ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

MASTER THESIS

Urban Port and Transport Economics

Exploring the relationship between the estimated cost of carbon emissions in passenger flights and the reported cost of compensation: a case study of KLM passenger flights from Schiphol Airport

Name Student: Sjors Smits

Student ID number: 665522

Supervisor: Susan Vermeulen MSc

Second assessor: dr. Yannis Kerkemezos

Date final version: 30-08-2023

Acknowledgements

You will be reading my master thesis for the Master of Urban Port and Transport Economics. This thesis will mark the end of my study time at the Erasmus University. I hope my work will be of use in the field of air transport economics.

My interest in any form of transport that had wheels or would float has been with me from an early age. My study reignited this passion and made me look at the aviation sector from different perspectives. Sustainability never felt like a hot topic, but I started appreciating the technical challenges and their economic consequences. I heard of the concept of "carbon offsetting", which interested me as it felt like a commercial solution for a technical problem. I strolled down several websites and was surprised by carbon compensation options offering trees to compensate for your emissions. I was immediately interested in the concept and its relationship with the actual cost of carbon emissions. The passion for aviation and the urge to get to the bottom of this relationship made me write about this subject.

The writing process has been challenging but joyful and a good learning experience. I want to thank my supervisor, Susan Vermeulen, for the feedback and support throughout this process. I would also like to thank Yannis Kerkemezos for reading and assessing this thesis.

Abstract

The aviation sector, challenged by technological constraints and high costs, struggles to achieve sustainability despite the imperative to reduce its climate impact. While flying less remains an optimal strategy, the allure and necessity of air travel persist. Therefore, other ways of mitigating its impact have risen, like carbon offsets. However, this market is relatively unregulated, and the credibility and pricing of these offsets have been questioned in the literature. This paper will explore the relationship between the reported and the estimated cost of carbon compensation in aviation, using a case study of KLM passenger flights. Data on emissions and compensation costs from in- and outbound flights of Schiphol Airport is collected. These reported values will be compared with estimated values using a fuel-burn estimation model and the Social Cost of Carbon to estimate the cost of carbon. This analysis will be conducted using a paired sample t-test. The results suggest that, on average, the reforestation option is undervalued compared to the Social Cost of Carbon. However, using sustainable aviation fuel as a compensation option is a significantly higher valuation than the estimated cost of carbon. In addition, only small differences are found between the reported and estimated CO2 emissions in KLM flights. This study complements the understanding of reported and estimated costs of carbon emissions and highlights the importance of transparency, methodology refinement, and the critical evaluation of compensation alternatives. It could help future research on carbon valuation and compensation in aviation.

Keywords: cost of carbon, CO2 emissions, air travel, fuel-burn model, carbon offsets, Social Cost of Carbon, paired sample t-test

Table of Contents

1. Introduction

The problem of the negative externalities of flying, particularly its significant contribution to carbon emissions, has been in the news lately. True Price (2023), a corporation developing methods for measuring societal impact, published a report estimating the actual price of flying, considering environmental damage. They stated that, for example, an airline ticket from Amsterdam to Barcelona should be €239.22 instead of €90 in the off-season when considering all environmental costs (True Price, 2023). The Dutch public news organization NOS (2023) reported that, in the Netherlands, from 2023 onwards, the flight tax has been raised to €26, and airlines will pay for their carbon emissions on European flights. This shows that flying is widely considered environmentally damaging, especially for short distances where more sustainable alternatives are available. Corporations and governments are working towards a net zero set by the Paris Agreement (UNFCCC, 2015) and trying to find the best ways to price these emissions.

Aviation contributed 11.6% of the total CO2 emissions from transport worldwide in 2018 (IEA, 2021; Ritchie, 2020). Notably, the majority, about 74.5%, of emissions come from road vehicles. While this statistic might initially suggest that aviation's impact is relatively modest, the context changes when considering the number of air transport travellers. Merely 2% to 4% of the global population engaged in international air travel in 2018 (Gössling & Humpe, 2020). A minority of travellers, representing just 1% of the world's population, are responsible for over 50% of emissions from air travel (Gössling & Humpe, 2020).

The role of aviation in global carbon emissions and its broader impact shifts as man peers into the future. Aviation's relative contribution to carbon emissions is projected to grow towards 2070 (Ritchie, 2020). While there is an expectation that world transport will increase, advancements in cleaner energy sources and technological innovation can mitigate this growth's harmful effects in most transport modes (IEA, 2021). However, the aviation sector faces distinct challenges in decarbonization compared to other modes of transport, as some parts of the energy system are relatively hard to decarbonize, including aviation and long-distance transport (Davis et al., 2018). This is mainly due to the technological limitations of specific decarbonization methods in the aviation industry.

Therefore, other alternatives are considered to reduce aviation emissions. Fulton et al. (2015) emphasize the potential reliance on Sustainable Aviation Fuel (SAF) for carbon reduction in specific transport modes, emphasizing the intricate economic and technological hurdles associated with electrification and the use of hydrogen in aviation. These energy forms are less storage-efficient and space-effective compared to conventional fossil fuels, particularly concerning longer distances, making the decarbonization of aviation technically intricate. Thus, the pursuit of a net-zero carbon aviation industry remains a challenging objective, as analyses of the IEA (2021) still show expectations of carbon emissions from the transport sector in 2070.

The interesting part of the sustainability challenge in the aviation sector is where business meets with sustainability. Airlines are trying to find ways to balance the social pressure of having to become sustainable. At the same time, they struggle with the involved cost and technological limitations of reaching these sustainability goals. In this environment, concepts like carbon compensation arise. The actions of airliners can observe this balance between business and sustainability. The article from Frost (2023) on the website of Euronews highlights an example of this: “Ryanair: Low-cost airline warned about misleading carbon offset claims”. Airlines sometimes tread on legal boundaries to present themselves as environmentally responsible. Researchers have questioned the credibility of these schemes as they lack transparency and sometimes seem too optimistic (Gössling et al., 2007). While offset schemes appear to offer an easier path toward sustainability for airlines, the question of their credibility and quality remains.

As van Houten, Director of the Dutch Authority for Consumers and Markets, stated in the article of Frost (2023): “Airlines may offer CO2 compensation schemes, but they cannot give the impression that CO2 compensation will make flying sustainable”. A gap can be seen in this ambiguous tool of sustainability. In one way, it allows people to contribute to more sustainable flying, or at least mitigate the adverse effects attributed to it; however, on the other end, the unclear structure and legislations surrounding it make the actual value of this compensation in some scenarios debatable. Literature has covered emissions estimation and offset schemes' credibility (Brueckner et al., 2020; Yanto & Liem, 2018; Gössling et al., 2007). However, the gap observed in the literature is studying the relationship between an estimated social cost of carbon and the reported cost of compensation in aviation.

The central research question and the accompanying hypotheses will answer this research gap. The question this paper will be answering is:

> *What is the relationship between the estimated cost of carbon emissions in passenger flights and the reported compensation cost?*

The first hypothesis assisting in answering the central question is as follows:

> ***Hypothesis 1:*** *The reported per-passenger emissions are lower than the estimated emissions per passenger.*

The second hypothesis is as follows:

> ***Hypothesis 2:*** *The reported cost of CO2 compensation per passenger emissions is lower than the estimated cost of carbon per passenger.*

This paper conducts a case study of KLM passenger flights departing from Schiphol Airport to provide insights into the research question. Given KLM's comprehensive carbon compensation scheme integrated into the booking process, it serves as an appropriate subject for this study. The relationship between the estimated cost of carbon emissions and the reported compensation cost will be compared using two paired samples. These two samples consist of emissions and cost of compensation reported by KLM (n.d., -b) and the estimated values by this study. These estimations are conducted using a fuel-burn estimation model developed by Seymour et al. (2020) and the methodology used by KLM (n.d., -c). The comparison of reported and estimated values will be done using a paired sample t-test.

This paper will start with a review of the existing literature on this subject. The topics of externalities, SCC, carbon offsetting, fuel burn models and the methodology used by KLM are discussed. After that, the methodology used in computing the estimations and the method of comparing the reported and estimated values will be explained. The results of these analyses will then be given and further discussed, adding limitations and recommendations for further research.

2. Literature Review

The carbon cost of air travel and its compensation have been extensively debated in the literature. However, the integration of multiple concepts related to these matters offers room for enhancement. This chapter will analyze and review the existing literature on the different ways of pricing carbon and estimating emissions in flying.

2.1 The Concept of Externalities

To first comprehend the concept of carbon compensation in the aviation sector and why a form of this exists, an understanding of the concept of externalities is necessary. However, it starts with welfare economics discussed by Pigou (1920) and Marshall (1890). Marshall (1890) provided the foundation of neoclassical economics and the modern welfare theorem, and his concept of the consumer surplus is especially applicable in the case of passenger air travel emissions. The consumer surplus can be explained by the difference between what a consumer is willing to pay and the amount paid for a product or service (Marshall, 1890). The producer surplus is the difference between the actual market price and the lowest price a producer is willing to accept. The demand and supply curve in a Marshallian cross returns a consumer and producer surplus; however, when the market is not efficient, and there is a difference between social and private cost, in other words, there is the case of externalities (Pigou, 1920). Pigou (1920) explains that such an externality occurs when a party's actions affect others' well-being, which is not considered in the price. Pigou (1920) identified two types of externalities: positive and negative. Positive externalities involve third parties benefiting without direct compensation. Conversely, negative externalities arise when an entity's actions impose costs on others without bearing the financial burden.

The economic concept of externalities is also described in the paper of Dahlman (1979) and is explained as side effects of an activity. Dahlman (1979) states that when speaking of an externality, there is some form of divergence between private and social costs. When every voluntary contractual arrangement has been entered into, there are still interactions which should be internalized into the market; however, when leaving the market on its own, the market cannot cope with it (Dhalman, 1979). It can be seen as a market failure, and the reason for it is that the cost of finding out these externalities and paying for the cost of the externality can be seen as more extensive than the expected benefits. This is described by Dhalman (1979) as the presence of transaction costs. However, the question is what the consequences of this market failure are. As stated before, in the case of negative externalities, the social costs are higher than the private costs, so resources are not allocated efficiently, and welfare is not internal as society incurs damages. At the same time, these are not paid for or compensated for in reduced demand.

Using the concept of externalities by Dahlman (1979) discussed above in the case of carbon emissions in aviation, it starts with the voluntary contract between the aircraft passenger and the airliner. However, as Dahlman (1979) explained, there are still interactions outside the market. In this case, the externality can be seen as the emissions from flying negatively impacting the environment. The divergence between the social and private costs is that one uses the plane but does not pay any personal price (or insufficient) for the emissions that negatively influence society. This could be explained by the fact that there are very high and unknown transaction costs involved in discovering the cost of externalities. The first is finding out the actual emissions (externalities) released by flying, and the second part is valuing these externalities, which are full of uncertainties, as discussed by Litterman (2013). In this case of externalities, effectively integrating these social costs into the market is demanding. There are several ways of approaching this, which will be discussed in the following sections.

2.2 Social Cost of Carbon (SCC)

What the price of carbon compensation should be is dependent on how you interpret this question. In broad terms, one could argue that it depends on whether one sees this price as the SCC or the price the market systems give to compensate for it. This SCC can be explained as “the estimate of the monetary value of worldwide damage done by anthropogenic CO2 emissions” (Pearce, 2003). One could discuss that these SCCs and the price of carbon should be the same as the compensation, which should result in a state of no damages. However, the prices for the technology or resources needed for this compensation differ per region, and the different interpretation of this compensation makes it seem that these two concepts might not necessarily have the same monetary value (Pearce, 2003). At the same time, they are intended to display the same damages done. Arguing that the SCC should be equal to the price of carbon offsetting also means that these offsets’ quality is perfect. However, as discussed in the introduction, there are indications that these offsets are not always perfect. The following part will discuss the SCC. Literature uses the definitions of the “price of carbon” and the “social cost of carbon” interchangeably, as finding out the SCC is, in a way, putting a price on carbon. In this paper, the actual compensation prices and their credibility will be discussed later and noted as the “cost of compensation”.

It is difficult to calculate actual damages created by emissions and give it a monetary value. As Litterman (2013) explained in his article on a discussion of the right price for carbon emissions: “The unknown potential for devastating effects from climate change complicates pricing” (Litterman, 2013). There are two issues for economists to put an appropriate price on carbon emissions. First, the possible long time before the harmful effects of these emissions can be realized makes it challenging to put a value on them today. The second issue is that the possibility of a very high impact but low probability environmental occurrence happening is, and probably will be, uncertain (Litterman, 2013). The fundamental problem of coming to a correct carbon price is that the answer to this depends on something unknowable (Litterman, 2013). Litterman (2013) would suggest that a cautious approach to this unknown catastrophe is needed, and the market price of carbon should be on or above the expected damage in the future. It could be said that this expected damage is part of the challenge, not the solution.

The cost of carbon has been a topic of research by government authorities. A study by the US government managed to get to an SCC of $20 a ton in 2010 (Greenstone et al., 2011). However, the accuracy of this number and the research is questioned by Pindyck (2013) in his article on carbon pricing. Pindyck (2013) challenges the simulation models as they were based on most likely scenarios and the current situation, limiting their predictive value. This critique seems reasonable as the impact of unlikely but highly impactful events could be substantial and should be considered. Furthermore, Pindyck (2013) indicates that the choice of discount factor has considerable influence on the outcome, and the likely or acceptable level of discount rate is not necessarily the sole truth. This shows that government entities' findings are debatable and primarily based on assumptions and low probability, but high-impact events are not considered.

Multiple complex, integrated assessment models (IAM) are used to calculate an internally consistent SCC (Nordhaus, 2017). One of the major models used is the DICE model (Dynamic Integrated Model of Climate and the Economy); in 2018, Nordhaus (2018) revised the model he developed. The estimated SCC in this new 2016R model is $31 per ton of CO2 (in 2010 U.S. Dollars) for 2015 (Nordhaus, 2018). These IAM models have a significant estimation error; the 5% to 95% confidence interval gives an SSC range of $6 and $93 per ton of CO2 (in 2010 U.S. Dollars). This is due to the total effect of all uncertainties and assumptions in the model. This highlights the difficulty of giving a precise value for the SCC.

A trend that can be observed in the literature surrounding the SCC is the increase in its prediction values in the last years. Nordhaus estimated $31 a per ton of CO2 for 2015 (Nordhaus, 2018). However, Hänsel et al. (2020) find higher values using updated climate model predictions in the DICE model. They find a cost of $37 per ton of CO2 in the same year as the $31 of Nordhaus (2017). Further looking into the recent predictions and the trend of increased SCC, the carbon price calculated from the updated Hänsel et al. (2020) model changed to the year 2020 at $82. However, when Hänsel et al. (2020) considered expert opinions on the SCC by using a voting system on discount factors, it resulted in carbon prices of $119 and $208 per ton of CO2, depending on the year the zero emissions goal is set. This trend continues with values found by a recent study of the EPA (2022). Their model finds values between $125 and $351 per ton of CO2 depending on the discount factor. Similar values are found by Rennert et al. (2022), ranging between $80 and $308 again depending on the discount factor and showing that CO2 emission mitigation efforts are seen to be more beneficial. This exploration of the SCC shows the difficulty in assessing the correct value of the SCC. This paper will focus on the most recent findings of the SCC to incorporate the most up-to-date knowledge on climate change and use these in estimating the cost of carbon in flying.

2.3 Carbon Pricing Systems

As discussed in the section on externalities, there are multiple ways of bringing negative externalities into the market system. This way, a pricing system is created to put a tradeable value on carbon emissions. In general, they are categorized into several systems (The World Bank, n.d.):

- Emission Trading Systems (ETS)
  - Cap-and-trade systems
  - Baseline-and-credit systems
- Carbon Tax
- Crediting Mechanism
- Results Based Climate Finance (RBCF)
- Internal Carbon Pricing

The ETS is a system where carbon emitters can use a trading scheme to meet their emission requirements. Entities can require carbon emissions units on the market, and the market price is established by demand and supply systems (The World Bank, n.d.). The cap-and-trade system applies a cap to the total emissions within the ETS, and then emissions allowances are distributed. This can be for free or by using an auction. The baseline-and-credit system uses an emissions baseline for individual regulated entities, and credits are given to entities that reduce their emissions below this threshold. The remaining credits can be sold to other entities that exceed their baseline (The World Bank, n.d.).

The carbon tax is a straightforward way of setting carbon prices. This puts an explicit tax rate on carbon emissions, usually a price per ton of CO2 emitted. The difference between the tax and the ETS is that the price is predetermined, but the total emissions reduction is not (The World Bank, n.d.).
The crediting mechanism creates carbon emissions reductions or compensation by using projects. These projects issue carbon credits, which can be used to offset emissions by using corporate citizenship objectives, international agreements, domestic policies or voluntary reasons (The World Bank, n.d.).

RBCF is a funding approach to the solution of pricing carbon. Financial rewards are paid out after specific predetermined goals are met. It often serves a dual purpose: reducing emissions and focusing on poverty and community benefits (The World Bank, n.d.). Internal carbon pricing is a tool organizations use to support decision-making regarding the organization's climate impact. Organizations put a value on their carbon emissions to create a positive change relating to climate change (The World Bank, n.d.).

Government entities mostly use the systems of ETS and carbon tax. One of those uses depends on the context and political choices. Cooperations and individual consumers use carbon crediting systems. This system applies to the case of carbon offsetting in flying. These crediting systems are based on market demand and supply and do not necessarily display the SCC. These trading schemes are a cost-effective regulatory approach to reducing emissions. It is based on a market system created to trade the rights of carbon compensation. Alternatively, as Conte & Kotchen (2010) explained on the market prices of carbon offsets, the price is established by the equilibrium of regulated entities' and offset projects' abatement costs. However, this would follow, as mentioned by Conte & Kotchen (2010), the "law of one price", but the way that those prices are determined in the market for voluntary carbon offsets is unclear. The offsets in a voluntary carbon offsetting market reflect more than just the marginal costs of producing these offsets. It seems they present a broader bundle of characteristics. Buyers possibly seek co-benefits from these offsets, like the conservation of biodiversity or poverty reduction (Conte & Kotchen, 2010). The concept of offsetting and voluntary carbon offsets will be further discussed in the following section.

2.4 Introduction to Carbon Offsetting

The purpose of an offset program can be explained in different ways. Gillenwater (2012) describes it as it is to create certain public benefits "in a way that is more cost-effective than would be possible using other policy mechanisms" (Gillenwater, 2012). He explains that these programs achieve higher cost-effectiveness by using mechanisms based on the market to get the private sector to search for low-cost opportunities. Gössling et al.(2009), in their article on voluntary carbon offsetting in air travel, state that: "Carbon offset providers offer to 'neutralize' emissions caused by consumption in one sector through compensation in another sector" (Gössling et al., 2009). Bumpus & Liverman (2008), in their research on the governance of international carbon offsets, explain that advocates see these schemes as a cheaper, faster and easier way of reducing environmental impact than doing this domestically and thus resulting in more significant benefits.

There is not a single correct explanation of carbon offsetting schemes. Experts in the field have different views, which shows the challenge in assessing any boundaries to an offsetting scheme.

However, getting to an overall definition of different views is possible. At least, carbon offsetting schemes are used to neutralize the adverse effects of emissions on the public by using market systems to attain compensation with higher cost-effectiveness than achieving this compensation through its original sector, thus aiming for greater benefit to the public.

2.4.1 History of Carbon Offsetting

The history of carbon offsetting can be traced back to the Clean Air Act in the United States, as it was initially passed in 1963 and had amendments in 1970, 1977 and 1990 (Greenstone, 2002). Before 1970 the government in the United States had no significant role in regulating air pollution. However, because of the lack of regulation, there came interest in regulating the increasing pollution of The Clean Air Act in response to increasing pollution of CO, O3, SO2 and TSPs (Greenstone, 2002). The cornerstone of the legislation was based upon air quality standards that every county was required to meet. The additions to the Clean Air Act in 1977 resemble the idea of carbon offsetting schemes as we know them today. As stated by Greenstone (2002), “The 1977 amendments added the requirement that any increase in emissions from new investment is offset by a reduction in emissions from another source within the same county.” This concept of offsetting comes from one of the first acts of emissions trading, as stated by Gillenwater (2012). A company could increase its emissions only if it paid another business to compensate for these emissions.

