) how immediacy is supplied to offset these trading pressures; therefore, the volatility is nothing but changes in demand and supply of an asset for a specific time and volume. According to Lee et al. (2001: 543), the main features of stock returns are classified as compliance with mean-reversion, carriage of long and short memory, vary-in-time, persistency and predictability, and fat tail-short tail (normal distribution). There are two important volatility components: market risk and idiosyncratic risk. It should be added here that the assumptions that the market risk-return relationship is positive are affirmed according to CAPM (Capital Asset Pricing Model) by Guo and Savickas (2006: 43). However, according to them, idiosyncratic volatility is negatively related to future stock market returns; it is a pervasive, macro and forecastable variable. Besides these, Ang et al. (2006: 259) find that stocks with high sensitivities to innovations in aggregate volatility have low average returns. Stocks with high idiosyncratic volatility relative to models have abysmally low average returns. In the volatility and news dimension, in parallel with this logic, Campbell and Hentschel (1992) found that volatility feedback normally has little effect on the returns, but it can be important during periods of high volatility. So, it can be thought that volatilities are the products of idiosyncratic and financial market behaviour. Financial markets work under one main instinct that always tries to overcome uncertainties. Angelini et al. (2018:437) declare that uncertainty is an exogenous source of decline in economic activity. The effects of uncertainty shocks amplify in periods of economic and financial turmoil (volatility regimes). The financial description of the volatile behaviour in the stock returns maintains that volatility is a subject of variance, so there has been a change in the returns over time since Markowitz. Conversely, Baillie and DeGennaro (1990: 203) offer that investors consider some other risk measures to be more important than the variance of portfolio returns in their analysis. Therefore, for investors, there is no optimal choice regarding volatilities; they can move in different patterns. Meanwhile, Aggarwal et al. (1999) indicate the importance of significant events such as crises as a jump in the volatility of emerging countries' stock markets via volatility models such as Autoregressive Conditional Heteroskedasticity (ARCH) analysis and its derivatives. Also, these indicators are the contagion process of a crisis. Besides these explanations, Engle et al. (2013: 796) prove the relationship between the volatility of the stock market and macroeconomic components such as inflation and industrial production growth for longer horizons. Nonetheless, Schwert (2011) asserts that unemployment rates can be a suspicious variable or an indicator of the volatile behaviours of stocks. French et al. (1987: 3) confirm three important findings in the relationship between stock return and stock market volatility, i) stock return volatilities are in a relationship with the difference of expected stock returns minus treasury bill yield; ii) unexpected stock returns are negatively related to the unexpected change in the volatility of stock returns, iii) therefore there is an evidence on the positive relation between expected risk premiums and volatility. Hamilton and Lin (1996) affirm the relationship between economic recessions and volatility, so the variance of stock returns. Nevertheless, it is an

important feature of the volatilities that although they include a lot of information, they still have unknown and unresolved elements, especially in stock price samples (Shiller, 1987: 33).

On the other side, the volatility structures can be problematic for investors regardless of the industry. The dynamics within the industrial structure can gain significance. Accordingly, Horobet et al. (2022) confirm the long-term relationships between airline companies' stock prices, oil price risk, financial market volatility, currency risk, inflation, and maturity risk. Li and Su (2024) state that airlines can stabilize stock returns under conditions of uncertainty, but they need extra efforts regarding the mitigation of the negative impact of uncertainties on the airline industry. According to Deb (2023), short-term volatility forecasts give more accurate results in the airline business. Cai et al. (2025) underline the importance of economic activity shocks such as labour, capital (aircraft), fuel and other materials in the airline industry. Therefore, this research contributes to describing one of the most volatile financial industries of the globe under three scenarios, which are formed according to artificial volatility shocks. By explaining so, it will serve to complete a research gap which forms around the financial uncertainties of an industry. As the research completes this gap, it has benefited from several assumptions, such as threshold impacts or return cutbacks that can be caused by extreme shocks like the COVID-19 crisis period, sudden closure and opening of the financial markets and other important international, macro, and micro events. For the missing data, "the principle of previous day-data-use" is activated. The analysis is limited to a determined period. Therefore, the research mainly concentrates on a stable mean (return) and standard deviations (riskiness) around it; in this way, by playing with the standard deviations of data, it only arranges riskiness.

