

ERASMUS UNIVERSITY ROTTERDAM
Erasmus School of Economics
Master Urban, Port and Transport Economics

Title: Forecasting air cargo volume based on economic indicators

Name: Martijn Rosingh

Student number: 543808

Supervisor: Ir. Floris de Haan

Second assessor: Jeroen van Haaren MSc.

Date: 1-5-2021

The views stated in this thesis are those of the author and not necessarily those of the supervisor, second assessor, Erasmus School of Economics of Erasmus University Rotterdam.

Abstract

This paper intends to investigate the main determinants of air cargo volume and to what extent we can predict this volume. The leading economic indicators researched are GDP, high-tech export, oil price, inflation rate and globalisation. It is one of the few papers where endogeneity in the independent variables is solved in various manners. GDP was transformed to three years average GDP growth, and for oil price, an instrumental variable was used to eliminate the endogeneity problem. After a two-stages-least-squares analysis, it could be established that GDP, high-tech export, inflation rate and globalisation all have a positive effect on air cargo volume. In contrast, oil price, as expected, was found to have a negative effect. With data only available until 2017, a forecast was done for 2018 on eleven of the biggest cargo airports in the world. After verifying the forecast with the actual volume, most of the predicted volumes were close to the actual volumes. However, it can also be concluded that for some airports, the volume was positively or negatively driven by factors outside of this study.

Keywords: Air cargo; Forecasting; Instrumental variable; GDP; High-tech export; Oil price; Inflation; Globalisation

Table of Contents

Abstract	2
1. Introduction.....	4
1.1 Problem statement.....	4
1.2 Research question	5
2. Literature review.....	7
2.1 Gross Domestic Product	7
2.2 Inflation rate	8
2.3 (High-tech) export	10
2.4 Oil price.....	11
2.5 Globalisation.....	13
3. Hypotheses.....	15
4. Data	17
4.1 Dependent variable.....	17
4.2 U.S. airports.....	17
4.3 European airports.....	18
4.4 Asian airports	19
4.5 Independent variables	19
5. Methodology.....	22
5.1 Endogeneity problem	22
5.2 Instrumental variable	23
5.3 Regression equation	24
5.4 Forecasting	25
6. Results.....	27
6.1 Descriptive statistics	27
6.2 Regression results	28
6.3 Forecast results	32
7. Forecasting.....	34
8. Discussion and conclusion	38
8.1 Discussion of the results.....	38
8.2 Conclusion	40
8.3 Limitations.....	41
8.4 Policy recommendations.....	42
8.5 Suggestions for future research	42
Bibliography	44
Appendix.....	49

1. Introduction

Air cargo exists for more than a hundred years now. Especially in the last thirty years, we saw a massive increase in freight tonne carried from 20 million in 1990 to over 60 million in 2019 (IATA, 2021). Considering that the goods shipped by air are almost all expensive and relatively small, the increase over the last years is even more staggering when looking at the value of the goods instead of the volume. Nowadays, air cargo represents 35% of global trade by value but less than 1% of trade by volume (IATA, 2021).

Air cargo goods are, in general, time-sensitive or have high values per unit. Airfreight rates vary between \$1.5 and \$4.5 per kilogram. Therefore, the value of the goods shipped by air needs to have a high price per kilogram to make it profitable. Such goods are pharmaceuticals, perishable seafood and agricultural products, electronic parts, documents and live animals (Worldbank, 2009).

When you look at total merchandise trade, the highest-ranked countries are China, the USA, Germany, Japan and The Netherlands (WTO, 2021). The countries most involved in air cargo are the USA, China, United Arab Emirates, Hong Kong and Qatar (Indexmundi, 2021). For both, the numbers from 2018 are taken. For the UAE, crude petroleum and refined petroleum are the largest export products. This is generally shipped by sea, but gold, jewellery, and broadcasting equipment complete the top five exports and are the top three when we look at imports. The value of these goods are among the highest per unit; therefore, the UAE is such a high air cargo transport country (OEC, 2021a).

1.1 Problem statement

Aviation forecasting is a hot topic. Most of the largest international aviation institutions (IATA, FAA, Boeing, AF-KLM) have published a forecast on the aviation industry for the coming years or the following decades. Even outside traditional aviation companies, it is an interesting topic to investigate. Large consultancy companies like PwC or Deloitte make their forecast for the industry too. Knowing the exact numbers of passenger or cargo volume for the next year is valuable for airlines and airports. Hence, most in-depth and thorough reports are available against a significant price.

On the other hand, publicly available reports are helpful but miss out on key metrics. For example, in the 2021 outlook of PwC, a more general view of the aviation industry is outlined without being specific on air cargo volume or geographical location. It gives an overview of several aspects that might influence the aviation industry, like Covid-19 and environmental concerns (PwC, 2021).

In a report from the FAA (2020), an aerospace forecast is given from 2020 until 2040. This extensive report zooms in on almost all aviation applications, from the well-known passenger and cargo forecasts to urban air mobility and remote pilot forecast. Their projections on cargo mention that regional and worldwide GDP, adjusted for inflation, is the primary driver of air cargo. The report predicted an average growth rate of 4.2 per cent per year in revenue ton-miles between 2020 and 2040.

Several other studies investigated the factors that may determine air cargo as well. For example, by empirically examining eight emerging countries, Graham and Zheng (2018) found that export is a good predictor for air cargo. Kupfer et al. (2017) looked at exports and oil price, they found a positive relation for export as well, but a negative relation for oil price as an increase in oil price leads to too high operational costs.

1.2 Research question

Most studies isolated one or two economic indicators to investigate their effect on air cargo; this study will look at a broader range of indicators and look at their impact on air cargo together. After the effect is established, a forecast will be done to predict air cargo volume for some of the biggest international cargo airports. To do so, the following research question is formulated:

To what extent can we forecast air cargo volume?

To answer this question, five hypotheses will be formulated based on the leading indicators found to impact air cargo. Subsequently, a regression analysis will be performed to test the hypotheses. Based on the results, a forecast will be made for each individual airport.

This study tries to fill the research gap by first determining the effect of several economic indicators on air cargo, followed by a forecast based on the indicators. In prior literature, these two aspects have continuously been researched apart from each other. Furthermore, it provides a detailed forecast on an airport, instead of a general prediction of an increase or decrease of cargo volume worldwide. The results from this study are not only valuable for the airports involved, but also for other companies involved in the air cargo supply chain. By knowing cargo volumes in advance, capacity could be tailored to the demand.

This paper starts with a literature review in chapter 2, followed by the hypotheses in chapter 3. The data collection is presented in chapter 4 and followed by the methodology described in chapter 5. Results will be discussed in chapter 6; based on that, forecasts will be made in chapter 7. The discussion and conclusion are in chapter 8.

2. Literature review

The literature review will be structured as follows. For each economic indicator, first, the impact of that indicator on general trade is examined. Second, the specific effect on air cargo is established and finally, the predictive power of that indicator is checked.

2.1 Gross Domestic Product

The most widely economic indicator that has been researched is GDP, as it is one of the most apparent indicators of any trade-related research. Gao et al. (2016) looked at the relationship of different transportation modes and GDP of China between 1978 and 2014. They concluded a positive correlation between GDP and freight traffic, among which air cargo had a solid positive correlation.

F. Hsiao and M. Hsiao (2006) looked at FDI, exports, and GDP in several Southeast Asian countries. They noticed that while testing on both individual countries and as panel data on all countries, there are differences between the countries. In one country, there was a unidirectional relationship of GDP causing export. In another country, this was a bidirectional relation. However, on the panel data analysis, they found a bidirectional relationship between export and GDP.

Love and Chandra (2005) looked at this relationship too. They mentioned in their paper that many studies that supported export-led GDP growth instead assumed than established this causality. Furthermore, in other papers where this causality was tested, evidence was mixed. Their research, which they find superior to previous as a new Johansen multivariate framework was used, tried to fill this gap of causality in literature. They found both a short- and long-term relationship from GDP to export. However, they only looked at the numbers for Bangladesh, and as the previous paper suggested, differences in relationship can arise between countries.

Nonetheless, these studies looked at GDP and general trade. More interesting to see if similar or different results can be observed when we turn to air cargo instead of general trade. Air

cargo is part of total trade, but it does entail particular trade, as mentioned in the previous chapter.

Hakim and Merkert (2016) empirically examined the relationship between GDP and air cargo volume in South Asia. They found a causal relationship between GDP and air cargo, and they also established the direction of this causality. It was found that there is a unidirectional relation that GDP causes an increase in air cargo. This is a long-run causality with a 3 to 4-year time-lagged impact of GDP on air cargo. For this research, it is important that the direction of the relation has been established. This prevents reversed causality or simultaneity biases.

Suryani et al. (2012) modelled an air cargo demand forecast intending to plan terminal capacity for the Taiwan Taoyuan International Airport. They investigated several economic indicators such as import, FDI, GDP and GDP growth. They found that GDP growth had a strong effect on air cargo demand, more substantial than the other indicators. Based on an optimistic projection, a capacity shortage of around 7.3 million tonnes is expected for Taiwan.

Jiang et al. (2003) analysed future air cargo demand in China. Based on different GDP projections, they tried to forecast the total throughput of air cargo in China. However, before making such forecasts, it was essential to establish the relationship between GDP and air cargo. They found a positive relationship where a one billion increase in GDP causes cargo to increase by 0.0096 thousand tonnes. On top of that, they made airport-specific forecasts for several airports in China, Hong Kong and Taipei. What is interesting to see in this paper is that GDP was used as a predictor for future air cargo too. In the paper, however, it was the only economic indicator used. The authors concluded that the projections were too optimistic for some airports because of rapid GDP growth in the past. Therefore, in this study, more indicators will be added.

2.2 Inflation rate

The second indicator which will be discussed is the inflation rate. Inflation rate is attractive as it impacts the real amount people can spend in a country. Furthermore, it is captivating because it is different for every country, even within euro countries. It can create international competitiveness and, therefore, increasing the trade of a nation.

First is the paper from Mwakanemela (2014). The author investigated with the use of an OLS model the impact of inflation on trade performances. Data was collected for a period between 1980 and 2021 in Tanzania. Inflation was measured in the Consumer Price Index, and it was found that an increase of one in the CPI resulted in a decrease of exports of 13.1 manufacturing products. This was explained by the fact that inflation increases domestic prices and, therefore, less attractive for other countries to import their products.