As discussed by Bumpus & Liverman (2008), the actual start of these offsetting schemes is the Kyoto Protocol from the United Nations Framework Convention (United Nations, 1997). This agreement allowed countries to meet their emissions reduction requirements by using two different mechanisms of carbon offsetting. They could invest in emissions reductions in developing countries (CDM, Clean Development Mechanism) or Eastern European countries transitioning to a market economy (JI, Joint Implementation). This CDM is a regulated market; however, besides this, an unregulated market of Voluntary Carbon Offsets has been created since then (VCO) (Bumpus & Liverman, 2008).
Bumpus and Liverman (2008) state that the international community's commitments to reducing carbon emissions drive these schemes. They mention the Kyoto Protocol (United Nations, 1997) as an example. However, as the article of Bumpus and Liverman (2008) has aged, this can be attributed to, for example, the Paris Agreement of 2015 (UNFCCC, 2015). This is driven by the idea, as stated by Bumpus and Liverman (2008), that the carbon offset in the developing world is cheaper than that of the developed world, as the marginal cost of reducing domestic emissions is high, which would have a negative economic impact. This then allows developed countries and organizations to attain carbon credits to meet their reduction by investing in more cost-efficient projects in developing countries. At the same time, these developing countries can benefit from the investments of these countries or organizations (Bumpus & Liverman, 2008).

The emergence of VCOs (Voluntary Carbon Offsetting Schemes), as Bumpus and Liverman (2008) discussed, was parallel to the CDM. These VCOs could arise due to parties or countries who were not a proponent of the Kyoto Protocol or thought more should be done to the problem. These were mostly non-profit organizations working with large corporations to try and reduce the carbon footprint of investors. The World Bank's report on carbon crediting (The World Bank, 2022) explains that since the creation, and especially in the last years, these carbon crediting markets have grown further. The total carbon credits market in 2021 increased by 48% (The World Bank, 2022). The World Bank showed in their report on carbon crediting the carbon crediting mechanisms. This can be split up into the supply side of these schemes and the market/demand side (The World Bank, 2022). The supply side is the parties offering different ways of carbon crediting, and the demand side is the customers for this carbon crediting.

Supply-side

- International Crediting Mechanisms: Systems like the CDM.
- Domestic Crediting Mechanisms: Domestic systems like the Australia Emissions Reduction Fund
- Independent Crediting Mechanisms: independent systems by non-governmental entities.

Demand side:

- International Compliance Markets: Purchasing of credits to help countries meet their climate obligations.
- Domestic Compliance Markets: Purchasing of credits aimed at meeting carbon tax obligations.
- Results-Based Finance: Purchasing credits aimed at using it as a public tool for incentivizing emissions mitigation.
- Voluntary Carbon Market: Purchasing of credits intended to meet commitments or voluntary targets.

There is an interaction between these markets, meaning domestic compliance markets could purchase credits from international crediting mechanisms (State and Trends of Carbon Pricing 2022, 2022). However, one could assume that, in this case, voluntary carbon markets work primarily by using credits from an independent crediting mechanism. To clarify this, for the case of carbon compensation for passengers in air travel, the offsetting scheme looks as follows in this paper. The passenger buys

Voluntary Carbon Compensation (VCC), which is seen as the voluntary carbon market. These VCCs price carbon in the way of a crediting mechanism and fall under the independent crediting mechanisms.

It is observed that the most significant increase in carbon credit transactions is coming from these independent crediting mechanisms (The World Bank, 2022). The World Bank predicts that the CDM, from the Kyoto Protocol, will continue a gradual phasedown and be replaced by other international crediting mechanisms. The rise of the voluntary carbon market can be seen in the numbers, as in November of 2021, the total voluntary credit market first exceeded 1 billion US dollars (The World Bank, 2022). This market increase is due to rising demand for carbon compensation by corporations, and this also makes traders and investors hope to make a profit. One of the key drivers of this increase in demand in the voluntary carbon credit market, as stated by The World Bank (2022), is the increase of commitment of corporations to the net zero goals of 2050 from the Paris Agreement (UNFCCC, 2015). The aviation sector also participated in this commitment as the International Air Transport Association announced a net zero target for the industry for 2050; 19% of this target is expected to be met using carbon credits (IATA, 2021).

2.4.2 Critique on Offsetting Schemes

At first sight, these offsetting schemes offer a good way of reducing or mitigating carbon emissions. However, there are also critical sounds from researchers on these schemes. This started with Lohmann (2005) critiquing the Kyoto Protocol and its followers, stating that the scale and contradictions of developing this carbon market had been underestimated. Lohmann (2005) notes the problems of unverifiability in this market and suggests that it has no attention to any structural change. These issues can be seen in the market of VCO today as well. However, addressing these issues could improve their credibility and unlock more potential for these schemes.

Bumpus and Liverman (2008) discuss the complicating governing factors of these schemes, as they explain that there is very little organization in the VCO market in terms of, among others, governance structure and definitions. Gillenwater (2012) addresses the concept of additionality and baseline. He argues that something can be an offset if “one does something that results in extra good that is equivalent in magnitude, approximate timing and recipient population to the original harm done” (Gillenwater, 2012). He states the problem of difficulty in explaining the “extra” term and how one should measure it. The current definitions of additionality are ambiguous and circular. The offset should be better than a particular baseline. However, this is not always the case or is hard to control. These two articles show the problem of a relatively unregulated market with fundamental values of correctly using these schemes being broadly interpretable.

Watt (2021) questioned practitioners of carbon offsetting schemes; these interviews show practitioners questioning the additionality of particular projects. It shows that there are doubts about their credibility from within organizations. Watt (2021) argues that these schemes are more of a fantasy from a psycho-analytical ideology perspective and that interviews with practitioners suggest that it is sustained by trust in others' authority and the desire for carbon offsetting schemes' organizations promises to be true. The research shows fundamental issues. However, the question to what extent to which these issues exist still needs to be answered.

Gössling et al. (2007) went deeper in to the source of these possible issues in aviation offsetting schemes. They discuss the issues arising from aviation institutions using these carbon offsetting schemes to compensate for carbon emissions. The main problem they address is the approaches chosen for calculating these emissions, the compensation measures and their respective price level (Gössling et al., 2007). One of these topics is the value of the so-called Radiative Forcing Index (RFI), which shows the additional impact of aircraft emissions besides that of CO2. The value of this multiplier is different per organization. Another part is the calculation of CO2 emission, which is done mainly according to predetermined factors determining the emissions per liter of jet fuel used. However, as shown by (Gössling et al., 2007), even if these factors are the same, they still get different results. These per-passenger emissions are, however, also dependent on the aircraft type and other determining factors, as discussed before.

Another aspect of the debate is that the pricing of these emissions is also done differently, as seen by (Gössling et al., 2007). The same RFI and emission can still lead to different valuations of pricing. "The prices of compensation might thus rather depend on the time horizons over which projects are calculated, the validity and reliability of projects, administrative costs or profit margins taken out by profit entities" (Gössling et al., 2007). These different factors contribute to the unclear picture of these schemes and suggest that some might not be scientifically substantiated. This contributes to the literature on the credibility of carbon offsetting schemes.

2.5 Fuel Burn Estimation Models

The impact of flying on the environment has been explored from various angles and was written with different purposes. To estimate the cost of carbon in flying, data on the emissions of passenger flights is needed. Since an aircraft's emissions are proportional to its fuel consumption, modelling emissions can be done by modelling aircraft fuel usage (Brueckner & Abreu, 2017). Research first focused on modelling fuel usage to reduce operational costs. This can be seen in the paper of Collins (1982); the research was based upon primary concepts of energy balance, as previous research had focused on complex aircraft dynamics or historical data; Collins (1982) created a model based on path profile data. It assessed the impact of changes in air traffic control procedures on aircraft fuel consumption.

The report of Penner et al. (1999) from the Intergovernmental Panel on Climate Change was the first extensive report on the impact of aircraft on climate and atmospheric ozone. It created the groundwork for further research on reducing the harmful effects of flying on climate change. The focus of studies after this report shifted from lowering operational costs to reducing climate impact.

Lee et al. (2001) used the Brequet range equation (Breguet, 1923; Coffin, 1920), like Collins (1982), to compute predictions for future efficiency gains in aviation based on historical trends of the reduction in energy usage due to technological development in aviation. The Brequet range equation is a primary form of fuel consumption modelling (Seymour et al., 2020). It only models flights as a cruise phase without considering a landing, take-off, climbing and descent phase. This makes it a basic approximation, so researchers have been trying to extend this approximation by using more comprehensive models.

The article of Babikian et al. (2002) looks into the effects of regional aircraft type on fuel usage and efficiency. This has been an ongoing topic lately, with the most recent response on this being a new law from the French government banning domestic flights shorter than 2.5 hours (République Française, 2023). In their research, Babikian et al. (2002) show that regional aircraft have 1.5-2 times higher energy usage than larger passenger aircraft (Babikian et al., 2002). These findings indicate the possible differences between aircraft types, operational procedures, and travel distance. They show that smaller aircraft spend a disproportionate amount of time on the ground, taxiing or maneuvering, compared to larger aircraft due to shorter stage lengths.

2.5.1 Choice of Fuel Burn Model

Flight performance analysis is needed to decide on a policy or analysis of the environmental effects of flying, especially the fuel burned during this flight (Yanto & Liem, 2018). A fuel burn model will be needed to estimate aircraft emissions. Several different models will be discussed below, and a model will be chosen that fits the needs and scope of the research best.

Recent research has focused on finding a balance between creating accurate and computationally efficient fuel burn models. This is because the scale of analyzing the fuel burn of the whole world is complicated, time-consuming and thus expensive as it would involve the simulation of around 35 million flights of 350 different aircraft types (Yanto & Liem, 2018). Another aspect is the availability of data, which is not always freely accessible or not accessible at all (Yanto & Liem, 2018; Seymour et al., 2020). Currently, there are several systems available. Yanto & Liem (2018) reviewed a number of these systems. They range from being low-fidelity to being high-fidelity. This means how closely the estimation models represent real-life physics. The high-fidelity model models flight trajectories considering the conditions at the time. The low-fidelity models rely on an empirical base and use simplified assumptions (Yanto & Liem, 2018). The trade-offs between these models are based on computational time and accuracy.

Government entities or large organizations develop some of the models available. One of the systems is the Aviation Environmental Design Tool (AEDT), developed by the Federal Aviation Administration (FAA). The AEDT assesses aircraft fuel burn, emissions, and noise using flight schedules, trajectories, aircraft performance models, and emission factors (AEDT, 2017). The AEDT uses radar flight data and, when not available, makes estimations. It provides a very high degree of detail but relies on extensive data input, which is not freely available (Seymour et al., 2020). This makes it not useful for the scope of our research.

Another system is that of the International Civil Aviation Organization (ICAO), which developed the ICAO Carbon Emission Calculator (ICAO, 2015). The ICAO Carbon Emission Calculator is designed to work with minimal input data, using distance, which is widely available data. It can be easily and freely accessed online and is used as a base for several offsetting schemes. The ICAO Carbon Emission Calculator uses data from over 190 countries, including aircraft types, fuel use, passenger-to-freight ratios, and load factors. It uses averages of these numbers in its calculation. However, this low-fidelity system lacks accuracy in computing the different stages of flight. It is based on average consumption per distance and does not consider any take-off or landing phase. The goal is to get an accurate value for the emissions; therefore, this model is considered basic.

The third model was developed by The European Organization for the Safety of Air Navigation (Eurocontrol), which is named the Advanced Emission Model (AEM) (Nuic et al., 2010). AEM can generate aircraft trajectories and estimate fuel consumption, which uses the BADA database to make these estimations (Mouillet, 2019). The system is a very high-fidelity model simulating aircraft performance. However, the limitation of this system is that it requires a very high computational time. Using this system will require that three flight trajectories be computed manually (take-off, descent, cruise) for every individual flight. Making a fuel use database of thousands of flights is unrealistic regarding time, as these three trajectories should be computed for every flight. The system is not freely available and requires a license, making it harder to implement.

The AEDT and AEM mentioned above are high-fidelity, not readily available, and are not very applicable to this research as they do not fit the time frame of this research and scope. The ICAO model is easy to operate, and the methodology is provided; however, the flight modelling is rather basic. These three models can offer a good prediction. However, it is impossible to put in any different parameters for certain assumptions, making the ICAO calculator less applicable and transparent.

Researchers have tried to create fuel burn prediction models that are typically physics-based and not empirical. Two pieces of research will be discussed, which both derive a regression equation per aircraft type, which makes it easy to implement and use as an estimation model. Yanto & Liem (2018) tried to create an accurate but efficient approximation model for aircraft fuel burn. A regression model per aircraft type is derived from a fuel-burn database created by using US flight mission data and applying their medium-fidelity model to this data to compute the fuel burn of the aggregate flights (Yanto & Liem, 2018). This medium-fidelity model is a compromise between the existing high and low-fidelity models. The model they created has drastically reduced the computation time while having an estimation error of less than 6%. Seymour et al. (2020) pointed out that the model of Yanto & Liem (2018) does depend on payload data, which is harder to come by outside the US. One could use an estimation of the average payload. However, this requires an extra estimation and assumption while it greatly influences the emissions (Yanto & Liem, 2018).

Seymour et al. (2020) created a fuel burn model that is seen as a compromise between the high-fidelity and low-fidelity models. They used a model where the high fidelity model, based on the BADA database and model, simulates several flights and their fuel burn per aircraft type. This creates several points of fuel burn related to distance. These points can then be linked using ordinary least squares regression. This formula can be seen below.

$$F_i = \alpha_i * d_{gc}^2 + \beta_i * d_{gc} + y_i$$

It provides the estimated total fuel used by a specific type of aircraft for a given distance d_{gc}. This model comprises the advantages of high-fidelity accuracy and still be easy to implement and use for estimations. One advantage of this study for this paper is that the aircraft used by KLM at the time of this paper were all modelled by Seymour et al. (2020). Therefore, it would suit the needs of this study well.

The literature discussed above shows the potential difficulty in creating a predicting model that is accurate, easy to operate and uses freely available data. Discussing these models also shows the first part of the problem of answering the research question. Calculating the predicted emissions of a flight is the first part of answering the question of the costs of these carbon emissions. The credibility of these predictions relies on the accuracy and fidelity of the model. However, the difficulty in judging these models as right or wrong means there is no real consensus on which model is the best. However, the best for the scope of the research will be a model based on the methodology by Seymour et al. (2020). The model of Seymour et al. (2020) uses an accurate high-fidelity flight model while maintaining computable efficiency. This is within the scope of this research, as the connection between emissions and cost is the main point of interest.

2.6 KLM Emission and Pricing Methodology

In order to explain any differences between the estimated emissions and the values reported by KLM, it would be good practice to understand the methodology used by KLM. The KLM provides a short methodology explanation for emissions and allocation calculations (KLM, n.d.-c). However, this methodology is not very clear and complete. The writing lacks clarity and would not be reproducible in how it is presented. It does, however, give information which can be used in the estimation. Therefore, its content will be discussed in the following section.

2.6.1 Carbon Compensation Options

The booking process of KLM provides four different options for carbon compensation. This booking process can be found in Appendix A1. These four options consist of reforestation and sustainable aviation fuel (SAF), and the two other options are a combination of these two forms of compensation. Let us discuss the options of SAF and reforestation. Reforestation is explained by KLM (n.d. -d) as planting new trees where forests were lost due to the activities of humans or any natural disturbances. This is done as trees can absorb CO2 and reduce the current carbon dioxide in the atmosphere. With the funds from the reforestation option, KLM supports three reforestation projects in Panama, Uganda and Colombia KLM (n.d. -d). This is done by using a carbon credits system. KLM buys a carbon credit at Forliance, an agency managing offsetting projects, for these projects, which relates to compensating for 1 ton of CO2 (Forliance, 2022; KLM, n.d. -d). KLM reports that these projects are all Gold Standard certified (KLM, n.d. -d). This Gold Standard was founded in 2003 by the WWF and other international corporations to ensure that carbon reduction schemes are of quality and integrity (Gold Standard, n.d.). The next option in the booking is that of SAF. SAF is a different type of aviation fuel that can reduce the total lifecycle CO2 emissions compared to regular kerosene by about 75% (KLM, n.d. -d). The fuel consists of multiple components like cooking oils and other waste oils of organic origin. KLM reports that they only buy SAF made from “raw materials” and not from soy or palm oil, as these sources can be attributed to deforestation (KLM, n.d. -d). However, no clear explanation is given about these “raw materials”. KLM already adds 1% of SAF to the fuel system of every flight from Amsterdam Schiphol, using the SAF as compensation; therefore, it comes on top of this 1%. KLM states that this SAF is 3 to 4 times more expensive than regular kerosene, and the availability of SAF is limited; this makes it difficult and maybe impossible to entirely switch to SAF at this time (KLM, n.d. -d). With the funds acquired by passengers choosing the SAF compensation option, more SAF is added to the aircraft's fuel system. However, this is not on your own flight due to logistic limitations (KLM, n.d. -d). This means the overall fleet reduction is the emission reduction you pay for. KLM does not report any calculations but is audited yearly to ensure these reported emissions reductions are correct.

2.6.2 KLM Emission Calculation

The report on the emissions calculation methodology by KLM explains that the calculation is based on the KLM network's average fuel consumption per passenger (KLM, n.d.-c). The data used for their calculation is based upon actual flight data gathered by the flight onboard systems (KLM, n.d.-c). The calculation on fuel usage per aircraft type is based upon ton-kilometers travelled, passenger-kilometers travelled and the fuel use per 100 kg payload (which equals a passenger and their luggage) per 100 km great circle distance. It is gathered from the previous calendar year and converted to the fleet's fuel efficiency.

The first principle KLM discusses is the split of fuel burn between passengers and cargo. This allocation is proportional to the overall mass of these passengers and cargo (KLM, n.d.-c). The following formula can explain the overall mass:

$$Overall\ mass = Payload + Equipped\ mass$$

- $Overall\ mass$ - Total mass onboard
- $Payload$ - Passengers, Luggage, Cargo
- $Equipped\ mass$ - Equipment needed for transportation of payload

KLM states that "the two equipped masses were estimated for each type of operation" (KLM, n.d.-c); however, it is unclear what they mean by two equipped masses. It is assumed that the payload and equipped masses are intended. The operation types are the short-/medium- and the long-haul distance groups. These masses are then used to get the fuel usage per passenger and cargo for each aircraft type. KLM uses average factors for the cargo load and equipment weights per passenger from an older version of the methodology of the ICAO carbon emission calculator (ICAO, 2008).

The second principle discussed in their methodology is the evaluation of flight distances. The great circle distance and the actual flying distance are different (KLM, n.d.-c). KLM uses distances from flight plans as the actual flying distance to express the emission of CO2 per km.

The third principle discussed by the methodology is the calculation of CO_2 emissions per origin and destination pair. They base this on the expected fuel efficiency per passenger (KLM, n.d.-c). This is done by taking the weighted average of all the aircraft types used on the origin and destination routes for the coming year. This average fuel consumption is then multiplied by the distance related to the origin and destination pair. It is then stated that the CO_2 emissions of a flight are calculated by multiplying the fuel burn per passenger by an emission factor (KLM, n.d.-c). This seems odd as this will result in CO_2 emissions per passenger, not per flight. However, it seems they intend the emission per passenger per flight. The factor they use to convert fuel usage to emissions is 3.16kg of CO_2 per kg of kerosene (ICAO, 2008).

The fourth part of the methodology explains the calculation of the CO_2 emissions per cabin class. This is done because a business class passenger takes up more space in the plane than an economy class passenger (KLM, n.d.-c). KLM defines specific ratios to re-divide these emissions per class, which is based on the extra economy class seats that could have been placed in the space of the premium class. This is divided between the short- and medium-haul and long-haul groups. For the short and medium-haul, 98% of the seats are assumed to be economy seats; for the long-haul, this is 80%.

These four parts of KLM's methodology, the emission calculation method explained above, are then used to calculate the emissions per passenger. They state that they consider the efficiency of KLM to be the best in its class, and therefore, the emission estimations might be undervalued (KLM, n.d.-c). This methodology provided by KLM will be used to convert the estimations made in this paper to be comparable to the reported values by KLM. This will be further discussed in chapter 3.

