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Master Thesis Urban, Port and Transport Economics

Evolution of the emergency freight transport in Europe: What are the effects on cargo demand after implementing a fuel tax on air cargo?

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Abstract

Strategies to reduce undesirable effects of aviation on the environment are extensively discussed by governments. This research determines if taxation could be used as an instrument for CO_2 reduction policies by studying the effect of implementing fuel taxes on domestic air cargo in Germany. This research is a case study of the express critical service provider Time:Matters GmbH, owned by Lufthansa Cargo. The effects of implementing a fuel tax on air cargo will be studied by the price elasticity of demand. Furthermore, the cross-price elasticity between air and rail cargo demand will indicate whether a fuel tax on air cargo will result in a modal shift to rail transport, the more environmental-friendly mode of transport.

The elasticities of demand are estimated by a two- and three-least squares model. This research shows that the price elasticity of air cargo demand ranges from -0.052 to -0.177 on specific, domestic routes in Germany and is thus price inelastic. These results indicate that aviation fuel tax could have a positive environmental impact by reducing CO_2 emissions, however, due to the price inelasticity the scope and size of the impact is very limited. The price elasticity of rail cargo demand ranges from -0.171 to 0.062. Furthermore, a negative cross-price elasticity, ranging from -2.693 to -0.791, suggests that air and rail transport are complementary services according to this research. Both air and rail cargo demand of Time:Matters GmbH will decrease as a result of the fuel tax on air cargo. Additionally, this research concludes that the rail cargo demand is more sensitive to the level of taxation than the air cargo demand.

Key words

(Cross) price elasticity of demand, taxation, freight transportation, modal shift, CO_2 emissions

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Table of Contents

1. Introduction 4
1.1 Time:Matters GmbH 6
1.2 Research questions 8
2. Literature review 11
2.1 The cargo market 11
2.1.1 Air cargo market 11
2.1.2 Rail cargo market 13
2.2 Price elasticity of demand 14
2.3 Previous research on price elasticity in the cargo sector 16
2.4 Aviation fuel tax 21
2.4.1 European Energy Tax Directive 2003/96/EC 21
2.4.2 Aviation fuel tax in non-European countries 23
2.4.3 Previous research on aviation fuel tax 24
2.5 Cross-price elasticity of cargo demand 26
3. Data 29
3.1 Data description of air cargo 30
3.2 Data description of rail cargo 34
4. Methodology 37
4.1 Scenario analysis 41
5. Results 42
5.1 Hypothesis 1: Air cargo demand is price inelastic 42
5.2 Scenario analysis hypothesis 1 46
5.3 Hypothesis 2: Rail cargo demand is price inelastic 48
5.4 Hypothesis 3: An increase in the price of air cargo will result in a higher demand of rail cargo . 50
5.5 Scenario analysis hypothesis 3 53
6. Conclusion and discussion 55
6.1 Limitations and further research 58
7. References 60
8. Appendix 65

1. Introduction

Over 19 billion tonnes of goods are transported every year in Europe, which account for 6% of the European GDP. The freight sector is expected to grow 30% by 2030 (UIC, 2020). The overall contribution to the economy is positive, however, the sector has a substantial impact on the environment. In 2017 27% of the total European greenhouse gas emissions came from the freight transport sector (European Environment Agency, 2019). Figure 1 and Figure 2 illustrate respectivitely the modal split of freight transport and the share of greenhouse gas emissions per transport mode in Europe. The highest share of greenhouse gas emissions of road transport results from the highest share of modal split. However, it is remarkable that air cargo transport accounts for only 0.4% of the total freight, while it emits 13.9% of the greenhous gas emissions. Furthermore, the European Commision (2019) expects that global aviation emissions in 2020 will be 70% higher compared with 2005. For the rail freight sector the opposite of aviation occurs. This illustrates that the rail freight sector could contribute to a more sustainable freight sector (UIC, 2020).

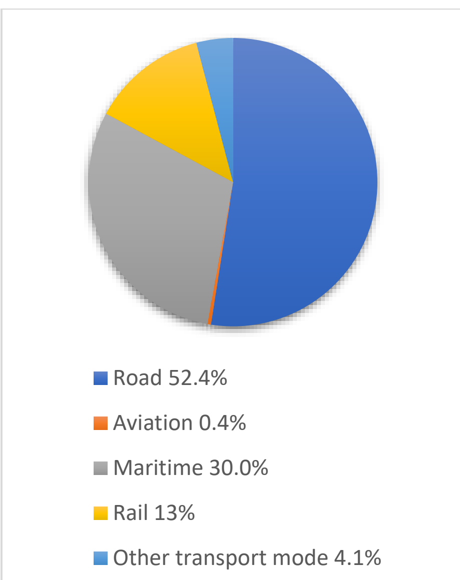

Figure 1 Modal split of freight transport in Europe in 2018

Source: (Eurostat , 2020)

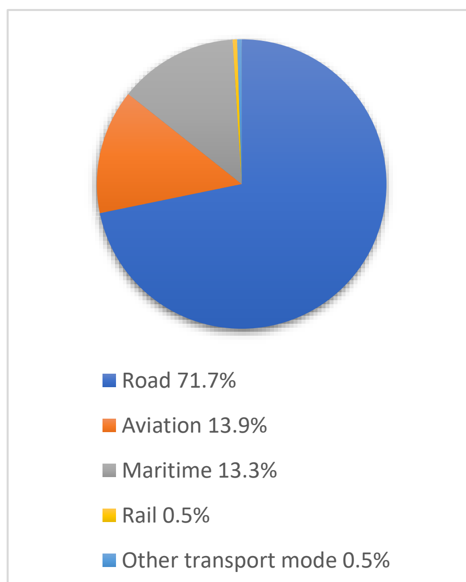

Figure 2 Share of transport greenhouse gas emissions per transport mode in Europe 2017

Source: (European Environment Agency, 2019)

This suggests that any attempt to address climate change in Europe must pay attention to the emissions of the transport sector. Therefore, strategies to reduce the undesirable effects on the environment are extensively discussed by governments. For instance, in June 2019 the Dutch government organized a conference to move towards agreements on aviation taxes to help to achieve climate goals (Government of the Netherlands, 2019). Moreover, in 2017 the German government implemented a plan to improve the rail freight sector and to encourage the use of a more environmentally-friendly mode of transport; rail (BMVI, 2017).

Brouwer, Brander, & Beukeringen (2008) aim that effective financial instruments, for instance taxes, could discourage climate unfriendly activities. However, it is remarkable that multiple aviation activities are exempted from taxations, while the aviation sector emits relatively the most CO_2 emissions. For instance, only domestic aviation is often subjected to value added tax (VAT), while international aviation is exempted from VAT, both on their inputs, for instance fuel and on their revenues, for instance freight prices. Moreover, due to bilateral agreements and the European Energy Tax Directive 2003/96/EC, fuel taxes are prohibited in Europe for international aviation, while road and rail transport are mandated to fuel taxes (CE Delft, 2013). However, according to the European Energy Tax Directive every European Member States could tax aviation fuel for domestic flights and in such cases even below the minimum rate of 0.33 euro per liter. No European Member State has implemented the fuel tax on domestic aviation yet (CE Delft, 2019).

Therefore, this research will determine if taxation could be an instrument for CO_2 reduction policies by studying the effect of implementing fuel taxes on domestic air cargo in Germany. Additionally, on short-haul and/or domestic transport, the high-speed rail is often promoted as a lower-carbon transport alternative (Clewlow, Balakrishnan & Sussman, 2013). Therefore, this research will also study if a fuel tax on air cargo will result in a modal shift towards rail transport. The choice of Germany lies in the fact that Germany carried the most tonnes of air cargo in Europe in 2017 (Eurostat, 2020) and rail cargo (UIC, 2019). Furthermore, this research is a case study of the express critical service provider Time:Matters GmbH, owned by Lufthansa Cargo, whose headquarters are located in Germany.

1.1 Time:Matters GmbH

Time:Matters GmbH, from now on Time Matters, is a express critical service provider specialized in special speed logistics by offering worldwide highly flexible and customized transportation solutions for extremely urgent or complex logistical challenges by different modes of transport (Lufthansa Cargo AG, 2019). In 2002 Lufthansa Cargo acquired the company Time Matters and is currently the only shareholder of Time Matters. (Time:Matters, 2012). The main focus of Time Matters is transporting shipments from destination A to destination B via air, rail or road and by perhaps using intermodal transport. Per year, Time Matters transports approximately 500.000 shipments and has offices in Germany, The Netherlands, Austria, United Arab Emirates and Asia (Time:Matters, 2019). Furthermore, due to the cooperation agreements, Time Matters has access to the Lufthansa Cargo network, but has also contracts with other airlines. Lufthansa Cargo operates on a hub-to-spoke network. This hub-and-spoke network results in an increase of the number of city pair markets that Lufthansa Group, and thus Time Matters, can serve (Brueckner, Nichola, & Spiller, 1992). The major hub of the Lufthansa Group is Frankfurt and Munich airport (Lufthansa Group, 2019). Consequently, most of the Time Matters shipments transfer in Frankfurt and therefore Time Matters has his own courier terminal at Frankfurt airport (Time:Matters, 2019). Moreover, Time Matters distinguish itself from other express logistics service providers by considering each shipment separately instead of consolidating shipments. This implies that Time Matters operates directly to the final destination through perhaps a central hub, whereas other express logistics service providers transfer from a regional hub to another regional hub and then redistribute the shipment to the final destination.

Additionally, Time Matters offers different services which are pending on the size and weight of the shipment. The first service is the *Sameday Air* service with stations in Europe, United States of America and Asia. Shipments booked under the *Sameday Air* service are packed in special sameday bags, with a maximum weight of 32 kilograms, and are loaded in the luggage department of passenger flights. The *Sameday Air* service is also possible for shipments up to 300 kilograms, however, the shipments will be manifested on the flight and are pending on aircraft space availability (Time:Matters, 2019b).
Secondly, the *IC:Kurier* service transports shipments by rail up to 20 kilograms and is only bookable for passenger trains. The train network mainly operates in Germany with three foreign train stations located in Amsterdam, Paris and Vienna (Figure 6, appendix). The *IC:Kurier* shipments can be transported via stations throughout Germany that have an InterCity, EuroCity and InterCity-Express connection (Time:Matters, 2007). Furthermore, Time Matters offers Global Express airfreight on both passenger and

cargo aircrafts. This service has no weight restriction and is pending on aircraft space availability. Lastly, Time Matters maintains a platform to offer personally accompanied transport via the *On-Board Courier* service. Besides the aforementioned options, Time Matters also offers customized and daily contracted services (Time:Matters, 2019b).

As mentioned, this research will study the relationship between air and rail cargo demand. Since the *IC:Kurier* service has a maximum weight of 20 kilograms, this research will only consider the *Sameday Air* service packed in the special sameday bags to make the two services comparable. Therefore, maximum weight of the *Sameday Air* service will be reduced to 20 kilograms. However, the maximum size of both services differs. For the *Sameday Air* service the maximum length, width and height is respectively 90x50x50 centimeters. Contradictory, for the *IC:Kurier* service a maximum of three shipments is bookable on a specific train and the dimensions have a maximum belt size of two meters per shipment (Time:Matters, 2019). This research however does not consider the size of the shipments to compare both transport modes.

For an express service provider time is a critical characteristic (CE Delft 2018b) and the two services differ in the delivery time. One could argue that a specific mode of transport is faster than the other mode of transport. However, both transport modes differ in the latest accepted time (LAT) and time of availability (TOA) of the specific service. For instance, the LAT and TOA for the *IC:Kurier* service is on average 20 minutes prior to departure and after arrival, while the *Sameday Air* service within Germany has a LAT and TOA of a minimum of 45 minutes and a maximum of 135 minutes (Time:Matters, 2019). The following two examples will elaborate more on this issue. Considering a shipment from Dusseldorf to Frankfurt, the *IC:Kurier* service could transport the shipment within 1:50 hours while the *Sameday Air* service needs in total 3:00 hours. However, considering a shipment from München to Hamburg, the *IC:Kurier* service needs 6:41 hours while the *Sameday Air* service could transport the shipment within 3:10 hours.

Furthermore, internal reports show that multiple strategies are already implemented by Lufthansa Cargo to decrease the negative effects of the aviation sector on the environment[1]. Firstly, Lufthansa Cargo concentrates on green flying by optimizing the fuel consumption and aims for energy efficiencies by green ground handling services. Furthermore, data transparency and offering CO_2 offsets to customers are

[1] Internal source: Corporate Responsibility PowerPoint of Lufthansa Cargo

other examples of the environmental strategies of Lufthansa Cargo. For instance, in December 2019 Time Matters announced to offer the first CO_2-neutral on-board courier service (Time:Matters, 2019c). Even though these strategies could have an impact on the negative externalities of Lufthansa Cargo, governmental policies might have a bigger impact on larger scale. Regulations could for instance reduce the negative externalities of society (Coase, 1960). Therefore, this research will study the effect of implementing a fuel tax on domestic aviation in Germany on the air and rail cargo demand.

1.2 Research questions

Taxation could be used as an instrument for CO_2 reduction policies in the aviation sector, since aviation taxes could have a negative impact on the aviation demand and could therefore potentially influence aviation emissions (CE Delft, 2018). The effect of implementing a fuel tax will be calculated by the price elasticity of demand. Price elasticity of demand analyzes the effect of price changes for the demand of a specific product or service and are commonly used for policy decisions (IATA, 2008).

Previous research has discussed the price elasticity of air cargo demand, however, all of the researches have either focused on the U.S. freight market or on some Asian freight markets. While price elasticity of the European, and thus German, air cargo market has not been studied before. Both Wang, Maling, & McCarthy (1981) and Tally & Schwarz-Miller (1988) concluded that the U.S. domestic air cargo demand has a negative negative relationship with the price. Hwang & Shiao (2011) studied the price elasticity of air cargo demand on international routes of Taiwan. The price elasticity is also found to be negative in this market, however, the absolute value is lower than in the studies of Wang, Maling, & McCarthy (1981) and Tally & Schwarz-Miller (1988). The autors concluded that the lower estimates indicate that the air cargo demand is less sensitive to the freight rate than previous studies. Lo, Wan, & Zhang (2015) controlled for different shocks, for instance the 2008 financial crisis, when estimating the price elasticity of air cargo demand on international routes of Hong Kong. The estimates of this research also indicate a lower absolute values than previous studies, but the relationship between air cargo demand and price is still negative.

Furthermore, the previous research of the effects of an aviation fuel tax is very limited. Both Olsthoorn (2001) and Fukui & Miyoshi (2017) studied the effects of the aviation fuel tax in the United States on the fuel consumption and CO_2 emissions. The studies found that an aviation fuel tax would reduce the CO_2 emissions, however the size and scope are every limited. Gonzalez & Hosoda (2016) researched the effect of the aviation fuel tax in Japan. According to Gonzalez & Hosoda (2016) global reductions of aviation CO_2 emissions could be achieved if other countries would implement an aviation fuel tax. However, all previous research focus on the general aviation sector and a study of fuel taxes on air cargo specifically is omitted.

Additionally, the previous research on price elasticity of rail cargo demand is also very limited and varies in methods and data set. Oum (1979) studied the price elasticity of the Canadian freight transport market. The author found a negative correlation between the price and demand of rail cargo with a decreasing absolute value over time. Moreover, Ramanathan (2001) used more modern time series econometric techniques to estimate the determinants of rail cargo demand of the domestic Indian market. Ramanathan (2001) concluded that the price elasticity of rail cargo demand is negative, however, the demand is less price sensitive than previous studies. Lastly, only Mitra & Leon (2014) studied the price elasticity of both air and rail cargo demand mode in North Dakota, U.S. The estimates indicated that rail cargo demand is less sensitive to price change than air cargo demand. As for previous research on air cargo, none of the researches on rail cargo demand have studied the European market.

The substitution effect between air and rail cargo demand after implementing a fuel tax on air cargo will be studied by the cross-price elasticity of demand. The study of Mitra & Leon (2014) is the only accessible, previous research found on the cross-price elasticity of air and rail cargo demand. The authors concluded that the cross-price elasticity is significanly low and that a shift of cargo from air to rail, and vice versa, is not likely even for a significant price change in one of these two transport modes.

Since the research on own-price and cross-price elasticity of cargo demand and the effects of taxes on cargo demand is very limited, this research will contribute to the existing literature by studying the effects of a fuel tax on the air cargo sector for air and rail cargo demand. The following two research questions will study the effects of implementing a fuel tax on air cargo.

1. *What are the effects of implementing a fuel tax on the air cargo demand in Germany for the express critical logistics service provider Time:Matters GmbH?*

2. *To what extent has a German fuel tax on air cargo effect on the substitution between air and rail cargo transport for the express critical logistics service provider Time:Matters GmbH?*

To be able to answer the research questions, this research is divided as follows: chapter two provides an overview of the relevant literature and discusses the hypotheses of this research. Chapter three introduces the data to estimate the different models. Furthermore, chapter four explains the methodology of the data to estimate the different models per hypothesis. Chapter five presents the empirical results of the price elasticity per transport mode and the cross-price elasticity. Lastly, the conclusion, limitations and suggestions for further research will be discussed in chapter six.