In Stockman (1985), the effects of inflation on international trade is being discussed. He declared that an increase in inflation could result in different scenarios for a country's trade depending on its return on capital and labour. However, in general, with a low inflation rate, capital intensive goods are traded more, and with a high inflation rate, labour-intensive goods are the prevalent traded goods. For air cargo, it is appealing as a specific type of good which is handled chiefly; high-value capital-intensive goods. This would imply a negative relation between inflation rate and air cargo.

According to Alici and Akar (2020), there is a negative relation between inflation rate and air cargo demand. They explained that a high inflation rate decreases firms and individuals' real income, which leads to less demand and less air cargo. This was supported by their empirical research on the thirteen countries with the highest air cargo capacity. After a random-effects OLS model over data from 1980 until 2018, they found this negative effect. A one percentage point increase in inflation leads to a minus 2.18 in freight-tonnes-kilometres.

Totamane et al. (2014) performed a study on the forecasting of demand in air cargo. They tested several economic indicators to predict air cargo demand, but without giving in what direction they would change air cargo. They found inflation rate, as well as GDP, were good predictors for future air cargo.

Furthermore, Aderamo (2010) investigated factors responsible for the demand of passenger-kilometre, aircraft-kilometre and cargo-tonne-kilometre in Nigeria. Among other variables, the author found that GDP and the consumer price index were vital in explaining air transport demand. With data on these variables from 1975 until 2005, OLS regressions were run on each of the dependent variables mentioned above. For this study, cargo-tonne-kilometre is

especially interesting. With a logarithmic function of the consumer price index, it was proven that a one per cent increase resulted in a minus 1.525 cargo-tonne-kilometres.

2.3 (High-tech) export

The impact of export on trade and air cargo is evident. On the predictive power, however, mixed evidence is found in the literature. Totamane et al. (2014) found export as a weak predictor. Kupfer et al. (2012) found a strong positive relation between merchandise trade and air cargo demand and good predictive power of the former on air cargo. They found this after studying multiple routes in Europe and Asia between 1983 and 2007. Furthermore, Graham and Zheng (2018) concluded in an empirical study on air cargo demand forecast in eight emerging markets that export is a good predictor of air cargo demand too.

This study, however, will not address total export but will specifically look at high-tech export. Gong et al. (2018) noticed that it is vital to not only look at the size of the economy, but the composition of the economy might be as important. They mentioned high-tech and capital intensive products as vital goods when considering trade drivers of air cargo. In a case study on the Chinese air cargo sector, they hypothesised that the tertiary industry, such as information technology, pharmaceutical and telecommunication sector, is an essential indicator for air cargo. After an OLS regression, it was identified that a greater tertiary industry creates a larger air cargo share.

In the book of Morrell and Klein (2018) on moving boxes by air: the economics of international air cargo, the specific commodities in high-tech export goods are discussed. The largest share of products imported by the EU by air is high-tech machinery, automotive and computer parts. Almost two-thirds of total air cargo consists of these products. The second-largest commodity in air cargo, around 18 per cent, is also a product class discussed before but not considered high-tech; agricultural products and live animals. Nonetheless, as such a high share of air cargo is composed of high-tech products, it will be more interesting to study high-tech export than general export.

2.4 Oil price

Oil price is affecting air cargo volume through increased operational costs. In figure 1, the U.S. Gulf Coast kerosene jet fuel spot price change is displayed together with the price change of a barrel of crude oil. As can be observed, the price changes are almost identical, implying an increase in oil price directly affects the kerosene price. The portion of fuel cost on the total operating cost of an aircraft depends on whether it is used for short- or long-haul flights and the age of the aircraft. Various sources mentioned different portions; Martino et al. (2019) estimated it in a report on the impact of oil price fluctuations on transport, to a third of operational costs. The Worldbank (2009) mentioned that, during a spike in oil price, it could add up to 50 percent of operational costs.

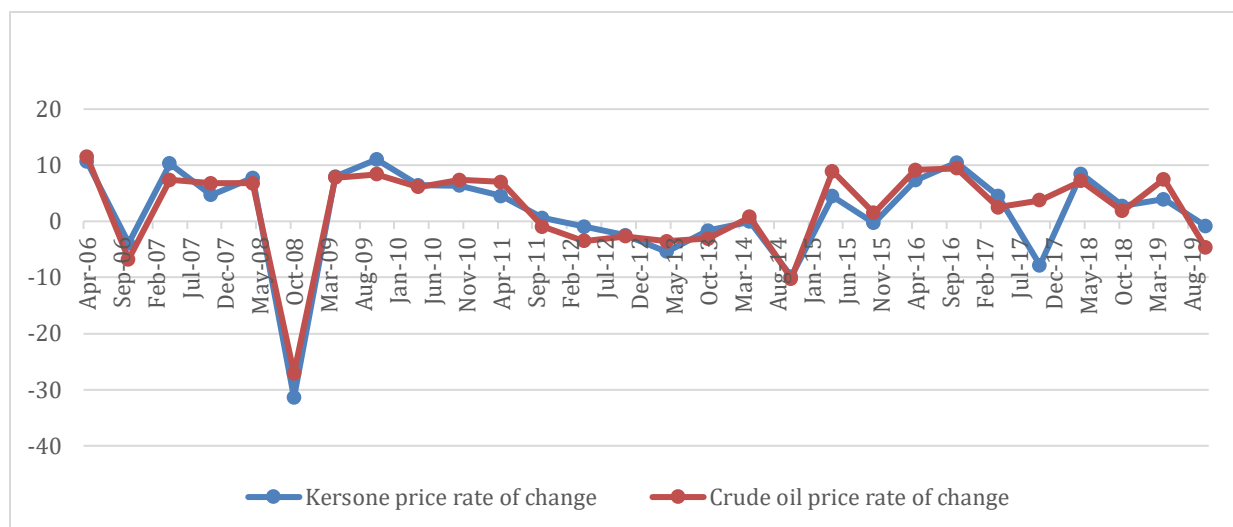


Figure 1 – Rate of change kerosene price and crude oil price
(Data source: U.S. Energy Information Administration, 2021a)

An apparent problem for the air cargo industry is the shift in transportation mode after oil price fluctuations. Although, as mentioned earlier, goods that are shipped by air are generally specific types of goods. The air cargo industry still can suffer from a shift in transportation mode as for some goods, it can become too costly to be shipped by air. Not only maritime shipping is a substitute, rail transport and inland navigation should also definitely be considered as not all transportation by air is long-haul per se. The U.S. domestic is an important market for air cargo too. In this market, a high oil price can lead to a shift in transportation mode, especially when transit time is less critical. According to Martino et al.

(2009), energy cost is generally not a significant component in the rail freight sector. On average, the share of energy cost on the total transport cost for rail freight and inland navigation is approximately 20 per cent.

A shift from air transport to maritime transport, or the other way around, is also possible due to fluctuations in oil price. For both modes of transport, oil price is a significant component of the transportation cost. Percentage-wise, fuel price is a more prominent component of the total cost for the maritime freight industry than for the air freight industry. However, planes still use significantly more fuel than ships. Therefore, a high oil price leads can lead to a shift in transportation choice from air to sea (Martino et al., 2009). Hence, a high oil price is expected to have a negative effect on air cargo volume.

To statistically measure the exact impact of oil price on air cargo can be found challenging. Hansman et al. (2014) tried to estimate this by studying air cargo transport in the US. According to the authors, direct response in air cargo from changes in oil price could not be shown based on the available data.

However, two studies did find a statistically significant effect. First, Wadud (2014) performed research on the asymmetric effects of income and fuel price on general air transport demand by looking into U.S. data from the deregulation until 2013. The author found a sizeable negative relation between oil price and air transport demand in the long run. In the short run, a small but highly significant negative relation.

Second, in Kupfer et al. (2017), they built upon Kupfer's previous research (2011). Now, not only the effect of merchandise trade was investigated, but also oil price was added to the regression. They hypothesised that higher oil prices increase the freight rates, and hence demand for air transport will decrease. Data was taken from 1981 to 2013 on a worldwide level. It was discovered that oil price and world air freight in tonne-kilometres have a negative relation. A one per cent increase in oil price resulted in an 8% decrease in world air freight.

2.5 Globalisation

Although quantitative studies on globalisation is somewhat limited, it is an interesting factor to include in this study. It figuratively shrinks the world, and air cargo could profit from this. Again Kupfer et al. (2017) stated that international cargo transport experienced considerable growth in the past decades due to increased globalisation.

To measure globalisation, the KOF Globalisation Index is used. This index is even more interesting as not only economic globalisation is involved, but also social and political globalisation is used to calculate the index. The index is an average of these three components. Social globalisation consists, for example, of information flows, personal contact and cultural proximity. The economic component consists of financial- and trade globalisation. Political globalisation is mostly on involvement in international organisations and treaties (Savina et al., 2019). By including this variable, a broader range of factors that could affect air cargo are now involved in this study.

Fung et al. (2005) performed a literature study on the implications of globalisation on the air cargo industry in China. In the case of China, globalisation already led to a significant push in air cargo as China opened up its borders and involved more in global trade. Furthermore, in the article, it is mentioned that it is likely that China will move towards a U.S. model of air cargo. This U.S. model entails a sizeable domestic market with dedicated express carriers. In the United States, most of the air cargo handled is domestic cargo. For China, international air cargo is more dominant. As the surface area of China and the United States are similar in size, there is the market potential for China to increase its domestic and thus total air cargo volume.

As mentioned, globalisation also entails political components as international treaties. Open Skies Agreements in aviation are part of this. These Open Skies Agreements have had a significant impact on the aviation industry as a whole, but certainly on cargo as well. The EU – U.S. agreement which started in 2008, for example, made it possible for EU cargo carriers to fly between the U.S. and third-party countries without touching their home country. (Button, 2009). By increasing the geographical market, airlines and airports can increase their cargo volume.

Furthermore, globalisation enhanced the forming of strategic alliances in aviation (Button, 2008). Airlines form these alliances, but airport hubs can profit from this as well. SkyTeam Cargo alliance is the largest cargo alliance. Some members of this alliance are the cargo divisions from Air France, KLM, Delta and Korean Air. The hubs they use, amongst others, are Charles de Gaulle, Schiphol, Los Angeles and Incheon, respectively. These airports benefit from the alliances too.

