Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Measuring the impact of long-haul low-cost carriers on lowering fares: A quasi-experimental design to assess the pre-COVID market

Chikage Miyoshi *, Jesus Rubio Molina-Prados
Cranfield University, Bedford, England, MK43 0AL, United Kingdom

ARTICLE INFO

Keywords:
Long haul low cost carrier
Difference in difference method
Causal inference
Propensity score matching method
Market recovery

ABSTRACT

This paper aims to investigate the impact of the introduction of the long-haul low cost carrier in the North Atlantic market to present the competitive situation before the COVID-19. There are a number of challenges in estimating the incremental effect of LH LCC. Therefore, several strategies were taken. Firstly, a difference in differences estimation and propensity score matched methods were employed using six major routes in the North Atlantic market with IATA’s ticket sale data from January 2015 to December 2019; a granulated data to present the characteristics of flight and economy class fares. The outcomes indicate that a 17.2–20.6% fare reduction in average on the routes where Norwegian operated during 2015 and 2019 after Norwegian’s entry, compared to what it would have happened if they didn’t operate. It implies the LH LCC entry lowered fares significantly, and the level of fare competition in the North Atlantic market before the COVID-19 was high. In addition, a certain level of viability as an LH LCC has been implicated. This output can be used for the airline’s strategic implication and the policy proposition, particularly when LCC expands the longer routes after the COVID recovery. Frequent and specific (detailed) assessments by market and period are imperative.

1. Introduction

The air transport industry is facing the challenge of climate change at the same time as the COVID-19 pandemic has struck, reducing air transport passenger revenues by an estimated $252 billion (44%) below 2019’s figure (IATA, 2020). This is expected to lead to a USD76 billion loss at airports (ACI, 2020) and a decline in international tourism receipts of more than USD1.1 trillion in 2020 compared to 2019 (UNWTO, 2020). The impact of COVID-19 has certainly been pervasive. It has had a particularly negative effect on airline finances. Particularly, in the last decade pre-COVID-19, air traffic demand was booming, and competition was fierce with long-haul low-cost carrier (LH LCC) entry on some markets.

Additionally, the situation has significantly altered previous standard practices in the industry, our lifestyle and society as a whole – within a very short period. We are required to accept that our new ‘normal’ and our perceptions regarding travel could be different even after the COVID-19 pandemic and its many related uncertainties have resolved. In particular, due to the significant traffic drop in a very short time, it is uncertain when and how much traffic demand will recover and what level will be achieved (Czerny et al., 2021). Meanwhile, we are required to achieve the greener recovery by balancing the air transport growth and impacts on the climate change. For achieving the challenging task, it is crucial to understand the pre-COVID position quantitatively. Therefore, we aimed to present the market situation and competitive market during the pre-COVID-19 pandemic from 2015 to 2019, when competition among airlines was severe along with the introduction of the basic economy class fare. Specifically, this paper attempted to investigate the impact of the introduction of LH LCC on fares on the long-haul North Atlantic market using data from 2015 to 2019.

Prior to the COVID-19 pandemic, competition among air carriers was fierce, with high traffic growth (>5% p.a.) Consequently, legacy carriers were adapting their pricing strategies to find the most efficient way to compete with LCCs and minimise the loss of market share to their discount rivals (Ben Abda et al., 2012; Burghouwt and De Wit, 2015). To remain competitive with lower prices, legacy carriers started an unbundling strategy in 2008, whereby basic product features that were once included in the ticket fare such as meals, first checked bag and seat selection, were now only available for an additional fee (Garrow et al., 2012).

However, while adopting a no-frills strategy helped legacy carriers

* Corresponding author.
E-mail address: c.miyoshi@cranfield.ac.uk (C. Miyoshi).
Examples of previous studies about the impact assessment on fares in the air transport market.