2. Literature review

2.1 The cargo market

As dicussed in the introduction the freight sector has a substantial impact on the environment. Since the rail freight sector could contribute to a more sustainable transport sector (IUC, 2019), this study will research the effects of implementing a fuel tax on aviation on air cargo and rail cargo demand. The following two sections will discuss the air and rail cargo market respectively.

2.1.1 Air cargo market

With increasing globalisation, the air cargo industry has played a key rol in global trade. Although only 1% of the volume of the world trade shipments is transported by air cargo, the value of air cargo shipments accounts for around 35% (IATA, 2016). Within Europe approximately 16.3 million tonnes of air cargo was transported in 2017. Figure 3 illustrates the distrubition of the European transport of air cargo. Germany carried around 4.7 million tonnes of air cargo in 2017, which is significant more than the other European Member States.

When analyzing the air cargo demand, one should consider the different types of players and traffic flows. In the air cargo industry, there are two types of players: the integrated and nonintegrated air cargo carriers. Most players in the industry operate on nonintegraded services, for instance forwarders and all-cargo carriers who provide air cargo deliveries. However, the integrated carries, or integators, control the transport chain from shipper to consignee (Kupfer, Meersman, Onghena, & van de Voorde, 2017). Due to E-commerce and the inscreasing demand for “door-too-door” services rather than “airport-to-airport” services, the integrators, for instance air express carriers like DHL, have expanded their air cargo services over the past two decades (Park, Choi, & Zhang, 2009).

Another feature of the air cargo industry is the traffic flows between all-cargo traffic and combinated traffic. The all-cargo traffic is generated by freighters, while the combinated carriers transport cargo in an all-cargo aircraft or in the belly of a passenger aircraft. Only between 5% and 15% of air cargo shipments is transported in an all-cargo aircraft, mainly because of the dimensions or hazardous characteristics (Kupfer, Meersman, Onghena, & van de Voorde, 2017). Additionally, due to cost allocation strategies, belly operators can offer lower prices compared to dedicated freighter operators. For this reasons, combinated carriers have removed or reduced the full freighter operations over the past years and increased the belly operations (Kupfer, Meersman, Onghena, & van de Voorde, 2017).

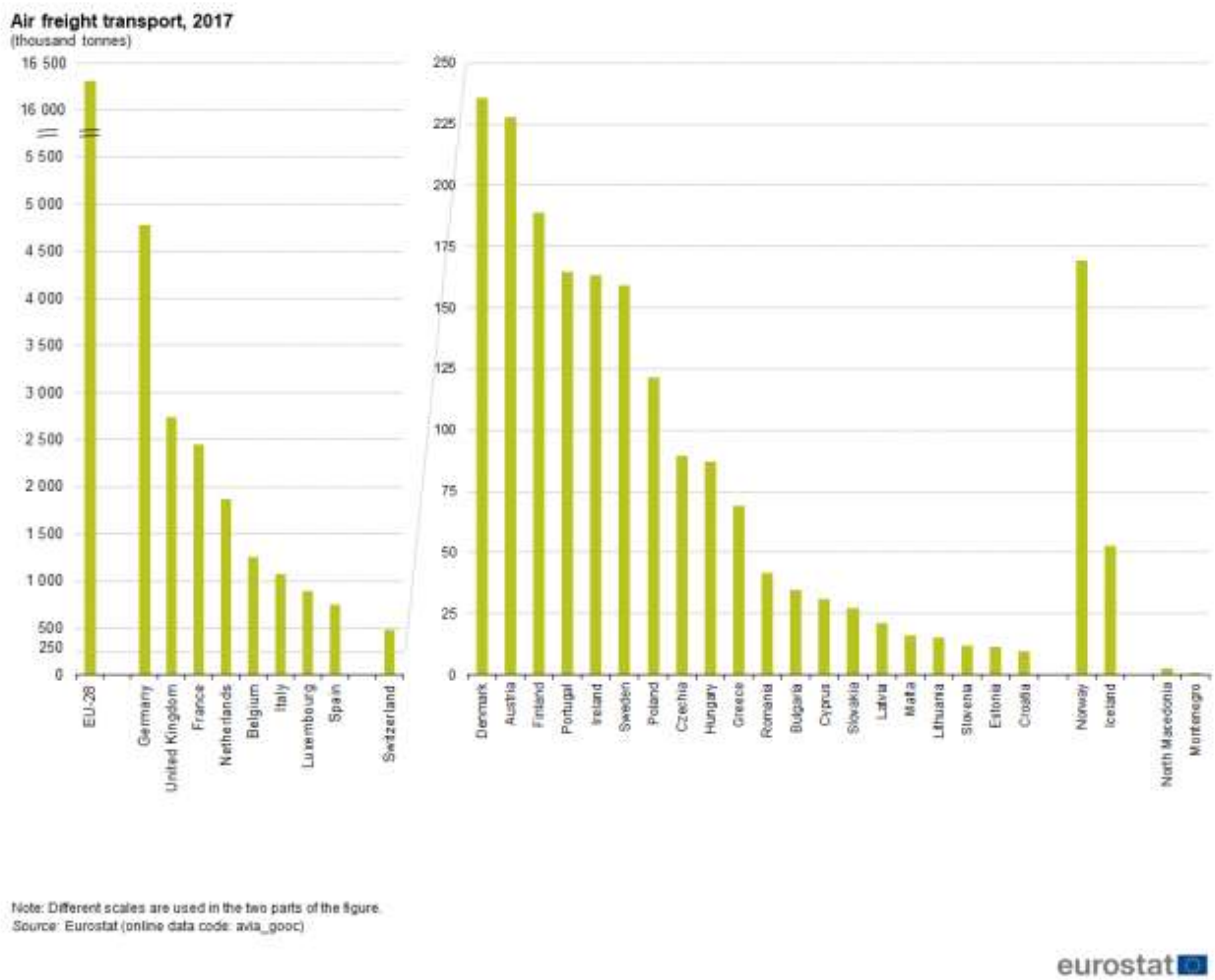

Figure 3 Air freight transport in Europe in thousand tonnes in 2017.

Source: (Eurostat , 2020)

As mentioned, Time Matters mainly transport shipment in the belly of passenger aircrafts. In 2017 the domestic passenger flights in Germany counted for 10% of the total flights departuring from Germany (DFS - Deutsche Flugsicherung, 2018). Currently, Germany levies two different taxes on the aviation market. First of all the VAT of 19% is levied on all domestic flights. Secondly, the German Air Transport Tax levies a ticket tax on all departing passengers from Germany, including domestic and international flights. The tax rate is pending on the distance from Frankfurt Am Main airport (CE Delft, 2019). However, the ticket tax is solely applicable on passengers and air cargo is reempted from an aviation tax, besides the VAT on domestic flights.

2.1.2 Rail cargo market

Between the European Member States, Germany also carries the most rail cargo in terms of tonnes. Germany carriers transported approximately 32% of the 801 million tonnes of rail cargo that was transported through Europe in 2019. In terms of tonnes kilometers, German carriers transported approximately 35% of the rail cargo (UIC, 2019). Furthermore, in 2018 approximately 19% of inland cargo in Germany was transported via rail (Eurostat, 2020).

Freight transportation via rail emits less CO_2 emissions than other modes of freight transport. Due to the potential need of intermodal transport, rail is expected to become competitive for longer distances. The turning point is expected to be around 300 kilometers (CE Delft, 2018b). On short-haul and/or domestic transport, the high-speed rail is often promoted as a lower-carbon transport alternative (Clewlow, Balakrishnan & Sussman, 2013). One of the opportunities for rail freight transport is therefore the overall need for low carbon freight transport. Climate policies could be the key for a modal shift to rail transport (CE Delft, 2018b). In 2017 the German ministery of Transport and Digital Infrastructure presented the “Masterplan for rail freight transport”. The aim of the plan is to improve the market situation for rail freight transport and therefore the use of a more environmentally-friendly mode of transport. The ministery is providing financial support to ensure lower prices for rail freight transport and futher infrastructure investments to increase the network’s capacities and efficiencies (BMVI, 2017).

Rail transport is however often not yet offered as a service for express freight transport. Demand for express freight transport is mostly satisfied throught road transport or for longer distances through intermodal air and road transport. However, these transport modes include high costs, high energy consumption and high emissions (Ohnell & Woxenius, 2003). In an intermodal transport system, rail could replace road transport by co-operarting with air transport for intercontinental shipments and could compete with air transport for inta-continental shipments. In the U.S. for example, express freight provider UPS is the biggest customer of intermodal rail services. One advantage of rail transport compared to air transport is the avaibility of being able to stop along the route (Ohnell & Woxenius, 2003). However, one should also consider the drivers of express freight demand. Express freight providers normally transport products that need fast transportation like high-value products, such as electronics and medicines, and perishable products, such as flowers and vegetables (Ohnell & Woxenius, 2003). CE Delft (2018b) ranged some drivers of continental freight transport for high value and persihable products. The criteria *cost* appears not to be the most important driver of transport for these types of goods. *Delivery time* and *punctuality* are according to CE Delft (2018b) more important decision criteria for express freight transport. Rail transport is often cheaper than air transport, however, air transport could often deliver shipments faster. The opportunity for a modal shift towards rail transport for express freight lies in the trade-off of these decision criteria from shippers.

2.2 Price elasticity of demand

Elasticity measures are commonly used to provide insights into the impact of different economics actions and policy decisions (IATA, 2008). Price elasticity of demand analyzes the effect of price change for the demand of a specific product or service. Marshall (1890) defined the principle as follows

"The elasticity of demand in a market is great or small according as the amount demanded increases much or little for a given fall in price and diminish much or little for a given rise in price"

To simplify, this principle is the proportional change in demand given a proportional change in price. Due to the Law of Demand, one could argue that the magnitude of the price elasticity of demand should be negative. The Law of Demand suggests that the demand of a specific product will increase when the price of the specific product decreases, ceteris paribus, and vice versa. This implies that the demand of a product is sensitive for the changes in price, however the degree of sensitivity will vary in different situations. Therefore, there are different types of price elasticities. If the price elasticity of demand is minus one or stronger negative, than the product is price elastic. When the price elasticity is smaller than mines one, the product is price inelastic. The difference implies that the proportional change in price has a stronger effect on the demand for an elastic product than for an inelastic product (Anderson, McLellan, Overton, & Wolfram, 1997).

The demand of a specific product (Q) can be described by the following function of the price (p) (Sydsaeter & Hammond, 2012)

$$\mathbf{1.}\ Q = D(p)$$

When the price changes from *p* to *p + Δp,* the demand, *Q*, will also change. The absolute change in demand, Q, is ΔQ = D(*p + Δp) – D(p)* and the relative change in demand is $\frac{\Delta Q}{Q}$. The ratio between the relative change in demand and the relative change in price can be written as follows

$$\mathbf{2.}\ \ \frac{p}{Q} * \frac{\Delta Q}{\Delta p} = \frac{p}{D(p)} * \frac{\mathrm{D}(p\ +\ \Delta p) - D(p)}{\Delta p}$$

Formula 2 can be rewritten to the price elasticity of demand (ε) and is as follows

$$\mathbf{3.}\ \ \varepsilon = \frac{p}{Q} * \frac{\Delta Q}{\Delta p}$$

Additionally, the demand function is related to the utility function of a customer, since a rational customer tries to maximize the overall utility, which is subjected to a budget constraint. Meaning that the demand function will be obtained by maximizing the utility function subjected to the budget constraint (Frank & Cartwright, 2013). When choosing a destination, the customer will choose the destination with the highest utility. If the price of a specific market will increase, the customer may reconsider the options and may search for a less expensive option with nearly the same or higher level of utility (Brons, Pels, Nijkamp, & Rietveld, 2002).

Moreover, the price elasticity of demand is also directly related to the possibilities of substitution for a specific product. An elastic demand will imply a relatively large number of substitutes, while a relatively small number of substitutes indicate an inelastic demand (Brons, Pels, Nijkamp, & Rietveld, 2002). In the aviation sector, the possibilities of substitution are related to the distance of a flight. For instance, road and rail transport might be substitutional modes of transport for short-haul and medium-haul flights, while long-haul flights might have smaller amount of substitutions, especially for intercontinental flights. The difference in substitutional modes of transport per distance indicates a negative relationship between the distance and price sensitivity. Contradictory, one could argue that the relationship between distance and price sensitivity is positive, since long-haul flights are generally more expensive than short-haul flight. Therefore, the effect between distance and price elasticity of air cargo demand is uncertain (Brons, Pels, Nijkamp, & Rietveld, 2002).

2.3 Previous research on price elasticity in the cargo sector

The estimation of price elasticities of demand can be quite difficult due to data availability on the variables needed. Brons, Pels, Nijkamp, & Rietveld (2002) suggest to use the research synthesis from several previous studies as an alternative to find common factors. This research will follow the same method to calculate the price elasticities of cargo demand.

The price elasticity of transport demand has been discussed in the literature for different modes of transport (e.g. Oum, Waters, & Yong (1990)). Studies on air transport demand have mainly focused on determining the price elasticity of demand of passengers (e.g. Oum, Zhang, & Zhang (1993); Brons, Pels, Nijkamp, & Rietveld (2002); IATA (2008)). Although there is sufficient research on passenger aviation demand, the research on air cargo demand is limited. Table 1 illustrates all the accessible, previous academic researches on price elasticities of air cargo demand. The researches vary in methods and data sets. Wang, Maling, & McCarthy (1981) used Box-Cox transformation techniques to calculate the price elasticity of aviation demand by using data from U.S. domestic air cargo transport from 1950 to 1977. The autors used two different time-series models: the all-cargo model and the passenger and cargo model. The models concluded that cargo demand is price elastic when carriers transport both passengers and cargo. The cargo demand is price inelastic for all-cargo aviation activities. Furthermore, both Tally & Schwarz-Miller (1988) and Oum, Waters, & Yong (1990) concluded that the price elasticity of air cargo demand is price elastic. Additionally, Chi & Baek (2012) used a fully-modified ordinary last square (OLS) model with air cargo rate and GDP as a proxy for income as independent variable and a dummy variable capturing market shocks, for instance the 9/11 terrorist attacks. When comparing the outcome with earlier researches, the autors concluded that the longrun price elasticity of air cargo demand of -5.6 suggests that the price elasticity value is significant more elastic today than in previous decades (Chi & Baek, 2012). However, the model could potentially suffer from omitted variable bias, since for instance a variable explaining the distance between origin and destination is not included in the model. As discussed in the previous section, distance is correlated with the price of aviation activities (Brons, Pels, Nijkamp, &

Rietveld, 2002) and should be included in the model. The use of route distance reflects the travel time and the availability of substitutes. When the distance increases, the effect of substitutes of other modes of transports will decrease (IATA, 2008).

Contradictory, the more recent studies of Yamahuchi (2008), Hwang & Shiao (2011), Mitra & Leon (2014) and Lo, Wan, & Zhang (2015) found a price inelastic demand of air cargo. Hwang & Shiao (2011) used a gravity model with fixed effects to estimate the price elasticty of air cargo demand. The model included air cargo services on international routes at Taiwan Taoyuan International Airport from 2004 to 2007. When comparing the price elasticity of air cargo demand with previous research, the autors concluded that the lower estimates indicate that the air cargo demand is less sensitive to the freight rate than other studies. One possible explanation according to Hwang & Shiao (2011) is the market and data of the research. Electronic products, which covers a large porportion of the Taiwanese import and export, have a high value-to-weight ratio and is thus less price sensitive compared to low value-to-weight ratio products (Hwang & Shiao, 2011). Mitra & Leon (2014) analyzed the shipper's decision characteristics of choosing air cargo as a transport mode in North Dakota, U.S. A survey of 347 manufacturers, freight forwarders and other third-party service providers is conducted to obtain the preference data. This data is used in a mixed logit model to give an understanding of the sensitivity of the shippers by examine the price elasticity of air, rail and road cargo demand. The variables of shipper's decision characteristics are the rate, cost, time, delay, commodity density, quantity, perishability, equipment availability and loss and damage. The estimate of the price elasticity of air cargo demand is -0.03. However, it is questionable whether this model is suitable and not suffering from omitted variable bias. The variable of the model indicates only shipper's decision factors, while for instance marcoeconomic factors, like GDP as a proxy for income, are not included in the model. Furthermore, the distance between origin and destination is omitted in the model, which is an important factor when analyzing the elastiticy of the aviation sector, as discussed by the research of Chi & Baek (2012). Lastly, only Lo, Wan, & Zhang (2015) controlled for the endogeniety problem when estimating the price elasticity of demand by using a two-stage least squares (2SLS) and three-stage least squares (3SLS) model. The problem of endogeneity appears when X causes Y, but Y also causes X (Wooldrigde, 2013). Aviation prices are influenced by the demand, while demand is also influenced by the prices (see Chapter 4). Lo, Wan, & Zhang (2015) included the following variables in the model: cargo volume, air cargo price, real GDP, internet traffic, jet fuel price, transport sector wage index, monthly dummy variable, dummy variable for the the 9/11 terrorist attacks, dummy variable for the economic crisis from 2009 and a fixed effect. The autors also concluded that air cargo demand has a negative price elasticity, however the absolute value is lower than the estimated values in previous literature.