In light of these arguments, this research is designed with a motivation to measure the impacts of the different volatility patterns on the stock returns of the main American Air Carriers with a correlation relation of stable oil returns and state bond returns. By doing so, it aims to create a framework and collect more information on the airline's industrial financial structure. Therefore, it answers which volatility clusters impact airline stock returns derived from daily data from the period of 1.02.2018 and 16.02.2024. The analysis will have 3 different scenarios and conditions to make the Monte Carlo experiments for these stock returns.

2. LITERATURE REVIEW

The returns, which are the difference between two asset prices, are the main motives behind the decision of investors, with the simple explanation of $R_t = (P_t) - (P_{t-1}) / (P_{t-1})$. In this explanation, the situation of t , so the time component is one of the main indicators of the risk. Because it gives idiosyncratic and market risk characteristics to an investment that vary with time. Statistically, the distribution form of returns is subjected to much research because of normality assumptions. Officer (1972) underlines this feature and determines that return series have fatter tails than the normal distribution. Hjalmarsson (2010: 49) warns that the dividend price and earnings price (EP) ratios, the short interest rate, and the term spread as four common forecasting variables in stock return predictability; on the other hand, the short interest rate and term spread are fairly robust predictors of stock returns in developed markets. Nevertheless, Kon (1984) determines that the return series can be described with a normal distribution rather than the student model, emphasizing significant differences in the mean estimates that can explain the observed skewness and significant differences in the variance estimates that can explain the observed kurtosis. Besides these, the frequency of returns is decisive. For example, autocorrelation is weak for daily and weekly holding periods but stronger for longer horizons because of the slow mean-reverting component of

stock prices (Fama and French, 1988: 246). Time is an important component; even investment periods are important to detect specific statistical anomalies in the returns. Amihud and Mendelson (1987) find that opening returns show greater dispersion, greater deviations from normality and a more negative and significant autocorrelation pattern than closing returns. Another important context that may give detailed information on returns is the market efficiency approach. Market efficiency is described with the expectations. Over and above, Fama et al., (1969:20) underline that stock prices adjust very rapidly to new information. Fama (1990) described market efficiency regarding financial returns utilising three variations that are expected returns, shocks to expected returns, and shocks to expected cash flows. Schwert (1990) accept the existence of these three variables and states that the value of future real (industrial) production gives a robust positive relation with stock returns even when time-varying expected returns and shocks to expected returns are included in the regressions. This reasoning brings the financial world to the CAPM (Capital Assets Pricing Model), but CAPM includes an ambiguity as the β coefficient that is hard to calculatable and commentable (Fama and French, 1996). Hou et al. (2011) emphasize the importance of cash flow to price factor is related to a covariance risk model; on the other side, CAPM utilizes size and book-to-market factors. Size (market capitalization or market cap) and combinations of the book-to-market equity ratio, profitability and investment are important variables in defining a portfolio model and expected returns, according to Fama and French (2016) and Fama and French (2020). In these ambiguities, information imperfections such as asymmetric information and incomplete information are raised by accounting quality (Callen et al., 2013). More importantly, regarding this paper, Fama (1965: 99) and Capaul et al. (1993) maintain that Monte Carlo techniques can be used for sampling to understand the behaviours of the prices and returns. Random walk theories can be another approach to explaining the mysticism of the stock return, and Fama (1985) states that the psychological situation of investors can be beyond the fundamental analysis or complicated procedures, therefore, investors can easily make random movements in financial markets.