3. Methodology

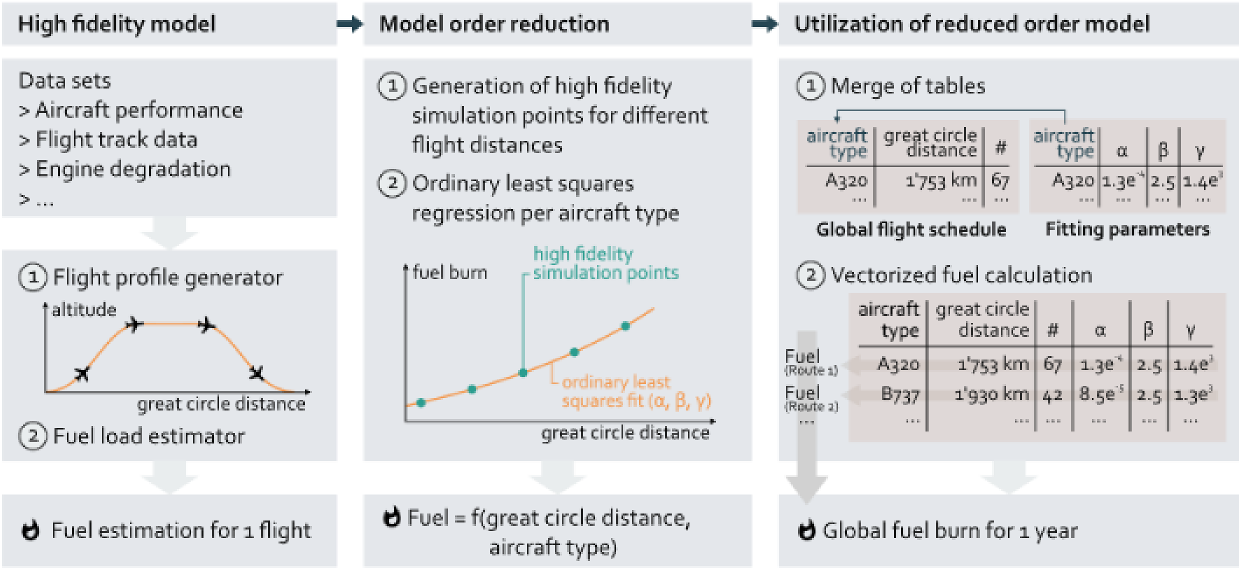
This part of the paper will display the methodology used to collect the needed data and the method used to analyze and compare different models. The statistical models and calculations will be explained in the following sections. As discussed in the literature review, the approach to this study will be based on two hypotheses. The first hypothesis concerns the comparison between the reported emissions and the estimated emissions. The second hypothesis concerns comparing the reported cost of emissions compensation and the estimated cost of these emissions. The explanation of the methodology will follow this same structure and start with the estimation model of the emissions and follow up with the methodology used on pricing. The reported emissions and cost of compensation from KLM do not require any further calculations and can be directly used to compare estimated and reported values. However, the calculations for the estimations will be explained in the following section 3.4.

3.1 Fuel Estimation Model

As discussed in the literature review, the fuel estimation model used will be based on the methodology and results of the research of Seymour et al. (2020) and the methodology of KLM. Some assumptions made by Seymour et al. (2020) and the methodology structure used are vital in explaining any possible deviations between the estimated emission from this paper and the reported emissions by KLM (KLM, n.d.-c). The model constructed by Seymour et al. (2020) is a fuel estimation model. As stated in the methodology of the ICAO emissions calculator tool, a constant factor can be applied to burn one kilogram of jet fuel to get to its related emissions (ICAO, 2018). Therefore, creating a fuel burn model to estimate emissions is standard practice. The following sections will, therefore, first explain the fuel burn model, an emissions factor that will be applied later on.

The model of Seymour et al. is made to be used with minimal required data inputs and computation costs while maintaining model accuracy (Seymour et al., 2020). The model is called the Fuel Estimation in Air Transportation (FEAT) model. The model consists of two components: (1) a high-fidelity flight profile simulator based on simulation made in BADA (Mouillet, 2019), which is used to derive (2) a reduced-order fuel burn approximation model. The only inputs for this reduced order model are the aircraft type and great circle distance. An overview of the model as produced by Seymour et al. (2020) can be seen below:

Figure 3.1:



Source: Seymour et al. (2020)

The figure shows the methodology used by Seymour et al. (2020). Seymour et al. (2020) used this model to estimate the total global fuel burn; this means that the two left sections are of interest in this explanation. The high-fidelity model estimates 25 flights per aircraft type to create data points for the reduced order model, which is a quadratic regression equation fitting to these points. This reduced order model can then estimate fuel usage per flight, varying aircraft types and great circle distance (Seymour et al., 2020).

3.1.1 High-Fidelity Model

The high-fidelity model uses BADA (Mouillet, 2019) based on the total energy model (TEM). Eurocontrol developed the BADA model, which combines theoretical models and related datasets to simulate the behaviour of different aircraft with high fidelity (Mouillet, 2019). This model equates the forces acting on an aircraft to kinetic and potential energy increases. It can be used to determine the needed thrust at certain speed levels. This is the base of the BADA model, which calculates the fuel burn linked to a specific thrust value (Seymour et al., 2020).

The high-fidelity model of the FEAT accurately simulates 25 missions per aircraft type; these flight missions consist of 8 stages: taxi-out, take-off, climb, cruise, descent, approach, landing, and taxi-in. The objective is to find the fuel flow for each of these stages. The fuel used in take-off, taxi-in and taxi-out phases are assumed to be constant in time and are based on engine testing fuel flow rates. However, the fuel usage of the climbing cruise and descent phase is determined using BADA and the TEM equation (Seymour et al., 2020). The total fuel burn summarizes the fuel burn in the eight flight stages.

Aircraft mass has a significant impact on fuel burn; therefore, in this model, the take-off weight is considered. It depends on the aircraft's weight, passenger, cargo and fuel. In the high-fidelity model, the mass of the aircraft is updated after every phase of flight, as fuel burned during these phases affects the aircraft mass and, therefore, the fuel consumption (Seymour et al., 2020).

3.1.2 FEAT Reduced Order Model

The high-fidelity model simulates 25 flying distances per aircraft type and their related fuel burn. These distance points create a regression equation per aircraft type to estimate fuel burn (Seymour et al., 2020). The model takes the form of a quadratic regression function:

$$F_i = \alpha_i * d_{gc}^2 + \beta_i * d_{gc} + y_i$$

- F_i - Fuel burn in kg
- α_i, β_i, y_i - Regression parameters
- d_{gc} - Great circle distance in km
- i - Aircraft type

The resulting regression equations from this model will be used to analyze the estimated emissions on all the direct connections of KLM inbound and outbound of Schiphol airport. Seymour et al. (2020) reported these regressions for 133 aircraft types, including the 12 aircraft types KLM uses. The table below shows the regression equations for these 12 aircraft.

Table 3.1: Estimation Models for Fuel Burn By Great Circle Distance

Aircraft type:	**Reduced order estimation equation:**
Boeing 737-700	$F_i = 8.45e - 05 * d_{gc}^2 + 2.49d + 1254.80$
Boeing 737-800	$F_i = 7.38e - 05 * d_{gc}^2 + 2.92d + 1218.82$
Embraer 195-E2	$F_i = 9.30e - 05 * d_{gc}^2 + 2.34d + 916.10$
Boeing 737-900	$F_i = 5.87e - 05 * d_{gc}^2 + 3.08d + 1193.96$
Embraer 190	$F_i = 2.52e - 05 * d_{gc}^2 + 2.27d + 890.10$
Embraer 175	$F_i = 6.23e - 05 * d_{gc}^2 + 1.74d + 765.14$
Boeing 787-9	$F_i = 1.18e - 04 * d_{gc}^2 + 3.89d + 3252.75$
Boeing 777-200ER	$F_i = 1.91e - 04 * d_{gc}^2 + 5.78d + 3631.80$
Boeing 787-10	$F_i = 6.97e - 05 * d_{gc}^2 + 4.98d + 2688.35$
Boeing 777-300ER	$F_i = 2.10e - 04 * d_{gc}^2 + 6.45d + 4650.53$
Airbus A330-300	$F_i = 2.64e - 05 * d_{gc}^2 + 6.52d + 2090.64$
Airbus A330-200	$F_i = 1.75e - 04 * d_{gc}^2 + 4.90d + 3603.04$

-Rounded to two decimals. Source: Seymour et al. (2020)

3.2 Estimating Emissions

Part 3.1.3 discusses the reduced order model for the different aircraft types; these regression equations can estimate the total fuel used by great circle distance per aircraft type. Some calculations are needed to compare it to the reported emissions of KLM. This is based on the methodology by KLM (KLM, n.d.-c).

3.2.1 Average Fuel Burn per Flight

The emissions emitted largely depend on the type of aircraft used. This aircraft type is also crucial for distributing emissions over passengers, as the different aircraft types have different seat capacities. For this reason, an estimation is needed for the type of aircraft used on the 293 flights considered in this paper. Then, the weighted average fuel consumption of all the aircraft used on a route can be created just as KLM performed in their methodology.

The type of aircraft KLM uses is not mentioned during the booking process. The website of KLM reports a list of the fleet of aircraft used with some accompanying routes. However, this does not span all their flights; some routes are served by multiple aircraft types (KLM, n.d. -a). This implies that routes do not always use the same type of planes. The types of aircraft used on the considered routes are estimated using historical flight data from the website of Flightradar24.com (Flightradar24, n.d.). 12312 flights on the considered routes were gathered, and the relative usage of the different aircraft types was gathered. The formula below provides the average aircraft fuel usage per route based on relative aircraft usage:

$$Af_r = \sum \frac{\sum M_{i,r}}{\sum M_r} * F_i$$

- Af_r - Average fuel consumption in kg of fuel
- $M_{i,r}$ - Total flight missions per route and type of aircraft
- M_r - Total flight missions per route
- F_i - Fuel burn in kg per aircraft type from regression

This calculation provides the average fuel usage on a route based on the relative aircraft usage and the regression equations on expected fuel usage per aircraft type discussed in section 3.1.2.

3.2.2 From Fuel Burn to Emissions

To be able to convert the fuel burn to the emissions associated with this fuel burn, an emission factor is needed. KLM uses an emission factor of 3.16 kg of CO2 for every kg of jet fuel burned (KLM, n.d.-c). This is considered a standard value reported by multiple governmental and environmental institutions (EIA, 2022; ICAO, 2018). This, therefore, seems to be an accepted value. However, another factor influencing the impact of emissions, which was addressed by Gössling et al. (2007), is that of the Radiative Forcing Index (RFI). It is a factor intended to incorporate any non-carbon effects on climate change in the carbon emissions. Aviation warms the Earth’s surface through CO2 and other factors (Lee et al., 2021). However, there is no genuine consent of its value in literature. Therefore, the International Air Transport Association (IATA) and the International Civil Aviation Organization (ICAO) do not use any value of this RFI. As KLM follows the emissions calculation methodology by ICAO (2018), they do not include this RFI (KLM, n.d.-c). The estimation of this RFI ranges between a factor of 3 and 1.7 (UK Department for Energy Security and Net Zero, 2023; Leet et al., 2021). Literature, however, shows that not all these estimations for the different effects can be backed up by robust evidence and display high agreement within the field of research (Lee et al., 2021). Therefore, no RFI will be used in the research, but its possible impact will be discussed in the discussion and conclusion.

This results in the conversion of the last average fuel consumption per route to the average emissions per route:

$$E_r = r * Af_r$$

- E_r - Average emissions per route in kg of CO2
- r - Emissions factor in kg of CO2 per kg of fuel
- Af_r - Relative aircraft fuel usage per route in kg of fuel

3.2.3 Defining Flight Haul Type

This concept of flight haul type has been swiftly discussed in the methodology used by KLM in section 2.6. The IATA (n.d.) distinguishes three different haul types based on the duration of the flight. These are the short-haul, medium-haul and long-haul. These flight haul types will be used, just like in the methodology of KLM (KLM, n.d.-c), to explain the effect of flight classes, and this paper will also use the flight haul types to compare any possible differences between the types.

Table 3.3: Flight Haul types

Flight Haul Type	Duration
Short-haul	Up to 3 hours
Medium-haul	Between 3-6 hours
Long-haul	More than 6 hours

-Source: IATA (n.d.)

The raw data set contains 293 flight routes, of which only 11 are medium-haul. This low sample size makes it less accurate to do proper statistical analysis. The methodology of KLM takes short- and medium-haul as one group in their calculations. For these two reasons, analyzing possible differences in estimated and reported values will be done using the short-/medium- and long-haul groups.

3.2.4 Determining Passenger Numbers

The average emissions per route is known; however, the amount of passengers onboard the plane is not. It is needed to estimate the amount of emissions that should be allocated to a passenger. The first part of getting the number of passengers is the passenger capacity per aircraft type; this list can be found in Appendix C1.

In order to make a valid comparison between the values claimed by KLM and the estimation based on the FEAT model (Seymour et al., 2020), the seat distribution of classes in the aircraft and the load factor of passengers is also needed. For this research, only the economy class passenger is taken into consideration. KLM provides a distribution of economy and premium seats in their methodology report on CO2 calculation (KLM, n.d.-c). These values used by KLM show that on short- and medium-haul flights, 98% of the seats are economy class; on long-haul flights, 80% of the seat space is used for economy passengers (KLM, n.d.-c). This can be used to calculate how much of the total CO2 should be attributed to one economy-class passenger.

A passenger load factor is given per region in the methodology of the ICAO emissions calculator. However, this is relatively old data from 2016 (ICAO, 2018). This data does show that there can be significant differences between regions on load factor. Seymour et al. (2020) used an average load factor published by IATA as these are more up-to-date. Therefore, the regional load factors of the ICAO (2018) will be used and adjusted to the newest available average load factor from IATA (2023); this is an approximation but gives a better judgement of regional differences and is still up-to-date. The average load factor will be 84.8%, which is the average load factor of airlines situated in Europe for May 2023 (IATA, 2023), and between regions differences are still possible. A table with the different load factors per region can be found in Appendix C2.

3.2.5 Estimated Emissions per Passenger

The emissions per passenger is a combination of the calculated average emissions per flight and the retrieved data on passenger numbers per aircraft. This results in the following equation:

$$E_{p,r} = \frac{E_r}{l * c_{rc} * P_r}$$

- $E_{p,r}$ - Estimated CO2 emissions in kg per passenger and route
- E_r - Average emissions per route in kg of CO2
- l - Average passenger load factor
- c_{hc} - Class correction factor per route flight haul class
- P_r - Average passenger capacity per route

The equation divides the CO2 emissions per route for the whole aircraft with the expected passengers aboard the aircraft adjusted for the seating class. This provides the estimated emissions per economy passenger per route.

3.3 Estimating Cost of Carbon

After establishing the estimated emissions per passenger, the next part will explain the methodology for comparing the reported cost of compensation by KLM and the estimated cost of carbon. This relates to the second hypothesis.

The cost of carbon will be estimated using the in section 2 discussed SCC. The pricing of the SCC will be an average of the results found in recent literature grouped by the discount rate. A higher discount rate lowers the value of the SCC as more value is given to the present. The values for the SCC will be an average of the SCC values calculated by the U.S. Environmental Protection Agency (2022) and the research of Rennert et al. (2022). This choice is made because these are results from very recent and well-accepted studies or entities. This choice of recent estimations is essential as the literature shows signs of increasing estimation values of the SCC. Therefore, newer research can use the newest forecasts regarding climate change.

The average values used for this SCC can be seen in the table below, which is corrected for inflation and converted to Euros of the values given in the reports of the Environmental Protection Agency (2022) and Rennert et al. (2022), which were reported 2020 US dollars (Appendix F1).

Table 3.4: SCC Estimation

	Discount rate		
Report	**SCC 1.5%**	**SCC 2%**	**SCC 2.5%**
U.S. EPA	362.65	207.69	125.91
Rennert et al.	331.45	199.08	126.98
Average	347.05	203.39	126.45

-Values are in 2023 Euros per metric ton of $CO2$ estimated for 2020 rounded to 2 decimal points. Currency conversion has been done on 02-08-2023. The base values of the SCC are acquired from the EPA(2022) and Rennert et al. (2022).

The values are calculated for 2020; the EPA (2022) does report values for 2023. However, the research of Rennert et al. (2022) does not. Therefore, it is chosen to take the SCC for 2020. This will result in a slightly lower estimation of the SCC, as the EPA (2022) reports a value of 351 US dollars for the 1.5% discount rate. This is roughly 4% more than that of 2020.

3.4 Comparing Reported and Estimated Values

The following section explains the methodology for comparing the reported emissions and cost by KLM and this paper's estimated emissions and cost using the SCC. The comparison will be done by conducting a paired t-test. Ross & Willson (2017) explain that the paired t-test compares the mean of two matched groups; in this case, that is the estimated and reported emissions. This method will be used and executed on the whole sample and the distance category. Three distance groups can be considered; in that case, an ANOVA would be more appropriate. However, as discussed above, the alteration of the groups leaves two groups, making the paired t-test suitable for this analysis.

The formulas for this t-test can be found below:

$$t = \frac{\bar{d}}{s_d / \sqrt{n}}$$

Where:

$$\bar{d} = \frac{\sum_{i=1}^{n} d_i}{n}$$

And:

$$s_d = \sqrt{\frac{\sum_{i=1}^{n} \left(d_i - \bar{d}\right)^2}{n-1}}$$

- t - t-statistic
- $\bar{d}$ - mean difference of the paired observations
- s_d - sample standard deviation of the paired differences
- n - number of routes
- d_i - difference between estimated and reported emissions for the i route

This test will be executed using R as statistical software, providing the t-statistic and p-value and showing if the null hypothesis, assuming no emissions or cost mean differences, can be rejected.

The paired t-test requires several assumptions to be met for the results to be valid (Hsu & Lachenbruch, 2014). The dependent variable should first be continuous; this is the case as the emissions or cost can have any value. The second assumption is that the pairs should be related. In this case, the pairs are related flight routes as they are the same route for the estimation and the reported values. The sample should be random. The sample has been chosen to be direct flights, which is a choice. However, no selection is made for certain types of flights and thus can be considered random. The pairs should also be considered to be independent. This is met as the reported emissions from KLM or the estimated emission pairs on a specific route do not influence other routes. Next, the data must (approximately) satisfy the normality condition (Kim, 2015). The sample size is relatively large, so the paired t-test is quite robust for non-normality. However, it is checked by making a histogram, which will be done in section 4, and conducting Q-plots, which can be found in Appendix Figure E1. The final assumption is that there should be no outliers in the differences between the reported and estimated emissions; this will be checked in section 4.

4. Data

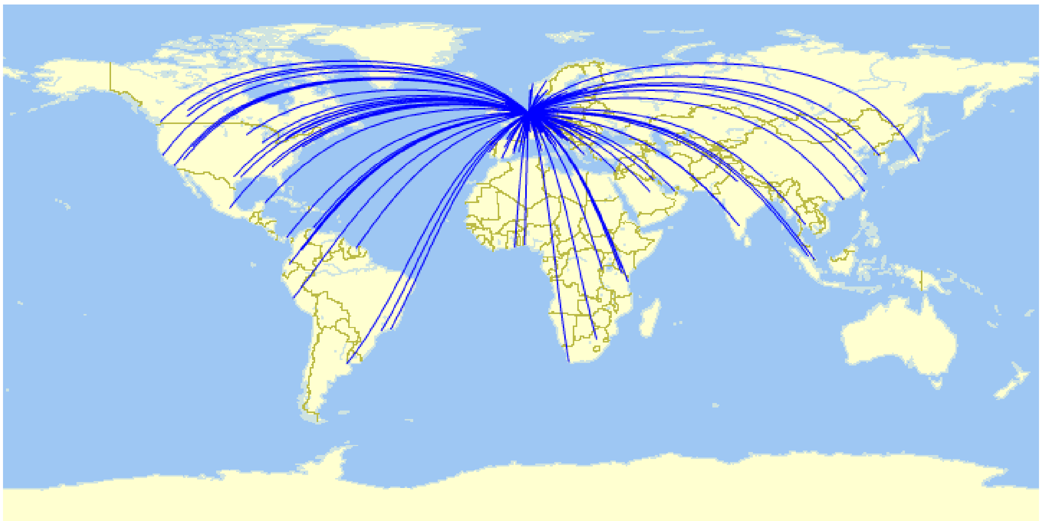
This chapter will discuss the collected data and further explain the transformation made to the data for further statistical analysis. The assumptions are addressed, and summary statistics are provided.

4.1 KLM Booking Data

For this research, data on emissions of individual flights and the corresponding compensations and price of compensation were needed from KLM. This data is not freely available in a readymade data set. These values can only be acquired through booking on the KLM website (KLM, n.d. -b).
The preferred data collection approach was web scraping, as no dataset was available. Web scraping is a technique to extract data from a webpage and save it into a database or file for analysis (Zhao, 2017). This would be an appropriate technique. However, the website of KLM does not allow web scraping in the booking process as this data is likely valuable and, therefore, protected. Therefore, the only way to collect the data was manually through the booking process. For example, the booking process of a flight from Amsterdam Schiphol Airport to London Heathrow Airport is shown in Appendix A1. During this collection process, access to the website of KLM was denied multiple times as a confirmation of the sensitive nature of the data collected.

