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Macroeconomic Determinants of Financial Failure Risk in Airlines

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Abstract

The objective of this study is to identify the macroeconomic factors that influence the risk of financial failure in the aviation industry. Within the parameters of the study, a sample of 11irline firms operating between 2009 and 2019 was analyzed to determine the factors influencing the likelihood of financial failure. The cost of fuel, interest rates, inflation rates, and currency rates were utilized as macroeconomic variables that could have an impact on airline enterprises' ability to meet ends. Financial data and macroeconomic data of the airline companies in the sample were obtained from Thomson Reuters Eikon Datastream. The methodology of the study consists of 2 stages. In the first stage, Altman Z" Score method is used. Then, panel data analysis method is preferred to reveal the relationship between financial failure and macroeconomic factors. According to the findings of the random effects panel data study, exchange rates and interest rates have a negative impact on financial failure. The results of the changes in interest and exchange rates suggest that governments and airlines should concentrate on policies that will strengthen the aviation sector's financial viability. To manage these risks more effectively, financial managers must closely examine the effects of rising macroeconomic risk and the corresponding financial failure effects. Airline managers, private and institutional investors should monitor policy uncertainty, assuming that exchange rate uncertainty is a driving force in financial failure. In addition, airline companies should review their hedging strategies against exchange rate risk.

1. Introduction

Complex issues have been brought on by the airline industry's rapid growth and relentless speed of change. Lack of infrastructure, safety, sustainability, social and environmental concerns, privatization and commercialization of airports and air traffic, airline mergers and alliances, market liberalization, and low-cost carriers are a few of these. Due to these demands and difficulties, airline managers have begun to assess and manage airline performance using a variety of performance management methodologies (Francis et al. 2005).

One of the financial performance measures of airlines is to predict financial failure. Airline managers and/or shareholders, investors and lenders pay close attention to financial failure. Especially in times of economic fluctuations and increased financial uncertainty, the analysis of financial failure may be the most important performance analysis for businesses. As all businesses are affected in times of crisis, airline businesses are also adversely affected. There are many factors affecting airline businesses. The 1978 oil crisis, the 1990 Iraqi invasion of Kuwait, the 1997 Asian crisis, the 2001 September 11 terrorist attack, the 2003 SARS outbreak, the 2008 global financial crisis and the 2019 Covid-19 outbreak, as well as social, political, economic, war and terrorist incidents have caused significant crises in the airline industry. As seen in the historical process, airline businesses have suffered great losses by facing economic negativities, especially changes in fuel prices, wars between countries, economic recession, and epidemics. As a result of these crises, airline businesses have faced financial stagnation and bankruptcy problems. In this context, airline managers can perform better by predicting financial failure before facing these problems.

When a company cannot satisfy its payment obligations on time or when cash flow forecasts indicate that the company will soon be unable to do so, these are signs of financial disaster. Financial failure is an early indicator that a company's situation is unhealthy, therefore with such a warning, the company is expected to avoid bankruptcy (Brigham and Daves, 2018). Changes in macroeconomic policies have an impact on important macroeconomic indicators like interest rates, inflation, gross domestic product, exchange rates, and exports, which all have an impact on the firm's overall need for overtime and cash flows. As a result, a sizable amount of the accounting figures and ratios on organizations' balance sheets are dependent on the current or anticipated macroeconomic conditions. Therefore, it is crucial to consider how the macroeconomic environment affects the onset and severity of financial failure (Sehgal, 2021). Therefore, it is necessary to look into and identify the key elements that affect the beginning and severity of financial failure for policymaking and monitoring. The search for instruments that can foresee future conditions has also unquestionably become crucial to assist managers in averting further downturn or eventual bankruptcy by taking the essential actions in advance.

A company's viability is impacted by macroeconomic conditions, and external forces are frequently outside of an industry's direct control. Business financial failure can be predicted in part by macroeconomic conditions. Changes in interest rates, exchange rates and oil prices, as well as inflation, can also affect businesses due to increased production and service costs or create higher pricing, which can lead to weaker demand. Overall, macroeconomic conditions offer a strong explanatory power to predict financial failure (Loudon, 2007; Tsai, 2008; Sehgal, 2021).

As with all businesses, airline businesses have a fragile structure against economic fluctuations and negativities. Therefore, there are many financial risk factors affecting airline businesses. The most common financial risks in the literature are fuel price, exchange rate, interest rate, inflation rate and liquidity risks (Morrell, 2007; Vasigh, 2015; Bood and Ison, 2017; Fernando, 2006; Loudon, 2007; Tsai, 2008). Accordingly, fuel price, exchange rate, inflation rate and interest rate variables are preferred in this study. Extensive explanations about these factors are mentioned in the conceptual framework and literature section of the study.

The subject of this study is the reciprocal financial relationships between airline financial failure and macroeconomic factors. In this context, the main objective of the study is to identify the macroeconomic factors affecting the financial failure of traditional airline companies around the world. Many studies have been conducted in different sectors examining the relationship between financial failure and macroeconomic factors and significant results have been reached. There is a study on the airline sector (Güngör, 2019), and only the relationship between inflation rate and financial failure among macroeconomic factors along with internal factors was examined. In this study, only macroeconomic factors were analysed. In this respect, it is thought to make great contributions to the literature. There are many methods measuring financial failure in the literature (Altman (1968, 1983, 2000), Springate (1978), Beaver (1966), Tamari (1966) and Meyer and Pifer (1970)). Another contribution of this study to the literature is that Altman Z" (1983) score test and panel data analysis methods are analysed together. In addition, another point that distinguishes the study from similar studies is the use of these 3 factors together, thus it is aimed to obtain more reliable results.

The study responds to four primary research queries: I How do exchange rate fluctuations affect the financial failure of traditional airlines? What effect do fluctuations in oil prices have on the financial failure of conventional airlines? What effect do changes in interest rates have on the financial failure of conventional airlines? (iv) How do changes in the inflation rate affect the financial failure of conventional airlines? According to the study's hypothesis, financial failure is significantly and negatively impacted by macroeconomic factors, including the exchange rate, oil price, interest rate, and inflation rate.

The goal of the study is to determine whether stock prices are impacted by macroeconomic data. In this context, a conceptual framework is used to describe the relationship between macroeconomic conditions and stock prices before the analysis begins, and the relevant literature is also mentioned. The analysis methodology is then described. Findings are acquired and interpretations are presented regarding the findings in the study's final section.