Oil and state bond returns are two important financial returns in a description of the aviation market. It should be understood that oil is not only an actor but plays a basic role in the development of the combustion process, which gives the necessary thrust to aircraft engines. It is also a product component of an aircraft through composite materials and as a balancing element in flight operations. Financially, oil is a volatile-priced commodity. Its price, naturally, and financial returns have easily been affected by extraordinary events around the world.

Akyıldırım et al. (2020) state that the aviational financial markets have great vulnerabilities regarding their dependence on international aviation disasters and catastrophic events such as oil crises and great accidents. This claim also affirms for oil demand and supply crisis, so shocks, Furthermore, jet fuel demand shocks have positive impacts on the U.S. aviation industry, while the effects of jet fuel supply shocks are generally negative (Atems, 2021: 1). On the other side, oil prices have determinative impacts on airline profitability that can be observed in reel and financial industries. Kaufmann (2017: 521) states that airfares are affected by the persistent changes in oil prices. This finding is so important because the main financial revenue resource of passenger carriers is airfares. And also, fuel prices and fuel conservation mechanisms are important in the decision of fleet selection processes and airline ratios such as ATM (Total Available Ton Miles) and Load Factor (Brueckner and Abreu, 2020: 1). To diminish the negative impacts of Brent and crude oil prices, aviation industry tries to utilize hedging strategies as such in India (Kar and Khandelwal, 2020). Besides these, Treanor, Rogers, Carter, and Simkins (2014) underline that air carriers that augment their hedging activity due to increasing fuel price exposure should not receive a

premium in their valuation when compared to those air carriers that have more stable hedging strategies. Nonetheless, Yun and Yoon (2019) maintain that there is a return and volatility spillover impact between crude oil prices and the stock prices of air carriers and that the stock prices of relatively small airlines in South Korea and China are relatively more sensitive to fluctuations in oil prices. Kristjanpoller and Concha (2016) discovered a strong positive relationship between fuel price changes and air carriers' stock returns using ARCH-family methodologies. According to another work that supports this finding, Kang et al. (2021) empirically find that oil price increases, economic uncertainty and jet fuel price volatility have statistically significant adverse impacts on real stock returns of airlines both at the industry and firm levels. Considering the time dimension, this finding is also true, as emphasised by Dar (2022: 168), but in the short run. There is no important relationship between oil price movements and aviation stocks in the long run. In a general form, crude oil prices have miscellaneous impacts on stock price volatility. As such, Bagchi (2017) claims this kind of impact on BRIC (Brazil, Russia, India and China) stock indices statistically.

As a projection of the state's financial power, treasury bonds are always a good alternative investment opportunity for investors and air carriers. For example, Maneenop and Kotcharin (2020) offer the air carriers the opportunity to purchase state bonds in complex conditions of COVID-19 as a financial requirement. Because, the investment nature of treasury bonds is stable and relatively less dangerous for investors (Nowak, 2008), and stock market uncertainty has important cross-market pricing influences and stock-treasury bond diversification benefits increase with stock market uncertainty (Connolly et al., 2005: 161) at the same time, Flouris and Walker (2005) support this idea. Besides these, innovations to stock and treasury bond market liquidity and volatility are significantly correlated, implying that common factors drive liquidity and volatility in these markets (Chordia et al., 2005: 85). Meanwhile, Cappiello et al. (2006) state that bonds and equities exhibit asymmetry in conditional correlation. At the same time, the correlation between jet fuel returns and treasury bonds is relatively low (Carter et al., 2006). With this explanation, Li (2002: 27) states that the correlation between stocks and bonds is determined primarily by uncertainty about expected inflation, and Baele and Inghelbrecht (2009) describe the comovements between stock and treasury bond returns with catalysing impacts of macroeconomic variables such as interest rates, inflation, the output gap and cash flow growth.