The choice of data was restricted to Amsterdam Schiphol as the departure and arrival airport and all the direct destinations that KLM serves from Schiphol. This choice was made as this research will focus on direct flights. According to the website of FlightsFrom.com (FlightsFrom.com, n.d.), 147 routes, from which six were currently inactive, resulted in 147 direct connections as of 21-06-2023. These connections can be seen in the figure below, and a list of all the routes can be found in Appendix B1. This list includes 154 flights, as six inbound flights arrive from a different airport than the destination of the outbound flight. The figure below shows all the routes considered and their GCD. This GCD was calculated using the website of Great Circle Mapper (Swartz, n.d.).

Figure 4.1:



-Computed for 153 routes with Great Circle Mapper (Swartz, n.d.)

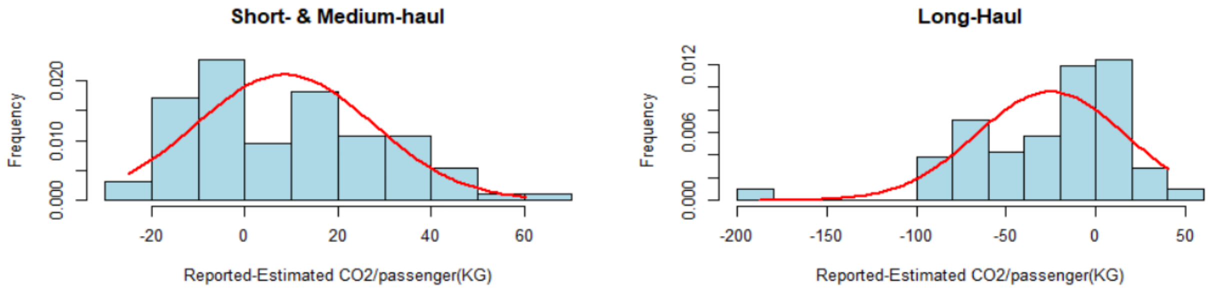
The data on the flights was manually collected in the time of 4 days: 21-06-2023, 22-06-2023, 23-06-2023, and 27-6-2023, the flight price data was collected between 16:00 and 17:30. As stated in the publication of KLM of their methodology (KLM, n.d. -c), the prices of compensation can be adjusted twice a year. Therefore, the majority of the collection phase was done in these three days, and during this phase, multiple checks were conducted to ensure the prices did not change.
The dates selected as departure and return are 1-11-2023 and 8-11-2023. This date was chosen to ensure flight tickets were available at the time of collection. However, not all flights were available at that time due to their weekly schedule or seasonality; for 27 flights, another date was chosen at the moment these flights were available.

The 147 destination pairs shown in the table in Appendix B1 are 294 inbound and outbound flights, as there is an inbound flight from the corresponding airport pair and an outbound flight. For the efficiency of data collection, the individual flight data was collected by selecting a round trip and then dividing the collected emissions and compensation data by two. This is possible as it shows that for almost all flights, with some exceptions, the displayed emissions, compensation and cost of compensation of a round trip is exactly half of these values for the one-way trip. There are two exceptions to this rule. The first is flights whose compensation price, emissions or reductions end on an odd number. These are rounded up for one of the flights and rounded down for the other flight. This is adjusted in the dataset. The second exception is flights containing in-between stops. Inbound flights from Aruba, Bogota, Riyadh, Kilimanjaro, Kigali, Quito, Sint Maarten and Zanzibar have an in-between stop at a nearby airport. Therefore, the outbound flights of this destination are used, and the inbound flights from the destination airport are replaced by the inbound flights coming from the in-between stop. The inbound flight of Zanzibar was left out, as it uses the same in-between stops as Kilimanjaro; this flight is thus already in the dataset.

4.2 Emission Data Assumptions

At first, the assumption will be tested for the collected data of KLM and the estimated data. The assumption that will need to be tested is normality. The histogram of the frequencies of the differences between the reported and estimated emissions can be seen in figure 6.1 below.

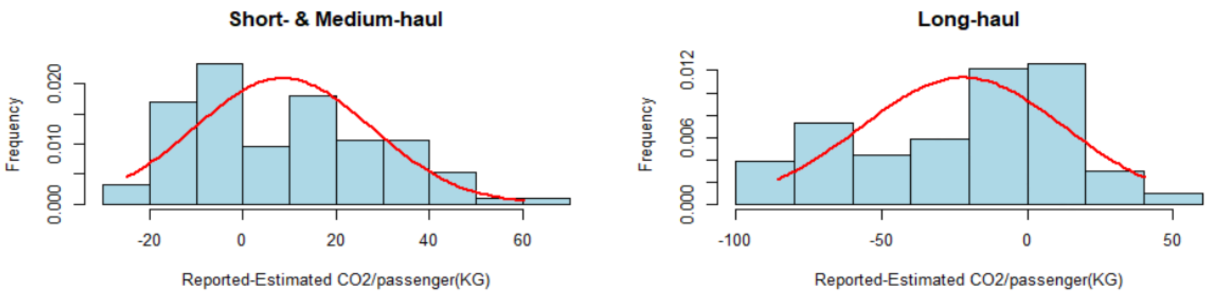
Figure 6.1: Histogram Emission Differences



The negative values in the plot indicated flight routes where the estimated emissions are higher than the reported; this is the other way around for the positive values. It seems that there is a normal distribution. However, there seem to be outliers on the long-haul group's left side of the distribution graph. These could also be observed when making a boxplot. As one of the other assumptions stated in the methodology, there should be no outliers in the difference between reported and estimated emissions.

The outliers for the long-haul group with a difference of 187.70 KG of CO_2 per passenger are that of flights KL0809 and KL0910 between Kuala Lumpur and Amsterdam. These could be qualified as an outlier as they differ significantly from the other observations. Removing the outlier gives the following results shown in figure 6.2.

Figure 6.2: Histogram Emission Differences Without Outliers



This new histogram without any outliers seems to show an okay normal distribution. However, the short-/medium-haul group is slightly positively skewed, and the long-haul group is slightly negatively skewed. An extra check for the normality using Q-plots can be seen in Appendix Figure E1.

4.3 Historical Flight Data

The next part of data needed to estimate emissions is the type of aircraft used on the flight routes selected before. The fuel used differs per aircraft type, so to make a fitting estimation of the difference between the claimed emissions and related compensation, the aircraft type is needed. During the booking process, there is no mention of the type of aircraft used. The website of KLM does report a list of the fleet used with some destinations where these aircraft are used. However, this does not span all their flights, and multiple aircraft types serve multiple routes. This implies that routes do not always use the same type of planes. Therefore, another approach was taken to collect this aircraft-type data. The website of Flightradar24.com (Flightradar24, n.d.) offers historical flight data per flight number. The free version of the website displays seven historical days of flight data. A free trial version of the gold version was used to collect a more significant number of flights than was available if using the free version. The downside of this data is that this data cannot be downloaded per flight number. The option of web scraping was also protected on the website of Flightradar24.com. Therefore, this data was collected manually during two days, 28 and 29 of June 2023 and processed in Excel.

The choice was made to collect data for aircraft type for the outbound flights, and the assumption was made that the inbound flights used the same planes. A visual inspection of the data showed that most of the time, the planes used on the outbound flights were the same as on the inbound flights. This seems like a reasonable assumption to make. One exception was made for the flights which have in-between stops, which were mentioned before. These inbound flights are collected as these are not the same routes. Data was available for all the outbound flights except that of flight KL0807 to Taipei and KL0861 to Tokyo. These routes have not been flown recently. However, KLM has scheduled them for 2-11-2023 and 1-11-2023. Therefore, the same plane type was used as that of the destination of Hong Kong for flight KL0807 and Seoul for flight KL0861, as these are similar distances and areas. A quick scan also shows that similar plane types are used in that flight range.

The primary collected historical flight data consisted of 13922 flights. This data was cleaned by removing any cancelled flights, diverted flights and any scheduled flights that did not depart yet, and flights that have the same flight number as our flight of interest but do not have the same departure and arrival destination. This led to a dataset of 12312 flights corresponding to the 294 connections from KLM to and from Schiphol. Not every flight route has the same amount of flights per period.

This makes it so that the number of historical flights collected fluctuates per flight number. Between 21 and 100 historical flights were gathered per flight number. The aircraft used in these 12312 flights correspond to 12 different aircraft types. These are the same as the aircraft reported in use by KLM (KLM, n.d. -a); this report of the KLM also shows data on passenger numbers. This will be useful to calculate the prediction model of the emissions reported by KLM per flight, as KLM only reports CO2 per passenger. As not every flight is filled with passengers, an estimation has to be made concerning the average passenger load factor. An average passenger load factor of 84.8% will be used, translating to the average load factor of airlines situated in Europe for May 2023 (IATA, 2023).

4.4 Summary Statistics

Table 4.1 shows the summary statistics of basic flight data retrieved from the booking process of the KLM website. This is grouped into the short-/medium- and long-haul distance groups. The shortest flight distance is only 158 km, corresponding to flights KL1720 and KL1721 and the Amsterdam and Brussels airport pair. The most expensive flight is that of KL0609 from Amsterdam to Salt Lake City; this is, however, not the longest flight in terms of distance or duration.

Table 4.1:

KLM Flights Summary Statistics

	Total (N=291)	LH (N=103)	SH/MH (N=188)
Distance (km)			
Mean (SD)	3350 (3430)	7760 (1630)	931 (514)
Median [Min, Max]	1240 [158, 11400]	7840 [4360, 11400]	826 [158, 3320]
Flight time (minutes)			
Mean (SD)	281 (245)	592 (126)	111 (40.1)
Median [Min, Max]	135 [45.0, 875]	580 [350, 875]	105 [45.0, 305]
Price (€)			
Mean (SD)	430 (400)	884 (342)	180 (86.9)
Median [Min, Max]	209 [51.0, 1740]	788 [195, 1740]	168 [51.0, 884]

Source: KLM Booking Website

In total, 12312 flights were gathered to get the relative aircraft usage per route. The summary statistics of these flights can be looked up in Appendix D1, and the summary statistics of the estimated and reported emissions and the cost of carbon emissions are in Tables D2 and D3, respectively. These statistics show that the average estimated emissions per flight on long-haul routes is 176 tons of CO2. To put this into perspective, this equates to roughly the same amount of emissions as 38 passenger cars emit driving for a year(40.000 km) (EPA, 2023).

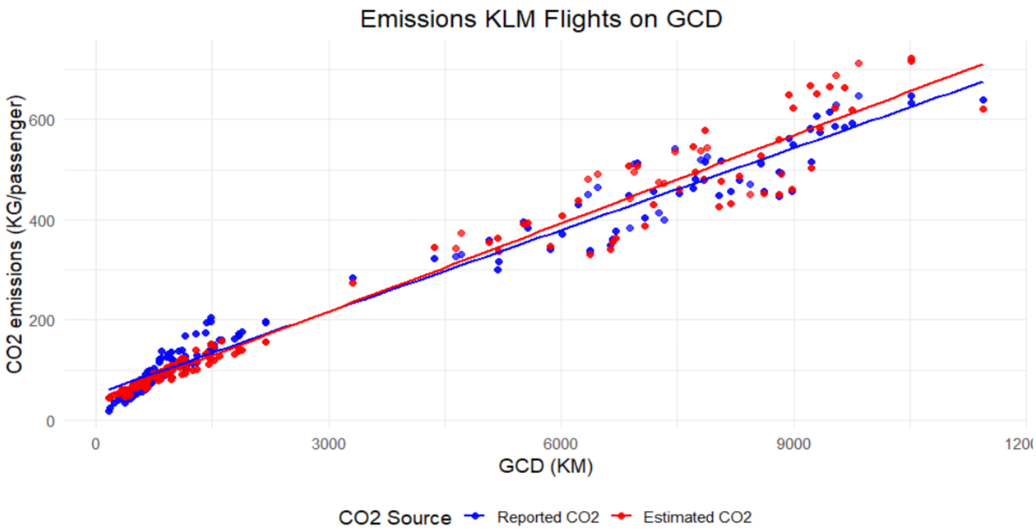
5. Results

This chapter will discuss the results from the calculations discussed in the methodology, and the resulting statistical test will be discussed. These results will be placed in context, and their significance will be discussed.

5.1.1 Reported and Estimated Emissions for All Flights

First, looking at the plot of the reported and estimated emissions on GCD is interesting. To observe any possible visual relationship between the reported and estimated emissions.

Figure 6.1:



The figure above shows the emissions reported by KLM in blue and the estimations in red. The linear regression line is added to see possible differences in relationships. There seems to be a visual difference between the estimated and reported emissions. It is hard to observe visually if the average emissions of the reported or estimated are statistically different; however, the graph does show that there might be a difference between longer distances flights and shorter distances flights, looking at the ab line. It can be observed that under 3000 km GCD, the reported emissions seem to be higher than the estimated emissions. For distances longer than 3000 km GCD, the estimated seem to be higher than the reported emissions.

As discussed in the methodology, the difference between the reported and estimated emissions will be tested using a paired sample t-test. The table below shows the results of the paired sample t-test for the whole sample of short-, medium- and long-haul flights, as observed in figure 6.1.

Table 6.1: Difference between Reported and Estimated Emissions

				95% Confidence interval		
Group	**T-statistic**	**N**	**P-value**	**Lower bound**	**Upper Bound**	**Mean difference**
All flying distances	-1.302	290	0.194	-5.696	1.162	-2.268

-Rounded to three decimal points. *** p<0.01, ** p<0.05, * p<0.1

The first hypothesis in the introduction stated that the reported per-passenger emissions are lower than the estimated emissions per-passenger. However, the results show that the null hypothesis of there being no difference between the estimated and reported emissions cannot be rejected, as the p-value is 0.194. The t-test shows signs that the reported emissions' mean is lower than estimated. However, this is not significant at any acceptable level of alpha. This does not support the first hypothesis, stating that the reported emissions are expected to be lower than the estimated emissions.

5.1.2 Reported and Estimated Emissions per Haul Type

In Figure 6.1, it can be seen that there is a possible difference between the short/medium and long-haul groups. Therefore, the plots of the separate groups in Figure 6.2 can be found below.

Figure 6.2:

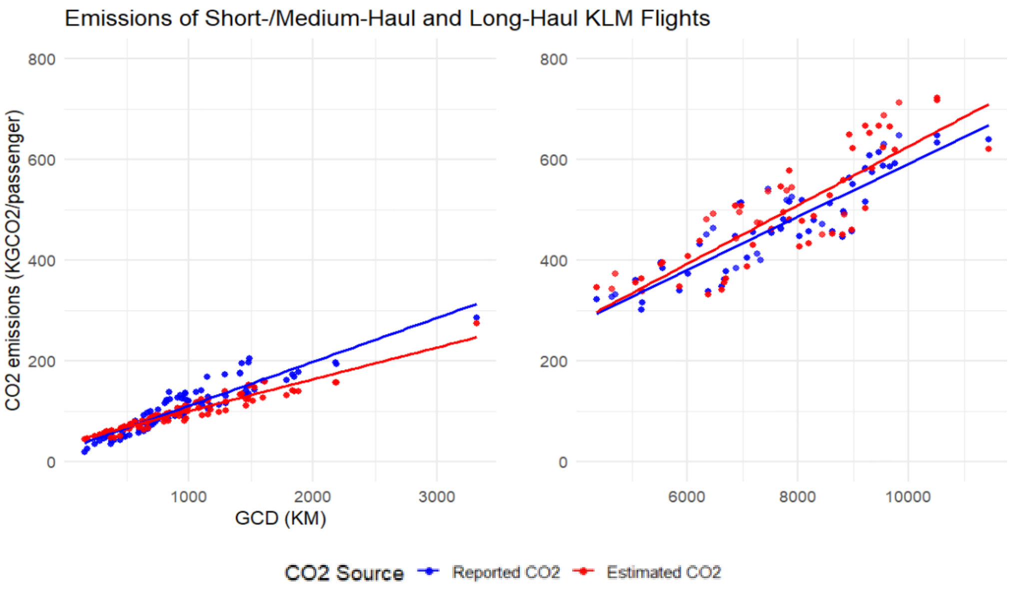


Figure 6.2 shows the possible differences between the short-/medium-haul and long-haul groups, confirming the first visual observations of Figure 6.1. The short-/medium-haul group seems to have higher emissions from KLM, and the long-haul group seems to have higher emissions from the estimation. To check these visual observations on any significance, the short-/medium-haul and long-

haul groups will be individually tested in the same way as the whole dataset. The results of these two groups can be seen in Table 6.2.

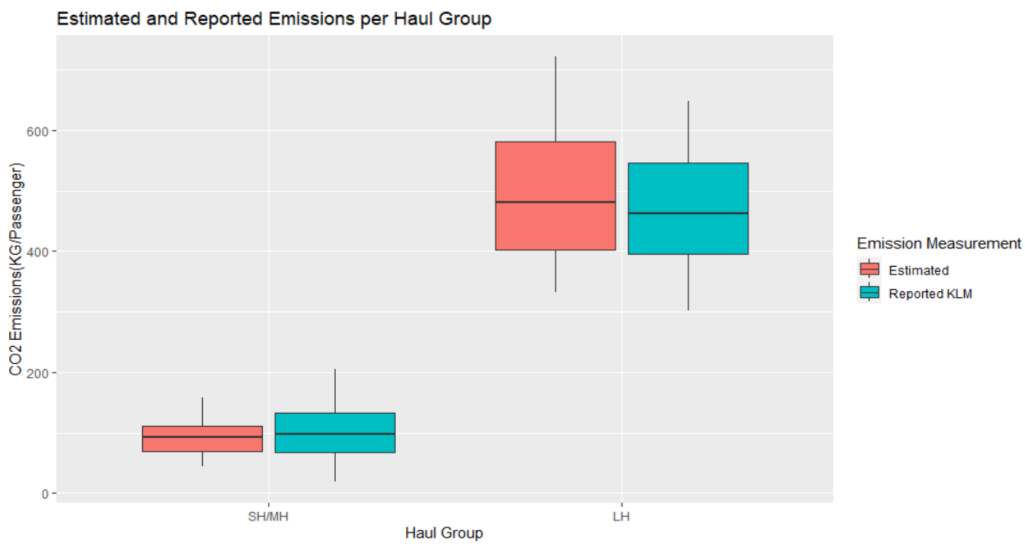
Table 6.2: Difference Between Reported and Estimated Emissions per Haul Group

				95% Confidence interval		
Distance Group	**T-statistic**	**N**	**P-value**	**Lower bound**	**Upper Bound**	**Mean difference**
Short/Medium-Haul	6.158	187	3.821e-09***	5.8451	11.320	8.583
Long-Haul	-6.375	102	5.384e-09***	-28.9382	-15.204	-22.071

-CI intervals and mean difference are in 2023 Euros. Rounded to three decimal points. *** p<0.01, ** p<0.05, * p<0.1

The test results confirm the first visual expectations from Figures 6.1 and 6.2. For both haul groups, the null hypothesis of there being no significant difference between the reported and estimated emissions can be rejected based on a significance level of 5%. Observing the results of the short-/medium-haul group shows that the reported emissions by KLM are, on average, 8.56 kgCO2/passenger higher than the estimated emissions. The long-haul group paints a different picture. The reported emissions of KLM are, on average, 22.07 kgCO2/passenger, lower than the estimated emissions. The histogram below shows a visualization of this difference.