Table 1 Previous research on price elasticities of air cargo demand

Source	**Price elasticity**	**Method**	**Market**	**Time period**
Wang, Maling, & McCarthy (1981)	**-2.5 to -2.33** **-0.81 to -0.42**	Box-Cox transformation	U.S. domestic	1950-1977, time series data
Tally & Schwarz-Miller (1988)	**-1.318**		U.S. domestic	1983, cross sectional data
Oum, Waters, & Yong (1990)*	**-1.6 to -0.82**			
Yamahuchi (2008)	**-0.571**	Gravity equation trade model	U.S. export	1998-2002, time series data
Hwang & Shiao (2011)	**-0.261**	Gravity model	International routes of Taiwan	2004-2007, panel data
Chi & Baek (2012)	**-5.6**	OLS	U.S. domestic	1996-2010, time series data
Mitra & Leon (2014)	**-0.03**	Mixed logit model	North Dakota, U.S.	2004-2010, time series data
Lo, Wan, & Zhang (2015)	**-0.74 to -0.29**	2SLS and 3SLS	International routes of Hong Kong	2001-2013, time series data

* Oum, Waters, & Yong (1990) did a literature survey to rank the recent price elasticity estimates of aggregated transportation demand.

Table 2 shows the previous research on price elasticity of the rail cargo demand. As for air cargo, the researches of rail cargo demand vary in methods and data sets. Oum (1979) estimated the price elasticity of three modes of transport (railway, highway and waterway) by using yearly data of the Canadian transport market. The estimate of the price elasticity of rail cargo demand in 1950 is -0.093, while for 1974 the estimate is -0.291. Therefore, Oum (1979) concluded that the demand for rail cargo is price inelastic with an decreasing absolute value over time. Following the general approach of Oum (1979), Lewis & Widup (1982) researched the price elasticity of road and rail cargo demand of assembled automobiles in the United States (U.S.) from 1955 to 1975. For this type of commodity the authors concluded that the price elasticity of rail cargo demand is close to -1. Furthermore, Abdelwahab (1998) estimated the price elasticity of road and rail cargo demand of eight different types of commodities in five different regions in the U.S. Abdelwahab (1998) concluded that the price elasticity of demand varies significantly across commodity groups and geographic areas. According to this research the price elasticity of rail cargo demand varies from -2.498 to -0.956, resulting that most commodities found to be price elastic. Moreover, Ramanathan (2001) used more modern time series econometric techniques to estimate the determinants of rail cargo demand. Ramanathan (2001) applied cointegrating and error correction analyses to examine the long-run behaviour of transport performance in India by using macroeconomic variables like GDP and industrial growth. The results show that long-run price elasticity of rail cargo demand is -0.188 and is relatively inelastic to price changes. Lastly, Mitra & Leon (2014) concluded that the price elasticity of rail cargo demand is -0.004 in their research. Comparing the elasticities of air and rail cargo demand, the authors concluded that air cargo shipments are more sensitive to price changes than rail cargo demand. However, this degree of sensitivity is relatively low.

Table 2 Previous research on price elasticities of rail cargo demand

Source	**Price elasticity**	**Method**	**Market**	**Time period**
Oum (1979)	**-0.29**	Maximum likelihood method	Canada domestic	1945-1974, time series data
Lewis & Widup (1982)	**-1.02 to -0.92**	Translog transport demand model	U.S. market for assembled automobiles	1955-1975, time series data
Abdelwahab (1998)	**-2.489 to -0.956**	Binary linear probit model	U.S. domestic	1977, cross sectional data
Ramanathan (2001)	**-0.188**	Single-equation framework to cointegration	India domestic	1956–1989, time series data
Mitra & Leon (2014)	**-0.004**	Mixed logit model	North Dakota, U.S.	2004-2010, time series data

Comparing the previous research of price elasticity on both air and rail cargo demand, one could argue that the estimations deviate significantly. Also, the estimates are pending on the methods, the data set and the market. The fourth column of Table 1 and 2 show that the European, and thus German, air cargo market has not been studied before. Additionally, only the research of Mitra & Leon (2014) compared the air and rail cargo transport market. Furthermore, only the research of Lo, Wan, & Zhang (2015) controlled for the potential endogeniety problem when estimating the price elasticity of air cargo demand. Additionally, previous research on the price elasticity of rail cargo demand have not addressed this problem yet. For this reasons, this research aims to fill in these gaps by using 2SLS and 3SLS models to analyze the German air and rail cargo market.

Looking at the data set and the outcomes of the previous air cargo demand research, it is noteworthy that most of the researches on the U.S. domestic markets indicates a price elastic demand, while the demand is price inelastic for U.S export, international routes of Hong Kong and international routes of Taiwan. Furthermore, the demand also seems to be price inelastic for the more recent studies, apart from the study of Chi & Baek (2012), which could potentially suffer from omitted variables bias. Additionally, the more recent studies use more modern time series econometric techniques than for instance Wang, Maling, & McCarthy (1981) and Oum, Waters, & Yong (1990). Furthermore, only the lastest research, Lo, Wan, & Zhang (2015), controlled for the potential endogeniety problem. Considering all of the above and considering the data set and the methodology of this research, this study expects that the air cargo demand is price inelastic. Therefore the first hypothesis to answer the research questions is as follows

Hypothesis 1: Air cargo demand is price inelastic

Based on the previous research, the expectations of the price elasticity of rail cargo demand is more difficult to address than the expectations of air cargo demand. Only Mitra & Leon (2014) studied the price elasticity of both air and rail cargo demand. The estimates indicated that rail cargo demand is less sensitive to price change than air cargo demand, however, the validity of the model is questionable. Most of the estimates of the research of Abdelwahab (1998) turned out to be price elastic, while the estimates of the other studies are price inelastic. When looking at the methodology, Abdelwahab (1998) is the only researcher who used cross sectional data instead of time series data. Furthermore, Abdelwahab (1998) used disaggregate demand, while the other studies used aggregate demand models. Since this research will use time series data on aggregate demand, it is expected that the rail cargo demand is price inelastic. The second hypothesis is as follows

Hypothesis 2: Rail cargo demand is price inelastic

2.4 Aviation fuel tax

Previous research concluded that the price elasticity of air cargo demand is negative. According to the price elasticity demand theory, the demand of aviation activities will decrease as a result of an increased price. However, the degree of sensitivity of air cargo demand varies between the previous studies. Therefore, it is uncertain to what extent the demand will change when implementing a fuel tax. A fuel tax could potentially reduce the fuel consumption and the decreased demand could potentially influence aviation emissions (CE Delft, 2018). Even though, the fuel tax cannot directly control the amount of CO_2 emissions, taxation could be an important instrument in a CO_2 emissions reduction policy (Fukui & Miyoshi, 2017). According to Mayor & Tol (2007), the optimal policy to reduce emissions would be to tax emissions directly, which could also lead to a change in flight behavior, aircraft technology and fuel choice. However, this research only considers changes in demand caused by an increase in the price of aviation due to a fuel tax.

2.4.1 European Energy Tax Directive 2003/96/EC

Within Europe, aviation has a unique tax regime that is characterized by a lower level of taxations or even exempted from taxations than other transportation activities (Transport & Environment, 2019). The European Energy Tax Directive 2003/96/EC exempt aviation fuel from taxation. Article 14(1)(b) relevant part states (European Commission, 2003):

"Member States shall exempt the following from taxation […]: energy products supplies for use as fuel for the purpose of air navigation other than in private pleasure-flying."

However, Article 14(2) of the European Energy Tax Directive states that intra-Community and domestic flights may abolish this exemption. The Article is as follows (European Commission, 2003):

"Member States may limit the scope of the exemptions provided for in paragraph 1(b) and (c) to international and intra-Community transport. In addition, where a Member State has entered into a bilateral agreement with another Member State, it may also waive the exemptions provided for in

paragraph 1(b) and (c). In such cases, Member States may apply a level of taxation below the minimum level set out in this Directive."

The Directive allows European Member States to tax aviation fuel for domestic flights. The minimum excise duty rate for kerosene is according to the Directive 330 euro per 1000 liters or 0.33 euro per liter kerosene used. It should however be noted that according to Article 14(2) Member States may apply a level of taxation below the minimum excise duty rate (European Commission, 2003). Currently, none of the European Member States levied a fuel tax on domestic aviation (CE Delft, 2019).

The European Energy Tax Directive 2003/96/EC is however not the only legal framework in the aviation sector. The fuel tax exemption is based on the Chicago Conventions on International Civil Aviation of 1944. Article 24 of the Chicago Convention states as follows (CE Delft, 2019):

"Fuel […] on board an aircraft of a contracting state, on arrival in the territory of another contracting State and retained on board on leaving the territory of the State shall be exempt from customs duty, inspection fees or similar national or local duties and charges."

Imposing taxes on fuel already on board of an aircraft upon arrival in another country is according to the Chicago Convention prohibited, however, the Convention does not forbit taxation on fuel sold in another country. Additionally, domestic aviation is not included in the Chicago Convention. Hence, the Chicago Convention does not prohibit fuel taxation on domestic aviation (Transport & Environment, 2019).

Furthermore, bilateral air agreements exempt fuel taxation on international level, but the agreements do not prohibit taxation on national level. For instance, the European Common Aviation Area (ECAA) agreement does not prohibit domestic fuel taxation (CE Delft, 2019). Furthermore, Article 11 of the EU-US Open Skies Agreements states (European Commission, 2019):

"There shall also be exempt, on the basis of reciprocity, from the taxes, levies, duties, fees and charges […] with the exception of charges based on the cost of the service provided:[…] fuel, lubricants and consumable technical supplies introduced into or supplied in the territory of a Party for use in an aircraft of an airline of the other Party engaged in international air transportation[.]"

To conclude, taxes levied on domestic aviation would not be contrary to the European law. However, there is one obstacle worth mentioning when implementing a fuel tax on domestic aviation. Taxation could encourage the phenomenon "tankering", which implies that airlines will fuel the aircraft as full as possible once the aircraft landed outside the country where the fuel is taxed. Airlines could choose to travel further than necessary to avoid the taxes, which leads to more fuel burned for the extra kilometers and extra weight of the full tank and will lead to an increasing level of aviation CO_2 emissions (Seely, 2019). This phenomenon could therefore be paradoxical with the intention of the fuel tax, however, this research will not take this into consideration.

2.4.2 Aviation fuel tax in non-European countries

The previous section clarified that the European Energy Tax Directive allows fuel taxes on domestic aviation in Germany. The following non-European countries already imposed a fuel tax on domestic aviation: Canada, the Unites States, Hong Kong, Australia, Japan, Armenia, Saudi Arabia, Laos, Myanmar, Philippines, Thailand and Vietnam (CE Delft, 2019). Table 3 shows the aviation fuel tax in euro's and the tax in percentage of the average jet fuel price for the countries where the data on taxation was accessible. The tax rates vary approximately between 0.022 and 0.15 euro's and has an average of 13.8% of fuel tax.

Table 3 Aviation fuel tax rate per country

Country	**Rate**	**Unit**	**Euro's per liter**	**Tax in Percentage***	**Source**
Canada	0.04	CAD per liter	**0.028**	**6%**	(Government of Canada, 2008)
The Unites States	0.044	USD per liter	**0.040**	**9%**	(Internal Revenue Service (IRS), 2018)
Australia	0.036	AUD per liter	**0.022**	**5%**	(Australian Government, 2019)
Japan	18	JPY per liter	**0.15**	**34%**	(Gonzalez & Hosoda, 2016)
Philippines	3.67	PHP per liter	**0.065**	**15%**	(IATA, 2013)

Note: There was no information regarding the fuel tax for the countries not included in this table.
*: Tax in percentage is based on the average jet fuel price of 0.44 euro per liter, see Chapter 3.

The tax rates in Table 3 are significantly lower than the minimum excise duty rate for kerosene of the European Energy Tax Directive. Additionally, the minimum rate of the Directive has a tax percentage of 82.5%, which is almost six times more than the average of the five countries in Table 3. Currently, no European Member State have implemented a fuel tax on domestic aviation (CE Delft, 2019). Since the Directive states that the Member States might apply a level of taxation below the minimum excise duty rate (European Commission, 2003) and since the non-European countries have a tax rate far below the minimum excise duty rate, this research will study different levels of taxation varying from 0.05 to 0.33 euro per liter, where 0.05 euro per liter is approximately the average rate of the countries listed in Table 3 and 0.33 euro per liter is the minimum excise duty rate.

2.4.3 Previous research on aviation fuel tax

The previous research on the effects of an aviation fuel tax is very limited. Olsthoorn (2001) estimated the price elasticity of world jet fuel consumption and researched the effects of imposing an international tax on kerosene. An autoregressive moving average model with the rate of development of fuel sales, the global GDP and world oil price as explanatory variables is used to estimate the effects. The author concluded that for international aviation the price elasticity of fuel demand is low. The reduction of $\mathrm{CO_2}$ emissions, when a tax not greater than the marginal external costs of $\mathrm{CO_2}$ emissions is implemented, is negligible. One drawback of the research of Olsthoorn (2001) is the use of crude oil prices instead of jet fuel prices. Fukui & Miyoshi (2017) studied the effect of the aviation fuel tax in the Unites States on the fuel consumption and $\mathrm{CO_2}$ emissions from 1995 to 2003. The authors used an OLS regression with the fuel cost of carriers, the total miles flown per carrier and for the industry and macroeconomic variables as GDP and unemployment rate as explanatory variables. The price elasticity of fuel consumption is found to be inelastic and therefore the authors concluded that the reduction of $\mathrm{CO_2}$ emissions as a result of a fuel tax is low. The current level of the U.S. aviation fuel tax, as stated in Table 3, needs to be 3 to 5 times higher if 1% reduction of $\mathrm{CO_2}$ emissions of the U.S. aviation sector wants to be achieved (Fukui & Miyoshi, 2017). However, one should be critical about the use of an OLS model, because of the possible endogeneity problem. Gonzalez & Hosoda (2016) researched the effect of the fuel tax of domestic aviation on the reduction of $\mathrm{CO_2}$ emissions in Japan for the years 2004 to 2013. Even though the Japanese government lowered the tax by 30% in 2011 due to pressure on the Japanese aviation, the authors found that a fuel tax has a positive significant effect on the reduction of CO_2 emissions. Global reductions of CO_2 emissions could be achieved if other countries would implement a similar tax regime (Gonzalez & Hosoda, 2016).

Comparing the studies, one could argue that an aviation fuel tax would result in lower fuel consumption and in a reduction of CO_2 emissions. However, the scope and size of the impact on CO_2 emissions are varying in the previous studies. Both Fukui & Miyoshi (2017) and Gonzalez & Hosoda (2016) studied the effect of fuel tax on a domestic market. However, as seen in Table 3 the tax rate of the U.S. fuel tax and the Japanese fuel tax differs significantly. Gonzalez & Hosoda (2016) found a larger impact of fuel tax on CO_2 emissions than Fukui & Miyoshi (2017), which could result from the higher tax rate. Therefore, the impact of a fuel tax should be controlled by different scenario's with different levels of taxation. Furthermore, based on these studies it is difficult to give an expectation on the German domestic aviation market. However, a leaked report from the European Commission (Transport & Environment, 2019b) studied the impact of introducing a ticket tax, VAT on passenger tickets and fuel tax for flights within and departing from Europe. Compared to other aviation markets, the European aviation market is significantly undertaxed. The report concluded that fuel taxes have a significant bigger effect in terms of CO_2 emissions reduction than other taxes. Additionally, imposing a fuel tax of 0.33 euro per liter kerosene on all departing flights in the European Union will cut CO_2 emissions by 11%. Furthermore, the European Commission modelled the effect of the fuel tax per European Member State. Based on this study, introducing a fuel tax in Germany will lead to the following results: number of flights, number of passengers and CO_2 emissions will all fall 12%, people affected by noise will drop 8% and fiscal revenues will rise with 4.8 billion euro. The tax will have no impact on the jobs in all sectors and on the GDP in Germany (Transport & Environment, 2019b).

However, all of the previous research and the leaked study focus on the general aviation sector and does not make a distinguish between aviation passengers and aviation cargo. The operations of aviation passengers and aviation cargo differ significantly. Air cargo transport has for instance higher uncertainties than aviation passenger transport. Furthermore, air cargo is more complex and flexible compared to passenger transport (Feng, Li, & Shen, 2015), while passenger transport depends on behaviour. Considering this, one could argue that air cargo is less price elastic than air passenger transport and a distinguish between the two should be made.

Looking at the general cargo industry, only one study of the effects of a fuel tax on CO_2 emissions is found. Transport & Environment (2010) studied the sensitivity of the European road freight transport and investigated the effects of transport policies. With an estimated price elasticity of -0.9, the report found that if the diesel tax of road freight transport would increase with 0.10 euro's per liter, the fuel consumption and CO_2 emissions will decrease 3% (Transport & Environment, 2010).

Since the researches on general aviation and the research of Transport & Environment (2010) found a positive correlation between fuel tax and the reduction of CO_2 emissions, this research expects that a fuel tax on domestic air cargo in Germany will result in lower CO_2 emissions. However, the scope and size are yet uncertain.

2.5 Cross-price elasticity of cargo demand

The previous sections discussed the own-price elasticity of air and rail cargo demand. A fuel tax on air cargo could potentially result in a change in demand of other modes of transport. The possibilities of substitution in the aviation sector are related to the distance of a flight. A modal shift could be possible for short-haul and medium-haul flights (Brons, Pels, Nijkamp, & Rietveld, 2002). This substitution effect will be examined by the cross-price elasticity of demand.