3. METHODOLOGY AND DATA

Monte Carlo simulation uses random sampling and statistical modelling to estimate mathematical functions and mimic the operations of complex systems (Harrison, 2010). To ensure this, the Monte Carlo technique uses random numbers as a means of predicting the magnitude of various events and as a way of selecting between possible scattering options (Joy, 1991). Bonate (2001) underlines that Monte Carlo models work under the principles of a real-world problem that is first identified and then converted to a conceptual model, which, for our purposes, will be defined as an abstraction of a real system containing inputs and outputs, of which the model inputs are predictive of the observed outputs. According to Raychaudhuri (2008), a Monte Carlo Simulation should follow the following processes: i) the detection of a deterministic model, ii) the identification of input data, iii) random variable generation and iv) analysis and decision-making. Its utilisation is general in financial risk management (Murtha, 1997) and portfolio management (Meher and Mishra, 2024). On the other side, the Monte Carlo simulation is a powerful and flexible tool that provides a probabilistic framework for marketing analysis in enterprise operations. By embracing uncertainty and quantifying risks, businesses can make more informed decisions, optimise

resource allocation, and develop resilient marketing strategies in dynamic markets (Abidovna, 2023). Smid et al. (2010) illustrate the strengths and weaknesses of Monte Carlo simulation models as in the following Table 1. Depending on the strengths of the Monte Carlo simulation, the Monte Carlo Model was selected as the research model of this paper.

Table 1. The strengths and weaknesses of Monte Carlo Simulations

Strengths	Weaknesses
Models can be complex systems	No interactive link between data and parameters
All kinds of probability distributions can be modelled	Approximate technique (because simulation-based)
Intuitive and relatively easy to implement	Unidirectional
Time to results is reasonably short	Validation is often ad hoc (by means of resampling)
Widely accepted and used	Does not allow “backwards reasoning”

Resources: Smid et al. (2010).

As it is thought, a matrix has two important dimensions regarding triangularity. In a Cholesky decomposition, the normal matrix structure is divided into subparts with the help of a decomposition process, which consists of a lower triangular matrix and its conjugate transpose ($A = \text{Lower triangular matrix } L * \text{conjugate transpose}$). This approach is especially developed to protect Monte Carlo Simulations from the negative impacts of correlations and standard deviations; therefore, Cholesky Decomposition finds a wide and comprehensive utilization field in science.

The daily research data, taken from investing.com for the period of 1.02.2015 and 20.09.2024 (2446 observations), includes 10 United States air carriers in Annex 1. Therefore, it represents approximately 95% of the industry market cap. The missing data problem was solved by using data from one day before. There is no adjustment for dividends. To reach market-adjusted daily returns (MAR), the following formulas are utilised. Secondly, oil returns and treasury bond (3-year maturity) returns are taken for the same period. The iterations of the Monte Carlo model are selected as 5000 in light of Mundform et al. (2011).

$$R_{t,i} = \frac{(P)_{t,i} - (P)_{t-1,i}}{(P)_{t-1,i}}$$

Equation 1.

Where,

i = company,

t =time,

R = Stock return,

P = Stock price,

$$R_{mar,i} = R_{ti} - R_m$$

Equation 2.

Where,

R_{mar} = Market adjusted return,

i = company,

R_m = market return

R_t = Stock return.

A cumulative dataset is organised with the following formula.

$$R_{cam} = \sum_{i=1}^{10} R_{mar,i}$$

Equation 3.

Where,

Tot_{cam} = Cumulative Market Value,

i = company,

The descriptive statistics of the cumulative market value data can be given in Table 2, and oil and treasury bond returns (3-year maturity) are given in Table 3. The Tot_{cam} method is the sum of the 10 airlines' daily returns.