Using information from conventional airlines, this study makes an effort to explore and pinpoint certain important macroeconomic factors that affect the likelihood of financial failure. In this context, the theoretical underpinnings of how macroeconomic conditions affect airline enterprises' ability to make money are described, and the relevant literature is presented. Then, Altman's Z is employed to gauge how financially unsuccessful conventional airlines are. Score analysis was used to identify financial failure, and Panel data analysis was used to examine the macroeconomic factors influencing financial failure. The study's results regarding the discoveries made as a result of the analysis are offered in the final section.

2. Conceptual Framework and Literature

The study aims to examine the relationship between macroeconomic factors and financial failure. In the literature, Altman Z score models (1968, 1983, 2000), Beaver model (1966), Springate model (1978), Tamari model (1966) and Meyer and Pifer model (1970) are among the frequently used methods that measure financial failure. In the study, Altman Z" score, one of the financial failure models that can also be applied for airline companies, was used. Information about the Altman Z" (1983) score model is explained in the method section.

Fuel price, exchange rate, interest rate and inflation rate variables are used as macroeconomic factors in the study. In this section, firstly, the importance of the macroeconomic factors used in the study in terms of airline companies and their relationship with financial failure are presented conceptually. Then, the studies in the literature are mentioned.

Jet fuel prices are volatile (fluctuating). A sudden increase in fuel prices increases the costs of airline businesses. If costs exceed revenues too much, it may cause the bankruptcy of many airline businesses. For example, during the economic downturn in 2008, fuel prices were extremely volatile. As a result, a number of airlines had to cease operations (Jackson, 2017). Changes in fuel prices can affect the short-term cash flows of airlines. Carter et al. (2002) found that cash flows and stock returns of airlines are negatively related to fuel price changes. Unsystematic risks in the airline industry can cause many damages to businesses. The biggest unsystematic financial risk factor is the price of oil. Increases in jet fuel prices (which increase in parallel with the Brent oil price) negatively affect stock prices by reducing the profitability of airlines (Vasigh et al., 2015; Morrell and Swan, 2006).

International airlines frequently generate revenue in different currencies to cover operating expenses like fuel and labor. They are so susceptible to changes in exchange rates (Pyke and Sibdari, 2018). The time and quantity of foreign exchange revenue and expense are not always same. As a result, airline managers analyze the exchange rate risk and adhere to a balanced approach. It is the responsibility of airline managers to manage revenues, expenses, assets, and obligations in both local and foreign currencies to reduce their exposure to significant currency swings. Currency fluctuations frequently cause airlines to report lower profitability (Morrell, 2007). As a result of a major percentage of their debt (90 percent) being in US dollars, AirAsia Airlines' share price fell in August 2017. At a rate of 3.23 Malaysian ringgit per dollar, the airline hedged two-thirds of its dollar debt. Despite this, unhedged debt caused the stock price to decline (Pyke and Sibdari, 2018).

Due to the widespread use of loans, operational leases, and financing leases to finance the purchase of aircraft, interest rate risk is a significant consideration in the airline industry. Given how heavily they rely on debt financing, airlines need to pay special attention to this. Because of the capital requirements and relatively high cost of equity, the airline industry frequently has significant leverage ratios. High earnings volatility can make it more challenging to attract equity capital, as evidenced by the aviation industry's often lower-than-average price-to-earnings ratios (Loudon, 2004; Tsai, 2008). Although interest rates are not as volatile as fuel prices or exchange rates, the amount of debt accrued by global airlines is seriously exposed to adverse changes in interest rates. Since the floating rate debt agreements issued by airlines are linked to the London Interbank Offered Rate (LIBOR), airlines will have to make higher interest payments if market interest rates rise. For example, at the end of 2012, American Airlines had outstanding debt of around 7 billion dollars (Vasigh et al., 2014). A 1% increase in the LIBOR interest rate would increase American Airlines' interest expenses by $70 million. The increase in interest expenses reduces profitability and leads to financial failure.

There are many studies on the relationship between macroeconomic factors and financial failure in different countries and sectors and models have been tested for the existence of a relationship. The related literature is summarized in the table 1 below.

Table 1. Studies on the relationship between macroeconomic factors and financial failure

Study	Period/Country/Sector	Model	Findings
Sehgal vd. (2021)	India - Corporate Sector (1991-2017)	ARDL, FMOLS	It is concluded that the **inflation** variable affects financial failure. No relationship was found for the **interest rate.**
Siregar and Siswanti (2022)	Indonesia - Real Estate and Real Estate Sectors (2010-2019)	Altman Z Score, Panel Data Analysis	The **exchange rate** variable has a negative effect on financial failure. **Interest and inflation** rates have no effect.
Mabkhot et. al. (2022)	Malaysia - Banks (2005-2020)	FGLS, PFMOLS, PDOLS	It is concluded that **inflation rate and oil price** variables have a negative impact on financial stability.
Nikodemus, and Oktasari (2021)	Indonesia - Real Estate Sectors (2010-2019)	Logistic Regression	It is concluded that **interest rate and inflation rate** do not affect financial failure.
Liou and Smith (2007)	UK-Manufacturing Industry (1981-2001)	Taffler (1983) Z Score Model	It is concluded that the **interest rate** is not related to financial failure.
Harjayanti et. al. (2022)	Indonesia-Trade, Services and Investment Sectors (2017-2020)	Altman Z Score Model, Panel Data Analysis	It is concluded that the increase in **the interest rate** is associated with financial failure.
Arilyn (2020)	Indonesia-Agriculture Sector (2013-2018)	Regression Model	It is concluded that macroeconomic variables do not affect financial failure.
Muien, Nordin and Badru (2022)	Pakistan-Non-financial businesses (2013-2017)	Logistic Regression	It is concluded that the **inflation** variable has a negative effect on financial distress.
Ceylan (2021)	Turkey-Small and medium-sized enterprises (2010-2019)	Springate S Score, Panel Data Analysis	Exchange rate and **inflation rate** variables are not found to be related to financial failure.
Gutu vd. (2015)	Romania -Industrial Sector (2008-2013)	Regression Model	It is concluded that **exchange rate, interest rate and inflation rate** are related to financial failure.
Nouri and Soltani (2015)	Cyprus (2007-2012)	Logistic regression	It is concluded **that inflation rate and interest rate** variables are not related to financial failure.
Liu (2013)	England (1966-1999)	ECM	There is a relationship between **interest rate** and financial failure.
McNamara vd. (2011)	Australia – (1985-2000)	Varimax principal component analysis	It is concluded that the **interest rate** variable has the power to explain financial failure.
Zikovic (2016)	Croatia – (2000-2011)	VECM	It is concluded that the long-term **interest rate** has a short-term effect on the bankruptcy rate.
Acosta-Gonzalez vd. (2019)	Spain -Construction Sector (1995-2011)	GASIC Method	It is concluded that there is a significant relationship between **the interest rate** variable and financial failure.
Güngör (2019)	30 Airlines (2010-2016)	Panel regression, linear regression and discriminant analysis	It is concluded that there is no significant relationship between inflation rate and financial failure.