Cross-price elasticity analyzes the effect on the demand of product Y to the change in price of product X, ceteris paribus, and vice versa. This implies that the demand of a product Y is sensitive for the changes in price of product X, however the degree of sensitivity will vary in different situations and therefore different types of cross-price elasticity exist. If the cross-price elasticity is positive, meaning that the demand of product Y will increase if the price of product X increases, than the products are substitutes. An example of positive cross-price elasticity is coffee and tea: if the price of coffee increases, than the demand of coffee will decrease and the demand of tea will increase, ceteris paribus. Contrarily, if the demand of product Y decrease as a reaction of the increased price of product X, than the products are complementary (Sydsaeter & Hammond, 2012).

The formula of the cross-price elasticity, $\varepsilon_{\boldsymbol{c}}$, is stated as follows

$$\textbf{4.}\ \varepsilon_{\boldsymbol{c}} = \frac{\Delta Q_y}{\Delta P_x} * \frac{P_x}{Q_y}$$

Where P_x is the initial price of product X, ΔP_x is the change in price of product X, Q_y is the initial demand of product Y and ΔQ_y is the change in demand of product Y (Sydsaeter & Hammond, 2012).

As mentioned, the high-speed rail is often promoted as a lower-carbon alternative to aviation on short-haul and/or domestic travel (Clewlow, Balakrishnan, & Sussman, 2013). With the cross-price elasticity analysis this research will therefore study the effects of implementing a fuel tax on air cargo on the demand of rail cargo.

A few studies analyzed the cross-price elasticity of cargo demand. However, most of these researches study the elasticity on road, rail or waterway cargo demand, for example Oum (1979), Lewis & Widup (1982), Abdelwahab (1998), Mitchell (2010) and Beuthe, Jourquin, & Urbain (2014), while the comparison with air cargo transport is mostly omitted. The research of Lewis & Widup (1982) from table 2 also analyzed the cross-price elasticity between rail and road cargo demand of assembled automobiles in the U.S. The authors concluded that the cross-price elasticity ranged from 1.45 to 1.68 for different types of static and dynamic models. The results of Oum (1979) also indicate a competitive relationship between rail and road cargo, however, the estimates of Oum (1979) of rail and road cargo seems to be less sensitive to a price change. Furthermore, Oum (1979) analyzed the subsitution effect of waterway cargo transport. The relationship between rail and waterway seems to be competitive with cross-price elastitities of 0.47. With a probit model, Abdelwahab (1998) researched the demand elasticities of the U.S. freight transport sector by analyzing the road and rail transport. The author concluded that the cross-price elasticity between road and rail ranged between 0.904 and 2.532. The positive elasticity shows the existence of some degree of competition between road and rail transport and this competition seems to strengthen when the own-price elasticity of one specific transport mode increases. Moreover, Mitchell (2010) analyzed rail cargo demand by using yearly freight movement data from 1973 to 2001 for seven Australian inter-capital corridors and estimated the cross-price elasticity between road, rail and sea freight transport. The estimates of the two different models, dynamic translog cost function and dynamic linear logit system, show quite some different values with negative and positive relationships between the transport modes. The estimates of the former model imply a negative relationship between rail and road transport, meaning that the transport modes are complementary to each other. However, Mitchell (2010) argued that the latter model is more suitable, which estimated a positive and inelastic cross-price elasticity between rail and road transport. The relationship between rail and sea transport is competitive in this model, however cross-price elasticity between rail and sea freight fluctuate more through the years compared to rail-road transport. Lastly, Beuthe, Jourquin, & Urbain (2014) studied the cross-price elasticities of road, rail and waterway modes by a multimodel freight network of the Rhine area market. The authors reported an inelastic cross-price elasticity between rail and road cargo demand in tonnes kilometer, varying between 0.09 and 0.65, and found that the elasticity becomes smaller when the distance in kilometers increases. The relationship between rail and waterway cargo is positive and inelastic, however, the elasticity increases when the number of kilometers travelled increases.

The study of Mitra & Leon (2014) is the only accessible, previous research found which addressed the cross-price elasticity of air and rail cargo demand. The model predicted a cross-price elasticity of 0.00004, which is basically insignificant. The authors concluded that a shift of cargo from air to rail, and vice versa, is not likely even for a significant price change in one of these two transport modes. However, as explained in section 2.3 the validity of the model is questionable.

In this research the cross-price elasticity of air and rail cargo demand in Germany will be analyzed by using a 3SLS model to control for endogeneity. The previous research on cross-price elasticity have not analyzed the cargo market in Germany yet and the research on the substitution of air and rail cargo demand is very limited. This research aims to fill in the gaps and provide a first study in this market. The aforementioned models, except for the dynamic translog cost function model of Mitchell (2010), suggest a positive cross-price elasticity between two transport modes, which indicates that an increase in the price of one transport mode results in a higher demand of the other transport mode. Based on this and the Law of Demand, this research expects that the air and rail cargo demand have a positive relationship and that the transport modes are substitutes. However, the degree of sensitivity varies between the models in the previous research and the sensitivity of air and rail cargo demand is yet unclear. The third hypothesis will analyze this effect and is as follows

Hypothesis 3: An increase in the price of air cargo will result in a higher demand of rail cargo

3. Data

To establish a start on this research, data of historical freight bookings is collected from Time Matters from January 2016 till August 2019. The data is solely available for this time period and therefore this time range is chosen. The data consist per booking of the market (origin to destination), the actual weight in kilograms, the actual price paid in euro's and the time needed to transport the shipment. Since this research aims to study the price elasticity of a specific mode of transport, the actual price paid in euro's should only reflect the costs of using a specific mode of transport. As mentioned, Time Matters offers transport options from destination A to destination B by perhaps using intermodal transport. In case of intermodal transport, the price reflects the different modes of transport used to transport a shipment. Therefore, the historical data of freight bookings will be minimized to airport-to-airport services or station-to-station services to remove the intermodal transport.

Additionally, as mentioned before, this research will solely focus on freight transport within Germany. When comparing Figure 6 and 7 in the Appendix, the network of Time Matters of the number of train station in Germany is significantly larger than the number of airports in Germany. To compare both transport modes, this research will therefore focus on market pairs of the biggest cities which are in both networks. Moreover, if there are more train stations in one city, only the Central Station of the specific city will be used as it can be seen as the most important station in the city. When analyzing the data, the biggest cities in terms of number of times the city was an origin or destination station are: Berlin, Cologne, Dresden, Düsseldorf, Frankfurt, Hamburg and Munich, and will be used in this research.

The distance in kilometers between the market pairs is retrieved from *Network of Transport Measures – environmental performance calculator* (2019). The calculator provides the route distance per market pair per transport mode. This calculator is reliable since it provides the distance on actual tracks of the specific transport mode and considers the great circle distance of flights. Since delivery time is an important decision criteria for express freight transport (CE Delft, 2018b), the distance is divided by the time needed to transport the shipment to obtain the kilometers transported per hour. Additionally, the growth of income is an essential driver of the aviation demand (IATA, 2008). Growth Domestic Product, GDP, will be used as a proxy for the growth of income in this research. The yearly GDP of Germany is obtained from Statista (2020).

3.1 Data description of air cargo

The dataset of the historical air cargo demand within Germany consist of 2728 observations. Table 4 shows the distribution of the observations per airport. Frankfurt and Munich are the largest airports in terms of the number of times the airport is used as an origin or destination station. This is not exceptional, since both airports are a hub airport for Lufthansa and Time Matters as discussed in the introduction (Lufthansa Group, 2019).

Table 4 The number of observations of air cargo demand per airport

Airport	Number of times as Origin station	Number of times as Destination station	Total
Berlin-Tegel Airport	522	472	994
Cologne Bonn Airport	82	207	289
Dresden Airport	27	46	73
Düsseldorf International Airport	127	377	504
Frankfurt Airport	969	696	1665
Hamburg Airport	517	318	835
Munich International Airport	484	612	1096
Total	**2728**	**2728**	

Furthermore, Figure 4 illustrates the number of air cargo bookings per month. The number of bookings is fluctuating and is not stable in the given time frame. Additionally, the figure shows a drop in the number of bookings after March 2017. However, one could argue that there is a pattern when comparing the number of bookings per month per year, see Figure 8 to 11 in the Appendix. For instance, there is a drop in the number of bookings in the beginning of the spring, which will increase again in May or June. In the

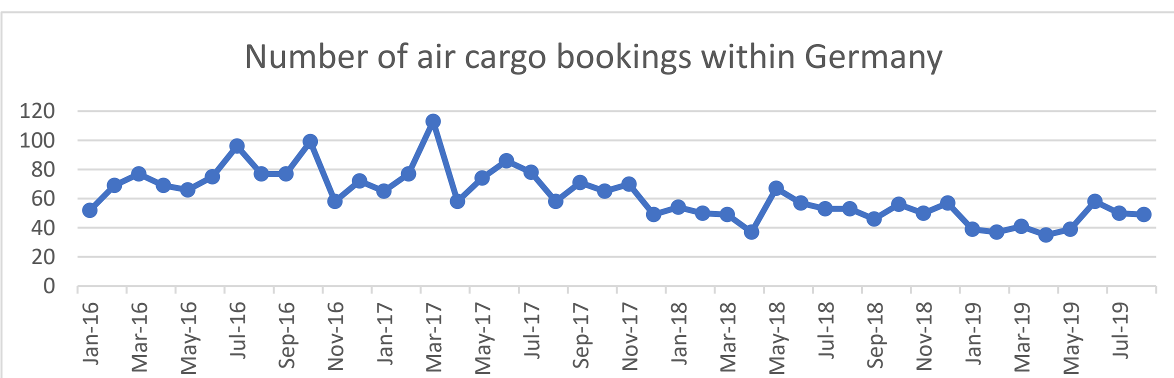

Figure 4 Number of air cargo bookings within Germany between January 2016 and August 2019

months afterwards, there is a drop in the summer period resulting with an increase in the autumn. Because of this pattern, this research will adjust for seasonality.

After analyzing the price elasticity of air cargo demand within Germany, this research will study the effects of implementing a fuel tax on domestic air cargo transport. This research assumes that the fuel tax is fully passed on to the person or company who is demanding the freight transport, which implies that the price will directly be increased with the fuel tax. According to the European Energy Tax Directive 2003/96/EC, a fuel tax could be levied per liter of consumpted kerosene. For this reason the total fuel consumption per booking should be calculated. To calculate the fuel consumption of a flight, this research assumes that the fuel consumption is proportional with the weight.

Table 23 in the Appendix provides an overview of the fleet of Lufthansa Group. The majority of the aircrafts are Airbus A321 and A320 and since both aircrafts mostly operates on short- and medium distance flights (Lufthansa Magazin, 2019), this research assumes that only Airbus A321 and A320 operates within Germany. The average, maximum number of passengers on an aircraft is 180 and the average, maximum cargo capacity is 2290 kilograms. Furthermore, internal documents of Lufthansa Group (eBase, 2019)[2] show the monthly loadfactors in percentages of Lufthansa Group for passengers and cargo on passenger flights, figure 12 in the Appendix illustrates this. It is interesting to note that the loadfactors of passengers and cargo show an opposite line. For instance, if the loadfactors of passengers decreases, the loadfactor of cargo increases and vice versa.

Additionally, Lufthansa Group (2017) reports that in 2018 passenger aircrafts needed on average 3.65 liters of kerosene to transport one passenger over 100 kilometers. The total fuel consumption per aircraft per market can be calculated as follows

5. $$Total\ fuel\ consumption\ per\ market\ in\ liters = distance * \frac{3{,}65}{100} * (number\ of\ passengers * load\ factor)$$

According to IATA (2014) the passenger weight of an aircraft can be calculated as per formula 6. Additionally, the total weight of a passenger aircraft is the sum of the passenger weight and the cargo

[2] Source derived from the intranet of Time:Matters GmbH.

weight. Since this research assumes that the fuel consumption is proportional with the weight, the total fuel consumption of cargo on a passenger flight per market in liters can be calculated by multiplying formula 5 with the ratio of cargo weight to the total weight, which is shown in formula 7.

6. $Total\ passenger\ weight\ in\ kg = (number\ of\ seats * 50) + (number\ of\ passengers * 100)$

7. $Total\ fuel\ consumption\ of\ cargo\ per\ market\ in\ liters = \frac{cargo\ weight}{total\ weight} * the\ total\ fuel\ consumption\ per\ market\ in\ liters$

With formula 7 the total fuel consumption of cargo on a passenger flight is calculated. However, the actual price paid is pending on the weight. Therefore, the fuel consumption of one kilogram of cargo in liters needs to be calculated, which is shown in formula 8.

8. $Fuel\ consumption\ of\ one\ kilogram\ of\ cargo\ per\ market\ in\ liters = the\ total\ fuel\ consumption\ of\ cargo\ per\ market\ / (maximum\ weight\ of\ bookable\ cargo * load\ factor)$

The total fuel consumption per liter per booking can be computed by multiplying formula 8 with the actual weight of the booking. However, to study the price elasticity of air cargo demand, the fuel price per booking in euro's in liters is required. Therefore, monthly jet fuel price is obtained from the U.S Energy Information Administration, EIA, (2019). The EIA is the offical energy statistics of the U.S. government. The fuel price per booking in euro's can be calculated by multiplying formula 8 with the monthly jet fuel price in euro's.

The descriptive statistics for the air cargo variables are shown in Table 5. Firstly, the mean of the price variable is 216.40 euro's with a minimum of 20 euro's and a maximum of 626.30 euro's. However, Figure 13 in the Appendix shows a right skew of the price variable, meaning that most of the oberservations are on the left side of the graph. Furthermore, the weight in kilograms varies from 0.1 to 32, which is the maximum weight of the *Sameday Air* service, as discussed in the introduction, and has an average of 5.83 kilograms.

The average distance of air cargo between the market pairs is 475.3 kilometers and on average a shipment travels 148.53 kilometers per hour. This implies that on average it takes approximately 3 hours to transport a shipment from airport to airport in this dataset. Since the km per hour variable also includes the LAT, TOA and possible transfer time, the minimum and maximum value of this variable vary significantly. The following two examples will illustrate on this matter. The distance between Cologne and Frankfurt is approximately 162 kilometers. However, it takes around 6 hours and 35 minutes to transport a shipment, since there are no direct flight options available in this market. Therefore, the kilometers travelled per hour is 24.61 in this market and is significantly low. Contradictory, in the Munich-Hamburg market a shipment travels approximately 205.26 kilometers per hour. The distance in this market is 650 kilometers and it takes approximately 3 hours and 10 minutes to transport from airport to airport. Therefore, for a express critical service provider, the kilometer per hour variable gives a better indication of the transport mode than the distance in kilometers since it considers the LAT, TOA and a potential transfer.

Lastly, the actual fuel price per booking varies from 0.004 to 4.195 euro's with an average of 0.351 euro's. However, the monthly jet fuel price differ from 0.25 to 0.59 euro's in the timeperiod and has an average of 0.44 euro.

Table 5 Descriptive statistics for the variables of air cargo demand

Variable	Number of observations	Mean	Standard deviation	Minimum value	Maximum value
Price in Euro's	2728	216.4	104.56	20	626.3
Weight in kg	2728	5.83	7.67	0.1	32
Distance in km	2728	457.3	97.96	162	650
Km per hour	2728	148.53	28.45	24.61	205.26
Monthly jet fuel price in Euro's	2728	0.44	0.09	0.25	0.59
Fuel price per booking in Euro's	2728	0.351	0.495	0.004	4.195
GDP in Euro's	2728	40652.08	1918.94	37904.04	42896.24

3.2 Data description of rail cargo

The dataset of rail cargo consists of 5780 observations and is more than double than the number of air cargo observations. The main focus of Time Matters regarding air cargo does not lie in offering services within Germany, but international, while the rail service of Time Matters mainly operates within Germany. It is therefore not exceptional that the number of observations of rail cargo is significantly larger than air cargo in this dataset. The distribution of the historical data of the number of bookings for rail cargo is shown in Table 6. Table 6 shows a shift in market pairs when compared with Table 4. For instance, in the rail cargo dataset Berlin and Hamburg Central Station are mostly used as origin or destination station for rail transport, while Frankfurt and Munich airport are mostly used for air transport. Furthermore, Berlin is used as origin or destination for approximately 30 percent of the number of bookings for rail cargo, while in the air cargo dataset Berlin is only used for approximately 18 percent of the number of bookings. This clearly shows the difference between the two transport modes. The air cargo services use a hub-and-spoke network with Frankfurt and Munich as the main airport, while the rail cargo services operate on a point-to-point network.

Table 6 The number of observations of rail cargo demand per train station

Station	Number of times as Origin station	Number of times as Destination station	Total
Berlin Central Station	1593	1902	3495
Cologne Central Station	1054	590	1644
Dresden Central Station	416	171	587
Düsseldorf Central Station	266	427	693
Frankfurt Central Station	552	831	1383
Hamburg Central Station	1312	897	2209
Munich Central Station	587	962	1549
Total	**5780**	**5780**	

The descriptive statistics for the variables to determine the price elasticity of rail cargo demand are stated in Table 7. As mentioned, the train service of Time Matters is only bookable for passengers trains. Due to the limited space availability and the maximum weight conductors are allowed to lift, the maximum bookable weight of this service is 60 kilograms which must be divided over three shipments. Additionally, an average intercity train in Germany weights between 425 and 667 ton (Railway Technology, 2019). Therefore, this research assumes that the fuel or electricity consumption of a train is not correlated with the actual fare of Time Matters, since *(1)* the maximum bookable weight is significant small compared with the total weight of a train and since *(2)* this research assumes that the fuel consumption is proportional with the weight. Consequently, the fuel consumption is not considered as a variable for rail cargo.