Table 2. The descriptive statistics of the air carrier return data

	<i>Average</i>	<i>Std.Dev</i>	<i>Variance</i>	<i>Min</i>	<i>Max</i>	<i>Skewness</i>	<i>Kurtosis</i>	<i>Median</i>
<i>AAL_{cam}</i>	-0.0007	0.0288	0.0008	-0.2052	0.4179	2.0509	24.1686	-0.001
<i>ALGT_{cam}</i>	-0.0005	0.037	0.0013	-0.3464	0.3736	-0.1494	13.158	0.001
<i>ALK_{cam}</i>	-0.0001	0.0205	0.0004	-0.1600	0.1702	0.1528	9.352	-0.0001
<i>DAL_{cam}</i>	-0.00009	0.0203	0.0005	-0.1924	0.1405	-0.092	10.6425	-0.0001
<i>HAV_{cam}</i>	0.0002	0.0544	0.002	-0.3145	1.9227	18.362	641.25	-0.0004
<i>JBLU_{cam}</i>	-0.0005	0.0282	0.0007	-0.2087	0.2890	0.8935	14.891	-0.0013
<i>LUV_{cam}</i>	-0.0002	0.0185	0.0003	-0.1547	0.1025	0.3119	6.632	-0.0001
<i>SAVE_{cam}</i>	-0.0009	0.0346	0.0011	-0.4613	0.2760	-0.4703	22.7816	-0.0015
<i>SKYW_{cam}</i>	0.0006	0.03008	0.0009	-0.4010	0.4136	0.5477	34.556	-0.0003
<i>UAL_{cam}</i>	-0.00008	0.0264	0.0007	-0.2354	0.1859	0.3063	11.4357	-0.0006
<i>TOT_{cam}</i>	-0.0010	0.1915	0.036	-1.876	1.7251	0.5665	14.626	-0.0073

Table 3. The descriptive statistics of the oil and treasury bond returns data

	<i>Average</i>	<i>Std.Dev</i>	<i>Variance</i>	<i>Min</i>	<i>Max</i>	<i>Skewness</i>	<i>Kurtosis</i>	<i>Median</i>
<i>Oil_{cam}</i>	0.0004	0.0254	0.0006	-0.2440	0.2101	-0.364	11.675	0.0014
<i>TREASURY</i>	0.0013	0.0424	0.0018	-0.3162	0.4915	1.069	19.926	0.001
<i>BOND_{cam}</i>								

Using a Monte Carlo Method, the sample size increased to 5000 observations, benefiting the mean and standard deviation values of the 1513 observations in the Excel program. The following results are taken, and the descriptive statistics of the first Monte Carlo Analysis-1 can be seen in the following Table 4.

Table 4. The First Monte Carlo-1 results of the following data.

	<i>Average</i>	<i>Std.Dev</i>	<i>Variance</i>	<i>Min</i>	<i>Max</i>	<i>Skewness</i>	<i>Kurtosis</i>	<i>Median</i>
<i>TOT_{cam}</i>	-0.4335	0.0673	0.0045	-0.4812	-0.3859	-0.0222	0.06094	-0.0001561
<i>Oil_{cam}</i>	0.00373	0.0114	0.0001	-0.0043	0.0118	0.0491	-0.0127	0.00024371
<i>TREASURY</i>	0.05080	0.0633	0.004	0.00597	0.095	0.0187	-0.0642	-0.0004442
<i>BOND_{cam}</i>								

Secondly, to complete the research design, the correlation and the Cholesky decomposition method are utilised so as not to destroy the correlation between oil, treasury bonds and total stock returns of the model.

Table 5. Correlation relationship and Cholesky decomposition (in parentheses)

	CUMULATIVE INDEX	Oil Return	Bond Return
CUMULATIVE INDEX	1		
Oil Return	0.009	1 (0.9999)	
Bond Return	-0.012	0.010 (0.0103)	1 (0.9998)

Thirdly, the Monte Carlo Simulation results considering correlations are given in Table 6.