3. Hypotheses

To answer the research question, five hypotheses are composed based on the literature review.

The first hypothesis is around GDP. What was observed is that there is a definite correlation between GDP and trade. Nonetheless, the causal relationship between GDP and trade has been difficult to determine. Where in one paper this was bidirectional, in another paper, a unidirectional relation was found. This problem was already less relevant when only air transport was considered. Both Hakim and Merkert (2016) and Suryani (2012) adjusted GDP to either a lagged version or GDP growth to minimise the possibility of a simultaneity bias. Furthermore, Jiang et al. (2003) established that GDP could be used to predict future air cargo volume. This brings us to the formulation of the first hypothesis:

Hypothesis 1: Three-year-average GDP growth will have a positive effect on air cargo volume

Second is inflation rate. First of all, the effect of inflation rate on general trade was defined as a negative relation. Aderamo (2010) and Alici and Akar (2020) found the same result when focusing on several countries for air cargo. However, it is important to note that the effect of inflation rate might also depend on country-specific factors, as mentioned by Stockman (1985). Finally, it was established by Totamane et al. (2014) that inflation has good predictive power on air cargo volume as well. Therefore, the second hypothesis is:

Hypothesis 2: Inflation rate will have a negative effect on air cargo volume.

Next, the effect of high-tech export on air cargo volume will be hypothesised. On high-tech export specifically, there was not much literature found. However, it was found that export has a clear impact on air cargo volume (Kupfer et al., 2012). On the predictive power of air cargo, Kupfer et al. (2012) and Graham and Zheng (2018) agreed that it was a good predictor. Only Totamane et al. (2014) disagreed on this and concluded that export was a weak predictor. Meanwhile, it was revealed by Morrell and Klein (2018) that high-tech export takes

on the majority of air cargo, and therefore, the impact of high-tech export on air cargo volume will be studied. The third hypothesis is formulated as:

Hypothesis 3: High-tech exports will have a positive effect on air cargo volume.

The fourth hypothesis focuses on the effect of oil price on air cargo. Oil price is an important factor that carriers take into consideration which transportation mode will be used. Especially air cargo is vulnerable to high oil prices as it is the least fuel-efficient mode together with a high portion it takes in total operational costs. Wadud (2014) found a negative relationship between oil price and general air transport demand. Kufper et al. (2014) found this same relation, but now for air cargo as well. A high oil price can affect air cargo in two negative ways. First, it causes transportation costs to increase and therefore less demand. On top of that, it might shift the choice to a more fuel-efficient transportation mode and thereby causes less air cargo volume. Hence, the fourth hypothesis is:

Hypothesis 4: Oil price will have a negative effect on air cargo volume

The final hypothesis is on globalisation. Although former quantitative research on the effect of globalisation on air cargo was not found, it is still expected to have a positive effect. Fung et al. (2005) showed that a country that initially lagged on air cargo saw and can expect more increase in its air cargo volume due to globalisation. Moreover, aviation specifically benefited from globalisation with the rise of Open Skies Agreements and alliances. The final and fifth hypothesis is:

Hypothesis 5: Globalisation will have a positive effect on air cargo volume

After evaluating the effect of the different variables on the air cargo volume, a forecast will be done to estimate the volume outside of the studied years. For this forecast, eleven of the largest international air cargo airports are addressed and discussed in the data section.

4. Data

This research requires data on GDP, the inflation rate, oil price, high-tech exports, globalisation and past air cargo volume.

4.1 Dependent variable

Cargo volume data is taken from the data centre of the Airports Council International's website. The data ranges from 2000 to 2017, and it is measured by the total loaded and unloaded freight and mail in metric tonne (ACI, 2020). There are also other sources for measuring air cargo available, like data from the World bank on total freight tonne-kilometres or data from Statista on worldwide air cargo volume. However, this source is chosen because it shows annual cargo volume for the twenty, and in the earlier years thirty, largest cargo airports in the world. Furthermore, according to Morrell and Klein (2018), airports are more interested in tonnes while airlines are more concerned by tonne-kilometres. As this study will also entail a forecast on airport level, measuring the dependent variable in tonnes was chosen.

The selected airports are the ones that are in the top 20 airports for the entire time of this study, which is between 2000 and 2017. Also, it was required that all the data on the other variables were known. Therefore, some of the largest airports had to be left out of this study—for example, Hong Kong's airport, which is actually the largest cargo airport in the world. The airports in the study are Amsterdam Schiphol (AMS), Charles de Gaulle (CDG), Frankfurt am Main (FRA), Incheon Korea Rep. (ICN), Los Angeles (LAX), London Heathrow (LHR), Miami (MIA), Memphis (MEM), Narita Tokyo (NRT), O'Hare Chicago (ORD) and Louisville (SDF).

4.2 U.S. airports

Some US' airports may come as a surprise to be among the largest cargo airports in the world. Chicago and Los Angeles are together with New York, the largest cities in the United States and, therefore, among the largest cargo airports. Los Angeles benefits extra from being the only large West coast airport and, therefore, relatively close to Southeast Asia. More interesting are smaller cities such as Miami, Memphis and Louisville.

Memphis is the largest US cargo airport, and there is a straightforward explanation for this; FedEx' headquarters are located in Memphis and uses it as their domestic hub. FedEx operates almost 400 flights per day at Memphis (Flymemphis, 2020). In 2018, it had more planes than Emirates, Etihad and Qatar Airways combined, resulting in being the largest cargo airline in the world (Aircargonews, 2020). Louisville is in the top ten because it houses the other leading delivery service company in the United States; UPS. Both companies and thus airports profited massively from the increase in e-commerce of the last few years. Retail e-commerce sales more than tripled over the previous seven years (Statista, 2021).

UPS and FedEx chose these relatively small and unknown cities, close to each other, because of their strategic location; both cities are within 300 kilometres from the mean population centre of the US, a small county in Missouri (U.S. Census Bureau, 2010). The US domestic market is the most critical market for the companies; therefore, they chose these cities as the average transit time for flights within the US is the shortest. Moreover, both these airports fall outside of the top ten cargo airports when we only consider international cargo. The only U.S. airports that remain then are LAX and Miami. Miami profits from its location, especially for international trade. Both UPS and FedEx use Miami as one their global hubs as it is a strategic position for trade lanes between the US and Europe, and South America (Morrell and Klein, 2019).

4.3 European airports

The cargo of Amsterdam Schiphol is characterised by a large number of air to air transfers or air to truck transfers (Morrell and Klein, 2019). Just by looking at national GDP levels, Schiphol is the odd man out among the other airports. There are two foremost reasons why Schiphol is still among the twenty largest cargo airports. First of all, the commodities exported by The Netherlands are precisely the commodities shipped by air; high-tech machinery, agricultural products and chemical products. Second, Schiphol is the primary hub of KLM and is the primary European hub of Nippon Cargo which partnered up with KLM (Morrell and Klein, 2019).

Charles de Gaulle is the second-largest cargo airport in Europe. It benefits from the fact that Air France uses it as its central European hub. On top of that, FedEx uses it as their European hub as well. Besides, Charles de Gaulle profits as being the airport of Paris. According to the website of Charles de Gaulle, the main cargo activities included pharmaceuticals, perishables, e-commerce and luxury goods (Parisaeroport, 2021). All these goods have previously been mentioned as typical air cargo products, and especially perishables like cheese and all types of luxury products France is worldwide known for.

Frankfurt is the smallest city on the airport list, but it is the most dominant cargo airport in Europe (Statista, 2020). This can be explained mainly by the fact that Lufthansa Cargo uses Frankfurt as their hub. Furthermore, Lufthansa opened up a joint venture with DHL, which uses Frankfurt as their second European hub (Lufthansa-Cargo, 2021). DHL is the largest third-party logistics provider and among the three largest integrated carriers in the world (3plogistics, 2020).

4.4 Asian airports

Finally, the two Asian airports in the study are Narita and Incheon, the busiest cargo airports in Japan and South Korea. Overall, Asian airports dominate the top twenty cargo airport worldwide, but unfortunately, as already mentioned, most of them fall outside of this study as data was not available. Both countries' economies focus on the export of electronic machinery and integrated circuits, also known as chips (OEC, 2021b). Narita is only the second airport in the country when you consider passenger movements as well. But, similar to Charles de Gaulle, it profits from FedEx as Narita is one of their main Asia-pacific hubs.

4.5 Independent variables

As data on the dependent variable is on airport level, the data was gathered on country-level or US' state level for the independent variables too.

The first independent variable is GDP. This is collected per country, and for the U.S. airports, it is collected per state. For the countries, the data is taken from the Worldbank (Worldbank, 2020). The U.S. data is from the Bureau of Economic Analysis, an official website of the U.S. government. GDP is in millions and from taken from 1998 until 2020 (BEA, 2020). Those extra

years were needed to calculate the three-year average growth of GDP; this will be further explained in the methodology section.

Next is high-tech exports. The Worldbank holds data on high-tech exports in current U.S. dollars for the countries involved in this study from 2007 until 2018. For this research, this variable will be measured in billion U.S. dollars. Measuring in million is more often used in general, but all the independent variables needed to be on comparable scales. This will be further elaborated on in the result section. According to the Worldbank, a product is considered high-tech when it requires high research and development intensity. Examples given are electrical machinery, computers, scientific instruments, aerospace and pharmaceuticals (Worldbank, 2021). Unfortunately, prior data on high-tech exports is not available. But as for the majority of the years researched in this study, the data is available, it is expected that a proper estimation of the effect of high-tech exports can be made. United States state-specific data on this is unfortunately not available. This was solved by looking at the portion of each state's contribution to total U.S.' exports. Data on general trade per U.S. state is available from the U.S. Census Bureau (2020). Florida, for example, accounts for almost four percent of total U.S. exports. An assumption was made that that ratio would be similar for high-tech exports, and thus Florida was given four percent of total U.S. high-tech exports. Total export is measured in U.S. dollars, and high-tech generally has a high price so; therefore, high-tech accounts for a large part of total exports. Thus this assumption could be made without too many concessions.

Fourth is the crude oil import prices and again collected per country. This also made some of the largest international cargo airports falling outside of this study. For some countries, data on this variable is not available, e.g. Hong Kong, Shanghai, Dubai and Doha. Data is from the OECD website, which registered the price in dollars per barrel of crude oil and taken from 2000 until 2018 (OECD, 2020).