| Authors (year)            | Market                       | Data                                             | Studied period                  | Estimation method | Parameters used                                                                 | Notes                                                                 |
|---------------------------|------------------------------|--------------------------------------------------|--------------------------------|-------------------|---------------------------------------------------------------------------------|----------------------------------------------------------------------|
| Windle and Dresner (1999) | US domestic                 | DB1B (quarterly fares)                           | 1993-1996                      | OLS    | Yield Distance, Passengers’ number, Population                                 | Delta (Incumbent carrier) lowered its fares on competitive routes terminating in Atlanta in response to competition by ValuJet (LCC) |
| Vowles (2000)             | US domestic                 | DB1B (quarterly fares)                           | Q1 1997                        | OLS    | Fare Distance, Resort cities                                                   | Lower the average fare in a market by $45.47                        |
| Alderighi et al. (2004)   | Intra-Europe Booking data from GDS | April 2001–July 2003                             | OLS                            |        | Hub destinations, Service class, Fare type, Distance, GDP, HHI                  | A fare decrease of around Euro 55 because of LCC entry.              |
| Chi and Koo (2009)        | US domestic                 | DB1B (quarterly fares)                           | Two years of data (2000 and 2005) | FGLS   | Fare Frequency, Capacity, Load factor, HHI                                     | The magnitude of the airfare differences to the other non-major carriers tends to be smaller in 2000 than that in 2005. |
| Oliveira and Huse (2009)  | Brazil domestic             | Brazil CAA                                       | Oct–Nov 2001                    | GMM    | Market Share, Fare, Market share, Seat availability, HHI, Distance             | The significant and negative effect on prices caused by LCC entry. The marginal effect of LCC entry in fare was studied. |
| Gaggero and Piga (2010)   | UK, Ireland                 | LCC website                                      | Jun 2003–Dec 2004               | RE     | Distance, Presence of LCC                                                      | Fares are higher in the British-Irish concentrated city-pair markets, or in markets with firms with high market shares. |
| Alderighi et al. (2011)   | Spain domestic              | Demand data from AENA                            | 2001–2007                       | 2SLS-IV| Demand Distance, GDP, Population                                                 | An average price reduction of about 45-50 euros due to LCC.          |
| Granados et al. (2012b)   | Not disclosed               | Booking data from anonymous international carrier | individual booking records for 40 city-pairs for travel in February and March 2009 and February to April 2010 | OLS    | Service class, Fare type, Distance, GDP, HHI                                  | Price elasticity: Leisure: –1.33 to –2.28 Business: –0.34 to –1.29 |
| Mumbower et al. (2014)    | Four Jetblue US domestic routes | Daily online prices and seat map data             | 13 flights, 21 dep dates (Sep 2-Sep 22, 2010) over a 28-day booking horizon. 7522 bookings total 2008-2010 | 2SLS -V | Advance booking, booking day, departure day, departure time                  | Price elasticity according to the booking date –1.32 to –1.97 –0.57 to –3.21 |
| Varella et al. (2017)     | Brazil domestic             | OTA website                                      | GMM                            |        | Fare Fuel unit cost, HHI                                                        | Incumbents enhance their airfare availability on the OTA website by 11% and reduce fares by between 3.4% and 9.0% for advanced purchases made two months before departure. |
| Scotti and Dresner (2015) | Domestic US operated by Southwest | DB1B (quarterly fares)                           | Q1 from 2007 to 2010            | 3SLS   | Total seats, Population, Income, HHI, MAS, Distance, Tourist                   | Price elasticity of –3.270                                        |
| Morlotti et al. (2017)    | 21 Easyjet routes from AMS | Daily online prices and seat map data            | 7211 bookings for period 8 Mar-23 Sep 2015 over a 45-day booking horizon       | 2SLS IV| Same as Mumbower et al. (2014)                                                 | Price elasticity: –0.535 to –1.915                                  |
retain price-sensitive customers, the downside was that it extended discounts to those who did not need them. As a result, carriers were suffering the effect of commoditisation in the industry. There were no significant differences among the products offered by both full-service and no-frills carriers using the same airports, same aircraft types, similar seat configurations and inflight services with comparable prices, especially in the economy class. It was under the new market scenario, airlines realised that they could employ a stripped-down type of unbundling strategy to offer different versions of the product and accommodate the needs of various market segments, from budget-conscious travellers to less price-sensitive passengers, to escape from ‘commoditisation competition’.

Thus, from late 2017, airlines were increasingly introducing a basic economy fare family in their long-haul markets as a ‘light’ version of their product offering in the economy cabin, just as they had done a few years earlier in their short-haul routes, excluding some of the amenities such as checked baggage and seat selection (Walczak and Kambour, 2014). The no-frills fare family helps airlines increase revenue by targeting the price-sensitive market without cannibalising revenue from customers who value a more comprehensive service (Madireddy et al., 2017).

Under the new competitive scenario, airlines required effective market segmentation methods to profit from the different levels of willingness-to-pay attributed to each market segment. There are a number of challenges in estimating the incremental effect of LH LCC. Extensive research has conducted the impact of LCC analysis using regression analysis methods (see Table 1), as well as recent studies about the impact of LH LCCs (Kuljanin et al., 2021; Soyk et al., 2021). Kuljanin et al. (2021) concluded that Norwegian’s entry into the North Atlantic market has created gains for passengers in terms of lower fares comparing the fare and traffic of British Airways (BA). Soyk et al. (2021) present a 11–18% reduction in overall economy fares with the entry of LH LCCs entry based on comprehensive analysis using instrumental variables (IVs). Most previous studies conducted fare regressions with airline specific dummy variables to investigate the magnitude of impact on fares using observational data. We have to assess the effect using data collected through the observation without any interventions implemented by randomised assignment rules (Rubin, 1986). Some important challenges are evaluating whether key covariates are measured satisfactorily and whether balance can be achieved on key covariates (Rubin, 1986). The IV approach is taken by the above papers to ease selection bias for solving endogeneity issues.