A general overview of Table 1 reveals that many studies have been conducted on the relationship between macroeconomic factors and financial failure. In most of the studies, inflation and exchange rate variables, especially interest rates, have been used. The studies have been conducted in different countries around the world and analyzed using regression and similar methods as methodology. Although most of the studies found significant relationships between macroeconomic factors and financial failure, a few studies (Liou and Smith, 2007; Arilyn, 2020; Ceylan, 2021; Nouri and Soltani, 2015) found insignificant relationships.

There is a study on the airline sector (Güngör, 2019), and only the relationship between inflation rate and financial failure among macroeconomic factors together with internal factors was examined. Nevertheless, a few studies have been conducted on financial distress in the airline industry.

In their study, Tunahan et al. conducted two different analyses comparing the financial failures between low-cost airlines and global airline alliances (Star Alliance, One World, Sky Team) with the fuzzy logic method. As a result of the first analysis, there is no significant difference between low-cost airlines and airline alliances in terms of financial risk. As a result of the second analysis, it was concluded that the financial risk level of low-cost airlines is lower than the average of airline alliances (Tunahan et. al., 2016).

In his study, Sakız analyzed the quarterly data of Turkish Airlines covering the years 2014-2016 with Altman Z' score method. According to the findings, it has been observed that Turkish Airlines has been in the risky (gray) area recently. In order for the airline to move to the safe area, it was recommended to increase long-range flights and capacity (Sakız, 2017).

In his study, Kroeze analyzed 6 bankrupt and 10 non-bankrupt airlines covering the years 1998-2003 by developing a new bankruptcy model with Altman Z" score. In his analysis, Kroeze revealed that the Altman Z" score model did not show accurate results and that he was able to predict some bankrupt airlines in advance according to the Kroeze model he developed (Kroeze, 2004).

In their study, Kumar and Anand conducted Altman Z" score analysis by using financial ratios of Kingfisher airlines covering the years 2005-2012. As a result of the analysis, it was observed that the Altman Z"score method consistently measures financial failure. As a result of the analysis, it was concluded that the financial performance was quite low in the relevant years (Kumar and Anand, 2013).

In his study, Mantziaris analyzed 40 airline businesses (20 successful and 20 unsuccessful) in Greece covering the years 2005-2013 with Altman Z" score analysis method. As a result of the analysis, it was concluded that the Altman Z" score model cannot consistently measure successful airlines, but it consistently measures unsuccessful airlines (Mantziaris, 2015).

Kiracı and Yaşar (2018) conducted an analysis using Altman Z score and Springate S score methods to predict financial failure in airline companies. 16 airline companies covering the years 2007-2016 were analysed. As a result of the analysis, it was concluded that airline companies in China failed according to both financial failure results, although they reduced their risks between 2009 and 2010.

In his study, Kiracı aimed to identify the factors affecting the financial risk of 13 airlines with low-cost airline business model for the period 2004-2017. Altman Z" score and Springate S-Score methods were used to measure financial risk. Panel data analysis method was used to determine the factors affecting financial risk. As a result of the analysis, it was determined that liquidity, operating profitability, operating leverage, and operating size ratios affect financial risk (Kiracı, 2019).

In his study, Hsu aimed to measure the usefulness of Altman Z" score method among financial forecasting methods in the field of aviation finance at undergraduate level. In this direction, the risk of financial failure of American Airlines and Southwest Airlines airline businesses in the 2009-2010 period was measured by Altman Z" score method. According to the analysis, it is seen that Southwest Airlines, which is a low-cost carrier, is more successful than American Airlines. It was also stated that the Z" score model can be used as a financial forecasting method in aviation finance trainings (Hsu, 2017).

In their study, Sakız and Ünkaya revealed the financial risk status of Turkish Airlines' 2002-2016 data with the Air Score method. They predicted the period between 2017-2019 with the artificial neural network model. According to the Air Score bankruptcy model, THY is in a healthy area, and as a result of the prediction with artificial neural networks, it was determined that THY will be in a healthy area in terms of bankruptcy risk (Sakız & Ünkaya, 2018).

In his study, Alıcı examined the relationship between airline industry-specific ratios (RPK, LF, CASK) and financial failure. The study was conducted on a sample of 11 traditional airline businesses between 2009-2019. Within the scope of the study, financial failure was calculated by Altman Z Score method and the relationship with operational ratios was analyzed by panel data analysis method. According to the results of the analysis, it was concluded that the cost per seat km supplied (CASK) indicator negatively affects financial failure (Alıcı, 2021).

According to the study conducted by Gritta et. al., it is stated that there are 6 methods that reveal the financial failure status specific to airline businesses (Gritta et. al., 2008):

- Altman Model (Z-score)
- Altman Zeta Model
- Airscore Model
- Pilarski Model (P-score)
- Gudmunsson Model
- Artificial Intelligence Models

Many studies have been conducted on financial failure in airline businesses. In most of the studies, the Altman "Z" score method has been used to measure financial risk, and it is understood that successful predictions about financial risk have been made with this method. Apart from this method, Springate S-score, Air Score and regression-correlation analysis have also been used.

In most of the studies conducted in the context of airline businesses, the degree of financial risk and failure of airlines have been measured. A few studies have examined the factors affecting financial risk. This study aims to measure the effects of macroeconomic factors on financial failure in airline businesses.

3. Method

In this study, macroeconomic factors affecting the financial failure of airlines are analysed. The study includes 11 airlines[1] with continuous financial data for the period 2009-2019[2]. Financial data and macroeconomic data of the airline companies in the sample were obtained from Thomson Reuters Eikon Datastream. The method of the study consists of 2 stages. In the first stage, Altman Z" Score method is used. Then, panel data analysis method is preferred to reveal the relationship between financial risk and macroeconomic factors.