The following variable is the inflation rate. Inflation is measured by the consumer price index and is transformed to annual percentages. This data is from the Worldbank and available from 2000 until 2018 for each country. (Worldbank, 2020).

Finally, data on globalisation is needed. The University of Zürich is the founder of the KOF index (Savina et al., 2019) used to measure globalisation. It is one of the most widely used indices to measure globalisation as it captures a wide variety of variables, from the number of McDonald's restaurants to internet bandwidth and trade regulations. Data on country level is available from 2007 until 2018, and it is transformed to a growth rate to better capture the differences between years.

5. Methodology

Primary, the data will be organised per airport in Excel. The eleven airports in the study will all be given a number instead of a name to enable Stata to read it and make a regression. First, the hypotheses will be tested to make sure that the selected variables significantly affect the air cargo volume. The dataset consists of panel data. For each airport, we have data for eighteen years on cargo volume and most of the independent variables. Only on high-tech export and the globalisation index, we do not have data points for all eighteen years. The panel variable will be Airport, and the time variable is Year from 2000 to 2017 with a delta of 1 unit.

For the regression analysis, Stata/MP 15.0 will be used. In Stata, a random effects and fixed effects model will be run. Subsequently, a Hausman test will be performed to determine whether random effects or fixed effects should be used. In the Hausman test, the two models are compared and established if there is a systematic difference between the models. If the p-value is below 0.05, the null hypothesis will be rejected, and a fixed-effects model will be used. If the p-value is above 0.05, random effects will be used.

5.1 Endogeneity problem

Furthermore, we will use an instrumental variable in the regression analysis. This is done because we might encounter an endogeneity problem. Endogeneity appears when one of the independent variables is correlated with the error term or when there is a simultaneity problem. A simultaneity bias is present when it is not sure if the independent variables cause the dependent variable or the dependent variable causes the independent variables, or they both cause each other simultaneously (Wooldridge, 2018). In this particular dataset, that might be the problem since for some of the independent variables and the dependent variable, it is difficult to establish which causes which. This is most present for the variable oil price as it is unsure if supply or demand causes oil price to increase. It is possible that due to an excess or limited supply, the price decrease, and therefore, air cargo increases or decreases. A second option is that first, the cargo volume increases, and that results in an increase in oil price due to the increased demand. Therefore, for oil price, an instrumental

variable will be used to filter out the demand-side price variance of oil price. For GDP, which might encounter the same problem, a different solution was found.

Hakim and Merkert (2016) established that in their study, there was no issue with simultaneity between GDP and air cargo. This is, of course, a positive result in order to get an unbiased estimation. However, to be even more confident about a correct estimation, we do not just take total GDP, but we transform it to the average growth over three years. Three years average GDP growth can be calculated in several manners. The calculation was done by first calculating the absolute growth from year to year. Second, taking the average of the absolute numbers of the year prior, year after and the year itself and finally dividing this by the total GDP in that year to come to an average three-year percentage growth. Taking an average growth rate causes outliers to have less influence on the GDP figure used and, therefore, less likely to follow the same trajectory as air cargo.

5.2 Instrumental variable

For the instrument of oil price, it is important that it should satisfy two critical assumptions to be a good instrument; it should be both relevant and valid. This means that it should be correlated with the endogenous variable, in this case, oil price. On top of that, it should be uncorrelated to the error term (Baum et al., 2003). These two assumptions can also be shown as the following equations:

$$Cov(z, u) = 0$$

$$Cov(z, x) \neq 0$$

Where z is the instrument, u the error term and x the instrumented variable.

To be valid, and argumentation is needed why the instrument will only affect the endogenous variable and not the dependent variable, i.e. via the error term. For this argumentation, the papers of Ciner (2001) and Lu (2011) are used. They used heating oil as an instrument for oil price in their research on the stock market price. As the name suggests, heating oil is used for furnaces and boilers in home heating. According to the website of Tradingeconomics (2021), it accounts for about 25% of the yield of a barrel of crude oil. Data on the historical price of heating oil is also taken from this website. Lu (2011) reasons that stock markets' performances do not affect the demand or supply of heating oil and therefore uncorrelated with the price

of heating oil. Simultaneously, crude oil is the most significant component of heating oil; hence the prices of both are heavily correlated. Air cargo does not affect the price of heating oil either, and thus it will be used for this study as well. To conclude, in theory, heating oil can be a good instrument for oil price as it is uncorrelated with air cargo and correlated with crude oil price.

Relevancy can be proved in Stata. The instrument should be correlated with the endogenous variable, and that can be tested by looking at the so-called first-stage regression. The instrument used should have a significant effect on the dependent variable, which is the endogenous variable investigated (Staiger and Stock, 1997). In this case, heating oil price should have a significant effect on oil price.

Then, the Durbin-Wu-Hausman test is performed to test the endogeneity in the instrumental variable regression estimation. This test estimates both an ordinary OLS and the IV regression and compares the coefficients. With the outcome of the test, the null hypothesis, OLS estimator is efficient and consistent, can be either be rejected or accepted. Under this hypothesis, both OLS and IV are consistent, but an OLS regression will be more efficient, and therefore it will be the preferred method (Baum et al., 2003).

5.3 Regression equation

When using an instrumental variable, there are basically two stages in which the regression analysis is performed. In the first stage, the endogenous variable, oil price, is predicted based on the instrument and the other independent variables. In the second stage, the predicted value of oil price and the other independent variables are used to estimate the dependent variable, which is air cargo volume.

The first stage of the regression is:

$$\widehat{Oilprice}_{it} = \alpha + \beta_1 Heatingoil_{it} + \beta_2 GDPgrowth_{it} + \beta_3 hightechEXPORTS_{it} + \beta_4 Inflationrate_{it} + \beta_5 Globalisationgrowth_{it} + \alpha_{it}$$

The second stage of the model is:

$$\begin{aligned} AirCargovolume_{it} = & \alpha + \beta_1 \widehat{Oilprice}_{it} + \beta_2 GDPgrowth_{it} + \beta_3 hightechEXPORTS_{it} \\ & + \beta_4 Inflationrate_{it} + \beta_5 Globalisationgrowth_{it} + \alpha_{it} + v_{it} \end{aligned}$$

After each independent variable's effect on the dependent variable has been established over the entire dataset, the coefficients and significance level will be discussed, and the hypotheses will be either confirmed or rejected.

5.4 Forecasting

Following a manual on air traffic forecasting by the ICAO (2006), there are three main types of forecasting methods; qualitative, quantitative and decision analysis. As it is believed that a quantitative method brings us closest to the actual volume, this method will be used. In quantitative methods, there are still several options to choose from, like trend projection and extrapolating, but it is believed that an econometric analysis is a superior form.

The ICAO provides a step by step manual on how to perform an econometric analysis on forecasting air traffic. In the first step, where the variables should be selected, GDP and oil price were even mentioned as key variables. Subsequently, data should be gathered, and the relationship between the variables and air cargo should be established. In the third step, the regression analysis should be carried out to test the relationships hypothesised as well as the estimates of the coefficients. Finally, the model should be established in its final form to enable to use the future values of the independent variables to forecast air cargo volume.

The model's form is chosen to keep it straightforward and easy to reproduce for every individual airport. On each airport, a time-series analysis is performed to get unique coefficients for every airport. The same regression equation is used as described in the former section, but now on airport level instead of panel data. The change in the independent variables from 2017 to 2018 is multiplied by the corresponding coefficient of that variable. This is added to the cargo volume of 2017 to get the forecast value of 2018. The coefficients are retrieved from the regression in Stata; subsequently, Excel is used to multiply the coefficients with the corresponding changes in the independent variables.

Data for 2018 was easily accessible for the independent variables, but the source used for data on air cargo was only until 2017. Therefore, the values of 2018 are predicted by this model. However, on each airport's website or the website of Aircargonews, the data of handled cargo volume was found. Although for some airports, the data from their own website on 2017 showed a discrepancy with the data from the ACI over 2017, these differences were only relatively small. Hence the predicted values by the model can be tested with the actual values found on the websites of the airports.

6. Results

6.1 Descriptive statistics

Table 1 – descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Airport	198	10.36364	4.726971	1	18
Year	198	2008.5	5.201279	2000	2017
TotalCargo	198	2021470	661443.5	1047917	4336752
Oilprice	198	61.72131	29.34481	22.07	114.75
Heatingoilprice	198	1.744794	.8435728	.5229	32794
Inflation	198	1.836238	1.184851	-1.352837	4.673796
Hightechexport	121	67.40082	62.66846	2.815982	216.297
GDP average growth	198	3.389973	4.212095	-12.46449	13.3892
Globalisationgrowth	121	0.454953	0.779502	-0.769016	4.013929

In table 1, the characteristics of the variables from the dataset are described. Of each variable, except high-tech export and globalisation, there are 198 observations as there is data on eleven airports and eighteen years. For high-tech export and globalisation, there was only data available for eleven years, and therefore the analysis will be based on only those years. The means of the independent variables that are used are all in a pretty similar size. It was also shortly mentioned in the data section that this was necessary. This is because, for the Durbin-Wu-Hausman test, the difference in coefficients between the two models are compared. Following that comparison, a conclusion is drawn if the differences are systematic. For Stata, the coefficients had to be on a relatively similar scale to make an objective comparison. If high-tech export, for example, had a coefficient in the range between 3 and 5 and GDP growth somewhere around 11000, Stata failed to make an objective comparison in the test. Therefore, to increase the coefficient of high-tech export, the initial value of high-tech export was divided by one thousand to measuring it in billions of dollar.