The question here was whether the fares in the markets where LH LCCs operated were lower than other markets? Were those fares cheaper than before the operation of LH LCC? How much the average fare of the route where Norwegian operated changed during 2015 and 2019 after their entry, compared to what it would have happened to the same routes had the intervention not occurred?

This paper attempts several strategies to answer the above questions using granular ticket sales’ data. A difference in differences (DID) estimation with and without propensity score matched (PSM) analysis were employed using seven major routes in the North Atlantic market from 2015 to 2019. The individual sales data were used, taken from IATA’s ticket sale data from January 2015 to December 2019; the granulated data present the characteristics of flight and economy class fares.

The remainder of this paper is organised as follows: previous studies are reviewed in Section 2, Section 3 introduces the methodology and data used. The estimation outputs are explained in Section 4, and Section 5 concludes with a discussion and limitations for further study.

2. Literature review: factors lowering fares

The market situation in the North Atlantic became very competitive with the introduction of the basic economic fare family along with the LH LCC. The basic economy fare family provided customers with a variety of choices offering the low core fare along with additional options (e.g., luggage, meal, seat selection). It is offered by direct online sales.

Commoditisation is the process by which products and services are perceived by customers as interchangeable, with no significant difference in their value propositions (Mahnke et al., 2017). A common factor that drives the commoditisation effect is an increase in transparency in both price and product features (Boudier et al., 2015), which in the airline industry came with the advent of the Internet as a key ticket distribution channel in the early 2000s. As Teichert et al. (2008) noted, the higher market transparency that the Internet provided to airline customers tipped the scale of market power towards the customers, who could make more informed decisions. Online reservation systems offered customers the opportunity to easily compare prices among competitors on a route, which puts pressure on the commoditised nature of airline tickets due to a lack of differentiation perceived by travellers among the product offerings of different airlines (Dogan et al., 2018).

Despite airlines’ efforts to innovate, many price-sensitive consumers perceive their products as undifferentiated (Granados et al., 2012a). Dempsey (2008) pointed out that commoditisation drives prices down. Travellers focus strongly on fares as the decisive factor for airline choice, which pushes companies to lower prices to gain market share, creating a downward spiral in ticket fares throughout the market and reducing margins across the board (Hamilton et al., 2012). In this regard, Henrickson and Scott (2011) found that unbundling allows airlines to reduce airfares. Scotti and Dresner (2015) also referred to this as one of the benefits of product unbundling, as it allowed airlines to advertise lower fares in price elastic markets, and as a result, increase total revenue in those markets. Belobaba (2011) emphasised the role of the LCC in simplifying the airline pricing model by removing fare restrictions, such as minimum stay requirements and round-trip purchases. Legacy carriers had to join this new way of pricing airline tickets to remain competitive.

In the early 2000s, fare families became a popular way to organise and market airline products. Typically, fare families correspond to product packages that include different features such as refundability, baggage allowance or advance seat selection (Walczak and Kambour, 2014). This airline product redesign was prompted by a shift in customer behaviour and the simplification of the airline pricing models that LCCs introduced with less restricted fares (Tretheway and Kincaid, 2005; Belobaba, 2011; Chen and Bell, 2012; Yeoman and McMahon Beattie, 2016). In an attempt to reverse the commoditisation effect, fare families have become an increasingly common approach to selling airline seats. Airlines are more actively selling their products in this way, using fare families as a market segmentation tool, with the strategic objective to highlight overlooked benefits by setting prices based on a set of features customised for the various market segments, helping customers understand what they are paying for (Granados et al., 2011).

The key to the ‘basic economy’ fare is not about the passengers who take this fare but about those who decide to accept a higher one with a more comprehensive product value. Basic economy helps passengers perceive the additional features of the standard economy fares, therefore triggering a ‘decommoditisation effect’, by presenting several ‘package’ options rather than a single, total fare, which leads customers to pick the lowest price, without assessing other qualities that make offers distinct (Skift-Amadeus, 2018). Indeed, the executives at several airlines admitted that business economy fares were designed as a market segmentation tool to encourage corporate travellers to pay for a more expensive regular economy class.