3.1. Altman Z'' Score Model

In the literature, the most preferred methods to measure financial failure or risk have been Altman's Z Score studies. Altman first developed the Z Score model in 1968 by using

[1] The list of airlines is appendix.

[2] To ignore the effects of the financial crisis in 2008 and the COVID-19 Pandemic in 2020 on the activities of the companies, the relevant years were not included in the sample.

multiple discriminant analysis to predict financial failure. A discriminant value below certain limits is defined as financial failure, while a value above certain limits is defined as financial success. According to the 1968 theory, financial performance and/or bankruptcy status can be observed as a result of this analysis by numerically revealing the financial failure status of enterprises (Kurtaran, 2009).

Altman Z Score success model has developed over time. Introduced in 1968, the Z Score model faced scientific criticism that it would be inadequate for other sectors since the theory was put forward in the manufacturing sector sample. In this direction, Altman developed the Z' Score model for special industries and the Z" score model for service businesses. Since this study was conducted in the sample of airline businesses, Altman Z" Score model was preferred. Altman Z" The fomula of the Score model is shown below (Altman, 2000):

Z" Score = 6.56T1 + 3.26T2 + 6.72T3 + 1.05T4

Z" Score Financial Failure Value

T1: Net Working Capital / Total Assets

T2 : Retained Earnings / Total Assets

T3 : Operating Profit / Total Assets

T4 : Book Value of Equity / Total Liabilities

After calculating the formula, the financial failure value Z" Score value is found. According to this, if Z" If the Score value is greater than 2.6, it is concluded that the enterprise is in the safe area or successful, if it is between 1.1 and 2.6, it is in the gray area (no financial failure), and if it is less than 1.1, it is concluded that the enterprise is in financial failure (bankruptcy probability) (Sakız, 2017).

3.2. Panel Data Analysis

Three types of data types can be mentioned in economic analysis. These are time series, horizontal cross-section and panel data. The series showing the change of any variable over time are called time series. Examples of time series are exchange rate data for the period 1990-2015 in Turkey or monthly non-farm employment data for the period 1970-2015 in the USA. The series that show the change of any variable in the same time unit (with time constant) by units are called horizontal cross-section series. Examples of horizontal cross-section series are inflation data of OECD countries in 2015 or export data of EU member countries in 2015. Panel data, on the other hand, is defined as the aggregation of cross-sectional observations of units such as individuals, countries and firms in a given period. Panel data consists of N number of units and N number of observations corresponding to each unit. Annual total debt ratio data of Star Alliance member airline businesses for the period 2010-2016 or monthly average rate of return data of the stocks of BIST-30 businesses for the period 2010-2015 can be given as examples of panel data (Güriş, 2015; Yerdelen Tatoğlu, 2009).

A regression model computed with panel data is essentially a panel data model. Because of this, panel data models can also use the tests, suppositions, and other elements specified in the regression model. One dependent variable and one or more independent variables are used in panel data models. The error term is also included in the model because it is a statistical or econometric model. Different indices will be utilized to indicate both units and time since the variables in the model will demonstrate change in both. In panel data analysis, the letters I and t stand for the units and the time period, respectively (Güriş, 2015). The following diagram illustrates the linear panel data model with panel data, where Y stands for the dependent variable and X for the independent variable or variables.

$$Y_{it} = \alpha_{it} + \beta_{it} + X_{it} + \varepsilon_{it}$$

It's here,

i= 1,2,...,N horizontal cross-section units,

t= 1,2,...,T time period,

Y it=the value of the dependent variable's i-th unit at time t,

X_it= the value of the independent variable’s i-th unit at time t,

ε_it= error term with a constant variance and a zero mean,

β = slope coefficient for a line.

Depending on the temporal and cross-sectional data, three alternative estimating approaches can be utilized in panel data analysis. These models are conventional ones with fixed effects and random effects (Gökbulut, 2009).

3.3. Definition of Variables Used in Panel Data Analysis and the Model Used

According to the relationship status in the literature, the dependent and independent variables affecting financial risk in traditional airline enterprises were identified for the study. The Z" Score value for the financial failure indication is employed as the dependent variable. As independent variables, the macroeconomic indices INT, INF, BOP, and DER are employed. The Table 2 below lists the acronyms, definitions, and methods of measurement for the variables utilized in the study.

Table 2. List of variables used in the model

Variables	Symbol	Measurement Indicator	Measurement Method
Dependent Variables	**ZSCORE**	Z’’ Score	Z’’ Score Value
Independent Variables	**INT**	Interest Rate	10-Year Bond Interest Rates of Countries
	DER	Dollar Exchange Rate	Exchange Rate Between the Currency of the Countries and the US Dollar (Ex: TL_USD)
	BOP	Brent Oil Price	Reel Brent Oil Price
	INF	Inflation Rate	Reel Inflation Rate

The panel data analysis model used in the study is constructed as follows:

$$ZSCORE_{it} = \beta_0 + \beta_1 INT_{it} + \beta_2 DER_{it} + \beta_3 BOP_{it} + \beta_4 INF_{it} + \varepsilon_{it}$$

The ZScore variable used in the model is a measure of financial failure and is the dependent variable. Other variables are independent variables. INT variable is interest rate, DER variable is dollar exchange rate, BOP variable is brent oil price and INF variable is inflation rate.

4. Findings

11 airlines applying the traditional business model were examined in line with the calculations made according to the Altman Z Score analysis. The findings are given in the appendices. In general, Altman Z When the Score results are analyzed, it is observed that not all airlines have been

financially successful over the 11-year period. Singapore airline has been the most successful financial performer among the airline businesses. It was observed that All Nippon airline had more times when the risk of financial failure was higher. The other airlines, on the other hand, showed a mostly unsuccessful profile.

In the second part of the analysis, the relationship between airline financial failure (Altman "Z" Score) and macroeconomic factors is analyzed using annual data for the period 2009-2019 by panel data analysis method. The analysis results were obtained by using GAUSS 10, E Views 9 and Stata 15 programs.

Preliminary tests such as descriptive statistics, correlation matrix, cross-sectional dependence and panel unit root test were performed. Then, tests (F, LM and Hausman tests) were conducted to choose between classical, fixed and random effects. Afterwards, tests for heteroscedasticity and autocorrelation are performed and panel data estimator results are presented.