6.2 Regression results

Table 2 – Regression results fixed vs random effects

VARIABLES	(Fixed) TotalCargo	(Random) TotalCargo
OilpriceperbarrelinUS	-3,596*** (643.3)	-3,527*** (637.5)
Inflation	40,241*** (14,803)	39,182*** (14,699)
HightechexportcurrentUSin	4,670*** (1,357)	4,148*** (1,281)
GDPthreeyearaveragegrowth	10,157*** (3,778)	10,444*** (3,755)
Globalisationgrowth	29,828* (17,683)	29,624* (17,591)
Constant	2.001e+06*** (90,674)	2.032e+06*** (261,664)
Observations	121	121
R-squared	0.320	
Number of Airport	11	11

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3 – Result Hausman test fixed vs random effects

	(b) fixed	(B) random	(b-B) Difference	sqrt(diag(V_b- V_B)) S.E.
Oilpricepe~S	-3,596	-3,527	-68.96	86.25
Inflation	40,241	39,182	1058.25	1747.95
Hightechex~n	4,670	4,148	522.30	447.21
GDPthreeye~h	10,157	10,444	-287.13	418.94
Globalisat~h	29,828	29,624	204.01	1800.74
Prob>chi2 = 0.9233				

Table 2 shows the first results of the panel data regression. They are followed by the results of the Hausman test in table 3. For the Hausman test, the null hypothesis is that the difference in coefficients is not systematic, and therefore, random effects is the preferred model. Following the P-value of 0.9233, we cannot reject the null hypothesis and consequently, a random-effects model will be used. Just by looking at the coefficients of the two regressions,

it can also be observed that the difference between those two is minor, and hence the random effects model should be used.

With this result, the correct effects model can be used for the instrumental variable regression. The results of the instrumental variable regression are displayed in table 4, followed by the Durbin-Wu-Hausman test to determine if the instrumental variable model is indeed a better estimator than a random-effects OLS model.

Table 4 – Instrumental Variable regression

VARIABLES	(IVMODEL) TotalCargo	(RANDOM) TotalCargo
OilpriceperbarrelinUS	-2,791*** (655.5)	-3,527*** (637.5)
Inflation	29,483** (14,903)	39,182*** (14,699)
HightechexportcurrentUSin	3,676*** (1,291)	4,148*** (1,281)
GDPthreeyearaveragegrowth	10,332*** (3,780)	10,444*** (3,755)
Globalisationgrowth	32,246* (17,718)	29,624* (17,591)
Constant	2.021e+06*** (260,184)	2.032e+06*** (261,664)
Observations	121	121
Number of Airport	11	11

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5 – Durbin-Wu-Hausman test Instrumental Variable vs OLS

	(b) ivre	(B) random	(b-B) Difference	sqrt(diag(V_b- V_B)) S.E.
Oilpricepe~S	-2,791	-3,527	736.34	152.62
Inflation	29,483	39,182	-9699.67	2454.82
Hightechex~n	3,676	4,148	-471.50	157.37
GDPthreeye~h	10,332	10,444	-111.57	439.08
Globalisat~h	32,246	29,624	2622.13	2113.05

Prob>chi2 = 0.0003

The P-value is this time smaller than 0.05. Hence, we reject the null hypothesis that OLS is a more efficient estimator. An instrumental variable regression with random effects is the preferred model in determining air cargo volume.

Table 6 – Final model with first stage

VARIABLES	(FIRSTSTAGE) TotalCargo	(IVREMODEL) TotalCargo
Inflation	0.410 (0.436)	29,483** (14,903)
HightechexportcurrentUSin	-0.034 (0.038)	3,676*** (1,291)
GDPthreeyearaveragegrowth	-0.159 (0.112)	10,332*** (3,780)
Heatingoilusdgal	36.97*** (0.712)	
Globalisationgrowth	-0.704 (0.522)	32,246* (17,718)
OilpriceperbarrelinUS		-2,791*** (655.5)
Constant	-4.425 (7.701)	2.021e+06*** (260,184)
Observations	121	121
Number of Airport	11	11

Standard errors in parentheses
 *** p<0.01, ** p<0.05, * p<0.1

Table 6 shows the final model together with the first stage results of the two-stage least-squares analysis. As mentioned in the methodology, the coefficient of heating oil should be significant in the first stage, where oil price is the dependent variable. This is indeed the case. In the second stage, most variables are 99% significant. Only Globalisationgrowth had a p-value of just over 0.05 and is therefore slightly less significant. Based on the results from table 6, we can now finally test the hypotheses.

The first hypothesis was that the average GDP growth rate has a positive effect on air cargo volume. Following the results of the regression, this hypothesis can be accepted. When the average growth rate increases by one percentage point, the cargo volume increases by 10,332 metric tonnes, ceteris paribus.

The second hypothesis was around inflation rate. It was expected that an increase in inflation would lead to a decrease in air cargo as it would decrease the real income of individuals. This hypothesis is rejected. A one percentage point increase leads to a 29,483 tonnes increase of air cargo volume.

The third hypothesis was on high-tech export. It was assumed that high-tech export would have a positive effect on air cargo volume. The regression results confirm this. An increase of one billion dollars in high-tech export will lead to an increase of 3,676 tonnes in cargo volume.

The fourth hypothesis assumed that oil price would have a negative effect on air cargo volume. This hypothesis can be accepted too. When using heating oil price as an instrument for crude oil price, an increase in the price of one dollar leads to a decrease of 2,791 tonnes in air cargo.

The final and fifth hypothesis stated that globalisation would have a positive effect on air cargo volume. Using the yearly growth rate of the KOF index, it can be established that a one percentage point increase in the growth rate results in an increase of 32,246 tonnes cargo volume. Hence, this hypothesis is accepted.

With this result, we can now look at the coefficients on airport level. A times-series instrumental variable regression is performed on each individual airport, and the results are in table 7, 8 and 9. Based on the results of those regressions, the forecast of the eleven airports has been made.

6.3 Forecast results

Table 7 – Regression results forecast: Amsterdam Schiphol, Charles de Gaulle, Frankfurt, Incheon

VARIABLES	(AMS)	(CDG)	(FRA)	(INC)
	TotalCargo	TotalCargo	TotalCargo	TotalCargo
OilpriceperbarrelinUS	-2,347 (4,104)	-3,300* (1,326)	-1,361 (1,380)	-4,681*** (648.9)
GDPthreeyearaveragegrowth	4,743 (13,881)	-12,780 (9,598)	-18,230 (25,173)	9,584 (5,866)
Inflation	-95,398 (93,564)	175,516** (48,618)	129,342 (77,673)	53,021** (15,672)
HightechexportcurrentUSin	22,094 (18,597)	-144.3 (1,720)	878.8 (3,254)	7,817*** (746.7)
Globalisationgrowth	-73,964 (81,769)	74,956* (30,302)	72,925 (56,634)	52,586*** (12,042)
Constant	226,019 (1.258e+06)	2.254e+06*** (177,008)	1.888e+06** (574,016)	1.699e+06*** (117,206)
Observations	11	11	11	11
R-squared	0.554	0.840	0.414	0.952

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 8 – Regression results forecast: Los Angeles, London Heathrow, Miami, Memphis

VARIABLES	(LAX)	(LHR)	(MIA)	(MEM)
	TotalCargo	TotalCargo	TotalCargo	TotalCargo
OilpriceperbarrelinUS	-5,757*** (1,215)	-3,174 (3,061)	-586.8 (491.2)	-4,369* (2,003)
GDPthreeyearaveragegrowth	54,115** (17,833)	-6,091 (15,018)	51,728*** (12,428)	164,030** (49,714)
Inflation	96,892** (32,839)	57,593 (55,874)	42,112* (18,399)	26,423 (57,542)
HightechexportcurrentUSin	-16,913 (12,119)	14,757** (4,258)	1,939 (21,749)	-58,444 (111,792)
Globalisationgrowth	-15,854 (39,999)	-106,447 (126,693)	-1,943 (29,947)	-43,574 (71,179)
Constant	2.168e+06*** (253,275)	656,410 (430,794)	1.720e+06*** (188,563)	3.969e+06*** (468,727)
Observations	11	11	11	11
R-squared	0.902	0.790	0.913	0.825

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 9 – Regression results forecast: Narita, O’Hare, Louisville

VARIABLES	(NRT) TotalCargo	(ORD) TotalCargo	(SDF) TotalCargo
OilpriceperbarrelinUS	-7,874** (2,042)	-8,626*** (1,874)	-3,564 (3,481)
GDPthreeyearaveragegrowth	-13,968 (8,684)	114,271 (59,176)	-45,740 (136,621)
Inflation	67,816 (36,900)	99,503** (38,004)	84,196 (80,291)
HightechexportcurrentUSin	11,351** (4,293)	9,863 (33,858)	-175,692 (100,933)
Globalisationgrowth	-8,592 (32,718)	-44,261 (67,248)	84,180 (155,536)
Constant	1.418e+06** (373,822)	1.492e+06*** (331,550)	3.379e+06*** (663,760)
Observations	11	11	11
R-squared	0.745	0.865	0.594

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

7. Forecasting

As described in the methodology chapter, the forecasting will be done by adding the changes of the independent variables multiplied with their coefficients to the last known value of the dependent variable. The forecasting of Schiphol will be discussed as an example.

The air cargo volume of 2017 was 1,778,382 tonnes. In table 10, the values and the difference between the values of the variables are displayed for the years 2017 and 2018. The difference is multiplied with the coefficients from the regression of Schiphol. The coefficients are -2347, 4743, -95398, 22094 and -73964 respectively. This will be added to the volume of 2017 to get a total air cargo volume of 1,885,878 tonnes for 2018.

Table 10 – Schiphol’s values of the independent variables for 2017 and 2018.

	Oil price	GDP growth	Inflation	High-tech export (in billion)	Globalisation growth
2018	69.99	4.50	1.70	85.69	0.04
2017	52.63	5.95	1.38	78.18	0.31
Difference	17.36	-1.45	0.32	7.51	-0.27

In table 11, the forecast for 2018 is presented for the eleven airports, followed by a graphical display in figure 2. Overall, the forecasts are reasonably close to the actual volumes. Only Schiphol, Charles de Gaulle and Memphis are somewhat off. Furthermore, for Louisville, the forecast was not far off volume-wise, but, based on the figures, a decrease was expected, and an actual increase was observed. For Memphis and Louisville, the model underestimated the actual 2018 value. As already mentioned, these two airports are relatively similar and unique in the sense that two companies dominate the cargo volume. The business operations and revenue of both FedEx and UPS, which increased by 8.51% and 7.92% in 2018, respectively, are not entirely incorporated in the model, but will have a significant effect on the volumes of the airports. GDP and high-tech export were measured at state level, and hence the operations of FedEx and UPS are somewhat captured by the model. Nonetheless, it can be concluded that it still underestimated the impact of the two companies. Especially the mail services, which does contribute to the cargo volume, is not captured by the model.