Table 7 Descriptive statistics for the variables of rail cargo demand

Variable	**Number of observations**	**Mean**	**Standard deviation**	**Minimum value**	**Maximum value**
Price in Euro’s	5780	99.18	20.1	35.8	199.35
Weight in kg	5780	6.04	6.12	0.02	20
Distance in km	5780	477.43	154.5	41	812
Km per hour	5780	117.18	11.42	66.95	146.26
GDP in Euro’s	5780	40652.08	1918.94	37904.04	42896.24

The weight of rail cargo shipments varies from 0.02 to 20 kilograms and weight on average less than the air cargo shipments. Furthermore, the average price paid for the rail service is 99.18 euro’s with a minimum of 35.8 euro’s and a maximum of 199.35 euro’s. Figure 14 in the Appendix shows the distribution of the price and one could argue that the price variable of rail cargo is more normal distributed than the air cargo price (Figure 13, Appendix). However, the price of rail cargo has some outliers. Moreover, the rail cargo service is usually cheaper than the air cargo service, but on average the air cargo service is faster than the rail cargo service. The average kilometer travelled per hour for the rail service is 117.18 kilometer, while the air cargo service travels 148.53 kilometers per hour. As mentioned, the kilometer per hour variable is pending on the LAT, TOA and potential transfer. Figure 5 illustrates the difference in time per transport mode. On short distance, the rail service is significantly faster than the air service, since the time for the LAT and TOA of the rail service is lower than for the air service, but on long distances the opposite occurs. Another aspect that should be considered is the frequency. Normally, trains operate more frequently than flights during one day which could be seen as an advantage in case of an offloading. However, this research does not take the frequency into consideration when comparing the transport modes.

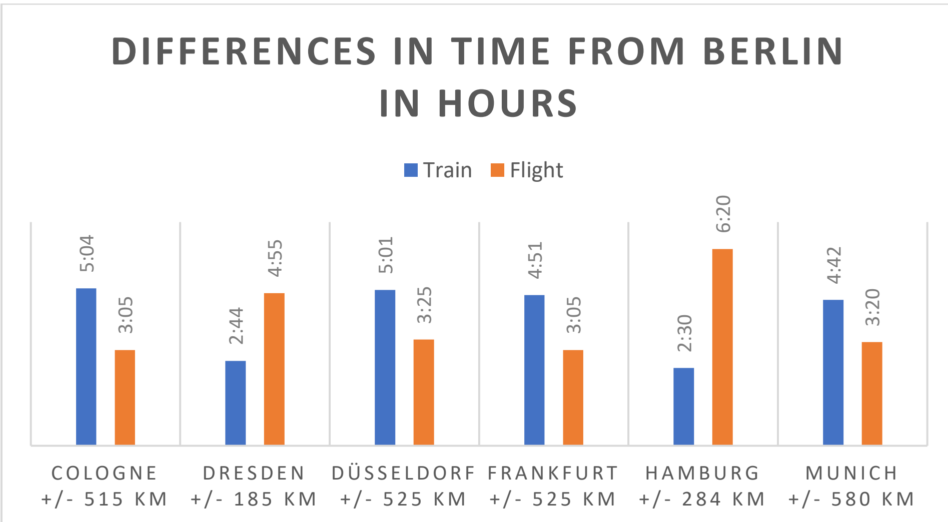

Figure 5 Differences in time in hours from Berlin to station per transport mode

4. Methodology

This research will study the effects of implementing a fuel tax on aviation for the network of Time Matters. To answer the research questions, this research will use a time series model to estimate the price elasticity of demand. Time series models are often used for price elasticity calculations, as can be seen in Table 1 and 2 in section 2.3. However, most of these models often have the problem of simultaneity. Simultaneity appears when X causes Y, but Y also causes X (Wooldrigde, 2013). Aviation prices are influenced by the demand, while demand is also influenced by the prices. Therefore, the aviation prices are endogenous, since the explanatory variable, price, is correlated with the error term, and an OLS model will be biased, since the coefficients of the price variable will be underestimated (Wooldrigde, 2013). In this research, the two-stage last squares (2SLS) model will be used to correct for the price endogeneity. In a 2SLS model instrumental variables are used to isolate the endogenous effect of the explanatory variable. The instrument must be correlated with the endogenous part of the explanatory variable but uncorrelated with the error term (Wooldrigde, 2013). Furthermore, this research will use a log-log functional form since the coefficient of the variable price shows the price elasticity of demand (Fukui & Miyoshi, 2017).

As mentioned in section 2.3, this research expects that the air cargo demand is price inelastic. Therefore, the first hypothesis to answer the research questions is as follows

Hypothesis 1: Air cargo demand is price inelastic

The price elasticity model will be split into two stages to answer the first hypothesis. The first stage of the 2SLS will isolate the endogenous effect of the price variable. Three different instruments will be used to control for this effect. Firstly, the natural logarithm of the variable kilometer per hour between the origin and destination. Distance has an impact on the price, but only influences the demand via the price and previous research has shown that distance is reliable instrument (IATA, 2008). Since the delivery time is an essential factor for an express critical service provider (CE Delft, 2018b), the variable kilometer per hour illustrates the correlation between the distance and the time. Therefore, the natural logarithm of the variable kilometer per hour will be used as an instrument. For the same reason the natural logarithm of the variable weight is used as an instrument. The weight of cargo does not affect the demand directly, but the price is pending on the weight of a shipment.

Lastly, the price of fuel will be used as an instrument. If the price of fuel increases, the price of air cargo will increase and according to the Law of Demand, the demand of air cargo will decrease, ceteris paribus. However, the fuel price has an indirect effect on demand and should therefore be used as an instrument to isolate the endogeneity of price. Additionally, the first, second and third lag of fuel price will be used to estimate the price elasticity. It is usually difficult for airlines to adjust in the short term to an increase of fuel price, since schedules and equipment allocations are relatively fixed. Therefore, the lagged fuel price variables are more realistic than using the fuel price variable of the same month (Fukui & Miyoshi, 2017).

The first stage regression for the model of hypothesis 1 is as follows

9. $Log\ (Price_t) = \beta 0 + \beta 1 * Log(KM\ per\ hour_t) + \beta 2 * Log(Weight_t) + \beta 3 * Log(Jet\ fuel\ price_t) + \beta 4 * Log(Jet\ fuel\ price_{t-1}) + \beta 5 * Log(Jet\ fuel\ price_{t-2}) + \beta 6 * Log(Jet\ fuel\ price_{t-3}) + \varepsilon t$

Where $Price_t$ is the historical price paid per booking in euro's, $KM\ per\ hour_t$ is the kilometres travelled per hour per market, $Weight_t$ is the actual weight in kilograms per booking, $Jet\ fuel\ price_t$ is the actual fuel price per booking and $Jet\ fuel\ price_{t-1}$, $Jet\ fuel\ price_{t-2}$ and $Jet\ fuel\ price_{t-3}$ are respectively the first, second and third lag of the $Jet\ fuel\ price_t$ and εt is the error term.

The second stage regression of the model is shown in formula 10.

10. $Log(Demand_t) = \beta 0 + \beta 1 * Log(Price_t) + \beta 2 * Log(GDP_t) + \beta 3 * Log(Month_t) + \varepsilon t$

Where $Demand_t$ represents the number of air cargo bookings in the given time frame, $Price_t$ is calculated in the first stage model as per formula 9, GDP_t is the yearly GDP per capita of Germany and $Month_t$ illustrate the month of the observation. As discussed in the data section, air cargo demand is season dependent. To control for the seasonality, this research includes a dummy variable of the month of the observation ($Month_t$). The month January will be used as a reference month and will not be included into the model. The error term is εt.

The price elasticity of the rail cargo demand is expected to be inelastic as well, as mentioned in section 2.3. The second hypothesis is as follows

Hypothesis 2: rail cargo demand is price inelastic

With the first and second hypothesis, the difference in price elasticity of the two transport modes and the degree of sensitivity between the transport modes will be addressed. As mentioned in the data section, this research assumes that the price of rail cargo is not correlated with the fuel consumption of a train. Therefore, the endogenous effect of the price variable will be isolated by two instruments: kilometer per hour and weight. The first stage regression model for hypothesis two is shown in formula 11.

11. $Log\ (Price_t) = \beta 0 + \beta 1 * Log(KM\ per\ hour_t) + \beta 2 * Log(Weight_t) + \varepsilon t$

Where $Price_t$ is the historical price paid per booking in euro's, $KM\ per\ hour_t$ is the kilometres travelled per hour per market, $Weight_t$ is the actual weight in kilograms per booking and εt is the error term.

The second stage regression is shown in formula 12, where $Demand_t$ represents the number of rail cargo bookings in the given time frame, $Price_t$ is calculated in the first stage model as per formula 11, GDP_t is the yearly GDP per capita of Germany, $Month_t$ illustrate the month of the observation and εt is the error term.

12. $Log(Demand_t) = \beta 0 + \beta 1 * Log(Price_t) + \beta 2 * Log(GDP_t) + Log(Month_t) + \varepsilon t$

Hypothesis one and two indicate that the demand of both air and rail cargo will decrease when the price of the transport mode increases. Since the high-speed rail is often promoted as a lower-carbon alternative to aviation on short-haul and/or domestic travel (Clewlow, Balakrishnan, & Sussman, 2013), this research will also examine the substitution effect of air and rail cargo transport. It is expected that the transport modes have a positive relationship, however, the degree of sensitivity between the transport modes is uncertain. The third hypothesis will examine this effect and is stated as follows

Hypothesis 3: An increase in the price of air cargo will result in a higher demand of rail cargo

To test the third hypothesis the 3SLS regression model will be used. Formula 9 and 11 calculated respectively the price of air cargo and rail cargo. However, to determine the cross-price elasticity of demand, the two transport modes should be equal. Therefore, the maximum bookable weight of the two transport modes will be adjust to 20 kilograms per shipment. All the observations of air cargo with a value above 20 kilograms will be deleted from the dataset. The number of observations of air cargo is reduced to 2555.

Since the rail cargo demand needs to be determined in hypothesis 3, the second stage regression is as follows

13. $Log(Train\ cargo\ demand_t) = \beta 0 + \ \beta 1 * Log(Train\ cargo\ Price_t) + \ \beta 2 * Log(Air\ cargo\ Price_t) + \ \beta 3 * Log(GDP_t) + \ Log(Month_t) + \ \varepsilon t$

Where $Train\ cargo\ demand_t$ represents the number of rail cargo bookings in the given time frame, $Train\ cargo\ Price_t$ is calculated in the first stage regression in formula 11, $Air\ cargo\ Price_t$ is calculated in the first stage regression in formula 9, GDP_t is the yearly GDP per capita of Germany, $Month_t$ illustrate the month of the observation and εt is the error term.

The cross-price elasticity can be calculated as per formula 4. Additionally, the coefficient of the price variable of formula 13 can be interpret as $\frac{\Delta Q}{\Delta P}$. The change in rail cargo demand is therefore as follows

14. $The\ change\ in\ rail\ cargo\ demand =$

$$price\ elasticity\ of\ air\ cargo\ demand * (\frac{Average\ price\ rail\ cargo}{average\ demand\ of\ rail\ cargo})$$

4.1 Scenario analysis

As mentioned before, the minimum excise duty rate for kerosene according to the European Energy Tax Directive 2003/96/EC is 0.33 euro per liter and every Member State may apply a level of taxation below the minimum excise duty rate (European Commission, 2003). To study the effects of implementing a fuel tax on kerosene, this research will perform three different scenario's for hypothesis one and three. In the first scenario the minimum excise duty rate of 0.33 euro per liter kerosene will be implemented. The second scenario will study the effect of a median rate of 0.20 euro per liter kerosene. Lastly, the third scenario will focus on a lower rate of 0.05 euro per liter kerosene. Additionally, this study assumes that the aviation market is a perfect competition, meaning that the tax is fully passed on to the customer and the price will therefore directly increase with the tax (Delipalla & O'Donnell, 1998).

The year 2018 will be used as the base year in the research, since this year is the most recent, complete year in the database. Furthermore, since the price elasticity is diffferent for every market, a 95% confidence interval of the price elasticity will be used to control for the amount of error in the sample mean (Sydsaeter & Hammond, 2012).

5. Results

5.1 Hypothesis 1: Air cargo demand is price inelastic

To test the first hypothesis, this research expects that the estimated sign of the coefficient of *Logprice Air cargo* is negative, meaning that the air cargo demand is price elastic or inelastic. Moreover, different models are predicted to test the degree of price elasticity. Firstly, normal OLS models are predicted to test whether the 2SLS model is valid. By comparing the coefficients of the OLS model to the coefficients of the 2SLS model, one could conclude whether the *Logprice Air cargo* variable is endogenous and which model is more accurate.

Table 8 shows the regression results of the OLS models with different variables. The first model only includes the months to control for seasonality. The month January is used as a reference, and therefore not included in the model. The coefficients of the months in all the six models are all significant, either on a 99% or 95% confidence interval. Furthermore, the signs of the month coefficient are the same in every model.

Model *(2), (3), (4)* and *(5)* include a different variable, which are respectively *LogGDP, Logweight, Log KM/per hour* and *Logfuelprice.* Moreover, model *(6)* includes all the mentioned variables. Out of the six models, only the coefficient of *Logprice Air cargo* in model *(2)* is negative, but not significant. The coefficient of *Logprice Air cargo* in the other models range from 0.157 to 0.745. The positive price elasticity implies that the air cargo demand will increase if the price of air cargo increases, which is contradictory with the theory of the Law of Demand and the expectation of this research. In model *(5)* and *(6)* the coefficient of *Logprice Air cargo* is the lowest, however, one could argue that the sign of *Logfuelprice* should be negative, since the fuel consumption of an aircraft has a positive correlation with the price, and therefore a negative relation with the demand. The same occurs for the *LogKM/per hour* variable, since the fuel consumption of an aircraft, and therefore the price, increases with the distance. Furthermore, the price is pending on the weight of a shipment and thus the expected sign of *Logweight* on demand is negative. Lastly, GDP has a positive correlation with the demand. Out of the five models with a positive, significant coefficient of *Logprice Air cargo,* model *(6)* including all of the variables seems to be the most accurate considering the above.

Additionally, the R-squared is the proportion of variance of the dependent variable, *LogDemand*, which can be predicted from the independent variable, *Logprice Air cargo,* (Sydsaeter & Hammond, 2012). One could argue that the higher the R-squared value, the better the model predicts. Considering all of the above, model *(6),* with a R-squared value of 0.738, is the most accurate OLS model and this particular model is chosen in this research. However, Table 9 shows the results of the Durbin–Wu–Hausman test for model *(6)*. The p-value indicates that the null-hypothesis needs to be rejected, meaning that the OLS model is inconsistent. According to this test, the OLS coefficients of model *(6)* are underestimated and *Logprice Air cargo* might be endogenous.

To test the validity of OLS model *(6)*, different 2SLS models are estimated, which are shown in Table 10. The 2SLS static model *(1)* is complementary to OLS model *(6)* in Table 8, however, the endogenous part of the *Logprice Air cargo* is isolated by different instruments. In 2SLS model *(1)* the variable *Logweight, Log KM/per hour* and *Logfuelprice* are used as an instrument. It is noteworthy that the coefficient of the *Logprice Air cargo* variable is significant and negative in the 2SLS static model *(1)* compared to the OLS model *(6)*. Furthermore, the magnitude and signs of the other variables remains approximately the same in both models. This shows that the OLS model is inconsistent and that the coefficient of the *Logprice Air cargo* is endogenous and thus underestimated in the OLS models.

As mentioned, it could be difficult for airlines to adjust to fuel price changes in the short term and therefore the lagged fuel price variables are more realistic (Fukui & Miyoshi, 2017). 2SLS model *(2)* and *(3)* include respectively one lag of fuel price and three lags of fuel price as an instrument. Comparing the three models, only minor changes in the magnitude of the variables are notable. Since the R-squared value of 2SLS model *(3)* is the highest, this research assumes that 2SLS model *(3)* is the most accurate model and the price elasticity of air cargo demand is -0.156.