Table 3. Descriptive statistics

	ZSCORE	INT	DER	INF	BOP
Mean	0.5101	2.9544	0.5658	2.3220	37619.7000
Medyan	0.4564	2.4460	0.7102	1.7769	7328.0000
Maximum	4.0782	16.98	1.4365	16.3000	367698.0000
Minimum	-1.9818	-0.1860	0.0083	-1.4000	1523.0000
Std. Dev.	0.9975	777.8789	2036.0990	2.7915	85002.6200
Skewness	0.8481	3.3039	4.6103	2.5463	2.8846
Kurtosis	4.8579	12.6284	22.2592	11.2674	9.7518
Jarque-Bera	0.5101	235.3994	421.4863	2.3220	37619.7000
Probability	0.4564	2.4460	0.7102	1.7769	7328.0000

According to the descriptive statistics results, the variable with the highest standard deviation is Brent oil price (BOP) and the variable with the lowest standard deviation is ZSCORE, which is an indicator of financial failure. All variables are right skewed. There is a difference of approximately 17% between the minimum and maximum values of the interest rate (INT) and inflation rate (INF) variables. This difference indicates that the macroeconomic variables in the countries differ.

Table 4. Correlation matrix

	ZSCORE	INT	DER	INF	BOP
ZSCORE	1	-0.24597	-0.068	0.129927	0.191576
INT	-0.24597	1	-0.06211	-0.14739	-0.11047
DER	-0.068	-0.06211	1	-0.00481	-0.08374
INF	0.129927	-0.14739	-0.00481	1	-0.19284
BOP	0.191576	-0.11047	-0.08374	-0.19284	1

The emergence of correlation between the variables included in the regression model causes the problem of multicollinearity. When the correlation matrix between the variables is analysed, the correlation rate between all variables is around 15% on average. If there is more than 50% correlation between the variables in the models, the problem of linearity is mentioned. In general, it is seen that there is low correlation and there is no linearity problem.

To find horizontal cross-section dependence between variables, a horizontal cross-section dependence test is run. The stationarity status of the variables is assessed using first generation unit root (stationarity) tests if there is no horizontal cross-section dependence between the series and second-generation unit root (stationarity) tests if there is.

According to the horizontal cross-section dependence test result, Ho hypothesis is accepted for all variables. In this case, it is understood that there is no horizontal cross-section dependence between the variables, so the first-generation unit root test should be applied.

Table 5. Horizontal cross-section dependence test results

Variable	CDLM adj.		
	Statistics	Probability	Decision
ZSCORE	-1.285	0.901	Ho Accept
INT	0.545	0.293	Ho Accept
DER	-0.328	0.629	Ho Accept
INF	-1.043	0.852	Ho Accept
BOP	-0.738	0.770	Ho Accept

Table 6. Panel unit root test results

Variable	Model	Levin, Lin& Chu-t		Lm, Paseran and Shin-W		ADF-Fisher Chi2	
		Statistics	Probability	Statistics	Probability	Statistics	Probability
ZSCORE	Constant	-8.0544	0.0000	-5.3754	0.0000	67.6485	0.0000
	Constant and Trend	-9.2651	0.0000	-3.5327	0.0002	55.2257	0.0001
∆ZSCORE	Constant	-13.2195	0.0000	-7.4381	0.0000	93.5170	0.0000
	Constant and Trend	-12.4649	0.0000	-2.9951	0.0014	66.6592	0.0000
BOP	Constant	-3.9069	0.0000	-2.8229	0.0024	51.2235	0.0004
	Constant and Trend	-7.5812	0.0000	-2.5721	0.0051	55.5782	0.0001
∆BOP	Constant	-5.3140	0.0000	-2.3697	0.0089	39.5192	0.0123
	Constant and Trend	-4.3197	0.0000	0.0159	0.5063	20.3997	0.5581
DER	Constant	-1.8424	0.0327	-0.2009	0.4204	20.5212	0.5505
	Constant and Trend	-7.9633	0.0000	-2.7007	0.0035	48.1496	0.0010
∆DER	Constant	-15.4802	0.0000	-7.6690	0.0000	91.8813	0.0000
	Constant and Trend	-13.1613	0.0000	-2.8183	0.0024	61.0656	0.0000
INT	Constant	-5.5232	0.0000	-4.5140	0.0000	62.9522	0.0000
	Constant and Trend	-11.3679	0.0000	-2.8541	0.0022	58.6509	0.0000
∆INT	Constant	-12.8680	0.0000	-7.0951	0.0000	93.3826	0.0000
	Constant and Trend	-6.2616	0.0000	-2.5741	0.0050	60.4936	0.0000
INF	Constant	-4.9352	0.0000	-3.3054	0.0005	49.3970	0.0007
	Constant and Trend	-4.4993	0.0000	-1.4754	0.0700	37.9640	0.0185
∆INF	Constant	-10.4837	0.0000	-6.0686	0.0000	79.2894	0.0000
	Constant and Trend	-18.0513	0.0000	-3.7559	0.0001	69.0434	0.0000

Notes: ∆ denotes the first order differenced series. The maximum lag length is taken as 1 and the optimal lag length is determined according to the SIC (Schwarz Info Criteria) criterion. All hypothesis tests are based on 0.05 (5%) significance level.

According to the results of 3 different unit root tests performed on the variables, all variables are found to be stationary at level.

Following the unit root and horizontal cross-section dependence tests, it is required to choose amongst the classical, fixed, and random effects models. The F test is used to test the classical model for fixed effects, the LM test is used to test the classical model for random effects, and the Hausman test is used to distinguish between random and fixed effects.

Table 7. F Test to test for the existence of unit and/or time effects

Test Hypothesis	Statistics	Probability	Decision
There is no fixed unit effect	1.385939	0.172715	Ho Accept
There is no fixed time effect	14.47527	0.0000	Ho Reject
There is no fixed time and unit effect	3.571165	0.0087	Ho Reject

According to the F Test, it is tested whether to use fixed effects or random effects instead of the classical model. According to the two results, Ho hypothesis is rejected. In this case, it is understood that the classical model is not appropriate.

Table 8. LM Test for the existence of unit and/or time effects

Test Hypothesis	Statistics	Probability	Decision
There is no random unit effect.	189.783	0.0000	Ho Reject
There is no random time effect.	1.244381	0.2646	Ho Accept
There is no random time and unit effect.	191.0274	0.0000	Ho Reject

Similar to the F Test, Ho hypothesis is rejected according to the two results. Likewise, it is understood that the classical model is not appropriate and estimation should be done with either fixed or random effects model. Hausman test is applied in order to test the application according to fixed or random effects.