Table 11 – Forecast for 2018

Airport	Known value	Forecast value	Actual value
	2017	2018	2018
Schiphol	1,778,382	1,885,878	1,738,468
Charles de Gaulle	2,195,229	2,276,053	2,156,327
Frankfurt	2,194,056	2,204,525	2,213,887
Incheon	2,921,691	2,992,033	2,952,123
Los Angeles	2,158,324	2,170,964	2,209,850
Heathrow	1,794,276	1,731,634	1,771,342
Miami	2,071,722	2,104,496	2,129,658
Memphis	4,336,752	4,369,197	4,470,196
Narita	2,336,427	2,249,463	2,261,008
O'hare	1,721,807	1,765,040	1,807,091
Louisville	2,602,695	2,588,280	2,623,019

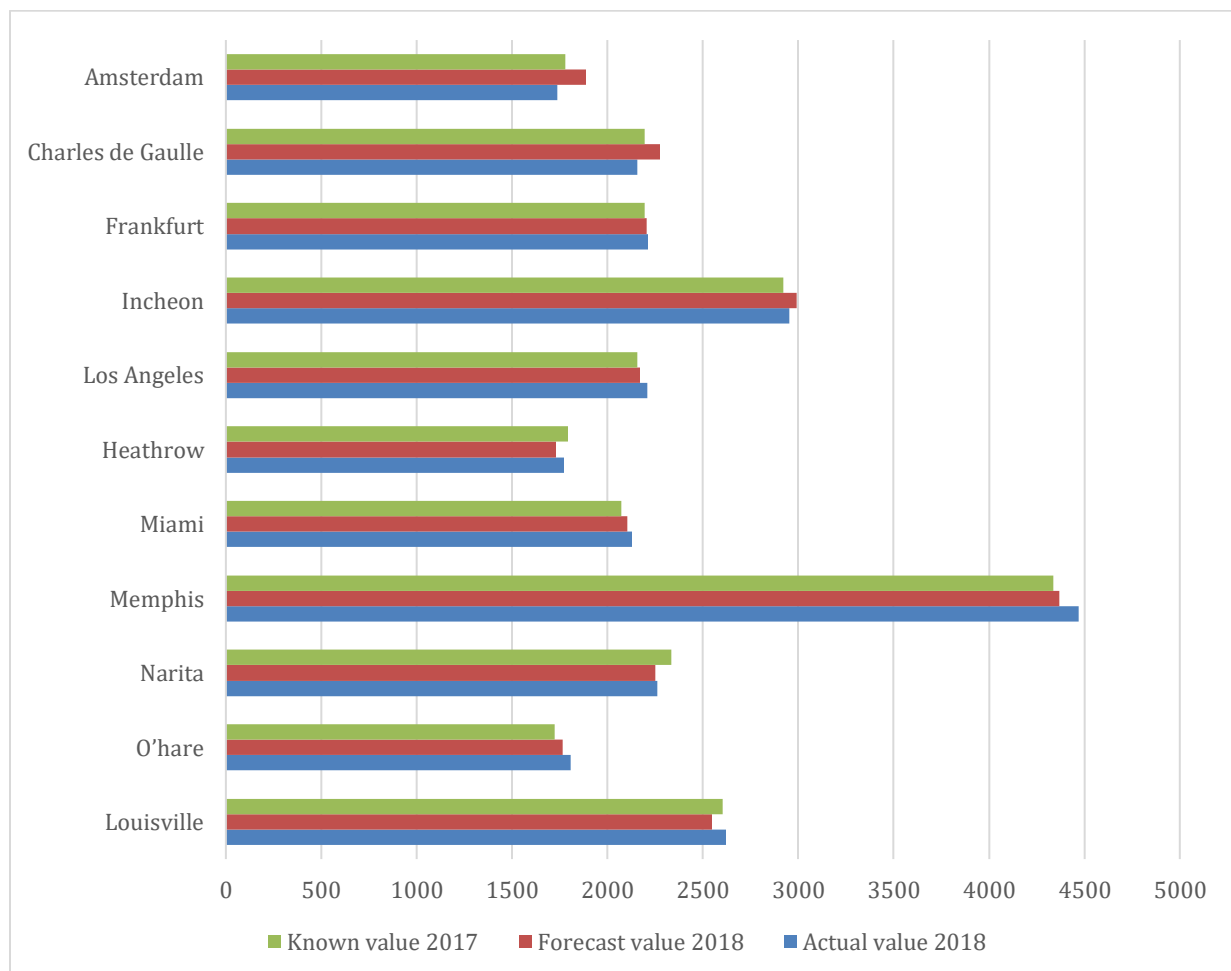


Figure 2 – Forecast 2018 with the actual values (in 1000 metric tonnes)

Moreover, the values for Schiphol and Charles de Gaulle were overestimated by the model. For Schiphol, based on the data, this increase was expected mainly by the rise in high-tech export together with a relatively high coefficient for high-tech export. For Charles de Gaulle, there was no specific outlier in the data. However, Charles de Gaulle, and Schiphol might as well, have suffered from large strikes by Air-France in the first half-year of 2018. A press release from Air France-KLM mentioned that the strikes cost the carrier 355 million euros (Air France-KLM, 2019). Furthermore, according to Nieuwsblad Transport (2019), the loss in cargo volume of Schiphol was due to a lack of cargo slots available at the airport.

Together with the coefficients, Stata provides us with the plus 95% confidence interval and minus 95% confidence interval. The coefficient Stata provides is just an estimation and will never be the exact value. But, we do know, for 95% confidence, that the coefficient will fall within a range of two numbers. By taking those extreme numbers and calculating in the same way as the exact forecast, the lower and upper bound can be computed. The lower and upper bound not only tell us the range in between the forecast is expected to fall, but also it gives an indication of the strength of the forecast. If the two numbers are close to each other, the forecast value of 2018 is more certain. As can be observed in table 12, only Schiphol falls outside of this range, but as already mentioned, there was a significant difference between the forecast and the actual value.

Table 12 – Upper and lower bound of the forecast

Airport	Lower bound of forecast	Actual value 2018	Upper bound of forecast
Schiphol	1,815,111	1,738,468	2,396,625
Charles de Gaulle	2,125,038	2,156,327	2,463,203
Frankfurt	2,090,347	2,213,887	2,227,964
Incheon	2,948,347	2,952,123	3,015,730
Los Angeles	2,094,259	2,209,850	2,247,679
Heathrow	1,595,675	1,771,342	1,867,611
Miami	2,074,789	2,129,658	2,134,198
Memphis	3,910,984	4,470,196	4,486,813
Narita	2,169,927	2,261,008	2,329,105
O'hare	1,651,289	1,807,091	1,878,802
Louisville	2,237,273	2,623,019	2,869,077

8. Discussion and conclusion

8.1 Discussion of the results

Opposed the former literature and the hypothesis, inflation was found to influence air cargo positively. One explanation could be that inflation in one country depreciates its currency compared to other currencies. As a result of this, it is cheaper to buy goods in a country where high inflation is present, and therefore the air cargo volume of that will increase. Another reason might be a difference in data or method. Also, Stockman (1985) already mentioned that the effect of inflation can be different for every country. As the panel data regression was on seven different countries, one country could have dominated to other countries.

Comparing this study to other publications on economic determinants of air cargo and forecasts of air cargo, it is the first study where the use of an instrumental variable analysis is used. There are numerous papers where the econometric analysis is not as thorough as this study. One example is Alici and Akar (2020), where they study macroeconomic determinants of air cargo using panel data. They look at similar determinants but just use an ordinary random-effects model without using an instrumental variable. Lakew and Tok (2015) looked at the determinants of air cargo in California, also using panel data on the largest airports in the area. One of these airports is LAX; hence it is discussed with greater interest. In the paper, employment, wage and traffic data are analysed with respect to air cargo volume. Endogeneity might be a problem as well, and there is no instrumental variable used.

Furthermore, Hakim and Merkert (2016) also solved the endogeneity problem. However, they did that by using lagged variables instead of instrumental variables. This is a well-known method to solve endogenous variables, but it can also lead to a loss in the estimation precision. On top of that, it is impossible to infer if the solution is adequate (Shepherd, 2009).

In this study, the coefficients of the independent variables have been calculated with the use of an instrument but also without using an instrument. Looking back to table 5, the benefit of using an instrumental variable regression versus an OLS can be observed. The coefficient of

inflation rate decreased significantly, but more importantly, the negative effect of oil price on air cargo overestimated in the OLS model by more than 25 per cent.

When comparing this study with the aviation forecasting reports discussed in the introduction, this study should be considered as a complement and not a substitute for these reports. A complement that provides specific knowledge on a method of forecasting where eleven of the largest cargo airports are used as an example, but what can be reproduced for other airports when the data is available. The method used is as relevant as the actual outcome of this study. Air cargo volume is forecast for these eleven airports for the year 2018 as there was only data available until 2017.

The method can be used in a way to make a forecast of future years as well. It will be based then on other predictions of the variables oil price, GDP, high-tech exports, inflation rate and the globalisation index. Inflation rate and a GDP forecast for 2021 and 2022 are available in the OECD data section. Oil price expectations are available for the same years from the website of the U.S. Energy Information Administration (EIA, 2021b). For high-tech exports, such a forecast does not exist. Nonetheless, a forecast on general trade of goods and services is accessible from the OECD website as well. With this data, a proxy of high-tech exports can be made. But, it will be challenging to exactly subtract the services and all the non-high-tech exports from the forecast. There is also no data on the KOF index for globalisation from 2019 on. The globalisation index does not change much from year to year, especially for developed countries. A figure for 2021 or 2022 could be gathered by extrapolating, but this again would be an assumption and will cost some strength in the forecast. In this study, it is chosen not to do that for two foremost reasons.

First, because as already mentioned, the method and the results of the hypotheses testing was equally important in this study. Second, the data source of the forecast data is different from the data source used in this study. Especially for data on oil price, the source is essential. The data from this study was taken from the OECD website and measured as import prices of a barrel of crude oil. Data on future oil prices are from the U.S. Energy Information Administration and distinguished between Brent crude oil price and West Texas Intermediate crude oil price. This distinguishment was not made on the OECD website, and therefore it is

difficult to say which price to follow from the forecast. On top of that, for high-tech export, a proxy from the prediction on general trade of goods and services should have been made, which would also weaken the certainty and strength of the forecast.