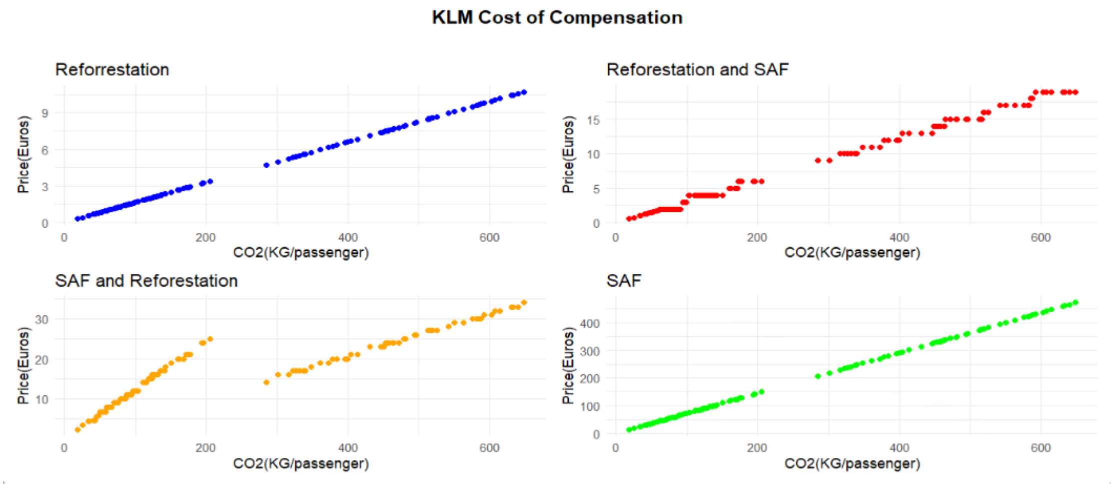
Figure 6.3:Boxplot



5.2.1 Reported and Estimated Cost of Compensation for All Flights

The following section will analyze the difference between the reported and estimated cost of compensation. This relates to hypothesis 2: “The reported cost of CO2 compensation per passenger emissions is lower than the estimated cost of carbon per passenger". KLM offers four different "compensation packages " (KLM, n.d. -b). This ranges from compensation solely by reforestation to compensation solely by using SAF and two options, which are a mix of those. The compensation options can be found in Appendix D4. The relationship between the prices of these options and the emissions they compensate for can be seen in Figure 6.4.

Figure 6.4:



-Source of data KLM (n.d. -b)

Figure 6.4 shows three linear relationships for reforestation, reforestation and SAF, and solely SAF. The option concerning SAF and reforestation seems to be a two-stepped linear relationship. In the case of SAF and reforestation for lower distances, there is a larger relative proportion of SAF in the compensation than for higher distances. The different compensation methods will be compared using reforestation, SAF and reforestation and SAF. However, the SAF and reforestation option will only be used in comparison in the split model, as the cost of compensation distribution is non-linear. These options provided by KLM are compared to the SCC, as discussed in section 3.5. The plot of the compensation cost of the different sources on GCD can be seen in Figure 6.5.

Figure 6.5:

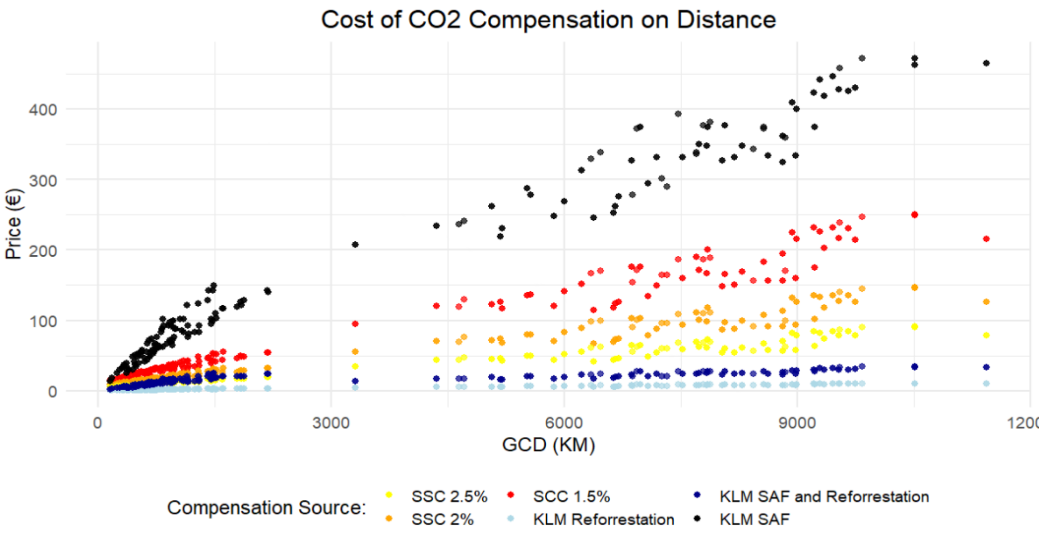


Figure 6.5 shows that, at first glance, the compensation price for SAF seems much higher than any other compensation measurement. However, the other compensation options by KLM seem to be, on average, all lower than valuing the cost of carbon using any estimation of SCC, regardless of any discount rate value used in this paper except for the SAF and reforestation option. This option seems relatively equal to the SCC estimation of 2.5% for the short-/medium-haul distances.

The comparison of the reported cost of compensation and estimated costs of carbon will be done using the same paired sample t-test as the comparison of emissions. The results of the paired sample t-test for the whole sample of flights (short-/medium-, long-haul) can be found in Table 6.4.

Table 6.4: Difference between Reported Cost of Compensation and Estimated Cost of Carbon

				95% Confidence interval		
Group	**T-statistic**	**N**	**P-value**	**Lower bound**	**Upper Bound**	**Mean difference**
Reforestation						
SCC 2.5	19.574	290	2.2e<-16***	23.495	28.745	26.121
SCC 2	19.662	290	2.2<e-16***	39.932	48.816	44.374
SCC 1.5	19.716	290	2.2<e-16***	70.623	86.287	78.455
SAF & Reforestation						
SCC 2.5	11.529	290	2.2e<-16***	10.906	15.396	13.151
SCC 2	15.299	290	2.2<e-16***	27.363	35.443	31.403
SCC 1.5	17.374	290	2.2<e-16***	58.066	72.903	65.485
SAF						

SCC 2.5	-21.413	290	2.2e<-16***	-154.003	-128.076	-141.040
SCC 2	-21.624	290	2.2<e-16***	-133.962	-111.611	-122.787
SCC 1.5	-22.183	290	2.2<e-16***	-96.576	-80.835	-88.705

-CI intervals and mean difference are in 2023 Euros. Values rounded to 3 decimal points. *** p<0.01, ** p<0.05, * p<0.1

These first results show that, while not making any distinction between flight distance groups, the null hypothesis assuming that there is no difference between the estimated cost of carbon compensation using the SCC and the reported cost of compensation using the option of reforestation can be rejected, for all proposed values of the discount rate in the SCC. The mean difference is estimated to be between €26.12 and €78.46. This means the estimated cost of carbon emissions using the SCC is all higher than the reported cost of compensation using reforestation provided by KLM. This supports the claim of the second hypothesis.

The results of the SAF & Reforestation option show that looking at all the flights, the valuation of the cost of carbon using the SCC is, in all cases, statistically significantly higher than that of the option of SAF & Reforestation. Depending on the chosen discount factor, this average difference is between €13.15 and €65.49.

Comparing the SCC to using SAF as a compensation source results in a different outcome. The null hypothesis stating that there is no difference between the reported cost of compensation and the estimated cost of carbon can be rejected for all the values of the SCC, as the p-value of the paired t-test is lower than 5%. However, this time, the mean differences are all negative, showing that the reported cost of compensation, using SAF as the source, reported by KLM, is higher than the estimated cost of carbon. This contradicts the second hypothesis, stating that the reported compensation cost will be lower than the estimated.

5.2.2 Reported and Estimated Cost of Compensation per Haul Type

The following results of interests would be the difference between the different haul groups. The first part of interest is the individual plots of the different haul groups. These can be seen in figure 6.5.

Figure 6.5:

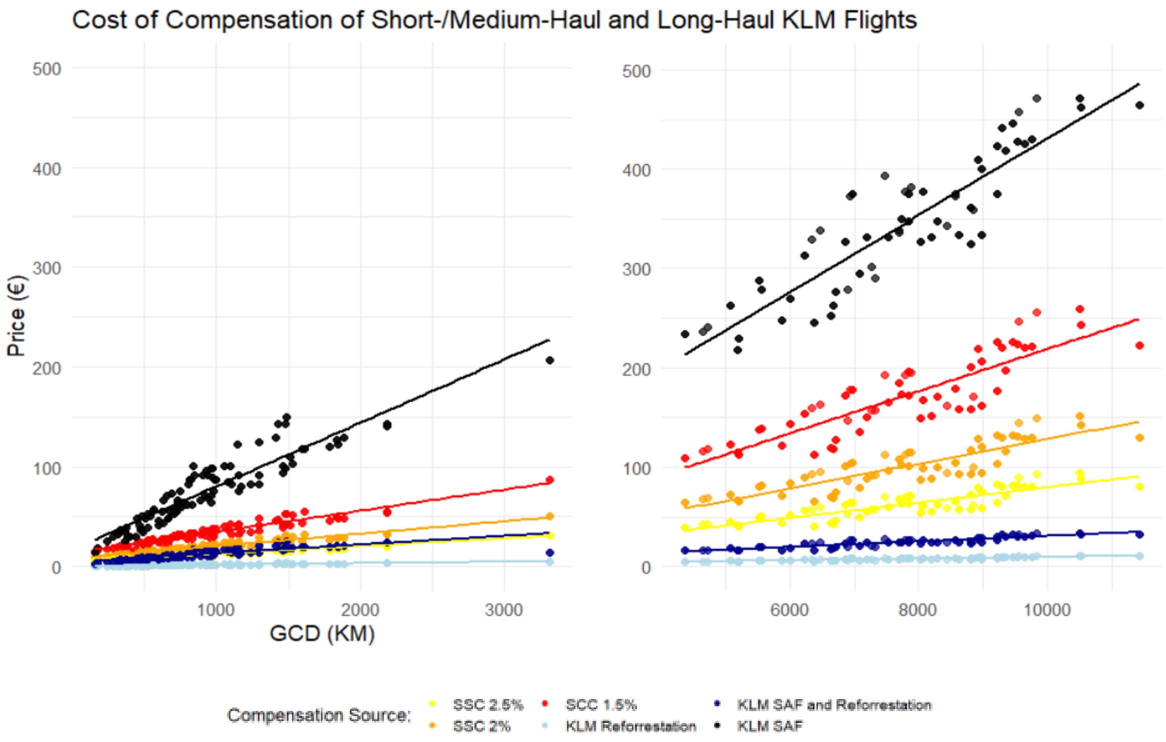


Figure 6.5 seems to confirm the observation that for the short-/medium-haul flights, the SAF and reforestation option shows almost equal cost of carbon to the SCC 2.5 valuation of the estimated cost of carbon. The paired sample t-test results grouped into distance groups can be seen in Table 6.5.

Table 6.5: Difference between Reported Cost of Compensation and Estimated Cost of Carbon by Haul-Group

				95% Confidence interval		
Group	**T-statistic**	**N**	**P-value**	**Lower bound**	**Upper Bound**	**Mean difference**
Short/Medium-Haul						
SCC-Reforestation						
SCC 2.5	40.086	187	<2.2e-16***	9.882	10.905	10.393
SCC 2	39.458	187	<2.2e-16***	16.877	18.653	17.765
SCC 1.5	39.066	187	<2.2e-16***	29.937	33.122	31.530
SCC- SAF & Reforestation						
SCC 2.5	-2.045	187	0.042**	-0.930	-0.017	-0.473
SCC 2	23.737	187	<2.2e-16***	6.325	7.472	6.899
SCC 1.5	35.547	187	<2.2e-16***	19.516	21.810	20.663
SCC-SAF						

SCC 2.5	-28.051	187	<2.2e-16***	-68.453	-59.458	-63.956
SCC 2	-26.923	187	<2.2e-16***	-60.730	-52.438	-56.584
SCC 1.5	-24.110	187	<2.2e-16***	-46.323	-39.316	-42.819
Long-Haul						
SCC-Reforestation						
SCC 2.5	43.715	102	<2.2e-16***	52.342	57.317	54.829
SCC 2	44.110	102	<2.2e-16***	88.763	97.129	92.943
SCC 1.5	44.354	102	<2.2e-16***	156.768	171.445	164.106
SCC-SAF & Reforestation						
SCC 2.5	40.340	102	<2.2e-16***	36.148	39.887	38.017
SCC 2	42.541	102	<2.2e-16***	72.581	79.680	76.130
SCC 1.5	43.584	102	<2.2e-16***	140.591	153.997	147.294
SCC-SAF						
SCC 2.5	-50.851	102	<2.2e-16***	-292.726	-270.747	-281.736
SCC 2	-51.224	102	<2.2e-16***	-253.057	-234.190	-243.623
SCC 1.5	-51.000	102	<2.2e-16***	-179.167	-165.752	-172.459

-CI intervals and mean difference are in 2023 Euros. Rounded to three decimal points. *** p<0.01, ** p<0.05, * p<0.1

Observing the results of these tests, it can be seen that comparing reforestation as a method of valuation to the SCC shows that the differences are all positively statistically significant. The cost of carbon emissions valued by the SCC using a discount factor of 2% is, on average, €17.77 higher on the short-haul routes and €92.94 higher on the long-haul routes. The splitting of the results shows more extreme differences than when looking at the whole model. This could be explained by the earlier observed differences between the estimated and reported emissions on the short/medium- and long-haul routes. The comparison of prices is a vertical transformation of these earlier observations, as the pricing of the emissions is done linearly.

Comparing the SAF and reforestation to the estimated SCC leaves a different picture. The SCC is, in all except one case, higher than the SAF and reforestation option. This exception is that of the SCC1.5 and the SAF and reforestation option in the short-/medium-haul group. The mean value of the estimated SCC1.5 is lower than that of the SAF and reforestation option on a 5% significance level; this is a slight mean difference of €0.47.

The comparison between SCC and SAF based on distance group shows the same relationship as in Table 6.4, but with higher differences. On the short/medium-haul distances, the cost of compensation using SAF is, on average, €56.58 higher than using the SCC (2% discount rate). This number increases to €243.62 when looking at the long-haul flights.

These results show that mixed evidence relates to the stated second hypothesis. Most of the results show that the estimated cost of carbon is higher than the reported cost of compensation for the option of reforestation and SAF & Reforestation. However, all the mean values of the SAF are higher than the SCC, and the comparison of the SAF & Reforestation option and the SCC1.5 on the short-/medium-haul groups shows that the reported compensation is higher than the estimated cost of carbon. Visualizing these in a boxplot format provides Figure 6.4.

Figure 6.4:

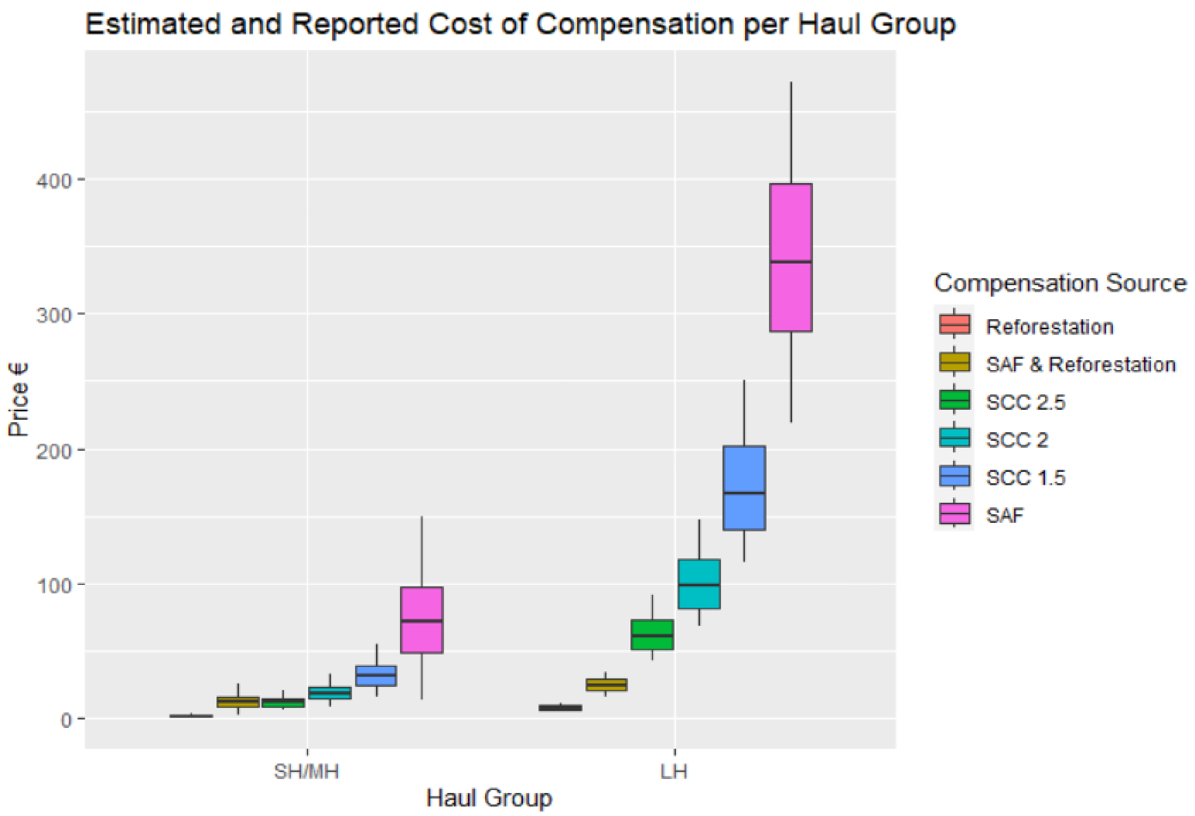


Figure 6.5 shows the reported cost of compensation and estimated cost of carbon using the SCC and the average prices of all flights; this shows the actual relative cost of the compensation options and valuations according to the estimated SCC. Table 6.6 displays these visual observations translated to percentages of the total average price of a ticket. It shows the average price of a ticket and the average cost of compensation or carbon as a percentage of the ticket price. This shows that using reforestation as a compensation option is, on average, less than 1% of the ticket price, while using SAF as a compensation method is, on average, around 40% of the average ticket price.

Figure 6.5:

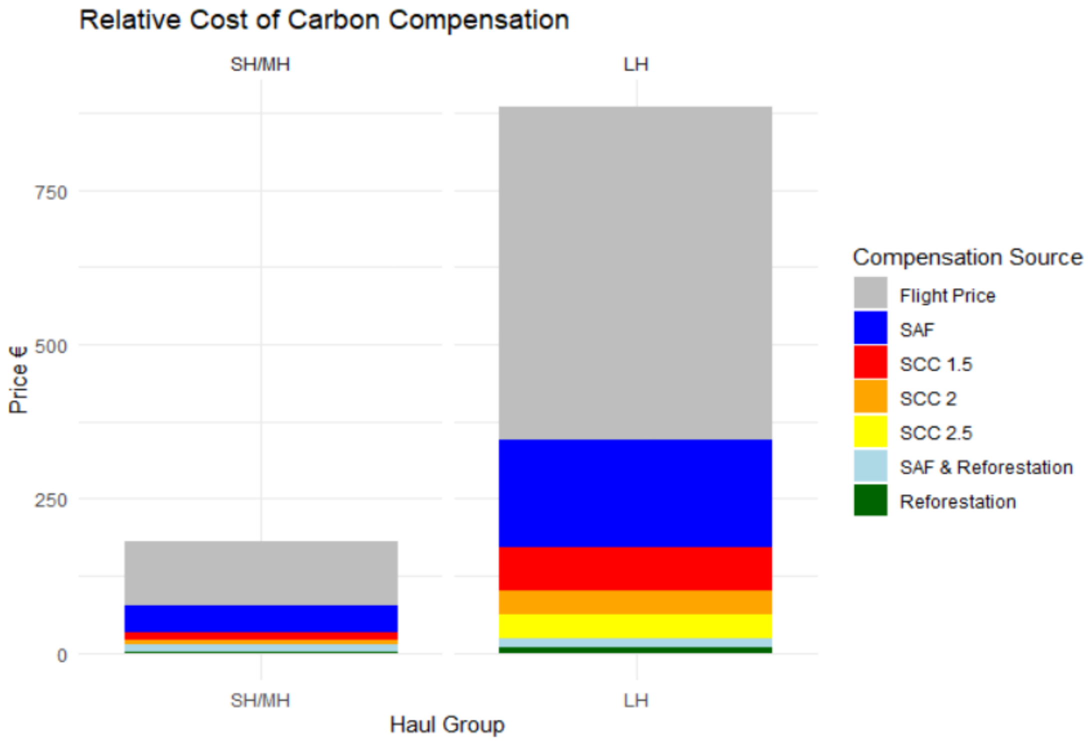


Table 6.6: Relative Cost of Carbon Compensation and Cost of Carbon in Percentages

Distance Group	**Flight price**	**Reforestation**	**SAF & Reforestation**	**SCC 2.5**	**SCC 2**	**SCC 1.5**	**SAF**
Short/Medium-Haul	180.44	0.95%	6.98%	6.71%	10.80%	18.43%	42.16%
Long-Haul	884.43	0.88%	2.78%	7.08%	11.39%	19.44%	38.94%

-Flight prices are in Euros. Other values are percentages.