Table 9. Hausman Test

Test Hypothesis	Statistics	Probability	Decision
The random effects model is appropriate	0.8000	0.9383	Ho Accept

Ho is accepted according to the hypothesis that the random effects model is appropriate. In this case, it is accepted that the random effects model is appropriate.

Table 10. Variance and Autocorrelation Tests

Modified	Wald Test	Durbin Watson	Baltagi-Wu
Statistics	**Probability**	**Statistics**	**Statistics**
97.80	0.0000	1.2183496	1.4893174

The modified Wald test was employed to test for variable variance. As a result, the Ho hypothesis is rejected, and it is determined that a variable variance problem exists. Autocorrelation was determined using the Durbin Watson and Baltagi-Wu tests. Autocorrelation is present in the model when these statistical values are less than 2. The autocorrelation test results demonstrate that both statistics are less than 2, indicating an autocorrelation issue. As a result of the testing, the analysis was performed using the Arellano Froot and Rogers random effects robust estimator, which takes into account shifting variance and autocorrelation.

Table 11. Random Effects Arellano Froot and Rogers Robust Estimator Results

Variable	Coefficient Estimation	St. Error	z	P	(95% Confidence Interval)	
INT	-0.000123	0.000052	-2.35	0.019*	-0.000225	-0.000020
DER	-0.000020	4.65e-06	-4.44	0.000**	-0.000029	-0.000011
INF	0.035084	0.063446	0.55	0.580	-0.089267	0.159436
BOP	8.02e-07	1.10e-06	0.73	0.466	-1.36e-06	2.96e-06
C	0.436200	0.204305	2.14	0.033	0.035768	0.836632

Number of observations: 121 Wald chi2(4) = 51.38 $R^2 = 0.1705$
Number of Groups: 11 Prob > chi2= 0.000

0.001>**, 0.005>*

According to the panel data results of the Random Effects Arellano Froot and Rogers Robust Estimator, INT and DER indicators have a negative effect at 5% significance level. INF and BOP variables, on the other hand, have no significant relationship. The variables used in the model have a 17% explanatory power for financial failure. It is concluded that a 1-unit increase in the interest rate causes a 0.0001% unit decrease in the financial failure score, and a 1-unit increase in the exchange rate causes a 0.0002% unit decrease in the financial failure score. Accordingly, it is concluded that interest rate and dollar exchange rate among macroeconomic indicators have a negative impact on airline failure. However, neither the inflation rate nor the Brent oil price have been linked to the demise of airlines.

5. Conclusion

This study focuses on the impact of macroeconomic factors on financial failure in traditional airlines. The analysis was carried out with data covering the years 2009-2019 of 11 airline businesses adopting the traditional business model. In this direction, first of all, Altman Z's" Financial failure was determined by using score analysis and macroeconomic factors affecting financial failure were analyzed by panel data analysis method.

According to the results of the Z" score analysis, which measures financial failure, it is observed that all airline businesses have not been financially successful in the 11-year period. Singapore airline has been the most successful financial performer among the airline businesses. It is observed that All Nippon airline has more times when the risk of financial failure is higher. In other airlines, it has been observed that the majority of the airlines have not been successful.

According to the findings of the fixed effects panel data analysis used to assess the relationship between macroeconomic factors and airline financial failure, interest rate and exchange rate variables have a negative impact on financial failure, whereas Brent oil price and inflation rate variables have no impact. The study's hypothesis is that macroeconomic factors (such as the currency rate, oil price, interest rate, and inflation rate) have a large and negative impact on financial failure. As a result of the analysis, the hypothesis concerning the interest rate and exchange rate is validated, however the hypothesis concerning the Brent oil price and the inflation rate is not proven. The result that the inflation rate does not affect financial failure in the study is similar to a study conducted in the aviation sector (Güngör, 2019).

As a result of the analysis, it has been revealed that increases in the dollar exchange rate negatively affect financial failure in airline businesses. This result confirms the theory of an inverse relationship between exchange rate and financial failure. At the same time, the result of the study on exchange rate confirms 2 studies in the literature (Siregar and Siswanti, 2022; Gutu et al., 2015). The most important foreign currency risk for airline businesses is the US dollar. Especially important cost items such as aircraft purchase, leasing, fuel, maintenance and overhaul costs are priced in US dollars (IATA, 2015). In this context, airline businesses are exposed to exchange rate risk to a great extent. Exchange rate fluctuations may adversely affect airline demand, airline supply and airline financing. In this sense, the depreciation of the country's currency in terms of US dollar may adversely affect the travel balance (supply-demand) on certain routes. Moreover, the cost of fulfilling the airline's obligations arising from aircraft purchase, leasing and/or fuel will be higher. Therefore, it is inevitable that increases in the dollar exchange rate will negatively affect the financial failure of airline businesses. Considering the impact of exchange rate changes on financial failure, airline businesses can mitigate financial failure by using hedging strategies more effectively to optimize the costs arising from exchange rates.

Panel data analysis reveals that an increase in interest rates has a negative effect on financial failure in airline businesses. This result is consistent with the hypothesis and theory. At the same time, the analysis result of the study on interest rate is similar to many studies in different sectors (Harjayati et al., 2022; Gutu et al., 2015; Liu, 2013; Zikovic, 2016; McNamara et al., 2013). Low interest rates provide financing cost advantage for airline businesses. However, increases in interest rates increase the capital costs and interest expenses of airline businesses and reduce their liquidity. At the same time, with the increase in interest rates, airline businesses cannot find cheap credit opportunities. The inability to obtain cheap credit results in the negative effect of financial leverage and negatively affects profitability and financial failure. The biggest capital burden for airlines is the financing arising from aircraft purchases. Airline businesses use loans extensively during the aircraft purchase or aircraft leasing stages. As a result of the increase in loan interest rates, the cost of capital will increase and as a result, it will negatively affect the financial failure of airline businesses. According to IATA's data, the debt amounts of airline businesses increased from 220 billion dollars to over 650 billion dollars during the pandemic (IATA, 2021). According to this data, both the increase in borrowing and the increase in interest rates indicate that there may be crisis signals in the airline sector.