8.2 Conclusion

To answer the research question: *“To what extent can we forecast the air cargo volume?”* we have to look at the different components involved in this forecast. First is the data collection and reliability of the gathered data. All the data comes from the largest (governmental) institutions globally and can generally be seen as trustworthy. A drawback is that there are only eleven years analysed, and hence we have a relatively small sample. As the model used is consistent, an increase in data will bring us closer to the correct estimation.

As discussed, the methodology is, especially compared to previous studies, quite exhaustive. It has already been discussed what the implications of using an instrument were on the total model, but it has not been discussed what the results would have been if an OLS regression was used on the eleven airports. In the appendix, the regression results of these OLS model are displayed. When comparing, the outcome is similar to what we have seen on the full model. The negative effect of oil price is overestimated in OLS. For some airports, this difference was minimal, and the coefficients were almost the same, but for other airports, the overestimation was in a magnitude of almost three. Thus, this gives us confidence in the strength of our estimation.

The predicted values are not the same as the actual value. But, in the question of to what extent we can predict it, the calculated upper and lower bound are also important. Based on the model used, we can say with 95% certainty that the expected value of air cargo lies in between those two boundaries. For one out of the eleven airports, the actual value was outside of these boundaries. This is more than expected and will have some negative effect on the overall strength of the forecast and this study.

Nonetheless, most importantly, is an actual prediction of cargo volume for future years. So far, the 'forecast' was around 2018. To make a forecast for the future, future values of the independent variables are needed as well. As mentioned before, these are, to at least some

extent, available. However, this would mean an extra uncertainty in the forecast; making a forecast on another forecast is never preferred. But it must be said that the predictions of these independent variables are at least made by well-renowned institutions like the OECD. These institutions have many years of experience in forecasting, and it can be expected that these forecasts are close to the actual values.

All in all, a broad forecast of future years of air cargo volume can certainly be given. So far, there are no other studies with exact numbers of air cargo on airport level. The purpose of this study was not only to forecast air cargo on eleven specific airports but also to explore a method on how to correctly measure the effect of certain economic indicators. After this study, it is possible to reproduce this for every other airport for which the data is available.

8.3 Limitations

There are some limitations in this study that needs to be taken into account. First is the relatively small sample size, especially on the airport level. Due to the availability of only eleven years of high-tech export data, the number of observations for the regression of the full model fell from 198 to 121. It is still a decent amount, but in general, a larger sample gives estimates closer to reality. At the airport level, a time-series analysis was done with now only eleven years available. This low number of observations increased the possibility of less significant coefficients. Also, actual data of high-tech export was not available at U.S.' state level. It is believed that the proxy used comes close to the actual value, but this is not entirely certain.

Moreover, the data on the cargo volumes for 2018 was taken from the airports' websites. This is a different source than what was used for data from 2000 to 2017. On the airports' website, data for 2017 was checked to see if it was the same as what the ACI recorded. For some airports, this was the same, but for other airports, there were some differences. This also resulted in small measurement errors of the predicted values of 2018, as the forecast was based on 2017, where the airports reported different values.

Then, there are, of course, possibilities of big disruptions in the global supply chain that no one can forecast. Until a bit more than a year ago, no one could have imagined what the

impact of a global pandemic like Covid-19 would have had. In a forecast, these types of events are hard to implement. In 2020, the cargo-tonne-kilometers fell by 10.6% year-on-year (IATA, 2020). Without forecasting based on different scenarios, it is not possible to build this into a forecast. Nonetheless, Merkert et al. (2017) noticed that structural changes after major disruptions, in their paper 9/11 or the economic recession of 2008, are not observed. This implies that immediately after a disruption, a forecast would probably be off, but in the long-term, the forecast is expected to still be close to the actual values.

8.4 Policy recommendations

The result of this study can be used by airports in their decision to expand or contract their cargo terminal capacity. With the model built, it is possible to forecast the future cargo volume based on available predictions from the independent variables. Especially for Narita, a large decrease in cargo was predicted, and a decrease was confirmed by the data as well. With this knowledge, terminal capacity could be planned, and already it could have been contracted.

Furthermore, if countries would like to increase air cargo activity in their country, the model can also be used to see how much an increase in one of the indicators results in increased air cargo. Policies to either increase or decrease the different indicators can immediately be checked on their efficiency, and choices can be made which policy is most efficient to increase air cargo volume. This can be done for the eleven countries or states, but this forecasting method is chosen to be easily replicable; thus, for other countries, this is possible as well when data on the independent variables can be gathered.

8.5 Suggestions for future research

In this study, only five economic indicators have been researched. While it is believed that those are among the most critical indicators, other indicators can always be added. Other interesting indicators might be exchange rates or interest rates. Furthermore, a recently introduced Baltic Air Freight Index might be an exciting indicator as well. As it has just been recently introduced, there is not much historical data, and it is not publicly available at the moment. From the same organisation, the Baltic Dry Index is considered as one of the most important indicators to predict future export demand.

Additionally, other airports can be added as well. In this study, some large Middle-Eastern and Southeast Asian airports fell outside of the study because there was no data available on each economic indicator. By using other indicators, other airports might become available too.

Moreover, as explained in the methodology chapter, there are different methods to forecast. Instead of a quantitative approach, a qualitative approach or a mix of these could be used. Other, more difficult to quantitatively address, factors like environmental or regulatory arguments can significantly affect cargo volume. Perhaps even more than some economic indicators. A study including these kinds of factors would be an interesting complement to this study. Finally, another approach to give an as complete as possible forecast might be using different scenarios. As stated before, disruptions like Covid-19 are hard to implement in a regression analysis, but by using multiple scenarios, such an event could be captured in the scenarios.

Bibliography

- ACI. (2020). Cargo Summary. Retrieved from: <https://aci.aero/data-centre/annual-traffic-data/cargo/2017-cargo-summary-annual-traffic-data/>
- Aderamo, A. J. (2010). Demand for Air Transport in Nigeria. *Journal of Economics*, 1(1), 23-31. doi:10.1080/09765239.2010.11884921
- Aircargonews. (2020). Top 25 cargo airlines 2019: FEDEX retains the top spot as Qatar climbs. Retrieved from <https://www.aircargonews.net/airlines/top-25-cargo-airlines-fedex-retains-the-top-spot-as-qatar-climbs/>
- Airfrance-KLM. (2019). Full year 2018 results. Retrieved from https://www.airfranceklm.com/en/system/files/q4_2018_press_release_en_vdeff.pdf
- Alici, A. and Akar, A. S. Macroeconomics determinants of air cargo demand: a panel data analysis. *Transport & Logistics: the International Journal*, 2020; Volume 20, Issue 48, June 2020, ISSN 2406- 1069
- Baum, C. F., Schaffer, M. E., & Stillman, S. (2003). Instrumental variables and GMM: Estimation and testing. *The Stata Journal: Promoting Communications on Statistics and Stata*, 3(1), 1-31. doi:10.1177/1536867x0300300101
- Bureau of Economic Analysis. (2020). Regional Data GDP and Personal Income. Retrieved from <https://apps.bea.gov/itable/iTable.cfm?ReqID=70&step=1&acrdn=1>
- Button, K. (2008). *The Impacts of Globalisation on International Air Transport Activity* (Rep.). Guadalajara: OECD & International Transport Forum. Retrieved from <https://www.oecd.org/greengrowth/greening-transport/41373470.pdf>.
- Button, K. (2009). The impact of US–EU “OPEN SKIES” agreement on airline market structures and airline networks. *Journal of Air Transport Management*, 15(2), 59-71. doi:10.1016/j.jairtraman.2008.09.010
- Chao, C.C., & Hsu, C.W. (2014). Cost analysis of air cargo transport and effects of fluctuations in fuel price. *Journal of Air Transport Management*, 35, 51–56.
- Ciner, C. (2001) Energy shocks and financial markets: nonlinear linkages. *Studies in Nonlinear Dynamics and Econometrics* 5, 203-212
- EIA. (2021a). U.S. Kerosene-Type jet Fuel wholesale/resale price By REFINERS (dollars per gallon). Retrieved May 01, 2021, from https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=EMA_EPJK_PWG_NUS_DPG&f=M
- EIA. (2021b). U.S. energy Information administration - eia - independent statistics and analysis. Retrieved from

<https://www.eia.gov/outlooks/steo/report/prices.php#:~:text=The%20U.S.%20Energy%20Information%20Administration,the%20remainder%20of%20the%20year.>

- FAA. (2020). *FAA Aerospace Forecast Fiscal Years 2020 - 2040* (Rep.). Retrieved from https://www.faa.gov/data_research/aviation/aerospace_forecasts/media/FY2020-40_FAA_Aerospace_Forecast.pdf
- Flymemphis. (2020). Properties and cargo - Memphis international airport. Retrieved from <https://flymemphis.com/properties-and-cargo/>
- Fung, M., Zhang, A., Leung, L., Law, J. (2005). "The Air Cargo Industry in China: Implications of Globalization and WTO Accession". *Transportation Journal*, 44 (4), 44-62
- Gao, Y., Zhang, Y., Li, H., Peng, T. Ve Hao, S., (2016), "Study on the Relationship Between Comprehensive Transportation Freight Index and GDP in China". *Procedia Engineering* 137, pp. 571 – 580.
- Gong, Q., Wang, K., Fan, X., Fu, X., & Xiao, Y. (2018). International trade drivers and freight network analysis - the case of the Chinese air CARGO SECTOR. *Journal of Transport Geography*, 71, 253-262. doi:10.1016/j.jtrangeo.2017.02.009
- Graham, A. and Zheng , X. (2018). Patterns and drivers of demand for air transport. *Routledge Companion of Air Transport Management*, 313 – 330.
- Hakim, M. M., & Merkert, R., (2016). "The causal relationship between air transport and economic growth: Empirical evidence from South Asia". *Journal of Transport Geography* (56), pp. 120–127.
- Hansman, J., Hansen, M., Peterson, E., & Trani, A. (2014). The Impact of Oil Prices on the Air Transportation Industry. *National Center of Excellence for Aviation Operations Research* pp. 74–75.
- Himakireeti, K., & Vishnu, T. (2019). Forecasting of Air Passengers using ARIMA Modeling. *International Journal of Innovative Technology and Exploring Engineering Special Issue*, 8(11S), 1050–1054.
- Hsiao, F. S., & Hsiao, M. W. (2006). FDI, exports, and GDP in East and Southeast Asia—Panel data versus Time-series causality analyses. *Journal of Asian Economics*, 17(6), 1082-1106. doi:10.1016/j.asieco.2006.09.011
- IATA. (2020). Air cargo market analysis December 2020. Retrieved from <https://www.iata.org/en/iata-repository/publications/economic-reports/air-freight-monthly-analysis---december-2020/>
- IATA. (2021) The value of Air Cargo. Retrieved March 11, 2021, from <https://www.iata.org/contentassets/4d3961c878894c8a8725278607d8ad52/air-cargo-brochure.pdf>