Table 6. Monte Carlo Simulation results considering correlations

	<i>Average</i>	<i>Std.Dev</i>	<i>Variance</i>	<i>Min</i>	<i>Max</i>	<i>Skewness</i>	<i>Kurtosis</i>	<i>Median</i>
<i>TOT_{cam}</i>	-0.4627	0.0045	2.0623E-05	-0.4659	-0.45957	-0.0222	0.0609	-0.4335
<i>Oil_{cam}</i>	0.0037	0.000128	1.64853E-08	0.0036	0.0038	0.0526	-0.0132	0.0037
<i>TREASURY</i>	0.0543	0.0039	1.57806E-05	0.0515	0.0571	0.0188	-0.0521	0.0507
<i>BOND_{cam}</i>								

Three scenarios regarding volatility shocks can be designed as follows, under the assumption of standard deviations as an expression of volatility (Brenner and Subrahmanyam, 1988; Majka, 2024), so large standard deviations mean large volatility structures and risky situations.

A. First volatility shock scenario

A first volatility shock, which is prepared with a Monte Carlo Model with μ (mean) = -0.0001 and σ^2 (standard deviation) = 0.01, is added to the Monte Carlo Model in Table 2. The main descriptive features of the first volatility shock are given in Table 7, and the Monte Carlo Simulation results are given in Table 8.

Table 7. The descriptive statistics of the first shock

	<i>Average</i>	<i>Std.Dev</i>	<i>Variance</i>	<i>Min</i>	<i>Max</i>	<i>Skewness</i>	<i>Kurtosis</i>	<i>Media n</i>
<i>TOT_{cam}</i>	-0.2475	0.3500	0.1225	-0.49506	0	-0.0267	0.0627	0.0005
<i>Oil_{cam}</i>	-0.0346	0.0243	0.0005	-0.05190	-0.01740	0.0175	-0.00325	0.0004
<i>TREASURY</i>	-0.0122683	0.067478	0.004553314	-0.05998	0.035445	-0.0362078	0.033559	0.0111
<i>BOND_{cam}</i>								1

Table 8. Monte Carlo Simulation Model (first shock)

	<i>Average</i>	<i>Std.Dev</i>	<i>Variance</i>	<i>Min</i>	<i>Max</i>	<i>Skewness</i>	<i>Kurtosis</i>	<i>Median</i>
<i>TOT_{cam}</i>	-0.3341	0.1225	0.0150	-0.42083	-0.24753	-0.0267	0.0627	-0.2473
<i>Oil_{cam}</i>	-0.0355	0.0005	3.11356E-07	-0.03592	-0.03513	0.0150	-0.0052	-0.0346
<i>TREASURY</i>	-0.0129	0.0048	2.36727E-05	-0.01634	-0.00946	-0.0400	0.0271	-0.0121
<i>BOND_{cam}</i>								

B. The second volatility shock scenario

The second volatility, which is formed with the Monte Carlo Model with $\mu(\text{mean})=-0.0001$ and $\sigma^2(\text{standard deviation})=0.0001$, is summed to the Monte Carlo results in the data of Table 2. The main features of volatility wave data are given in Table 9. After the summation process, a Monte Carlo simulation is utilized on the return series, considering the Cholesky decomposition. The results of this Monte Carlo Simulation are given in Table 10.

Table 9. The descriptive statistics of the second shocks

	<i>Average</i>	<i>Std.Dev</i>	<i>Variance</i>	<i>Min</i>	<i>Max</i>	<i>Skewness</i>	<i>Kurtosis</i>	<i>Median</i>
<i>TOT_{cam}</i>	-0.4336	0.0675	0.00456	-0.48142	-0.38590	-0.0222	0.060919	-0.0002
<i>Oil_{cam}</i>	-0.0346	0.0243	0.00059	-0.05190	-0.01740	0.0175	-0.00325	0.0004
<i>TREASURY</i>	-0.0122	0.0674	0.00455	-0.05998	0.035445	-0.0362	0.033559	0.01111
<i>BOND_{cam}</i>								