6. Conclusion and Discussion

This final section will make a final conclusion and summarize the results obtained by this study. The possible limitations of this study will be discussed, and some recommendations on policy and further research will be given.

6.1 Conclusion

The main objective of this research was to find the relationship between the reported and estimated cost of carbon based on a case study of KLM flights from Schiphol. The question that needed to be answered was: "What is the relationship between the estimated cost of carbon emissions in passenger flights and the reported compensation cost?". Two hypotheses were formed to assist in answering the main research question. The results related to these hypotheses will be discussed in the following section.

> ***Hypothesis 1:*** *The reported per-passenger emissions are lower than the estimated emissions per passenger.*

The first hypothesis was tested by first collecting per-passenger emission values reported by KLM on 291 direct routes flown to and from Schiphol by KLM. Subsequently, the estimated emissions were computed using a fuel-burn estimation model, converted to emissions, developed by Seymour et al. (2020) and computed per passenger. This resulted in two paired samples of per-passenger emissions, statistically analyzed using sample paired t-tests. The t-tests were conducted for the whole sample of flights and the short-/medium- and long-haul groups.

The results suggest that there is no significant difference between the estimated and the reported per-passenger emissions looking at all flight routes combined; this is, therefore, in contrast with the first hypotheses and the expectation of this study. However, a different outcome is observed when dividing the observations into haul groups. The t-tests show that, on average, the estimated per passenger emissions are 8.583 $kgCO_2$ lower than the reported emissions for short-/medium-haul flights. This is, on average, 8.2% lower than the reported emissions. When looking at the results of the long-haul group, the estimated emissions per passenger are, on average, 22.071 $kgCO_2$ higher than the reported emissions. This is, on average, 4.7% higher than the reported emissions. So, evidence supporting the first hypothesis is only found for long-haul flights. However, the relative differences are not that large in magnitude and comparable to differences found in the literature between fuel model estimations and actual fuel burned by airlines, which was roughly 6% (Yanto & Liem, 2018). As the fuel burn model calculation requires several assumptions on values known to the airlines, these significant differences do not seem to indicate any large differences between the reported and estimated per-passenger emissions.

> ***Hypothesis 2:*** *The reported cost of CO2 compensation per passenger emissions is lower than the estimated cost of carbon per passenger.*

The second hypothesis analyzed related to the relationship between the reported cost of compensation and the estimated cost of carbon. The earlier computed estimated emissions were transformed to cost by pricing this carbon using the SCC. This SCC was computed as an average of the SCC reported by Rennert et al. (2022) and the EPA (2022). This SCC was used for three different discount factors. The same paired sample t-test was used to compare the means of the estimated and reported cost of carbon. This comparison showed that when looking at all the flights combined, the estimated cost of compensation using the SCC was significantly higher than that of the reforestation option and the option of SAF & reforestation, no matter the discount factor. This result, which is in line with the expectations of this study, changes when looking at the reported option of SAF. The cost of compensation using an estimated value of the SCC is statistically significantly lower than any reported SAF option. This difference is relatively large and stands out as even when using a discount factor of 1.5%, giving more value to the future, the average difference in compensation cost is €88.71 lower. This means the reported average value of the SAF option's carbon compensation cost is 207.74% of the SCC1.5 estimation. This, therefore, contradicts the second hypothesis. When splitting up the routes of KLM into short-/medium-haul and long-haul, the results suggest the same conclusion, except for the comparison of the estimated SCC1.5 and the reported SAF & Reforestation option for the short-/medium-haul group. The average estimated compensation value is €0.47 lower than the reported SAF & Reforestation option. This suggests a minimal difference, although significant, between the estimated and reported values of these options. This contradicts the second hypothesis.

Summarizing the findings in answering the research question is not that straightforward. The results show mixed results, so some nuance should be given to the findings for interpretation. Some differences are found between the reported and estimated emissions, which differ in direction for the short-/medium-haul and long-haul. However, The differences are at the highest, around 8%, which does not seem large compared with the differences found in the pricing of emissions. The quality of accurate estimation of emissions relies for a large part on data availability. As stated by KLM (n.d.-c), KLM’s calculations are based on actual fuel burn, and KLM has exact figures on their passenger numbers and, therefore, can conduct accurate estimations. However, as not all data is public, there is no possibility to review KLM’s precise estimation method accurately. The results suggest small differences between the estimated and reported emissions. However, the literature and the methodology assumptions indicate that these differences could be due to several assumptions made in the estimation. The reason the long-haul flights have a higher estimation than the reported and the short-/medium-haul flights have a lower estimation is debatable. It could be that the used estimation model underestimates the inefficiencies of short-haul flights and overestimates efficiencies in long-haul flights due to the assumptions in the flight modelling. This, however, should be further analyzed. The estimated pricing of these emissions is the part of this study where the largest differences between the estimated and reported values can be found. The most obvious result is the relatively higher valuation of the SAF option. This valuation does not seem to be in relationship with the actual carbon cost, looking at the literature. The high end of the estimations of the SCC is still lower than this option. It seems it is related to the relatively high cost of SAF. However, the lack of transparency of this investment in SAF by KLM and its reduction numbers makes this option difficult to judge. For almost all other compensation options and flying distances, the estimated cost of compensation is higher than the reported cost of compensation except one. These results show that the relationship between the estimated cost and reported cost of carbon in flying is highly reliant on the source of compensation chosen. It gives mixed results depending on haul type. However, the results suggest that reforestation, at the price used by KLM, undervalues the actual cost of these emissions.

6.2 Limitations and Further Research

The limitations of this study are from different origins. The external validity of the research could be debated, as one airline, KLM, has been considered. However, the results could be comparable with an airline of equal market position. The research could be easily enlarged to include other airlines as the methodology could apply to any airline. Another possible limitation is the choice of the fuel burn model. The choice was made for the FEAT model of Seymour et al. (2020). This suited the scope of the research. However, this study does rely on the accuracy of the work of Seymour et al. (2020) and the underlying assumptions made in their research. This includes assumptions made on passenger numbers and load factors, among others. If accurate fuel burn data per flight were available, these assumptions would not have been necessary. These same assumptions made on load factors and passenger numbers also affect the allocation of emissions in this research. Estimations were made for load factors with relatively old data. Newer routes and airline-specific load factors could improve the accuracy of the estimations. The estimations of the relative use of aircraft type per route are also bound to some limitations. Data on historical flights does not have to represent future schedules. This makes it so that, for example, upgrades to more fuel-efficient aircraft cannot be considered. The average from two studies was taken to establish the cost of carbon because of the up-to-date values. However, one could debate whether a broader scope of estimations could be of value. Another aspect that could have altered the outcome is including a value of the RFI, including the extra damaging effects of CO2. The estimations range between 1.7 and 3, as the literature suggests, suggesting that the estimated emissions and cost of compensation would have increased by a low estimation of at least

70%. This is a significant increase and would dramatically increase the cost of carbon in flying. There is no real consensus in the literature on the RFI's value, so further research is needed to include it.

This research has shown that the quality of measurement of emissions is greatly dependent on the availability of data and the transparency of airlines. Therefore, it would be recommended that the methodology regarding emissions should be easily accessible to the public. The difference between estimated and reported emissions by KLM in this study was not large. However, a more open attitude towards the data would give more trust in its value. Literature shows that it is difficult to put a specific price on carbon emissions due to numerous uncertainties that are hard to predict or quantify (Litterman, 2013; Pindyck, 2013). This makes it challenging to price the carbon emissions of flying and could explain some carbon pricing variations. However, this paper points out that at least some pricing values are significantly lower than the estimated SCC. Whether these values are lower due to societies, including airlines, ignorance of the issue or not is another question. However, without proper regulation and unclear definitions of these offset schemes' critical factors, this open market allows organizations and consumers to choose the compensation source that suits them well. In the case of this study on flights from KLM, one could argue that few passengers would choose the compensation option of SAF over reforestation as they are claimed to compensate the same emissions while, on average, being 40 times more expensive. This can result in too low pricing of carbon emissions while the message to the consumer remains one of total compensation. This feeds into the idea of Watt (2021) that people want to believe the unrealizable offsets are valid as it leads away from the pressing issue of climate change, and this changes carbon offsetting from a valuable tool to mitigate carbon emissions to, as stated by Watt (2021), a fantasy solution leading society away from their responsibility. This research has shed light on the relationship between the reported and the estimated cost of carbon emissions in flying. More widely available data and further research on the value of the SCC could improve the estimations, and further research could use this methodology as a base or source of comparison.

References

AEDT. (2017). *Aviation Environmental Design Tool (AEDT) Technical Manual* (Vol. Version 2d). U.S. Department of Transportation, Federal Aviation Administration.

Babikian, R., Lukachko, S. P., & Waitz, I. A. (2002). The historical fuel efficiency characteristics of regional aircraft from technological, operational, and cost perspectives. *Journal of Air Transport Management*, *8*(6), 389–400. https://doi.org/10.1016/s0969-6997(02)00020-0

Breguet, L. (1923). Calcul du Poids de Combustible Consummé par un Avion en Vol Ascendant. *Comptes Rendus Hebdomodaires Des Séances de l'Académie Des Sciences*, *177*, 870–872.

Brueckner, J. K., & Abreu, C. (2017). Airline fuel usage and carbon emissions: Determining factors. *Journal of Air Transport Management*, *62*, 10–17. https://doi.org/10.1016/j.jairtraman.2017.01.004

Bumpus, A. G., & Liverman, D. M. (2008). Accumulation by decarbonization and the governance of carbon offsets. *Economic Geography*, *84*(2), 127–155. https://doi.org/10.1111/j.1944-8287.2008.tb00401.x

Coffin, J. G. (1920). *A Study of Airplane Range and Useful Loads, NACA-TR-69*.

Collins, B. P. (1982). Estimation of aircraft fuel consumption. *Journal of Aircraft*, *19*(11), 969–975. https://doi.org/10.2514/3.44799

Conte, M. N., & Kotchen, M. J. (2010). Explaining the price of voluntary carbon offsets. *Climate Change Economics*, *01*(02), 93–111. https://doi.org/10.1142/s2010007810000091

Dahlman, C. J. (1979). The problem of externality. *The Journal of Law and Economics*, *22*(1), 141–162. https://doi.org/10.1086/466936

Davis, S. J., Lewis, N. S., Shaner, M., Aggarwal, S., Arent, D., Azevedo, I. L., Benson, S. M., Bradley, T., Brouwer, J., Chiang, Y.-M., Clack, C. T., Cohen, A., Doig, S., Edmonds, J., Fennell, P., Field, C. B., Hannegan, B., Hodge, B.-M., Hoffert, M. I., … Caldeira, K. (2018). Net-zero emissions energy systems. *Science*, *360*(6396). https://doi.org/10.1126/science.aas9793

Flightradar24. (n.d.). *Live flight tracker - real-time flight tracker map*. Flightradar24.com. https://www.flightradar24.com/data/flights

FlightsFrom.com. (n.d.). *All scheduled direct (non-stop) flights from Amsterdam (AMS)* . FlightsFrom.com. https://www.flightsfrom.com/AMS?from=AMS&airlines=KL&state=1

Forliance. (2022, October 27). *Growing Climate Action*. Forliance. https://forliance.com/

Frost, R. (2023, January 27). *Ryanair weakens green claims after warning from Dutch regulator*. Euronews. https://www.euronews.com/green/2023/01/26/ryanair-low-cost-airline-warned-about-misleading-carbon-offset-claims

Fulton, L. M., Lynd, L. R., Körner, A., Greene, N., & Tonachel, L. R. (2015). The need for biofuels as part of a low carbon energy future. *Biofuels, Bioproducts and Biorefining*, *9*(5), 476–483. https://doi.org/10.1002/bbb.1559

Gillenwater, M. W. (2012, January). What Is Additionality? Part 1: A long standing problem. https://www.researchgate.net/publication/257945337_What_Is_Additionality_Part_1_A_long_standing_problem

Gold Standard. (n.d.). *A higher standard for a climate secure and sustainable world*. The Gold Standard. https://www.goldstandard.org/

Greenstone, M. (2002). The impacts of environmental regulations on industrial activity: Evidence from the 1970 and 1977 Clean Air Act Amendments and the census of manufactures. *Journal of Political Economy*, *110*(6), 1175–1219. https://doi.org/10.1086/342808

Greenstone, M., Kopits, E., & Wolverton, A. (2011). Estimating the social cost of carbon for use in U.S. federal rulemakings: A summary and interpretation. *NBER Working Paper*, *No. 16913*. https://doi.org/10.3386/w16913

Gössling, S., & Humpe, A. (2020). The global scale, distribution and growth of aviation: Implications for climate change. *Global Environmental Change*, *65*, 102194. https://doi.org/10.1016/j.gloenvcha.2020.102194

Gössling, S., Broderick, J., Upham, P., Ceron, J.-P., Dubois, G., Peeters, P., & Strasdas, W. (2007). Voluntary Carbon Offsetting Schemes for aviation: Efficiency, credibility and sustainable tourism. *Journal of Sustainable Tourism*, *15*(3), 223–248. https://doi.org/10.2167/jost758.0

Gössling, S., Haglund, L., Kallgren, H., Revahl, M., & Hultman, J. (2009). Swedish air travellers and voluntary carbon offsets: Towards the co-creation of environmental value? *Current Issues in Tourism*, *12*(1), 1–19. https://doi.org/10.1080/13683500802220687

Hsu, H., & Lachenbruch, P. A. (2014). Paired t Test. *Wiley StatsRef: Statistics Reference Online.* https://doi.org/10.1002/9781118445112.stat05929

Hänsel, M. C., Drupp, M. A., Johansson, D. J., Nesje, F., Azar, C., Freeman, M. C., Groom, B., & Sterner, T. (2020). Climate Economics support for the UN climate targets. *Nature Climate Change, 10*(8), 781–789. https://doi.org/10.1038/s41558-020-0833-x

IATA. (2021, October 4). *Our Commitment to Fly Net Zero by 2050*. IATA.org. https://www.iata.org/en/programs/environment/flynetzero/

IATA. (2023, July 6). *Air passenger market analysis - IATA May 2023*. IATA.org. https://www.iata.org/en/iata-repository/publications/economic-reports/air-passenger-market-analysis---may-2023/

IATA. (n.d.). *FHT flight haul type*. IATA Standards. https://guides.developer.iata.org/archive/docs/fht-flight-haul-type

ICAO. (2008). *ICAO Carbon Emission Calculator Methodology*.

ICAO. (2018). *ICAO Carbon Emissions Calculator Methodology*.

IEA. (2021, February). *Energy Technology Perspectives 2020 – analysis*. IEA. https://www.iea.org/reports/energy-technology-perspectives-2020

Kim, T. K. (2015). T test as a parametric statistic. *Korean Journal of Anesthesiology*, *68*(6), 540. https://doi.org/10.4097/kjae.2015.68.6.540

KLM. (n.d.-a). *All the aircraft types in the KLM fleet - KLM netherlands*. KLM Royal Dutch Airlines. https://www.klm.nl/en/information/travel-class-extra-options/aircraft-types

KLM. (n.d.-b). *Boek vluchten online - KLM Nederland*. KLM Royal Dutch Airlines. https://www.klm.nl/

KLM. (n.d.-c). *Calculation methodology and purpose KLM CO2 Calculator*. KLM Royal Dutch Airlines. https://img.static-kl.com/m/6346df510a9b6853/original/CO2-Calculator.pdf

KLM. (n.d.-d). *CO_2 compensation by reforestation and/or Sustainable Aviation Fuel (SAF) conditions*. KLM Royal Dutch Airlines. https://www.klm.nl/en/information/legal/extra-options/co2-impact-programme

Lee, D. S., Fahey, D. W., Skowron, A., Allen, M. R., Burkhardt, U., Chen, Q., Doherty, S. J., Freeman, S., Forster, P. M., Fuglestvedt, J., Gettelman, A., De León, R. R., Lim, L. L., Lund, M. T., Millar, R. J., Owen, B., Penner, J. E., Pitari, G., Prather, M. J., … Wilcox, L. J. (2021). The contribution of Global Aviation to anthropogenic climate forcing for 2000 to 2018. *Atmospheric Environment*, *244*, 117834. https://doi.org/10.1016/j.atmosenv.2020.117834

Lee, J. J., Lukachko, S. P., Waitz, I. A., & Schafer, A. (2001). Historical and future trends in aircraft performance, cost, and emissions. *Annual Review of Energy and the Environment*, *26*(1), 167–200. https://doi.org/10.1146/annurev.energy.26.1.167

Litterman, B. (2013). What is the right price for carbon emissions. *Regulation*, *36*(2), 38–51.

Lohmann, L. (2005). Marketing and making carbon dumps: Commodification, calculation and counterfactuals in climate change mitigation. *Science as Culture*, *14*(3), 203–235. https://doi.org/10.1080/09505430500216783

Marshall, A. (1890). *Principles of Economics*. Macmillan.

Mouillet, V. (2019). User Manual for the Base of Aircraft Data (BADA) Revision 3.15. *Technical Report EUROCONTROL*. https://doi.org/https://www.eurocontrol.int/publication/user-manual-base-aircraft-data-bada

Nordhaus, W. (2018). Evolution of modeling of the economics of global warming: Changes in the dice model, 1992–2017. *Climatic Change*, *148*(4), 623–640. https://doi.org/10.1007/s10584-018-2218-y

Nordhaus, W. D. (2017). Revisiting the social cost of carbon. *Proceedings of the National Academy of Sciences*, *114*(7), 1518–1523. https://doi.org/10.1073/pnas.1609244114

NOS. (2023, January 11). *Vliegbelasting omhoog, Maar Gaan we Ook Echt Minder Vliegen?*. NOS.nl - Nieuws, Sport en Evenementen. https://nos.nl/artikel/2459489-vliegbelasting-omhoog-maar-gaan-we-ook-echt-minder-vliegen

Nuic, A., Poles, D., & Mouillet, V. (2010). Bada: An advanced aircraft performance model for present and future ATM Systems. *International Journal of Adaptive Control and Signal Processing*, *24*(10), 850–866. https://doi.org/10.1002/acs.1176

Pearce, D. (2003). The social cost of carbon and its policy implications. *Oxford Review of Economic Policy*, *19*(3), 362–384. https://doi.org/10.1093/oxrep/19.3.362

Penner, J. E., Lister, D. H., Griggs, D. J., Dokken, D. J., & McFarland, M. (1999). *Aviation and the global atmosphere: a special report of the Intergovernmental Panel on Climate Change*. Cambridge University Press.

Pigou, A. C. (1924). *The Economics of Welfare*. Macmillan.

Pindyck, R. S. (2013). Pricing carbon when we don’t know the right price. *Regulation*, *36*(2), 43–46.

Rennert, K., Errickson, F., Prest, B. C., Rennels, L., Newell, R. G., Pizer, W., Kingdon, C., Wingenroth, J., Cooke, R., Parthum, B., Smith, D., Cromar, K., Diaz, D., Moore, F. C., Müller, U. K., Plevin, R. J., Raftery, A. E., Ševčíková, H., Sheets, H., … Anthoff, D. (2022). Comprehensive evidence implies a higher social cost of CO2. *Nature*, *610*(7933), 687–692. https://doi.org/10.1038/s41586-022-05224-9

Ritchie, H. (2020, October 6). *Cars, planes, trains: Where do CO2 emissions from transport come from?*. Our World in Data. https://ourworldindata.org/co2-emissions-from-transport

Ross, A., & Willson, V. L. (2017). Paired samples T-test. *Basic and Advanced Statistical Tests*, 17–19. https://doi.org/10.1007/978-94-6351-086-8_4

République Française. (2023, May 24). *Certains vols intérieurs de courte durée supprimés*. service-public.fr. https://www.service-public.fr/particuliers/actualites/A16193

Seymour, K., Held, M., Georges, G., & Boulouchos, K. (2020). Fuel estimation in air transportation: Modeling global fuel consumption for commercial aviation. *Transportation Research Part D: Transport and Environment*, *88*, 102528. https://doi.org/10.1016/j.trd.2020.102528

Swartz, K. L. (n.d.). Great Circle Mapper. http://www.gcmap.com/

True Price. (2023, January 18). *De Echte Prijs van Vliegen*. True Price. https://trueprice.org/echte-prijs-van-vliegen/

U.S. Energy Information Administration (EIA). (2022, October 5). *Independent Statistics and Analysis*. EIA.gov. https://www.eia.gov/environment/emissions/co2_vol_mass.php

U.S. Environmental Protection Agency (EPA). (2022, September). *Report on the Social Cost of Greenhouse Gases: Estimates Incorporating Recent Scientific Advances*. EPA.gov. https://www.epa.gov/system/files/documents/2022-11/epa_scghg_report_draft_0.pdf

U.S. Environmental Protection Agency (EPA). (2023, June). *Tailpipe Greenhouse Gas Emissions from a Typical Passenger Vehicle*. EPA.gov. https://www.epa.gov/greenvehicles/tailpipe-greenhouse-gas-emissions-typical-passenger-vehicle

UK Department for Energy Security and Net Zero (DESNZ). (2023, June 28). *Greenhouse Gas Reporting: Conversion Factors 2023*. GOV.uk. https://www.gov.uk/government/publications/greenhouse-gas-reporting-conversion-factors-2023

United Nations Framework Convention on Climate Change (UNFCCC). (2015). *The Paris Agreement*.