- ICAO. (2006). *Manual on Air Traffic Forecasting* (Rep.). ICAO.
- Index Mundi. (2018). Countries ranked by air Transport, freight (million ton-km) Retrieved March 11, 2021, from <https://www.indexmundi.com/facts/indicators/IS.AIR.GOOD.MT.K1/rankings>
- Jiang, H., Ren, L., & Hansman, R. (2003). Market and INFRASTRUCTURE analysis of future air CARGO demand in China. *AIAA's 3rd Annual Aviation Technology, Integration, and Operations (ATIO) Forum*. doi:10.2514/6.2003-6770
- Kupfer, F., Meersman, H., Onghena, E., & Van de Voorde, E. (2012). AIR freight and Merchandise TRADE: Towards a DISAGGREGATED ANALYSIS. *Journal of Air Transport Studies*, 2(2), 28-48. doi:10.38008/jats.v2i2.99
- Kupfer, F., Meersman, H., Onghena, E., & Van de Voorde, E. (2017). The underlying drivers and future development of air cargo. *Journal of Air Transport Management*, 61, 6-14.
- Lakew, P. A., & Tok, Y. C. (2015). Determinants of air cargo traffic in California. *Transportation Research Part A: Policy and Practice*, 80, 134-150. doi:10.1016/j.tra.2015.07.005
- Love, J., & Chandra, R. (2005). Testing export-led growth in Bangladesh in a MULTIVARIATE VAR framework. *Journal of Asian Economics*, 15(6), 1155-1168. doi:10.1016/j.asieco.2004.11.009
- Lu, P. (2011). Oil price and emerging stock markets: a panel data analysis
- Lufthansa Cargo. (2021). About us - lufthansa cargo. Retrieved from <https://lufthansa-cargo.com/meta/meta/company/about-us#:~:text=With%20a%20turnover%20of%202.8,employs%20about%204%2C400%20people%20worldwide>.
- Martino, A., Casamassima, G., & Fiorello, D. (2009). *The impact of oil price fluctuations on transport and its related sectors* (Rep.).
- Merkert, R., Van de Voorde, E., & De Wit, J. (2017). Making or breaking - key success factors in the air cargo market. *Journal of Air Transport Management*, 61, 1-5. doi:10.1016/j.jairtraman.2017.02.00
- Morrell, P. S., & Klein, T. (2019). *MOVING BOXES BY AIR: The economics of international air cargo*. S.l.: ROUTLEDGE.
- Mwakanemela, K. (2014). Impact of FDI inflows, trade openness and inflation on the manufacturing export performance of Tanzania: An econometric study. *International Journal of Academic Research in Economics and Management Sciences*, 3(5). doi:10.6007/ijarems/v3-i5/1198

- Nieuwsblad Transport. (2019). Schiphol Cargo hield schade in 2018 beperkt tot 64.000 ton. Retrieved from <https://www.nt.nl/luchtvracht/2019/01/22/schiphol-cargo-hield-schade-in-2018-beperkt-tot-64-000-ton/>
- OECD (2021a) /United Arab EMIRATES (ARE) exports, imports, and trade partners. Retrieved from <https://oec.world/en/profile/country/are>
- OECD (2021b) /Japan exports, imports, and trade partners. Retrieved from <https://oec.world/en/profile/country/jpn>
- OECD (2021) / Korea exports, imports, and trade partners. Retrieved from <https://oec.world/en/profile/country/kor>
- OECD. (2020). Crude oil import prices. Retrieved from <https://data.oecd.org/energy/crude-oil-import-prices.htm>
- OECD. (2020). *OECD Economic Surveys Korea* (Rep.). (2020, August). from OECD website: <https://www.oecd.org/economy/surveys/korea-2020-OECD-economic-survey-overview.pdf>
- Parisaeroport. (2021) Cargo. Retrieved from <https://www.parisaeroport.fr/en/professionals/cargo>
- PwC. (2021). *Aviation Industry Outlook 2021* (Rep.). Retrieved April 2, 2021, from <https://www.pwc.ie/reports/aviation-industry-outlook-2021.html>
- Savina, G., Haelg, F., Potrafke, N., Sturm, J. (2019).: The KOF Globalisation Index – Revisited, *Review of International Organizations*, 14(3), 543-574 <https://doi.org/10.1007/s11558-019-09344-2>
- Shepherd. (2009). Dealing with Endogeneity. Retrieved April 3, 2021, from https://artnet.unescap.org/tid/artnet/mtg/gravity09_tues3.pdf
- Statista. (2020). European airports: Airfreight volumes. Retrieved from <https://www.statista.com/statistics/434381/airfreight-volumes-in-europe-by-airport/>
- Statista. (2021). Global retail e-commerce market size 2014-2023. Retrieved from <https://www.statista.com/statistics/379046/worldwide-retail-e-commerce-sales/>
- Staiger, D. and Stock, J.H. (1997). Instrumental variables regression with weak instruments. *Econometrica* 65(3), 557-586
- Stockman, A. C. (1985). Effects of inflation on the pattern of international trade. *The Canadian Journal of Economics*, 18(3), 587-599. doi:10.2307/135021
- Suryani, E., Chou, S., & Chen, C. (2012). Dynamic simulation model of air cargo demand forecast and terminal capacity planning. *Simulation Modelling Practice and Theory*, 28, 27-41. doi:10.1016/j.simpat.2012.05.012

- Totamane, R., Dasgupta, A., & Rao, S. (2014). Air Cargo Demand Modeling and Prediction. *IEEE Systems Journal*, 8.
- Tradingeconomics. (2021). Heating oil 1980 – 2021 data. Retrieved from <https://tradingeconomics.com/commodity/heating-oil>
- U.S. Census Bureau. (2010) Centers of population. Retrieved from <https://www.census.gov/geographies/reference-files/time-series/geo/centers-population.html>
- U.S. Census Bureau. (2020). Total Merchandise Exports per State. Retrieved from <http://tse.export.gov/tse/TSEOptions.aspx?ReportID=100&Referrer=TSEReports.aspx&DataSource=SED>
- Wadud, Z. (2014). The Asymmetric Effects of Income and Fuel Price on Air Transport Demand. *Transportation Research Part A Policy and Practice*, 65.
- Wooldridge, J. M. (2018). Introductory econometrics: a modern approach. *Boston, MA: Cengage*.
- Worldbank Group. (2009). *Air Freight: A Market Study with Implications for Landlocked Countries* (Vol. TP-26, Rep.). Worldbank.
- Worldbank group. (2021). Database
- World Economic Outlook Database. (2020). Retrieved November 06, 2020, from <https://www.imf.org/en/Publications/WEO/weo-database/2020/October/select-aggr-data>
- World Trade Organisation Database. (2021) Retrieved December 08, 2020, from <https://data.wto.org/>
- 3plogistics. (2020). Top 3PLS: A&A'S top 50 Global Third-party logistics PROVIDERS (3PLS). Retrieved from <https://www.3plogistics.com/3pl-market-info-resources/3pl-market-information/aas-top-50-global-third-party-logistics-providers-3pls-list/>

Appendix

Regression results of an OLS times-series model over the eleven airports

VARIABLES	(AMS) TotalCargo	(CDG) TotalCargo	(FRA) TotalCargo	(INC) TotalCargo
OilpriceperbarrelinUS	-6,438 (5,204)	-3,017* (1,185)	-1,367 (1,456)	-4,611*** (668.6)
GDPthreeyearaveragegrowth	-6,420 (19,637)	-12,616 (9,823)	-18,250 (24,931)	9,387 (5,838)
Inflation	4,953 (128,894)	169,965** (45,354)	129,521 (77,314)	52,365** (15,781)
HightechexportcurrentUSin	29,409 (18,076)	-437.0 (1,712)	880.5 (3,274)	7,815*** (724.6)
Globalisationgrowth	-67,481 (80,626)	73,251* (29,647)	72,896 (57,044)	52,411*** (11,631)
Constant	-167,900 (1.199e+06)	2.270e+06*** (173,694)	1.888e+06** (574,936)	1.696e+06*** (115,368)
Observations	11	11	11	11
R-squared	0.604	0.842	0.414	0.952

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(LAX) TotalCargo	(LHR) TotalCargo	(MIA) TotalCargo	(MEM) TotalCargo
OilpriceperbarrelinUS	-5,850*** (1,188)	-3,078 (3,173)	-596.7 (496.9)	-4,941** (1,895)
GDPthreeyearaveragegrowth	54,038** (17,889)	-6,498 (15,122)	51,704*** (12,478)	164,877** (49,842)
Inflation	98,262** (31,961)	56,262 (59,161)	42,253* (18,425)	34,804 (52,816)
HightechexportcurrentUSin	-17,096 (11,968)	14,849** (4,284)	1,881 (21,844)	-63,051 (107,037)
Globalisationgrowth	-16,359 (39,620)	-103,041 (131,170)	-1,974 (29,846)	-47,858 (69,862)
Constant	2.176e+06*** (252,026)	643,896 (435,003)	1.721e+06*** (190,510)	4.011e+06*** (451,340)
Observations	11	11	11	11
R-squared	0.902	0.791	0.913	0.827

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(NRT) TotalCargo	(ORD) TotalCargo	(SDF) TotalCargo
OilpriceperbarrelinUS	-8,089** (2,149)	-8,969*** (1,783)	-5,881 (2,992)
GDPthreeyearaveragegrowth	-14,663 (8,459)	117,691 (59,301)	6,012 (108,499)
Inflation	67,647 (36,780)	103,653** (33,989)	109,619 (73,370)
HightechexportcurrentUSin	11,730** (4,241)	9,754 (33,057)	-161,549 (81,094)
Globalisationgrowth	-10,483 (33,128)	-49,035 (67,707)	33,452 (124,528)
Constant	1.393e+06** (361,018)	1.504e+06*** (327,232)	3.309e+06*** (486,684)
Observations	11	11	11
R-squared	0.745	0.866	0.628

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1