Table 10. Monte Carlo Simulation Model of the Second Shocks

	<i>Average</i>	<i>Std.Dev</i>	<i>Variance</i>	<i>Min</i>	<i>Max</i>	<i>Skewness</i>	<i>Kurtosis</i>	<i>Media n</i>
<i>TOT_{cam}</i>	-0.4629	0.004562	2.08181E-05	-0.4661	-0.4597	-0.0222	0.0609	-0.4336
<i>Oil_{cam}</i>	-0.0355	0.000588	3.46202E-07	-0.0359	-0.0351	0.0153	-0.0047	-0.0346
<i>TREASURY</i>	-0.0127	0.004622	2.13713E-05	-0.0160	-0.0094	-0.0399	0.0272	-0.0121
<i>BOND_{cam}</i>								

C. Third volatility shocks scenario

A third volatility shock is added to the return series in Table 2, which is formed with $\mu(\text{mean}) = -0.0001$ and $\sigma^2(\text{standard deviation}) = 0.000001$ and is added to the Monte Carlo Model of Table 2. The main descriptive features of the third volatility shock are given in Table 11, and the Monte Carlo Simulation results are given in Table 12.

Table 11. The descriptive statistics of the third shocks

	<i>Average</i>	<i>Std.Dev</i>	<i>Variance</i>	<i>Min</i>	<i>Max</i>	<i>Skewness</i>	<i>Kurtosis</i>	<i>Median</i>
<i>TOT_{cam}</i>	-0.4336	0.0673	0.0045	-0.48131	-0.38601	-0.0222	0.0609	-0.00025
<i>Oil_{cam}</i>	-0.0346	0.0243	0.0005	-0.05190	-0.01740	0.0175	-0.0032	0.000446
<i>TREASUR</i>	-0.0122	0.0674	0.0045	-0.05998	0.03544	-0.0362	0.0335	0.001117
<i>Y BOND_{cam}</i>								

Table 12. Monte Carlo Simulation Model (third shocks)

	<i>Average</i>	<i>Std.Dev</i>	<i>Variance</i>	<i>Min</i>	<i>Max</i>	<i>Skewness</i>	<i>Kurtosis</i>	<i>Media n</i>
<i>TOT_{cam}</i>	-0.4628	0.0045	2.06225E-05	-0.4661	-0.4596	-0.0222	0.0609	-0.4336
<i>Oil_{cam}</i>	-0.0355	0.0005	3.45501E-07	-0.0359	-0.0351	0.01509	-0.004	-0.0346
<i>TREASURY</i>	-0.0127	0.0046	2.13391E-05	-0.0160	-0.0094	-0.0397	0.0276	-0.0121
<i>BOND_{cam}</i>								

4. FINDINGS

The research findings bring another important option, the difference in bias. The calculation of the average biases is given in Table 13.

Table 13. Average biases

	<i>Model name</i>	<i>Reference model</i>	<i>Volatility model</i>	<i>Bias</i>
First Model	TOT _{cam}	-0.4627833	-0.3341804	-0.1286029
<u>Volatility Model:</u>				
μ (mean)=-0.0001;	Oil _{cam}	0.00375786	-0.0355259	0.03928376
σ^2 (standard deviation)=0.01	TREASURY	0.05435201	-0.0129005	0.06725251
	BOND _{cam}			
Second Model	TOT _{cam}	-0.4627833	-0.4629582	0.0001749
<u>Volatility Model:</u>				
μ (mean)=-0.0001;	Oil _{cam}	0.00375786	-0.0355424	0.03930026
σ^2 (standard deviation)=0.0001	TREASURY	0.05435201	-0.0127401	0.06709211
	BOND _{cam}			
Third Model	TOT _{cam}	-0.4627833	-0.4628895	0.0001062
<u>Volatility Model:</u>				
μ (mean) = -0.0001;	Oil _{cam}	0.00375786	-0.0355464	0.03930426
σ^2 (standard deviation) = 0.000001	TREASURY	0.05435201	-0.0127619	0.06711391
	BOND _{cam}			

The research findings are presented based on three research models with stable means and decreasing standard deviations, specifically 0.01, 0.0001, and 0.000001. Therefore, the biases between the reference model and the volatility model in the three models (-0.1286029; 0.0001749; 0.0001062) are caused by the decreasing standard deviations for the Cumulative Market Model (TOT_{cam}), which takes the volatility shocks and shows different behaviour patterns.