United Nations. (1997). *Kyoto Protocol to the United Nations Framework Convention on Climate Change*. UNFCCC.int. https://unfccc.int/resource/docs/convkp/kpeng.pdf

Watt, R. (2021). The fantasy of carbon offsetting. *Environmental Politics*, *30*(7), 1069–1088. https://doi.org/10.1080/09644016.2021.1877063

The World Bank. (2022). *State and Trends of Carbon Pricing 2022*. https://doi.org/10.1596/ 978-1-4648-1895-0

The World Bank. (n.d.). *What is carbon pricing?*. What is Carbon Pricing? | Carbon Pricing Dashboard. https://carbonpricingdashboard.worldbank.org/what-carbon-pricing

Yanto, J., & Liem, R. P. (2018). Aircraft fuel burn performance study: A data-enhanced modeling approach. *Transportation Research Part D: Transport and Environment*, *65*, 574–595. https://doi.org/10.1016/j.trd.2018.09.014

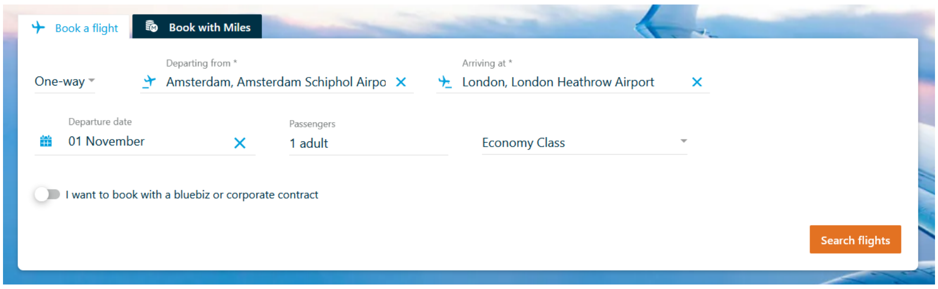
Zhao, B. (2017). Web scraping. *Encyclopedia of Big Data*, 1–3.

Appendix

Appendix A: Booking Process

A1: KLM Booking Process

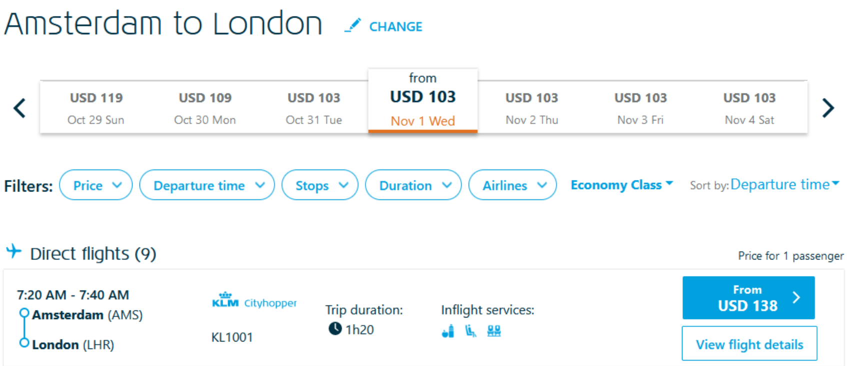
Step 1:



-Source: KLM (n.d., -b)

The first step involves choosing a departure date, passenger number and class. This is set to 1-11-2023, and economy class, respectively.

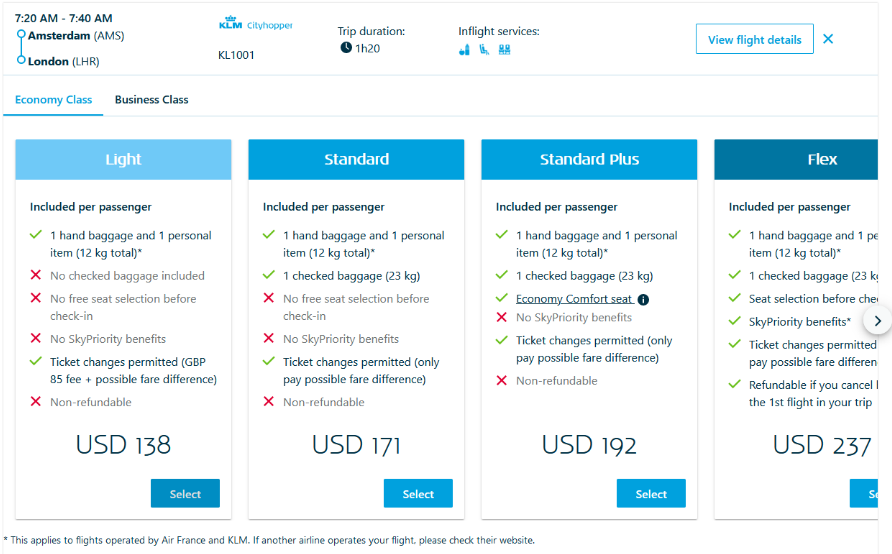
Step 2:



-Source: KLM (n.d., -b)

The second step consists of choosing the flight time. The first available flight is chosen as criteria, and no flights are chosen which are from other operators.

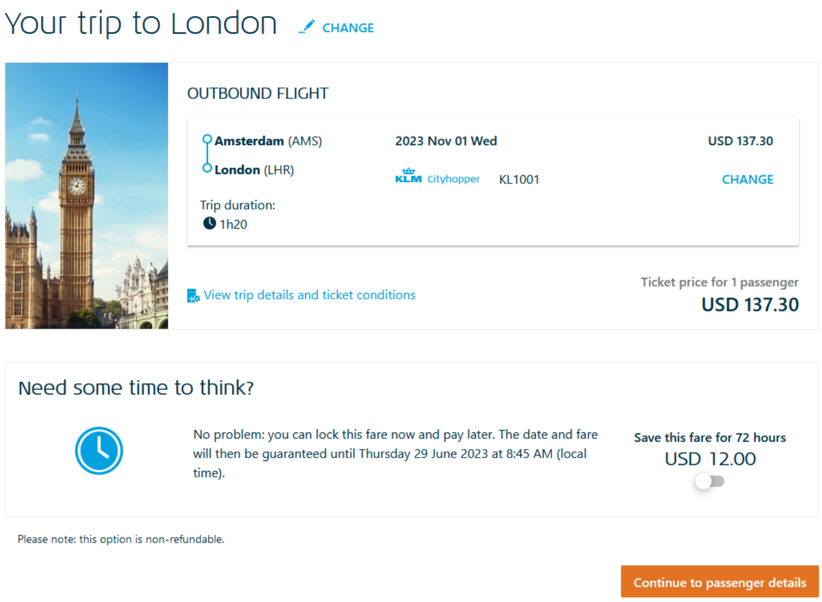
Step 3:



-Source: KLM (n.d., -b)

The third step consists of choosing the additional services, set at "light" for every flight chosen.

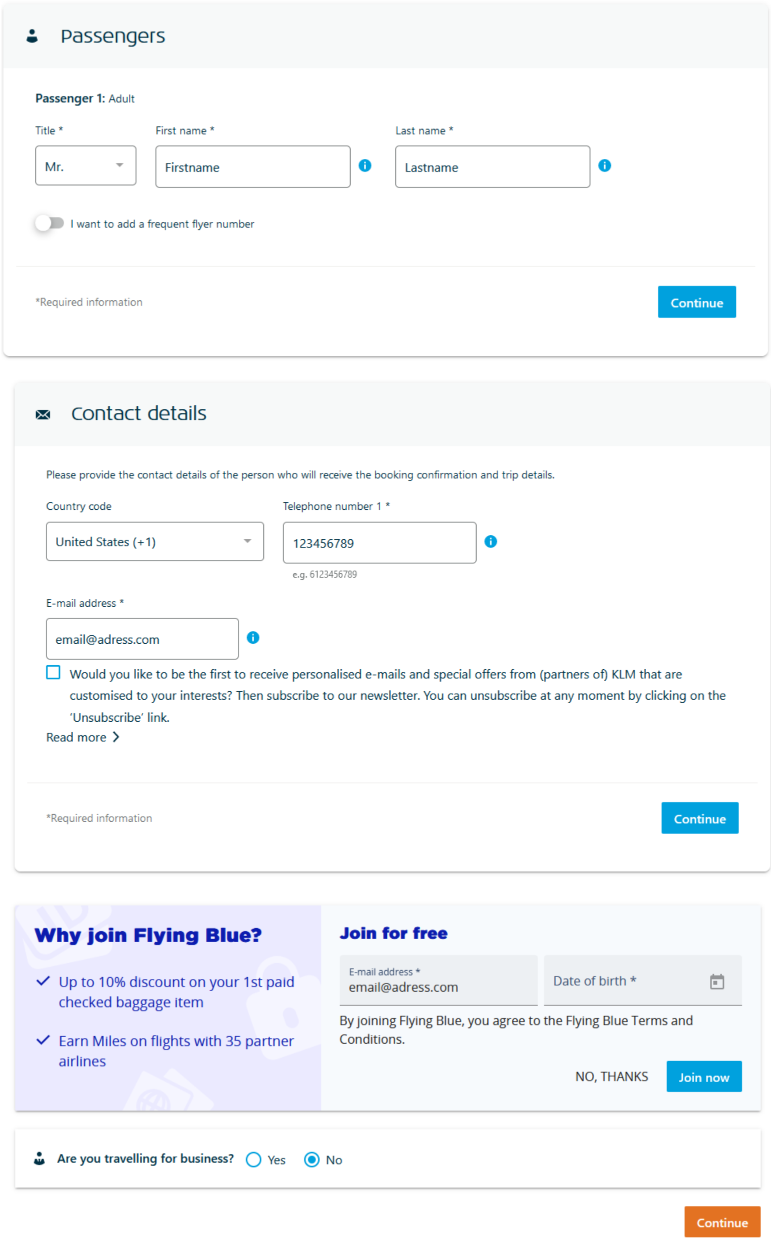
Step 4:



-Source: KLM (n.d., -b)

The fourth step shows an overview of the flight. From this page, the flight number and duration of the flight are extracted.

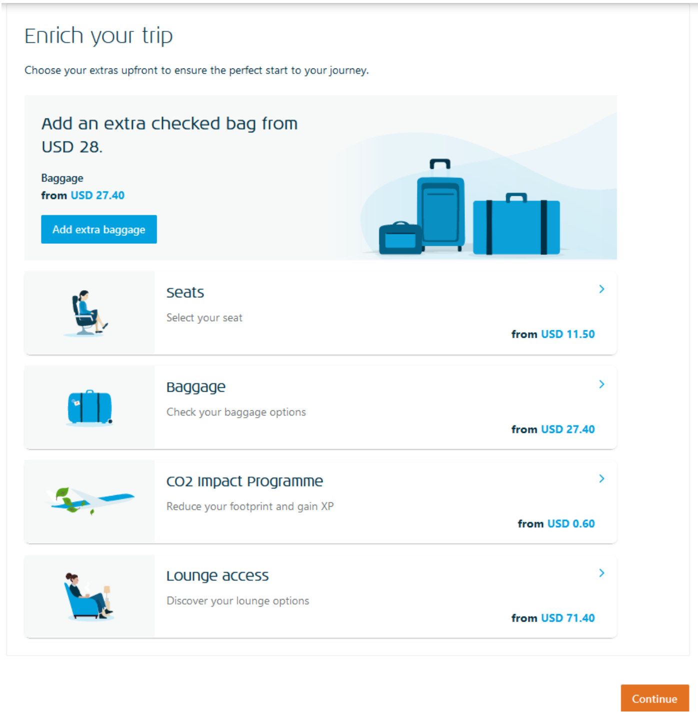
Step 5+6+7:



-Source: KLM (n.d., -b)

Step five, six and seven asks the user to give passenger information; a date of birth is also required when flying to the United States or Canada. Step seven asks the user if he wants to join the miles club of KLM, Flying Blue.

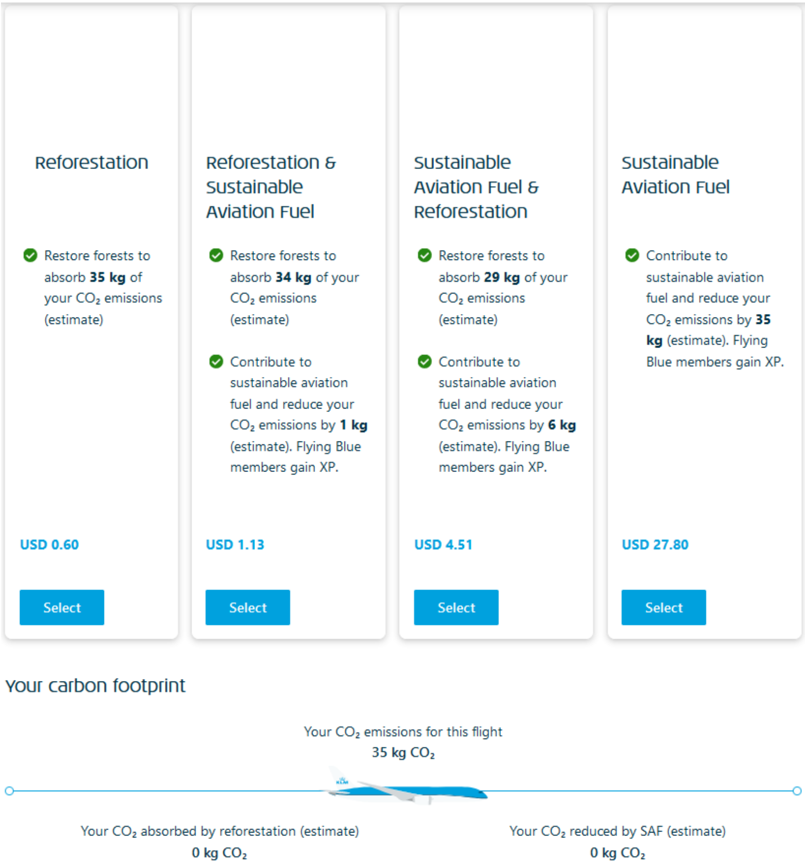
Step 8:



-Source: KLM (n.d., -b)

Step eight gives the user the choice of several extras, including the CO2 Impact Program, which is the carbon offsetting scheme of KLM.

Step 9:



-Source: KLM (n.d., -b)

Step number nine gives the user the choice of different options for carbon compensation and shows the carbon footprint. From this page, the emissions values and corresponding compensation costs are retrieved.

Appendix B: KLM Routes

Table B1: Unique KLM Routes

Flight Number	Date	Departure	Code Dep.	Arrival	Code Arr.	Price (€)	Duration (min)	GCD (km)
KL1721	1-11-23	Amsterdam	AMS	Brussels	BRU	167	45	158
KL1853	1-11-23	Amsterdam	AMS	Dusseldorf	DUS	179	45	179
KL1515	1-11-23	Amsterdam	AMS	Norwich	NWI	202	50	240
KL1753	1-11-23	Amsterdam	AMS	Bremen	BRE	184	55	284
KL1739	1-11-23	Amsterdam	AMS	Luxembourg	LUX	209	55	315
KL1903	1-11-23	Amsterdam	AMS	Hannover	HAJ	187	55	335
KL0981	1-11-23	Amsterdam	AMS	London	LCY	119	70	336
KL1763	1-11-23	Amsterdam	AMS	Frankfurt	FRA	124	65	367
KL1001	1-11-23	Amsterdam	AMS	London	LHR	130	80	371
KL1485	1-11-23	Amsterdam	AMS	Humberside	HUY	209	65	372
KL1777	1-11-23	Amsterdam	AMS	Hamburg	HAM	157	60	380
KL1223	1-11-23	Amsterdam	AMS	Paris	CDG	147	80	399
KL1421	1-11-23	Amsterdam	AMS	Birmingham	BHX	123	70	444
KL0915	1-11-23	Amsterdam	AMS	Southampton	SOU	181	70	450
KL1545	1-11-23	Amsterdam	AMS	Leeds	LBA	173	65	464
KL1341	1-11-23	Amsterdam	AMS	Billund	BLL	231	65	478
KL1533	1-11-23	Amsterdam	AMS	Durham Tees Valley	MME	213	75	479
KL1071	1-11-23	Amsterdam	AMS	Manchester	MAN	97	75	488
KL1867	1-11-23	Amsterdam	AMS	Stuttgart	STR	165	75	512
KL0957	1-11-23	Amsterdam	AMS	Newcastle	NCL	179	80	523
KL1049	1-11-23	Amsterdam	AMS	Bristol	BRS	101	75	526
KL1883	1-11-23	Amsterdam	AMS	Nuremberg	NUE	205	70	542
KL1985	1-11-23	Amsterdam	AMS	Basel Mulhouse	BSL	110	75	561
KL1059	1-11-23	Amsterdam	AMS	Cardiff	CWL	201	75	567
KL1821	1-11-23	Amsterdam	AMS	Berlin	BER	147	80	596
KL1953	1-11-23	Amsterdam	AMS	Zurich	ZRH	146	85	603
KL1329	1-11-23	Amsterdam	AMS	Aalborg	AAL	212	75	625
KL1809	1-11-23	Amsterdam	AMS	Dresden	DRS	167	75	635
KL1125	1-11-23	Amsterdam	AMS	Copenhagen	CPH	95	80	635
KL1255	1-11-23	Amsterdam	AMS	Rennes	RNS	203	95	661
KL1791	1-11-23	Amsterdam	AMS	Munich	MUC	131	85	665
KL1277	1-11-23	Amsterdam	AMS	Edinbrugh	EDI	124	90	668
KL1925	1-11-23	Amsterdam	AMS	Geneva	GVA	111	85	682

KL1247	1-11-23	Amsterdam	AMS	Kristiansand	KRS	220	85	689
KL1441	1-11-23	Amsterdam	AMS	Aberdeen	ABZ	211	90	705
KL1351	1-11-23	Amsterdam	AMS	Prague	PRG	147	90	707
KL1471	1-11-23	Amsterdam	AMS	Glasgow	GLA	95	90	720
KL1413	1-11-23	Amsterdam	AMS	Lyon	LYS	134	95	732
KL1197	1-11-23	Amsterdam	AMS	Stavanger	SVG	212	90	733
KL1455	1-11-23	Amsterdam	AMS	Nantes	NTE	357	90	734
KL0947	1-11-23	Amsterdam	AMS	Belfast	BHD	110	90	751
KL0933	1-11-23	Amsterdam	AMS	Dublin	DUB	93	95	753
KL1153	1-11-23	Amsterdam	AMS	Gothenburg	GOT	210	90	765
KL1631	1-11-23	Amsterdam	AMS	Milan	MXP	121	95	797
KL0929	1-11-23	Amsterdam	AMS	Inversess	INV	192	100	810
KL1555	1-11-23	Amsterdam	AMS	Turin	TRN	212	100	818
KL1273	1-11-23	Amsterdam	AMS	Poznan	POZ	197	100	821
KL1619	1-11-23	Amsterdam	AMS	Milan	LIN	121	95	831
KL1217	1-11-23	Amsterdam	AMS	Sandefjord	TRF	149	95	839
KL1271	1-11-23	Amsterdam	AMS	Wroclaw	WRO	204	100	848
KL1187	1-11-23	Amsterdam	AMS	Bergen	BGO	207	110	890
KL1085	1-11-23	Amsterdam	AMS	Cork	ORK	108	105	909
KL1315	1-11-23	Amsterdam	AMS	Bordeaux	BOD	210	100	924
KL1563	1-11-23	Amsterdam	AMS	Genoa	GOA	164	105	928
KL1653	1-11-23	Amsterdam	AMS	Venice	VCE	243	105	938
KL1917	1-11-23	Amsterdam	AMS	Gdansk	GDN	190	100	940
KL1141	1-11-23	Amsterdam	AMS	Oslo	OSL	87	110	961
KL1845	1-11-23	Amsterdam	AMS	Vienna	VIE	129	105	962
KL1179	1-11-23	Amsterdam	AMS	Linkoping	LPI	251	105	967
KL1895	1-11-23	Amsterdam	AMS	Graz	GRZ	166	105	970
KL1405	1-11-23	Amsterdam	AMS	Montpellier	MPL	220	110	972
KL1253	1-11-23	Amsterdam	AMS	Nice	NCE	138	115	978
KL1583	1-11-23	Amsterdam	AMS	Bologna	BLQ	208	105	989
KL1303	1-11-23	Amsterdam	AMS	Toulouse	TLS	242	110	997
KL1641	1-11-23	Amsterdam	AMS	Florence	FLR	238	120	1059
KL1993	1-11-23	Amsterdam	AMS	Krakow	KRK	216	115	1077
KL1943	1-11-23	Amsterdam	AMS	Zagreb	ZAG	171	110	1101
KL1363	1-11-23	Amsterdam	AMS	Warsaw	WAW	187	115	1105
KL1325	1-11-23	Amsterdam	AMS	Aalesund	AES	212	120	1145
KL1687	1-11-23	Amsterdam	AMS	Bilbao	BIO	179	125	1153
KL1105	1-11-23	Amsterdam	AMS	Stockholm	ARN	197	120	1155