Table 8 OLS results of six different models of hypothesis 1

Variable	OLS LogDemand (1)	OLS LogDemand (2)	OLS LogDemand (3)	OLS LogDemand (4)	OLS LogDemand (5)	OLS LogDemand (6)
Logprice Air cargo	0.488***	-0.0165	0.745***	0.608***	0.157**	0.224***
	(0.0455)	(0.0274)	(0.0699)	(0.0522)	(0.0642)	(0.0435)
LogGDP		16.21***				10.34***
		(0.223)				(0.397)
Logweight			-0.0981***			-1.337***
			(0.0203)			(0.0757)
Log KM/per hour				0.388***		-1.045***
				(0.0834)		(0.0838)
Logfuelprice					0.137***	1.298***
					(0.0190)	(0.0758)
February	0.211**	0.330***	0.217**	0.223**	0.217**	0.423***
	(0.0882)	(0.0514)	(0.0879)	(0.0879)	(0.0874)	(0.0488)
March	0.467***	0.601***	0.468***	0.468***	0.470***	0.598***
	(0.0846)	(0.0493)	(0.0843)	(0.0843)	(0.0838)	(0.0466)
April	0.490***	0.679***	0.485***	0.488***	0.484***	0.494***
	(0.0917)	(0.0534)	(0.0913)	(0.0913)	(0.0909)	(0.0516)
May	0.756***	0.777***	0.753***	0.759***	0.736***	0.537***
	(0.0871)	(0.0507)	(0.0867)	(0.0867)	(0.0863)	(0.0499)
June	0.819***	0.906***	0.826***	0.806***	0.779***	0.625***
	(0.0849)	(0.0494)	(0.0846)	(0.0846)	(0.0843)	(0.0495)
July	0.826***	0.984***	0.823***	0.820***	0.790***	0.569***
	(0.0848)	(0.0494)	(0.0845)	(0.0844)	(0.0842)	(0.0525)
August	0.972***	1.039***	0.970***	0.962***	0.927***	0.592***
	(0.0879)	(0.0511)	(0.0875)	(0.0875)	(0.0873)	(0.0548)
September	0.884***	1.127***	0.894***	0.882***	0.834***	0.714***
	(0.0924)	(0.0539)	(0.0921)	(0.0920)	(0.0918)	(0.0564)
October	0.899***	1.188***	0.899***	0.901***	0.873***	0.834***
	(0.0895)	(0.0522)	(0.0891)	(0.0891)	(0.0887)	(0.0535)
November	1.048***	1.222***	1.054***	1.045***	1.029***	1.074***
	(0.0945)	(0.0550)	(0.0941)	(0.0940)	(0.0936)	(0.0527)
December	1.049***	1.244***	1.046***	1.054***	1.043***	1.056***
	(0.0945)	(0.0550)	(0.0941)	(0.0940)	(0.0936)	(0.0531)
Constant	3.640***	-165.7***	2.366***	1.080*	4.996***	-102.0***
	(0.250)	-2.329	(0.362)	(0.605)	(0.310)	-4.347
Observations	2728	2728	2728	2728	2728	2728
R-squared	0.133	0.706	0.140	0.139	0.149	0.738

Robust standard errors in parentheses

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

Table 9 Durbin–Wu–Hausman test for OLS model (6)

F(1, 2713) = 8.21

Prob > F = 0.0042

Table 10 2SLS results of three different models of hypothesis 1

Variable	**2SLS static model LogDemand (1)**	**2SLS dynamic model with one lag LogDemand (2)**	**2SLS dynamic model with three lags LogDemand (3)**
Logprice Air cargo	-0.148***	-0.151***	-0.156***
	(0.0341)	(0.0335)	(0.0327)
LogGDP Air cargo	16.47***	16.42***	16.34***
	(0.227)	(0.223)	(0.218)
February	0.339***	0.314***	0.272***
	(0.0515)	(0.0507)	(0.0496)
March	0.599***	0.574***	0.531***
	(0.0493)	(0.0486)	(0.0476)
April	0.686***	0.661***	0.618***
	(0.0535)	(0.0527)	(0.0515)
May	0.777***	0.752***	0.711***
	(0.0507)	(0.0499)	(0.0489)
June	0.914***	0.889***	0.847***
	(0.0495)	(0.0487)	(0.0477)
July	0.986***	0.960***	0.918***
	(0.0494)	(0.0487)	(0.0477)
August	1.035***	1.010***	0.968***
	(0.0512)	(0.0504)	(0.0493)
September	1.119***	1.093***	1.049***
	(0.0540)	(0.0531)	(0.0520)
October	1.186***	1.160***	1.116***
	(0.0523)	(0.0515)	(0.0504)
November	1.222***	1.197***	1.155***
	(0.0551)	(0.0542)	(0.0530)
December	1.245***	1.220***	1.177***
	(0.0551)	(0.0542)	(0.0530)
Constant	-167.7***	-167.1***	-166.2***
	(-2.356)	(-2.317)	(-2.263)
Observations	2728	2727	2725
R-squared	0.704	0.708	0.714

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

Table 11 shows the 95% confidence interval of 2SLS model *(3)* of the coefficient of *Logprice Air cargo* and ranges between -0.22 and -0.093, meaning that the price elasticity of air cargo is between -1 and 0. When the price elasticity ranges from -1 to 0, the price elasticity is relatively inelastic (Anderson, McLellan, Overton, & Wolfram, 1997), which is in line with hypothesis one.

Table 11 95% confidence interval of the Logprice Air Cargo variable of the 2SLS model (3) of hypothesis 1

	Coefficient of Logprice air cargo	**95% confidence interval**	
Price elasticity of air cargo demand	-0.156	-0.22	-0.092

5.2 Scenario analysis hypothesis 1

In the previous section, the price elasticity of air cargo demand is discussed. The price elasticity of demand indicates the percentage change in demand if the price changes with 1% (Sydsaeter & Hammond, 2012).

This scenario analysis will elaborate on the effects of the air cargo demand after implementing the fuel tax. Three different levels of fuel tax will be analyzed, which are 0.33, 0.2 and 0.05 euro per liter kerosene used. Additionally, the actual price paid per booking will increase with the level of fuel tax multiplied by the actual fuel consumption per booking. Furthermore, the relative price change per booking is calculated by $\frac{new\ price - old\ price}{old\ price} * 100\%$.

In this research 2018 is used as a base year, therefore, the average relative price change in 2018 per level of fuel tax is calculated, which are respectively 17.01%, 10.31% and 2.58% for the different levels of taxation. Furthermore, in 2018 the number of air cargo bookings for Time Matters in the specific markets are 629. The percentage change in demand can be calculated by multiplying the average relative price change by the price elasticity. Table 12, 13 and 14 show the effect on the demand at the 95% confidence interval for tax level 0.33, 0.2 and 0.05 euro per liter respectively. This research expects that the air cargo demand will fall from 10.78% to 25.77% in scenario 1, from 10.16% to 24.29% in scenario 2 and from 9.44% to 22.59% in scenario 3, resulting that the air cargo demand will range between 467 and 570 in the scenarios. The upper side of the 95% confidence interval shows a bigger gap between the levels of taxation, than the price elasticity of -0.16 and -0.09 where the level of taxation differs approximately 2 percentage points.

Table 12 Scenario 1: change in air cargo demand because of the fuel tax with a rate of 0.33 euro per liter

	Price elasticity = -0.22	**Price elasticity = -0.16**	**Price elasticity = -0.09**
Demand in 2018	629	629	629
Percentage change in demand	-25.77%	-18.27%	-10.78%
New demand	467	514	561

Table 13 Scenario 2: change in air cargo demand because of the fuel tax with a rate of 0.20 euro per liter

	Price elasticity = -0.22	**Price elasticity = -0.16**	**Price elasticity = -0.09**
Demand in 2018	629	629	629
Percentage change in demand	-24.29%	-17.23%	-10.16%
New demand	476	521	565

Table 14 Scenario 3: change in air cargo demand because of the fuel tax with a rate of 0.05 euro per liter

	Price elasticity = -0.22	**Price elasticity = -0.16**	**Price elasticity = -0.09**
Demand in 2018	629	629	629
Percentage change in demand	-22.59%	-16.02%	-9.44%
New demand	487	528	570

5.3 Hypothesis 2: Rail cargo demand is price inelastic

To test the second hypothesis the same methodology as the first hypothesis will be used. However as discussed, the fuel price of rail cargo will not be included as a variable in the model, since this research assumes that the price of rail cargo is not correlated with the fuel consumption. Table 15 shows the results of the different models for hypothesis 2. For model *(1), (2), (3)* and *(4)* the OLS regression is used. The first model includes only the natural logarithm of the GDP and the months to control for seasonality, in model *(2)* the natural logarithm of kilometer per hour is added, in model *(3)* the natural logarithm of kilometer per hour is substituted by the natural logarithm of the weight and model *(4)* includes all the aforementioned variables. Comparing the four models, the magnitude and sign of the variables are approximately the same is all the models. However, the coefficient of the *Logprice Rail* variable is positive for the OLS models, while this research expected that the sign would be negative. Furthermore, the null-hypothesis of the Durbin-Wu-Hausman test, with p-value of 0.002, needs to be rejected, which indicated that the coefficients of the OLS models might be underestimated.

The natural logarithm of kilometer per hour and weight are used as instruments in 2SLS model *(5).* The coefficient of the *Logprice Rail* variable, and thus the price elasticity of rail cargo demand, has a negative value of 0.143. However, this variable is not significant. Besides the insignificance of the *Logprice Rail* variable, this research still assumes that the OLS parameters are biased and therefore the 2SLS Model *(5)* will be used. Table 16 shows that the 95% confidence interval of price elasticity of rail cargo demand ranges from -0.389 to 0.103. Due to the insignificance of the coefficient of the *Logprice Rail* the 95% confidence interval varies greater than the confidence interval of hypothesis 1 and hypothesis 2 can neither be accepted nor rejected.

Table 15 OLS and 2SLS results of five different models of hypothesis 2

Variable	OLS LogDemand (1)	OLS LogDemand (2)	OLS LogDemand (3)	OLS LogDemand (4)	2SLS LogDemand (5)
Logprice Rail	0.0867***	0.0954***	0.0961***	0.104***	-0.143
	(0.0329)	(0.0340)	(0.0329)	(0.0340)	(0.126)
LogKM/per hour		-0.0683		-0.0601	
		(0.0682)		(0.0681)	
Logweight			-0.0210***	-0.0209***	
			(0.00517)	(0.00517)	
LogGDP	16.07***	16.06***	16.08***	16.08***	16.26***
	(0.143)	(0.143)	(0.142)	(0.143)	(0.176)
February	0.461***	0.461***	0.460***	0.460***	0.461***
	(0.0350)	(0.0350)	(0.0349)	(0.0349)	(0.0351)
March	0.602***	0.601***	0.600***	0.600***	0.603***
	(0.0328)	(0.0328)	(0.0328)	(0.0328)	(0.0329)
April	0.809***	0.809***	0.810***	0.810***	0.808***
	(0.0331)	(0.0331)	(0.0331)	(0.0331)	(0.0332)
May	0.903***	0.903***	0.905***	0.905***	0.909***
	(0.0331)	(0.0331)	(0.0331)	(0.0331)	(0.0334)
June	0.988***	0.988***	0.988***	0.989***	0.995***
	(0.0335)	(0.0335)	(0.0334)	(0.0334)	(0.0338)
July	1.070***	1.070***	1.070***	1.071***	1.072***
	(0.0341)	(0.0341)	(0.0340)	(0.0340)	(0.0342)
August	1.162***	1.162***	1.162***	1.162***	1.167***
	(0.0332)	(0.0332)	(0.0332)	(0.0332)	(0.0334)
September	1.185***	1.185***	1.183***	1.183***	1.179***
	(0.0360)	(0.0360)	(0.0360)	(0.0360)	(0.0363)
October	1.204***	1.205***	1.210***	1.210***	1.203***
	(0.0363)	(0.0363)	(0.0363)	(0.0363)	(0.0364)
November	1.297***	1.297***	1.298***	1.298***	1.300***
	(0.0362)	(0.0362)	(0.0361)	(0.0361)	(0.0363)
December	1.305***	1.306***	1.305***	1.306***	1.309***
	(0.0368)	(0.0368)	(0.0367)	(0.0368)	(0.0370)
Constant	-164.1***	-163.7***	-164.2***	-163.9***	-165.1***
	-1.491	-1.529	-1.489	-1.527	-1.588
Observations	5780	5780	5780	5780	5780
R-squared	0.733	0.733	0.734	0.734	0.731

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 16 95% confidence interval of the Logprice Rail variable of the 2SLS model (1) of hypothesis 2

	Coefficient of Logprice	95% confident interval	
Price elasticity of rail cargo demand	-0.143	-0.389	0.103

5.4 Hypothesis 3: An increase in the price of air cargo will result in a higher demand of rail cargo

Hypothesis one and two both focus on one transport mode only. The third hypothesis will test the substitution effect of air and rail transport and therefore both transport modes are included in the model. A simple OLS regression is not suitable for hypothesis three, since hypothesis one and two concluded that the price of both transport modes is pending on different variables and multiple stages are needed to regress the model. Table 17 shows the results of the 3SLS models. The dependent variable of model *(1), (2) and (3)* is the rail cargo demand as per formula 13. Model *(1)* is the static 3SLS model where *Logweight, Log KM/per hour* and *Logfuelprice* are used as an instrument in the first stage of calculating the *Logprice Air cargo,* model *(2)* includes the first lag of the *Logfuelprice* variable in this stage and in model *(3)* the second and third lag of the *Logfuelprice* variable are added.

Also, in the models of hypothesis 3 the coefficients of the *Logprice Air cargo* variable are negative, range from -0.103 to -0.0822, however, the significance of the variable dropped to a 95% or 90% level. Besides this, the magnitude of the *Logprice Air cargo* variable dropped as well compared to Table 10 of hypothesis 1. The same occurs for the magnitude of the *Logprice Rail* variable when comparing to model *(5)* of hypothesis 2, however, the coefficient becomes significant on a 95% level in model *(3)*. A reason for the difference in magnitude and significance could be that the models of hypothesis 1 and 2 are suffering from omitted variable bias. The demand of rail cargo could be pending on the price of air cargo, vice versa, and therefore the coefficients of the 2SLS models of hypothesis 1 and 2 could be underestimated since the models do not include the price of the other transport mode. For this reason, the models in hypothesis 3 are better estimates.

Comparing model *(1), (2)* and *(3)* of hypothesis 3, the natural logarithm of GDP and the months do not show any significant difference in the models. Furthermore, since the R-squared value of model *(3)* is the highest and since the *Logprice Rail* variable becomes significant in this model, this research assumes that 3SLS model *(3)* is the most accurate model. The price elasticity of rail cargo demand is -0.055 and the 95% confidence interval ranges from -0.171 to 0.062, which varies less than the confidence interval of hypothesis 2.

As mentioned, the dependent variable of model *(1), (2)* and *(3)* is rail cargo demand. To obtain the price elasticity of the air cargo demand, the dependent variable in the model must be air cargo demand. Since 3SLS model *(3)* is the most accurate model, model *(4)* shows the results of using air cargo demand as the dependent variable with the same variables as model *(3)*. Comparing model *(3)* and *(4),* the magnitude and significance of the *Logprice Air cargo* variable differs significantly in both models, while the value of the magnitude of the *Logprice Rail* variable remains approximately the same but becomes insignificant in model *(4)*. Furthermore, the sign of natural logarithm of GDP and the months are the same in model *(3)*

Table 17 3SLS results of three different models of hypothesis 3 on rail and air cargo demand

Variable	**3SLS static model of LogDemand rail cargo (1)**	**3SLS dynamic model with one lag of LogDemand rail cargo (2)**	**3SLS dynamic model with three lags of LogDemand rail cargo (3)**	**3SLS dynamic model with three lags of LogDemand air cargo (4)**
Logprice Air cargo	-0.103**	-0.0925**	-0.0822*	-0.114***
	(0.0469)	(0.0457)	(0.0441)	(0.0320)
Logprice Rail	-0.0326	-0.0386	-0.0481**	-0.0549
	(0.0253)	(0.0247)	(0.0238)	(0.0594)
LogGDP	32.81***	32.75***	32.66***	16.19***
	(0.355)	(0.346)	(0.334)	(0.212)
February	0.807***	0.787***	0.754***	0.271***
	(0.0373)	(0.0364)	(0.0351)	(0.0493)
March	1.131***	1.111***	1.077***	0.533***
	(0.0345)	(0.0337)	(0.0325)	(0.0473)
April	1.373***	1.352***	1.318***	0.614***
	(0.0355)	(0.0346)	(0.0334)	(0.0513)
May	1.548***	1.527***	1.493***	0.713***
	(0.0353)	(0.0344)	(0.0333)	(0.0487)
June	1.709***	1.688***	1.654***	0.846***
	(0.0354)	(0.0346)	(0.0334)	(0.0475)
July	1.774***	1.753***	1.720***	0.920***
	(0.0364)	(0.0356)	(0.0344)	(0.0475)
August	2.142***	2.120***	2.084***	0.972***
	(0.0420)	(0.0410)	(0.0396)	(0.0491)
September	2.390***	2.368***	2.332***	1.060***
	(0.0432)	(0.0421)	(0.0407)	(0.0517)
October	2.496***	2.474***	2.438***	1.120***
	(0.0466)	(0.0454)	(0.0439)	(0.0501)
November	2.583***	2.561***	2.524***	1.157***
	(0.0451)	(0.0440)	(0.0425)	(0.0528)
December	2.660***	2.637***	2.600***	1.179***
	(0.0475)	(0.0463)	(0.0447)	(0.0528)
Constant	-340.5***	-339.9***	-338.9***	-164.7***
	-3,726	-3,637	-3,513	-2.241
Observations	2555	2554	2552	2552
R-squared	0.832	0.838	0.845	0.719

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

and *(4)*, but the value of the variables is significantly lower. Based on model *(4)*, the price elasticity of air cargo demand is -0.114 and the 95% confidence interval ranges from -0.177 to -0.052, which is shown in Table 18. Also in this model, the air cargo demand is price inelastic.