5. DISCUSSIONS AND CONCLUSION

During the research, three volatility shocks were added to the air carriers' return data between 02.01.2015 and 20.09.2024 with a stable mean and changing standard deviation. As it seems, when the standard deviation (volatilities) of the shocks increases, the amount of the return increases. This finding is also confirmed by Mumtaz and Theodoridis (2015). Besides these, volatilities are financial realities that they caused by macro and micro variables such as interest rate risks (Born and Pfeifer, 2014), and monetary policy shocks such as GDP shocks, unemployment shocks, spot commodity price index, and inflation (Lanne and Lütkepohl, 2008; Lewis, 2021; Beetsma and Giuliadori, 2012) and oil price shocks (Degiannakis et al, 2014). These variables can be added to the research model. Accordingly, Barigozzi and Hallin (2016) underline the importance of portfolio selection to save against the negativities of volatilities or volatility shocks. Another important finding is that the negative oil market shocks (volatilities) have stronger effects under bullish market

conditions, while the positive oil market volatilities (shocks) play a more important role during bearish periods (Xiao et al., 2019). Also, Bouri and Harb (2022) find that the propagation of volatility shocks within the system is not only shaped by the sign of the shocks (good versus bad volatility) but also by the shock size. Lastly, Engle and Patton (2001: 237) outline some stylised facts about volatility that should be incorporated into a model: pronounced persistence and mean-reversion, asymmetry such that the sign of innovation also affects volatility and the possibility of exogenous or pre-determined variables influencing volatility. On the other hand, the research model can be evolved to different shock structures, such as oil prices and treasury bond prices, that can be changed with suitable artificial shocks to measure market response in parallel with the discussion of this research.

At the end of the analysis, it can be said that the research proves that as the standard deviation (volatility) of a shock increases, the size of the volatility increases, so loss or gain increases in the airline market of the United States, while other variables or correlations are stable. On the other side, policymakers should focus on the standard deviations (changes) in economic conditions because civil aviation is a state-dependent matter, and the results can be efficient in approximately 95% of the market. To protect the air carrier industry from volatility shocks, balanced monetary and oil policies are a necessity. Air carriers should utilize more strict, stronger and comprehensive hedging policies regarding oil and other changes.

On the other hand, the more realistic or real-like results could be obtained with ARCH (Autoregressive Conditional Heteroskedasticity) Models, with possible utilisation advantages such as changing variances, the future impacts of shocks, and some opportunities to present more details about tail structures. Cointegration or causality analysis can be utilised, but the research can evolve to another stage in synthetic data production and its theory.

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Annex 1: The list of US air carriers and their markets.

LUV	Southwest Airlines Co (NYSE)
DAL	Delta Air Lines Inc (NYSE)
UAL	United Airlines Holdings Inc (NASDAQ)
AAL	American Airlines Group Inc (NASDAQ)
ALK	Alaska Air Group Inc (NYSE)
JBLU	JetBlue Airways Corp (NASDAQ)
SAVE	Spirit Airlines Inc (NYSE)
ALGT	Allegiant Travel Co (NASDAQ)
SKYW	SkyWest Inc (NASDAQ)
HA	Hawaiian Holdings Inc (NASDAQ)

MONTE CARLO SİMÜLASYON MODELİ İLE AMERİKA BİRLEŞİK DEVLETLERİ HAVA TAŞIYICILARI İÇİN FİNANSAL GETİRİ ANALİZİ

Araştırma ve Yayın Etiği Beyanı

Yazar(lar) verilerin toplanmasında, analizinde ve raporlaştırılmasında her türlü etik ilke ve kurala özen gösterdiklerini beyan ederler. Bu çalışmanın yazar/yazarları kullanmış oldukları resim, şekil, fotoğraf ve benzeri belgelerin kullanımında tüm sorumlulukları kabul etmektedir.

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