KL1975	1-11-23	Amsterdam	AMS	Budapest	BUD	168	120	1171
KL1665	1-11-23	Amsterdam	AMS	Barcelona	BCN	142	125	1241
KL1175	1-11-23	Amsterdam	AMS	Trondheim	TRD	289	135	1293
KL1597	1-11-23	Amsterdam	AMS	Rome	FCO	173	135	1297
KL1945	4-11-23	Amsterdam	AMS	Split	SPU	123	135	1298
KL1905	1-11-23	Amsterdam	AMS	Belgrade	BEG	162	145	1413
KL1679	1-08-23	Amsterdam	AMS	Palma de Mallorca	PMI	230	150	1426
KL1699	1-11-23	Amsterdam	AMS	Madrid	MAD	111	155	1459
KL1587	4-11-23	Amsterdam	AMS	Napels	NAP	139	150	1462
KL1503	1-11-23	Amsterdam	AMS	Valencia	VLC	203	145	1481
KL1803	1-08-23	Amsterdam	AMS	Dubrovnik	DBV	336	150	1483
KL1569	1-08-23	Amsterdam	AMS	Cagliari	CAG	273	145	1488
KL1497	1-08-23	Amsterdam	AMS	Ibiza	IBZ	186	155	1516
KL1165	1-11-23	Amsterdam	AMS	Helsinki	HEL	169	145	1525
KL1711	1-11-23	Amsterdam	AMS	Porto	OPO	181	160	1597
KL1509	4-11-23	Amsterdam	AMS	Alicante	ALC	175	160	1613
KL1373	1-11-23	Amsterdam	AMS	Bucharest	OTP	124	165	1788
KL0911	4-11-23	Amsterdam	AMS	Catania	CTA	366	170	1835
KL1693	1-11-23	Amsterdam	AMS	Lisbon	LIS	201	180	1847
KL1039	4-11-23	Amsterdam	AMS	Malaga	AGP	219	175	1883
KL1575	1-11-23	Amsterdam	AMS	Athene	ATH	349	190	2184
KL1613	1-11-23	Amsterdam	AMS	Istanbul	IST	211	205	2188
KL0461	1-11-23	Amsterdam	AMS	Tel Aviv-Yafo	TLV	338	265	3315
KL0445	1-11-23	Amsterdam	AMS	Kuwait	KWI	327	350	4361
KL0423	1-11-23	Amsterdam	AMS	Riyadh	RUH	679	360	4644
KL0587	1-11-23	Amsterdam	AMS	Lagos	LOS	616	405	5072
KL0427	1-11-23	Amsterdam	AMS	Dubai	DXB	616	390	5174
KL0589	1-11-23	Amsterdam	AMS	Accra	ACC	566	390	5198
KL0671	1-11-23	Amsterdam	AMS	Montreal	YUL	1087	470	5519
KL0617	1-08-23	Amsterdam	AMS	Boston	BOS	1607	455	5563
KL0641	1-11-23	Amsterdam	AMS	New York	JFK	1325	495	5863
KL0691	1-11-23	Amsterdam	AMS	Toronto	YYZ	1299	490	6007
KL0651	1-11-23	Amsterdam	AMS	Dulles	IAD	1414	525	6223
KL0871	1-11-23	Amsterdam	AMS	Delhi	DEL	783	500	6376
KL0535	1-11-23	Amsterdam	AMS	Kigali	KGL	808	495	6470
KL0611	1-11-23	Amsterdam	AMS	Chicago	ORD	1421	525	6631
KL0565	1-11-23	Amsterdam	AMS	Nairobi	NBO	580	490	6662
KL0655	1-11-23	Amsterdam	AMS	Minneapolis	MSP	1373	545	6705

KL0877	1-11-23	Amsterdam	AMS	Mumbai	BOM	765	505	6866
KL0569	1-11-23	Amsterdam	AMS	Kilimanjaro	JRO	727	505	6885
KL0787	4-08-23	Amsterdam	AMS	Sint Maarten	SXM	1084	540	6939
KL0675	4-11-23	Amsterdam	AMS	Edmonton	YEG	1173	535	6977
KL0623	1-11-23	Amsterdam	AMS	Atlanta	ATL	1538	580	7082
KL0677	1-11-23	Amsterdam	AMS	Calgary	YYC	1348	540	7189
KL0515	3-08-23	Amsterdam	AMS	Zanzibar	ZNZ	770	465	7261
KL0713	1-11-23	Amsterdam	AMS	Paramaribo	PBM	681	560	7521
KL0879	4-11-23	Amsterdam	AMS	Bengaluru	BLR	945	555	7698
KL0681	4-11-23	Amsterdam	AMS	Vancouver	YVR	1383	595	7731
KL0735	1-11-23	Amsterdam	AMS	Curacao	CUR	559	600	7838
KL0897	1-11-23	Amsterdam	AMS	Beijing	PEK	940	645	7850
KL0767	1-11-23	Amsterdam	AMS	Aruba	AUA	620	610	7883
KL0609	4-08-23	Amsterdam	AMS	Salt Lake City	SLC	1742	600	8031
KL0661	1-11-23	Amsterdam	AMS	Houston	IAH	1485	655	8067
KL0667	1-11-23	Amsterdam	AMS	Austin	AUS	1557	630	8189
KL0689	4-11-23	Amsterdam	AMS	Cancun	CUN	1473	665	8293
KL0855	4-11-23	Amsterdam	AMS	Seoul	ICN	745	710	8574
KL0635	5-11-23	Amsterdam	AMS	Las Vegas	LAS	1320	640	8619
KL0605	4-11-23	Amsterdam	AMS	San Fransisco	SFO	1419	660	8808
KL0757	1-11-23	Amsterdam	AMS	Panama City	PTY	648	665	8818
KL0741	1-11-23	Amsterdam	AMS	Bogota	BOG	705	655	8841
KL0895	1-11-23	Amsterdam	AMS	Shanghai	PVG	847	715	8930
KL0601	1-11-23	Amsterdam	AMS	Los Angeles	LAX	1438	660	8978
KL0591	1-11-23	Amsterdam	AMS	Johannesburg	JNB	659	650	8986
KL0875	1-11-23	Amsterdam	AMS	Bangkok	BKK	1123	660	9217
KL0685	1-11-23	Amsterdam	AMS	Mexico City	MEX	1463	725	9220
KL0887	4-11-23	Amsterdam	AMS	Hong Kong	HKG	832	710	9290
KL0861	1-11-23	Amsterdam	AMS	Tokyo	NRT	945	795	9342
KL0807	2-11-23	Amsterdam	AMS	Taipei	TPE	901	760	9460
KL0705	1-11-23	Amsterdam	AMS	Rio de Janeiro	GIG	1045	720	9536
KL0755	1-11-23	Amsterdam	AMS	Quito	UIO	800	720	9550
KL0597	1-11-23	Amsterdam	AMS	Cape Town	CPT	691	685	9653
KL0791	1-11-23	Amsterdam	AMS	Sao Paulo	GRU	819	725	9751
KL0809	1-11-23	Amsterdam	AMS	Kuala Lumpur	KUL	804	730	10240
KL0743	1-11-23	Amsterdam	AMS	Lima	LIM	788	750	10511
KL0835	1-11-23	Amsterdam	AMS	Singapore	SIN	972	735	10516
KL0701	1-11-23	Amsterdam	AMS	Buenos Aires	EZE	1678	835	11437

KL0423 *	11-11-23	Damman Dhahran	DMM	Schiphol	AMS	558	410	4709
KL0535 *	8-11-23	Entebbe	EBB	Schiphol	AMS	1013	510	6343
KL0569 *	8-11-23	Dar es Salaam	DAR	Schiphol	AMS	828	560	7327
KL0787 *	11-08-23	Port of Spain	POS	Schiphol	AMS	1373	545	7464
KL0767 *	8-11-23	Bonaire	BON	Schiphol	AMS	627	555	7796
KL0741 *	8-11-23	Cartagena	CTG	Schiphol	AMS	884	590	8436
KL0755 *	8-11-23	Guayaguil	GYE	Schiphol	AMS	1039	675	9832

*These are flights that are not unique in the list as KLM operates different lags of a round trip under the same flight number. Therefore, this list contains 153 flights.

-Source: KLM (n.d., -b). Selected flights are all unique direct flights, with 153 unique flights translating to 293 trips, including round trips. Prices were collected on the 27-6-2023 between 16:00 and 17:30.

Appendix C: Aircraft and Passenger Data

Table C1: Aircraft Types Data

Aircraft Type KLM	Type Code	Passenger Capacity	Range (KM)
Boeing 737-700	B737	142	3500
Boeing 737-800	B738	186	4200
Embraer 195-E2	E295	132	4815
Boeing 737-900	B739	188	4300
Embraer 190	E190	100	3300
Embraer 175	E75L	88	3300
Boeing 787-9	B789	294	11500
Boeing 777-200ER	B772	320	13080
Boeing 787-10	B78X	344	12000
Boeing 777-300ER	B77W	408	12000
Airbus A330-300	A333	292	8200
Airbus A330-200	A332	268	8800

-Source: KLM (n.d. -b)

Table C2: Load Factors per Region

Route Group	Passenger Load Factor (IACO)	Adjusted Passenger Load Factor
Europe - Middle East	74.5%	79.675%
Europe - North Africa	73.6%	78.775%
Europe - North America	83.1%	88.275%
Europe - North Asia	80.0%	85.175%
Europe - Pacific South East Asia	80.2%	85.375%
Europe - South America	84.9%	90.075%
Europe - Sub-Saharan Africa	78.4%	83.575%
Intra Europe	82.3%	87.475%
Mean	79,625%	84.8%

-Load factors are combined of IACO (2018) and IATA (2023) data. The adjusted passenger load factor is used.

Appendix D: Summary Statistics

Table D1: Summary Statistics Historical Flights:

KLM Flights Summary Statistics

	Total (N=291)
Collected Flights per Flight no.	
Mean (SD)	83.2 (18.4)
Median [Min, Max]	90.0 [21.0, 100]
Boeing 737-700	
Mean (SD)	2.61 (6.55)
Median [Min, Max]	0 [0, 39.0]
Boeing 737-800	
Mean (SD)	11.9 (24.9)
Median [Min, Max]	0 [0, 85.0]
Embraer 195-E2	
Mean (SD)	5.19 (12.5)
Median [Min, Max]	0 [0, 79.0]
Boeing 737-900	
Mean (SD)	1.98 (6.58)
Median [Min, Max]	0 [0, 62.0]
Embraer 190	
Mean (SD)	18.9 (25.1)
Median [Min, Max]	6.00 [0, 85.0]
Embraer 175	
Mean (SD)	15.9 (26.3)
Median [Min, Max]	0 [0, 97.0]
Boeing 787-9	
Mean (SD)	4.81 (16.0)
Median [Min, Max]	0 [0, 93.0]
Boeing 777-200ER	
Mean (SD)	6.03 (15.9)
Median [Min, Max]	0 [0, 81.0]
Boeing 787-10	
Mean (SD)	4.45 (16.9)
Median [Min, Max]	0 [0, 90.0]
Boeing 777-300ER	
Mean (SD)	6.81 (20.4)
Median [Min, Max]	0 [0, 90.0]
Airbus A330-300	
Mean (SD)	2.25 (9.67)
Median [Min, Max]	0 [0, 60.0]
Airbus A330-200	
Mean (SD)	2.46 (10.4)
Median [Min, Max]	0 [0, 88.0]

-Average amount of flights collected in total and per aircraft type

Table D2: Summary Statistics Reported and Estimated Emissions:

Summary Statistics Reported Compensation Distribution

	Total (N=291)	LH (N=103)	SH/MH (N=188)
Reforestation & SAF(1) (kgCO2/pass.)			
Mean (SD)	230 (186)	463 (93.9)	102 (47.5)
Median [Min, Max]	133 [18.0, 635]	453 [294, 635]	95.5 [18.0, 279]
Reforestation & SAF(2) (kgCO2/pass.)			
Mean (SD)	5.16 (3.81)	9.95 (1.89)	2.54 (1.01)
Median [Min, Max]	3.00 [1.00, 13.0]	10.0 [7.00, 13.0]	2.00 [1.00, 6.00]
SAF & Reforestation(1) (kgCO2/pass.)			
Mean (SD)	216 (184)	449 (91.0)	88.5 (42.4)
Median [Min, Max]	115 [16.0, 615]	439 [285, 615]	82.5 [16.0, 270]
SAF & Reforestation(2) (kgCO2/pass.)			
Mean (SD)	18.8 (7.26)	24.1 (4.80)	15.9 (6.70)
Median [Min, Max]	19.0 [3.00, 33.0]	24.0 [16.0, 33.0]	15.0 [3.00, 31.0]

-Source KLM (n.d.-b).

Table D3: Summary Statistics Cost of Carbon Emissions

Cost of Carbon Summary Statistics

	Total (N=291)	LH (N=103)	SH/MH (N=188)
Reforestation (*€)			
Mean (SD)	3.88 (3.13)	7.81 (1.58)	1.72 (0.799)
Median [Min, Max]	2.24 [0.310, 10.7]	7.64 [4.97, 10.7]	1.61 [0.310, 4.70]
Reforestation & SAF (*€)			
Mean (SD)	7.15 (5.80)	14.4 (2.86)	3.17 (1.59)
Median [Min, Max]	4.00 [0.570, 19.0]	14.0 [9.00, 19.0]	3.00 [0.570, 9.00]
SAF & Reforestation (*€)			
Mean (SD)	16.8 (7.86)	24.6 (5.04)	12.6 (5.51)
Median [Min, Max]	16.0 [2.26, 34.0]	24.0 [16.0, 34.0]	12.0 [2.26, 25.0]
SAF (*€)			
Mean (SD)	171 (138)	344 (69.7)	76.1 (35.3)
Median [Min, Max]	98.9 [13.8, 472]	338 [219, 472]	71.3 [13.8, 207]
SCC 2.5 (€)			
Mean (SD)	30.0 (25.9)	62.6 (14.2)	12.1 (4.31)
Median [Min, Max]	15.0 [5.57, 91.2]	60.9 [41.9, 91.2]	11.6 [5.57, 34.7]
SCC 2 (€)			
Mean (SD)	48.3 (41.6)	101 (22.9)	19.5 (6.93)
Median [Min, Max]	24.1 [8.95, 147]	97.9 [67.4, 147]	18.7 [8.95, 55.8]
SCC 1.5 (€)			
Mean (SD)	82.3 (71.0)	172 (39.1)	33.3 (11.8)
Median [Min, Max]	41.2 [15.3, 250]	167 [115, 250]	31.9 [15.3, 95.3]

-*are reported values from KLM (n.d.-b). Other values are estimated based on estimated emissions.

Table D4: Summary Statistics Distribution of Reforestation and SAF Compensation

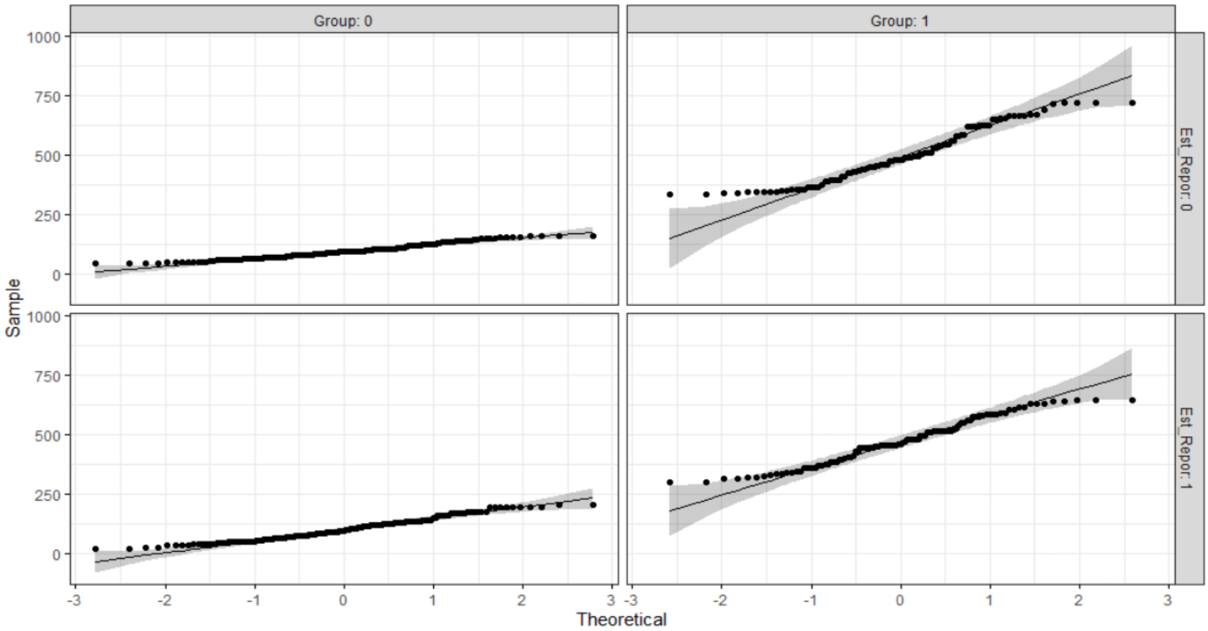
Summary Statistics Reported Compensation Distribution

	Total (N=291)	**LH (N=103)**	**SH/MH (N=188)**
Reforestation & SAF(1) (kgCO2/pass.)			
Mean (SD)	230 (186)	463 (93.9)	102 (47.5)
Median [Min, Max]	133 [18.0, 635]	453 [294, 635]	95.5 [18.0, 279]
Reforestation & SAF(2) (kgCO2/pass.)			
Mean (SD)	5.16 (3.81)	9.95 (1.89)	2.54 (1.01)
Median [Min, Max]	3.00 [1.00, 13.0]	10.0 [7.00, 13.0]	2.00 [1.00, 6.00]
SAF & Reforestation(1) (kgCO2/pass.)			
Mean (SD)	216 (184)	449 (91.0)	88.5 (42.4)
Median [Min, Max]	115 [16.0, 615]	439 [285, 615]	82.5 [16.0, 270]
SAF & Reforestation(2) (kgCO2/pass.)			
Mean (SD)	18.8 (7.26)	24.1 (4.80)	15.9 (6.70)
Median [Min, Max]	19.0 [3.00, 33.0]	24.0 [16.0, 33.0]	15.0 [3.00, 31.0]

-values are reported from KLM (n.d.-b).

Appendix E: Normality Assumption

Figure E1: Q-Plots for Normality



-Group "0" indicates the Short-/medium-haul group and Group "1" indicates the long-haul group. Est_Reported "0" shows reported emissions, "1" shows estimated emissions.

Appendix F: Social Cost of Carbon

Table F1: SCC Values in 2020 US Dollars

	Discount rate		
Report	**1.5%**	**2%**	**2.5%**
U.S. EPA	337	193	117
Rennert et al.	308	185	118
Average	322.5	189	117.5

-Values are in 2020 US dollars per metric ton of CO_2 estimated for 2020.

Source: EPA (2022), Rennert et al. (2022)