Table 18 95% confidence interval of the Logprice Air cargo variable of the 3SLS model (4) of hypothesis 3

	Coefficient	**95% confident interval**	
Price elasticity of air cargo demand	-0.114	-0.177	-0.052

Formula 14 shows the calculation of the cross-price elasticity. To obtain the cross-price elasticity, the price elasticity of the air cargo demand is multiplied by the ratio of average rail cargo price and demand. The 95% of the cross-price elasticity between air and rail cargo demand is displayed in Table 19 and ranges from -2.693 to -0.791. The negative value of the cross-price elasticity indicates that air and rail cargo are complementary services, which means that the demand of rail cargo decreases as a reaction of the increased price of air cargo. One critical note must be made here: the data of only one express critical service provider is used. Additionally, the main association of this service provider is airfreight. Therefore, it could be possible that customers switch to another service provider with different associations, for instance road or rail transport, when a fuel tax on air cargo is implemented. The negative cross-price elasticity suggests thus that the rail cargo demand of Time Matters will decrease, but a modal shift on industry level could still be feasible.

Table 19 95% confidence interval of the cross-price elasticity bases on 3SLS model (4) of hypothesis 3

	Coefficient	**95% confident interval**	
Cross-price elasticity	-1.734	-2.693	-0.791

5.5 Scenario analysis hypothesis 3

This scenario analysis will elaborate on the effects of air and rail cargo demand after implementing the fuel tax. The same levels of fuel tax as in scenario analysis of hypothesis 1 will be analyzed, which are 0.33, 0.2 and 0.05 euro per liter kerosene used. Additionally, the actual price paid per booking will increase with the level of fuel tax multiplied by the actual fuel consumption per booking. The average relative air cargo price changes in 2018 are 13.38%, 8.11% and 2.03% respectively to the level of fuel taxes.

The number of air cargo bookings with a weight of less than 20 kilograms within Germany in 2018 is 548. The percentage change in air cargo demand can be calculated by multiplying the average relative price change by the price elasticity. Table 20, 21 and 22 shows the effect on the demand at the 95% confidence interval for tax level 0.33, 0.2 and 0.05 euro per liter respectively.

Based on the price elasticity of air cargo demand in 3SLS model *(4),* this research expects that the air cargo demand will fall from 5.90% to 20.07% in scenario 1, from 5.62% to 19.14% in scenario 2 and from 5.31% to 18.06% in scenario 3, resulting that the air cargo demand will range between 438 and 519 in the scenarios. The drop of demand in the different scenario's is lower compared to the scenario analysis of hypothesis 1. This is a result of the less elastic price of 3SLS model *(4).*

Furthermore, the cross-price elasticity of demand indicates the percentage change in demand of product Y if the price of product X changes with 1% (Sydsaeter & Hammond, 2012). The demand of rail cargo can be calculated by multiplying the cross-price elasticity by the average relative price change of air cargo demand. The demand of rail cargo for the specified market in 2018 is 1509. This research expects that the rail cargo demand will fall from 10.59% to 36.03% in scenario 1, from 21.84% to 6.42% in scenario 2 and from 5.47% to 1.61% in scenario 3, resulting that the rail cargo demand will range between 965 to 1485 in the scenarios.

When comparing the percentage change in air cargo demand with the percentage in rail cargo demand, one could argue that the rail cargo demand is more sensitive to the fuel tax level than the air cargo demand, which is contradictory with the expectations of this research.

Table 20 Scenario 1: change in demand because of the fuel tax with a rate of 0.33 euro per liter

	Cross-price elasticity = -2.69	**Cross-price elasticity = -1.73**	**Cross-price elasticity = -0.79**
Price elasticity of Air cargo demand	-0.177	-0.114	-0.052
Percentage change in Air cargo demand	-20.07%	-12.93%	-5.90%
Air cargo demand in 2018	548	548	548
New demand air cargo demand	438	477	516
Percentage change in Rail cargo demand	-36.03%	-23.20%	-10.59%
Rail cargo demand in 2018	1509	1509	1509
New demand rail cargo demand	965	1159	1349

Table 21 Scenario 2: change in demand because of the fuel tax with a rate of 0.20 euro per liter

	Cross-price elasticity = -2.69	**Cross-price elasticity = -1.73**	**Cross-price elasticity = -0.79**
Price elasticity of Air cargo demand	-0.177	-0.114	-0.052
Percentage change in Air cargo demand	-19.14%	-12.32%	-5.62%
Air cargo demand in 2018	548	548	548
New demand air cargo demand	443	480	517
Percentage change in Rail cargo demand	-21.84%	-14.06%	-6.42%
Rail cargo demand in 2018	1509	1509	1509
New demand rail cargo demand	1179	1297	1412

Table 22 Scenario 3: change in demand because of the fuel tax with a rate of 0.05 euro per liter

	Cross-price elasticity = -2.69	**Cross-price elasticity = -1.73**	**Cross-price elasticity = -0.79**
Price elasticity of Air cargo demand	-0.177	-0.114	-0.052
Percentage change in Air cargo demand	-18.06%	-11.63%	-5.31%
Air cargo demand in 2018	548	548	548
New demand air cargo demand	449	484	519
Percentage change in Rail cargo demand	-5.47%	-3.52%	-1.61%
Rail cargo demand in 2018	1509	1509	1509
New demand rail cargo demand	1427	1456	1485

6. Conclusion and discussion

This research studied the effect of implementing a fuel tax on the air cargo sector for the company Time Matters by calculating the price and cross-price elasticity of air and rail cargo demand. The intuition of this research is to determine if fuel tax could be used as an instrument for CO_2 reduction policies, since multiple studies Brons, Pels, Nijkamp, & Rietveld (2002), Fukui & Miyoshi (2017) and Olsthoorn (2001) argue that effective financial instruments could discouraging climate unfriendly activities.

Hypothesis one of this study states that the air cargo demand is price inelastic. The results of this study imply that the 3SLS model, including both air and rail prices, is the most accurate model. According to this model, the price elasticity of air cargo demand ranges from -0.177 to -0.052 on specific, domestic routes in Germany and it thus price inelastic, which is in line with the first hypothesis. Previous research on price elasticity of domestic air cargo demand, found air cargo demand to be price elastic and thus more price senstitive (Wang, Maling, & McCarthy (1981), Tally & Schwarz-Miller (1988) and Chi & Baek (2012)). However, all of this studies focus on the domestic U.S. market. The German aviation market is significantly smaller than the U.S. aviation market. The use of different markets could be a possible explanation of the different values of price elasticity (Hwang & Shiao, 2011). Furthermore, the validity of the model of Chi & Baek (2012) is questionable due to the endogeneity problem and the research of Wang, Maling, & McCarthy (1981) could be outdated since data of before the deregulation of the U.S. airline industry is used (Goetz & Sutton, 1997). Looking at the methodology, this research is mostly in line with the research of Lo, Wan, & Zhang (2015), whoms results also reflect a price inelasticity of air cargo demand, but the air cargo demand is more price sensitive in the study of Lo, Wang & Zhang (2015). Lo, Wang & Zhang (2015) concluded that the air cargo demand becomes more price sensitive after a shock, for instance the 2008 financial crisis. Comparing the time range, the study of Lo, Wang and Zhang (2015) contained more shocks than this study, which could be an explanation of the lower price sensitivity.

Furthermore, the price elasticity of hypothesis one is used to determine the effects of a fuel tax in the scenario analysis. According to the scenario analysis, the domestic air cargo demand of Time Matters will result in a reduction of 5.31% to 20.07%, when 2018 is used as a reference year. However, the relative change of demand remains approximately the same among the three different tax levels and levels of price elasticity. One could argue that scenario 1, with a tax level of 0.33 euro per liter, is the most efficient tax level since the air cargo demand will decrease the most and the financial results will be the highest. However, if airlines can pass on all the extra cost to the customers without significantly decreasing the demand, than the effect of the policy is only increasing the authorities revenue (Brons, Pels, Nijkamp, & Rietveld, 2002). These extra authorities revenue could be used for climate policies such as the "Masterplan for rail freight transport" from the German ministery of Transport and Digital Infrastructure to improve environmentally-friendly modes of transports (BMVI, 2017). If policies makers are not using these extra revenues for related policies, than the effectiviness of the fuel tax policy is questionable. Moreover, the outcome of the scenario analysis suggests that the air cargo demand will decrease as a result of the fuel tax. The fuel tax could therefore have a positive environmental impact by reducing $\mathrm{CO_2}$ emissions. Due to the price inelasticity, the scope and size of the impact are however according to this research very limited, which is the same conclusion as the study of Olsthoorn (2001) and Fukui & Miyoshi (2017) on general aviation. Therefore, it is questionable if a fuel tax is the optimal policy to reduce $\mathrm{CO_2}$ emissions in the aviation sector.

The second hypothesis examined the price elasticity of rail cargo demand. According to the 3SLS model, the price elasticity of rail cargo demand is -0.055 and the 95% confidence interval ranges from -0.171 to 0.062 on specific, domestic routes in Germany and it thus price inelastic, which is in line with hypothesis 2. Comparing the price elasticity of air and rail cargo demand, one could argue that the rail cargo demand is slightly less price sensitive than air cargo demand, which is the same conclusion as Mitra & Leon (2014). Previous research of rail cargo demand of Table 2 mainly conducted a lower absolute value and thus a more price sensitive demand. However, the market of the previous studies could also for rail cargo be a possible explanation of the different values of price elasticity. The German rail cargo market differs from the U.S., Canadian and Indian rail cargo market. Furthermore, besides the study of Mitra & Leon (2014), the estimates of the previous research could be outdated since 1989 is the latest oberservation year. Additionally, none of these studies controlled for the endogeneity problem and could therefore give different estimates of the rail cargo price elasticity.

Lastly, the third hypothesis examined the substitution effect of air and rail cargo demand with the cross-price elasticity analysis. The results of the 3SLS model indicates a negative cross-price elasticity of air and rail cargo demand, meaning that the two transport modes are complementary. The negative relationship indicates that the demand of rail cargo will decrease as a reaction of the increased price of air cargo due to the fuel tax, which is contradictory with hypothesis 3. Additionally, the relative reduction of rail cargo demand for the different levels of taxation ranges from 1.61% to 36.3%, while the relative reduction of air cargo demand ranges from 5.31% to 20.07%. This indicates that the rail cargo demand is more sensitive to the fuel tax level than the air cargo demand. According to these results, a fuel tax on air cargo will not result in a modal shift towards the more environmental friendly mode of transport; rail.

However, one should be very careful when interpreting these results. The data used in this research solely focus on one express critical provider; Time Matters. The main focus of Time Matters, and Lufthansa Cargo, is air freight transport. The rail service only accounts for a small proportion of the business of Time Matters. It is therefore possible that customers associate this express critical provider only with air freight services. When a fuel tax on domestic aviation is implemented, the total demand of Time Matters could decrease and customers could potentially switch to other service providers whom association lies in other modes of transport, for instance road or rail. If this is the case, than the total demand of air and rail cargo of Time Matters will decrease as a result of the fuel tax, but that does not mean that a modal shift towards rail cargo on industry level is not feasible. Further research on industry level is required to examine this effect. Futhermore, the number of observations could give biased results. As mentioned before, the rail service of Time Matters mainly operates within Germany, while the focus of the air service is on international level. For this reason, the number of observations in this dataset of the domestic rail service is almost three times higher than the number of oberservations of the domestic air service.

Moreover, the research of Mitchell (2010) showed opposite results for two different types of models. The first model of Mitchell (2010) indicated a negative relationship between two transport modes, which is the same conclusion as in this research, while the second model a positive cross-price elasticity between the transport modes predicted. Therefore, the methodology used in this research could also be a reason of the contradictory results compared to the previous research on cross-price elasticity of cargo transport modes. According to Wijeweera, To, & Charles (2014), estimates of cargo demand could suffer from two major limitations; *(1)* the aggregation data bias and *(2)* the endogeneity bias. This research controlled for the endogeneity bias by using instruments to isolate the endogenous effect of the explanatory variable, price, in a 3SLS model. However, the estimates of this research could suffer from the aggregation data bias limitation. Previous research, for instance, Lewis & Widup (1982), Abdelwahab (1998) and Beuthe, Jourquin, & Urbain (2014) used disaggregate demand when analyzing the cross-price elasticity of two transport modes, while this research used aggregate demand. Abdelwahab (1998) found a significant variation of the price elasticity of demand between different commodity groups and geograpic areas. Additionally, according to Hwang & Shiao (2011) one possible explanation of different price sensitivities of air cargo demand is the market and data used in the research. For instance, electronic products have a high value-to-weight ratio and is thus less price sensitive compared to low value-to-weight ratio products

(Hwang & Shiao, 2011). Furthermore, the value of a shipment could determine the willingness to pay of a customer and be a relevant variable in explaining the air cargo demand (Chi & Baek, 2012). This illustrates that the commodity and/or value of the shipment could indicate the price sensitivity of the shipment. Therefore the use of aggregate demand could give biased estimates compared to a disaggregate demand. However, one should also note that the previous research of Lewis & Widup (1982), Abdelwahab (1998) and Beuthe, Jourquin, & Urbain (2014) did not control for the endogeneity bias and their estimates could therefore also be biased.

When implementing a fuel tax on aviation kerosene, this research found that the air cargo demand will decrease as a result of the tax. The fuel tax could therefore have a positive environmental impact by reducing CO_2 emissions. The scope and size of the impact are however according to this research very limited. Furthermore, the results show that a modal shift towards rail cargo transport is not feasible. The demand of rail cargo transport for Time Matters even decreases because of the aviation fuel tax. However, this research suffers from some limitations, which will be discussed in the next section.

6.1 Limitations and further research

The focus on one logistic service provider is also the first limitation of this research. The relatively small number of observations could give a biased estimation for the industry. Furthermore, the use of aggregate demand is the second limitation of this research. As mentioned in the previous section, the use of aggregate demand could give biased estimates compared to a disaggregate demand, since the commodity and/or value of the shipment could indicate the price sensitivity of the shipment. Due to the unavailable data on the commodity and the value of the shipment from Time Matters, this research did not include disaggregate demand and the value characteristic in the estimation of the price elasticity. For further research it is suggested to control for both the aggregation data bias and the endogeneity bias. Furthermore, this research only studied two transport modes and did not included the frequency of the transport modes in the model, while frequency is also a decision criteria for express critical services (CE Delft, 2018b). An avenue for further research is to control for the characteristic frequency and to include more transport modes, like road transport, into the model.

Additionally, this research assumes that the fuel tax is completely passed on to the customers. However, it is not likely that aviation markets are a perfect competition, since the competition in every market is different and price dispersion consists in aviation. An oligopoly market structure is more likely and therefore, a complete pass on to customers in all the markets is not realistic. Besides the pass on to customers, this research assumes that change in demand is only affected by an increase in the price due to a tax and does not control for any other effects on aviation demand, for instance fuel choices of airlines. Furthermore, as discussed in Chapter 2, this research does not consider the phenomenon “tankering”. Since only domestic aviation is not exempted from fuel taxes according to regulations, airlines could potentially choose to fuel the aircraft internationally. The estimates in this research could be biased since this research did not control for this phenomenon. For further research, it could be intestering to research the effects of a fuel tax on international level instead of a domestic level. Policy makers could control for the phenomenon “tankering”, but also need to modify the regulations, such as the European Energy Tax Directive 2003/96/EC. Additionally, further research should included different options on who could carry the financial burder of the fuel tax.

Furthermore, due to the price inelasticity of air cargo demand and the negative cross-price elasticity, it is questionable whether a fuel tax is the optimal policy for obtaining a modal shift in freight transport to reduce CO_2 emissions. According to Mayor & Tol (2007), the optimal policy to reduce emissions would be to tax emissions directly. An interesting avenue of research for further studies is to examine the effects of other types of taxes, for instance a carbon tax or noise tax. These taxes could have a direct impact on airlines by for instance giving them an incentive to operate with greener aircrafts and could therefore result in a positive environmental impact.

However, besides taxation, airlines could obtain another incentive to achieve a positive environmental impact. For instance, CORSIA aims for a carbon-neutral growth from 2020 onwards. As a result, aircraft manufactures produce more greener aircrafts and airlines, such as Lufthansa Group, concentrate on green flying and offers customers a program to offset CO_2 emissions. Additionally, governments are nowadays implementing or suggesting other policies than taxes to reduce CO_2 emissions from the aviation sector or to obtain a modal shift towards environmentally-friendly transport modes, for instance the “Masterplan for rail freight transport” of the German government (BMVI, 2017). Moreover, the Ministry of Infrastructure and Water Management of the Netherlands recently announced that from 2023 onwards the aviation sector needs to use biokerosene to reduce the CO_2 emissions (NRC, 2020). Further research is needed to study if policy makers could increase the incentive of airlines to reduce CO_2 emissions without the use of taxes.