In sum, this study provides evidence that exchange rate volatility and interest rate changes affect the financial failure of global airlines. There are several policy implications for airlines, practitioners, policymakers and investors to manage the related macroeconomic risks. First, the importance of exchange rate and interest rate variables among macroeconomic factors for the airline industry is re-emphasized. Airline managers, private and institutional investors should monitor policy uncertainty, assuming that exchange rate uncertainty is a driving force for financial failure. In addition, airlines should review their hedging strategies against exchange rate risk. With rising interest rates, the cost of financing will increase and the airline industry will start to struggle. This may be a source of concern for the airline industry as it may cause investors to change their portfolios. Exchange rate changes and interest rate mismatches always lead to volatile losses (gains). The results related to exchange rate and interest rate changes indicate that airlines and the relevant governments should focus on policies to increase the financial sustainability of the aviation industry. To better manage these risks, financial managers need to scrutinize more carefully the impact of macroeconomic risk spikes and related financial failure effects. Finally, this study is expected to contribute positively to the financial performance of airline businesses by providing new solutions to airline businesses in terms of reducing and eliminating financial failure.

This study has some limitations. First of all, the study was conducted only in the traditional airline industry sample. Although the macroeconomic indicators used in the study are the most important financial risks faced by airline businesses, the model can be built by including all macroeconomic factors together with the factors here. In addition, the number of airline businesses used in the study can be increased and more reliable results can be obtained if the period range of the data used is preferred more frequently. Finally, in addition to this study, new studies can be conducted on financial protection strategies that minimize financial failure.

Ethical approval

No ethical approval required

Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

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Appendixes

Appendix 1: List of Airlines

Airlines Sample	
Turkish Airlines	All Nippon (ANA)
United Airlines	Cathay Pacific
Air Canada	Air France
Singapore Airlines	Scandinavian Airlines (SAS)
Qantas Airlines	Air China
Lufthansa	

Appendix 2: Traditional Airline Businesses Altman Z" Score Table

Airlines	Year	Net Working Capital / Total Assets	Retained Earnings or Losses / Total Assets	Earnings Before Interest and Tax / Total Assets	Shareholders' Equity / Total Liabilities	Altman Z" Score	According to the "Z" Score Model Success Status
Turkish Airlines	2009	0.09928	0.10044	0.08598	0.67193	2.26200	Gray Area
	2010	0.08930	0.12011	0.04526	0.54296	1.85165	Gray Area
	2011	0.00744	0.08321	0.00616	0.37779	0.75809	Failed
	2012	-0.03465	0.07400	0.06072	0.40478	0.84697	Failed
	2013	-0.08335	0.08548	0.04882	0.37761	0.45644	Failed
	2014	-0.06090	0.08950	0.04260	0.40210	0.60074	Failed
	2015	-0.04410	0.09810	0.05220	0.41610	0.81820	Failed
	2016	-0.04850	0.11780	-0.01330	0.37940	0.37486	Failed
	2017	-0.03660	0.11100	0.05200	0.42000	0.91220	Failed
	2018	-0.03270	0.07520	0.05680	0.40290	0.83538	Failed
	2019	-0.04819	0.08188	0.03433	0.38458	0.58530	Failed
American Airlines	2009	-0.04269	-0.02410	0.03947	0.15896	0.07352	Failed
	2010	-0.07741	-0.00706	0.00821	-0.13588	-0.61829	Failed
	2011	-0.18928	-0.02908	-0.04892	-0.23163	-1.90846	Failed
	2012	-0.21093	-0.03753	0.00636	-0.25558	-1.73162	Failed
	2013	0.01223	-0.01805	0.03309	-0.06068	0.18004	Failed
	2014	-0.03092	0.02625	0.09931	0.03319	0.58491	Failed
	2015	-0.07477	0.03338	0.12814	0.23804	0.72938	Failed
	2016	-0.06618	0.02807	0.09856	0.17324	0.50162	Failed
	2017	-0.11768	0.02251	0.08016	0.23051	0.08203	Failed
	2018	-0.16060	0.00654	0.04384	0.24114	-0.48439	Failed
	2019	-0.16843	0.00790	0.05109	0.28819	-0.43324	Failed
Air China	2009	-0.26546	0.00196	0.11631	0.28529	-0.65385	Failed
	2010	-0.04050	0.01573	0.12279	0.35295	0.98131	Failed
	2011	-0.08464	0.01326	0.09503	0.37311	0.51839	Failed
	2012	-0.07807	0.00889	0.10155	0.37845	0.59661	Failed
	2013	-0.08991	0.00440	0.07383	0.36436	0.30322	Failed
	2014	-0.08952	0.00373	0.08911	0.35937	0.40105	Failed
	2015	-0.04739	0.00864	0.13370	0.40615	1.04215	Failed
	2016	-0.10805	0.01095	0.13839	0.46594	0.74613	Failed
	2017	-0.12991	0.01207	0.10759	0.61119	0.55186	Failed
	2018	-0.10296	0.00723	0.11840	0.65072	0.82706	Failed
	2019	-0.11259	0.01026	0.12655	0.59234	0.76721	Failed