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8. Appendix

Figure 6 The train stations of the IC:Kurier service. Retrieved from: Time:Matters (2019)

Figure 7 Airport of the Sameday service. The red airports are located in Germany. Retrieved from: Time:Matters (2019)

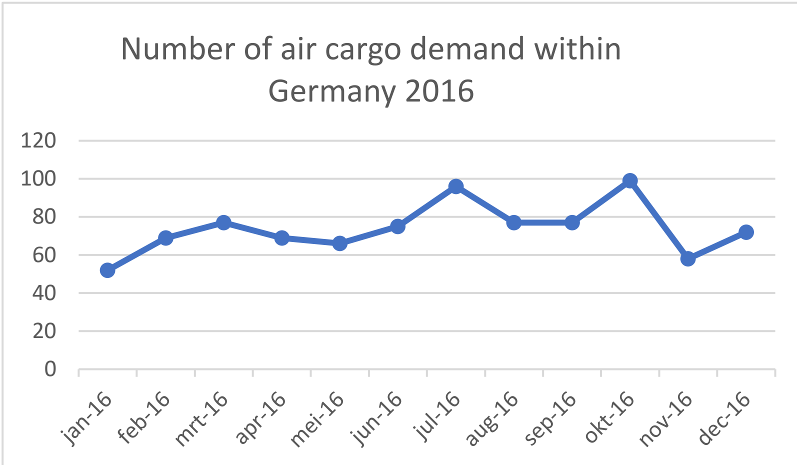

Figure 8 Number of observations of air cargo demand within Germany 2016

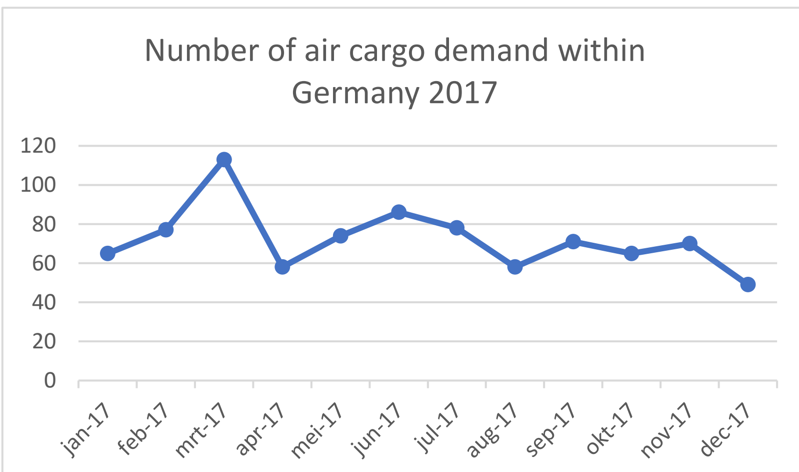

Figure 9 Number of observations of air cargo demand within Germany 2017

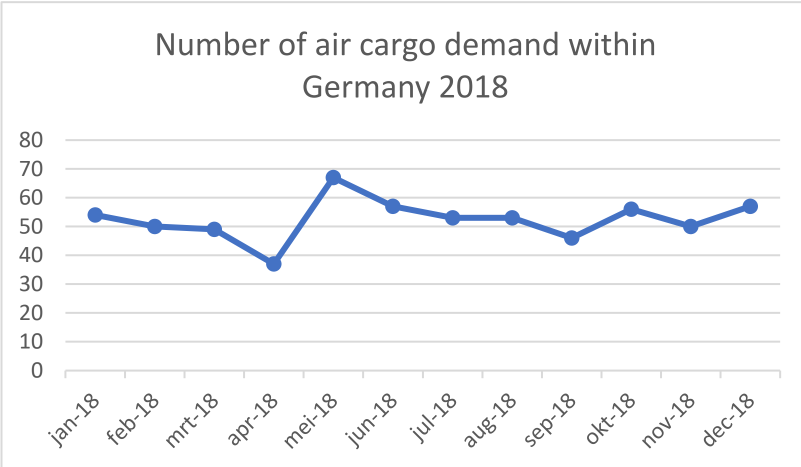

Figure 10 Number of observations of air cargo demand within Germany 2018

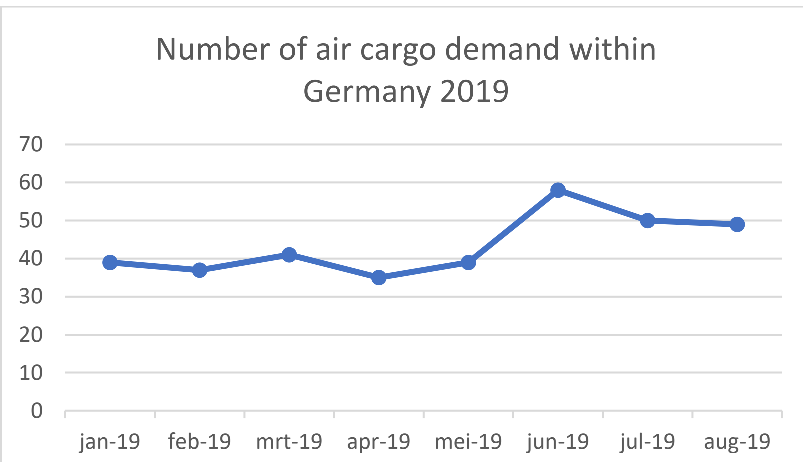

Figure 11 Number of observations of air cargo demand within Germany from January until August 2019

Table 23 Fleet of Lufthansa Group. Source: Lufthansa Cargo (2019) and Lufthansa Magazin (2019)

Aircraft	**Number in Fleet**	**Maximum number of passengers**	**Maximum cargo capacity in kg**
Airbus A380-800	14	509	11860
Boeing 747-8	19	364	16910
Boeing 747-400	13	371	12880
Airbus A350-900	12	293	Not known
Airbus A340-600	17	297	11420
Airbus A340-300	15	279	15780
Airbus A330-300	15	255	17230
Airbus A321-100/200	63	200	2830
Airbus A320-200	76	168 or 180	590 to 1750
Airbus A319-100	30	138	1640 to 2000

Embraer 195	17	120	1180 to 1620
Embraer 190	9	100	1180 to 1620
Bombardier CRJ900	35	90	Not known

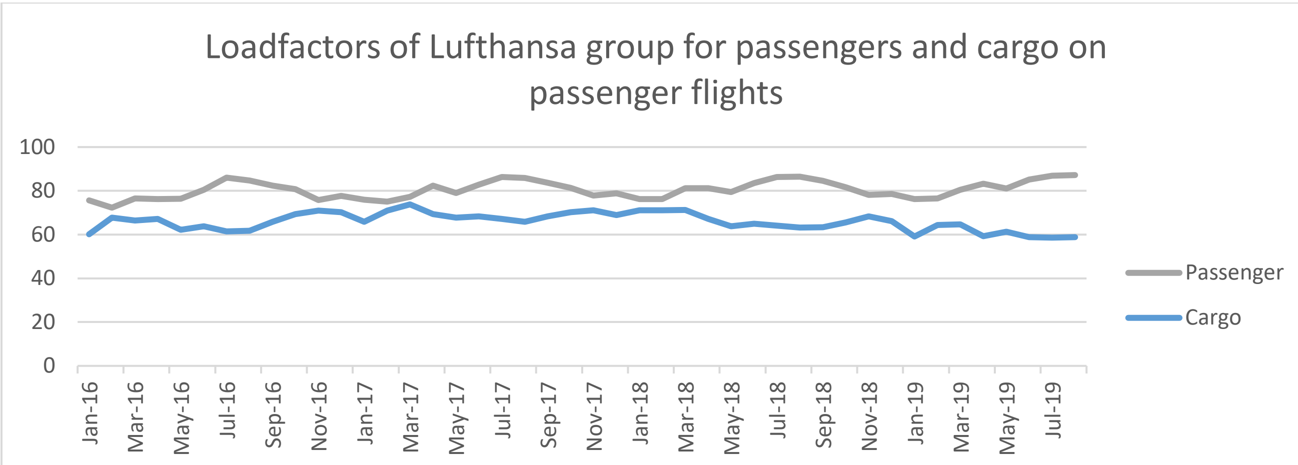

Figure 12 Load factors of Lufthansa group for passengers and cargo on passenger flights from January 2016 to August 2019

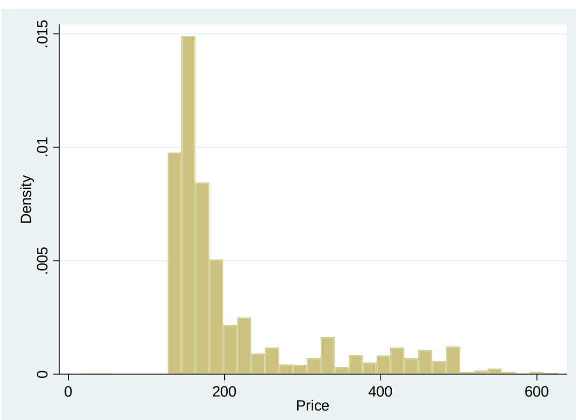

Figure 13 Absolute price levels of historical air cargo bookings

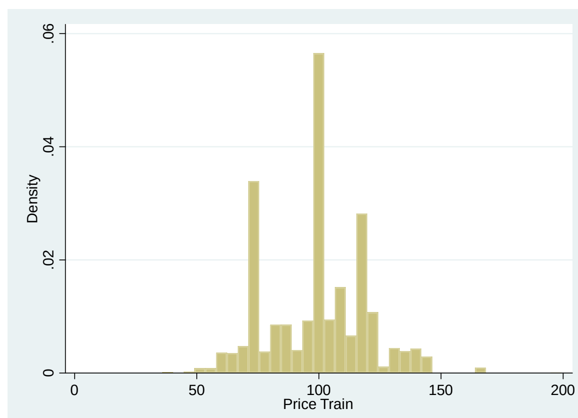

Figure 14 Absolute price levels of historical rail cargo bookings

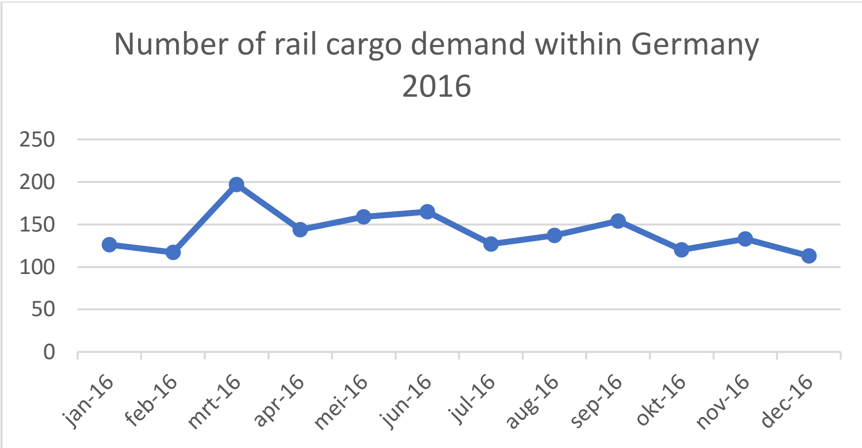

Figure 15 Number of observations of rail cargo demand within Germany 2016

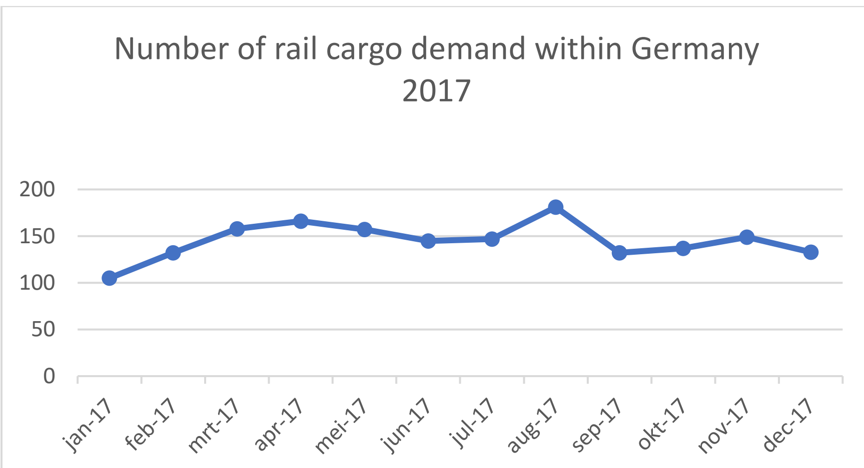

Figure 16 Number of observations of rail cargo demand within Germany 2017

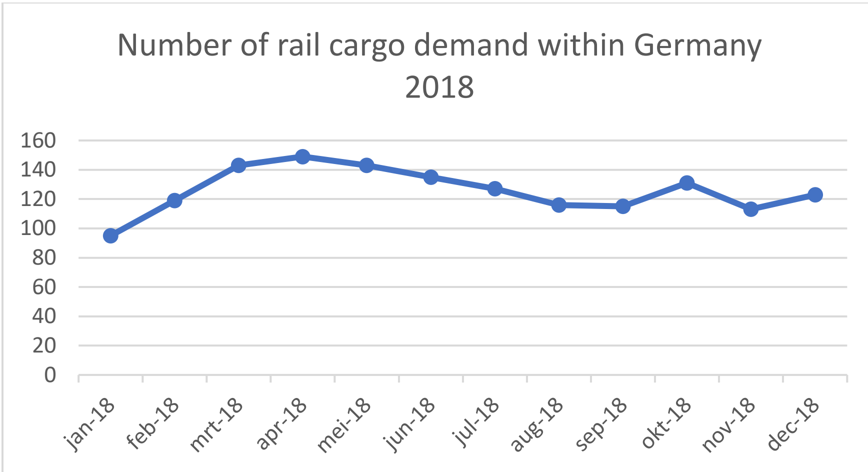

Figure 17 Number of observations of rail cargo demand within Germany 2018

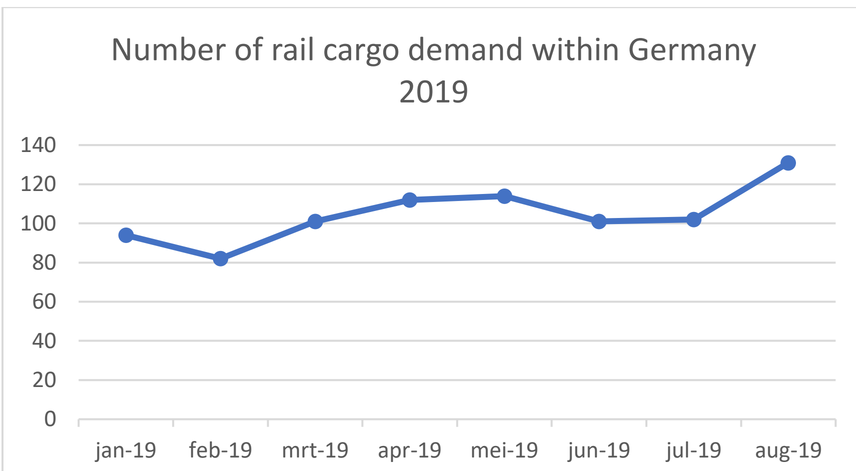

Figure 18 Number of observations of rail cargo demand within Germany 2019

Table 24 Description of the variables

Variable	Description	Type
GDP	The GDP per capita of Germany in euro's per year	Continuous
LogGDP	The natural logarithm of the GDP per capita of Germany per year	Continuous
Month	The order was booked in a specific month (1) or not (0)	Binary
	Air cargo	
Demand of Air cargo	Historical data of the number of bookings of air cargo	Discrete
Logdemand of Air cargo	The natural logarithm of the demand of air cargo	Discrete
Price Air cargo	Historical data of the price of air cargo bookings in euro's	Continuous
Logprice Air cargo	The natural logarithm of the price of air cargo	Continuous
Weight Air cargo	Historical data of the actual weight per shipment in kg	Continuous
Logweight Air cargo	The natural logarithm of the weight per shipment	Continuous
Distance Air cargo	The actual flight distance between airports in km	Continuous
Time Air cargo	The time needed to go from airport A to airport B	Continuous
KM/per hour Air cargo	The number of km travelled per hour (=Distance / Time)	Continuous
LogKM/per hour Air cargo	The natural logarithm of the KM/per hour	Continuous
Monthly jet fuel price	The actual jet fuel price per month in euro's	Continuous
Jet fuel price	The price of jet fuel consumption per actual booking in euro's	Continuous
LogJet fuel price	The natural logarithm of the jet fuel price per shipment	Continuous
Log Jet fuel price_1	The first lag of the natural logarithm of the jet fuel price per shipment	Continuous
Log Jet fuel price_2	The second lag of the natural logarithm of the jet fuel price per shipment	Continuous
Log Jet fuel price_3	The third lag of the natural logarithm of the jet fuel price per shipment	Continuous
	Rail	
Demand of Rail cargo	Historical data of the number of bookings of rail cargo	Discrete
Logdemand of Rail cargo	The natural logarithm of the demand of rail cargo	Discrete
Price Rail cargo	Historical data of the price of rail cargo bookings in euro's	Continuous
Logprice Rail cargo	The natural logarithm of the price of rail cargo	Continuous
Weight Rail cargo	Historical data of the actual weight per shipment in kg	Continuous
Logweight Rail cargo	The natural logarithm of the weight per shipment	Continuous
Distance Rail cargo	The actual flight distance between rail stations in km	Continuous
Time Rail cargo	The time needed to go from station A to station B	Continuous
KM/per hour Rail cargo	The number of km travelled per hour (=Distance / Time)	Continuous
LogKM/per hour Rail cargo	The natural logarithm of the KM/per hour	Continuous