Qantas	2009	-0.03731	0.00903	0.14135	0.40360	1.15836	Gray Area
	2010	-0.12742	0.01271	0.07107	0.42939	0.13398	Failed
	2011	-0.10974	0.02090	0.07911	0.41824	0.31898	Failed
	2012	-0.17565	-0.00817	0.08490	0.38518	-0.20396	Failed
	2013	-0.17530	0.01010	0.09772	0.41794	-0.02149	Failed
	2014	-0.14973	-0.21781	0.08673	0.19831	-0.90122	Failed
	2015	-0.13811	0.05978	0.16110	0.24476	0.62848	Failed
	2016	-0.21371	0.09835	0.20569	0.24247	0.55551	Failed
	2017	-0.23088	0.07955	0.19325	0.25875	0.31511	Failed
	2018	-0.21247	0.08227	0.18963	0.26919	0.43131	Failed
	2019	-0.22620	0.07483	0.17320	0.21554	0.15030	Failed
Singapore	2009	-0.04360	0.00332	0.07363	1.79227	2.10146	Gray Area
	2010	0.11295	0.04670	0.01592	2.37338	3.49223	Succeeded
	2011	0.19370	0.06258	0.07749	1.98359	4.07818	Succeeded
	2012	0.11569	0.02831	0.02670	2.09741	3.23291	Succeeded
	2013	0.11563	-0.04034	0.02855	2.06670	2.98895	Succeeded
	2014	0.11130	0.02991	0.02127	2.15647	3.23488	Succeeded
	2015	0.03979	-0.01500	0.02585	1.58611	2.05129	Gray Area
	2016	0.01769	0.06250	0.05599	1.69022	2.47079	Gray Area
	2017	-0.03190	0.03961	0.02816	1.66625	1.85863	Gray Area
	2018	-0.08274	0.09593	0.07963	1.35450	1.72734	Gray Area
	2019	-0.08125	0.03917	0.03758	0.98510	0.88159	Failed
United Airlines	2009	-0.07632	-0.00086	-0.03468	-0.13077	-0.87384	Failed
	2010	-0.05049	-0.00061	0.01972	0.19949	0.00876	Failed
	2011	-0.05634	0.00016	0.01557	0.21465	-0.03910	Failed
	2012	-0.07095	0.00011	-0.01725	0.03143	-0.54801	Failed
	2013	-0.09467	-0.00046	0.01708	0.09462	-0.40839	Failed
	2014	-0.13181	-0.00011	0.02972	0.07590	-0.58559	Failed
	2015	-0.11130	-0.07538	0.10330	0.28099	0.01334	Failed
	2016	-0.12439	0.03886	0.09533	0.27334	0.23832	Failed
	2017	-0.13171	0.02013	0.07091	0.26133	-0.04747	Failed
	2018	-0.13783	0.01073	0.05402	0.25761	-0.23566	Failed
	2019	-0.12841	0.01720	0.07440	0.28070	0.00844	Failed
All Nippon	2009	-0.02743	0.01345	-0.02905	0.35243	0.03872	Failed
	2010	0.01245	0.02023	0.03527	0.36876	0.77181	Failed
	2011	0.04393	0.01098	0.04443	0.37362	1.01491	Failed
	2012	0.12167	0.00983	0.04258	0.54985	1.69367	Gray Area
	2013	0.05612	0.00506	0.03036	0.52743	1.14244	Gray Area
	2014	0.01129	0.01129	0.03997	0.52368	0.92935	Failed
	2015	0.02064	0.01974	0.06101	0.59275	1.23213	Gray Area
	2016	0.04062	0.00475	0.06309	0.67122	1.41076	Gray Area
	2017	0.02927	0.03630	0.06440	0.63124	1.40597	Gray Area
	2018	0.00558	0.03163	0.06141	0.67660	1.26283	Gray Area
	2019	0.05517	0.03147	0.04623	0.71420	1.52506	Gray Area

	2009	-0.03373	0.00817	-0.03037	0.16509	-0.22537	Failed
	2010	0.03632	0.00759	0.03860	0.20151	0.73399	Failed
	2011	0.00768	-0.02595	0.01858	-0.29372	-0.21774	Failed
	2012	-0.02340	0.02064	0.04823	-0.26947	-0.04503	Failed
	2013	0.01035	0.00517	0.06536	-0.12855	0.38902	Failed
Air Canada	2014	-0.00554	0.00460	0.07654	-0.09617	0.39202	Failed
	2015	0.02255	0.00365	0.11396	0.00306	0.92886	Failed
	2016	-0.00509	-0.00007	0.08899	0.08773	0.65649	Failed
	2017	0.01665	0.02564	0.07710	0.23830	0.96113	Failed
	2018	0.06261	0.00203	0.06116	0.26596	1.10759	Gray Area
	2019	-0.00933	0.00263	0.05944	0.18836	0.54459	Failed
	2009	-0.11009	-0.00318	0.04973	0.59747	0.22899	Failed
	2010	-0.14466	-0.00683	0.14656	0.73927	0.78991	Failed
	2011	-0.09357	0.00788	0.05330	0.68909	0.49359	Failed
	2012	-0.16515	0.00143	0.01148	0.58534	-0.38693	Failed
	2013	-0.00927	0.00612	0.02087	0.58047	0.70882	Failed
Cathay Pacific	2014	-0.07148	-0.00355	0.02354	0.43169	0.13096	Failed
	2015	-0.09577	0.04324	0.37488	0.38522	2.43641	Gray Area
	2016	-0.07157	0.04173	0.00980	0.45556	0.21074	Failed
	2017	-0.04480	0.03270	-0.00311	0.48202	0.29796	Failed
	2018	-0.09842	0.00718	0.01705	0.50602	0.02369	Failed
	2019	-0.06649	0.04265	0.02546	0.56231	0.46438	Failed
	2009	-0.11598	0.01526	-0.04184	0.24575	-0.73423	Failed
	2010	-0.08810	0.02110	-0.07665	0.24234	-0.76980	Failed
	2011	-0.10027	0.00897	-0.03774	0.28714	-0.58064	Failed
	2012	-0.08182	-0.00098	-0.03982	0.22139	-0.57509	Failed
	2013	-0.11479	-0.03765	-0.02077	0.09914	-0.91120	Failed
Air France	2014	-0.20022	-0.00900	0.00271	-0.02649	-1.35233	Failed
	2015	-0.19087	-0.00129	0.10229	0.01184	-0.55648	Failed
	2016	-0.11050	-0.01282	0.11835	0.05990	0.09153	Failed
	2017	-0.09999	0.00070	0.15896	0.08786	0.50684	Failed
	2018	-0.15559	-0.00781	0.14513	0.06859	0.00114	Failed
	2019	-0.13372	-0.00247	0.13431	0.08085	0.10216	Failed
	2009	-0.12185	-0.01101	-0.02574	0.03822	-0.96810	Failed
	2010	-0.05310	0.00007	0.03400	0.52718	0.43389	Failed
	2011	-0.09088	0.01649	0.11686	0.46550	0.73164	Failed
	2012	-0.17481	-0.00778	0.06250	0.43582	-0.29454	Failed
	2013	-0.19397	0.09682	0.20263	0.40170	0.82660	Failed
SAS	2014	-0.10230	0.00522	0.12627	0.51728	0.73762	Failed
	2015	-0.06271	0.07351	0.04682	0.53408	0.70368	Failed
	2016	-0.10931	0.05958	0.04507	0.47874	0.28269	Failed
	2017	-0.08696	-0.00525	-0.00046	0.48251	-0.08405	Failed
	2018	-0.05404	-0.00076	-0.00023	0.38354	0.04418	Failed
	2019	-0.09949	-0.00226	-0.00065	0.37235	-0.27345	Failed