In recent years, both the low-cost and full-service business models and cost structures have been converging, blurring the lines that separate them, as LCCs have expanded their target markets into the business
segment, whereas legacy carriers have focused on reducing costs and improving productivity to compete with LCCs in price elastic market segments (Daft and Albers, 2013; Gillen and Lall, 2018). This trend has reinforced the idea among travellers that air travel today is increasingly a commodity. However, commoditisation is a psychological state as well as a physical one (Bertini and Wathieu, 2010). The value of basic economy therefore goes beyond the target market it addresses, and enters the topic of pricing psychology. Thaler (2015) stated that price is not the driver of consumer behaviour, but rather the client’s perception of the price is the driver. Thus, pricing management requires an understanding of how people perceive price. Pricing psychology, therefore, plays a critical role in the effectiveness of basic economy as a market segmentation mechanism to reverse the airline product commoditisation effect by reducing the price elasticity of economy passengers through a change in the perception of the standard economy product as a higher value when compared to the light version offered via the basic economy fare.

This not only applies to full-service carriers but also to LCCs, which historically had not implemented third-degree price discrimination through different travel classes but instead relied on time-based price variations to suit passengers’ different willingness-to-pay (Moreno-Izquierdo et al., 2015). LCCs’ recent orientation towards the business segment has, however, made it more important for them to understand passengers’ various levels of price sensitivity to avoid revenue cannibalisation. In particular, price elasticity fails below unity when the market is commoditised because the customer no longer focuses primarily on comparing prices. Passenger demand is likely to be more price inelastic as a result (Granados et al., 2012b).

This scenario has expanded to long-haul markets as well. In 2017, Norwegian became the largest LH LCC operator on the North Atlantic routes, with over 80% of LH seating capacity (Kuljanin et al., 2021). In terms of total market share on transatlantic routes, LH LCC operations went up to 6% in 2017 from 3% one year earlier, mainly driven by Norwegian expansion through their strategy of using Boeing 787s (CAPA - Center for Aviation, 2017). Norwegian’s main long-haul hub outside Scandinavia was established in London Gatwick, but it also launched transatlantic services from Paris, Amsterdam and Barcelona. In addition, Norwegian introduced the basic economy pricing model on the North Atlantic routes in 2016 with their ‘Low Fare’ pricing in economy class. This no-frills fare, which had already characterised the short-haul LCC product offering for almost a decade, led the incumbent full-service carriers to adapt their long-haul pricing strategies to remain competitive in a price-sensitive market segment. Consequently, the basic economy fare started to be introduced by legacy carriers in late 2017 and early 2018 across all long-haul markets operated by Norwegian (Hunt and Truong, 2019). At the same time, full service carrier (FSC)s started to provide potential competitive responses on routes contested by Norwegian, which eventually led to the relatively small cost advantage of the LCC rivals (Kuljanin et al., 2021). This triggered a decommoditisation process in the transatlantic market through a stronger focus on product differentiation and market segmentation, which by 2019, had reached its most competitive situation before the COVID pandemic.

Soyk et al. (2021) found a 11–18% reduction in overall economy fares driven by LH LCCs’ entry with comprehensive trans-Atlantic data from 2015 to 2018. Fare was regressed by LCC dummy with 2SLS with IVs (the hub presence dummy and the product of populations at both endpoints). Specifically, there was an estimated 10.5% decrease in case of the carrier fixed model (2SLS-IV), 18.1% for the carrier and origin and destination route fixed model, and 14% for the carrier and city pair fixed model using panel data from 2015 to 2018.

Kuljanin et al. (2021) examined Norwegian’s effect on BA’s fare with data from the period of 2015–2017. BA’s fare was regressed by the number of passengers on the city pair routes with 2SLS and 3SLS. BA offered lower fares despite the apparent growth in fuel costs to efficiently combat the competitive pressure induced by Norwegian. Unfortunately, these approaches might not be able fully to differentiate specific effects from unobserved LCC effects on fares during all of the periods covered by these studies.

Our key question is: to what extent can the net difference in outcomes (fares offered) on the routes were Norwegian operated be attributed due to the Norwegian’s entry? We address this question using data from the period 2015–2019.

### 3. Methodology and data used

#### 3.1. Data used in this analysis

We used ticket sale data from IATA, which includes daily sales records from both direct and indirect distribution channels (e.g. websites, ticketing offices and travel agencies). The data used for this study cover the period from January 2015 to December 2019 for the following six major North Atlantic routes: (1) Paris (CDG)—New York (JFK); (2) CDG—Los Angeles (LAX); (3) Frankfurt (FRA)—New York (JFK); (4) FRA—LAX; (5) Amsterdam (AMS)—JFK; (6) London Heathrow (LHR)—JFK (see Table 2).¹

The criteria used for selecting the six routes were as follows: they represent a good mix of both leisure and business travel, which allowed us to analyse the different responses to changes in price depending on the nature of the trip, as per the two most commonly accepted market segments (Dogannis, 2010; Bodea and Ferguson, 2014). All origins and destinations had a similar economic and demographical power in the US and Europe. To illustrate this with actual market data, we looked at the booking window (i.e., the number of days prior to departure that the ticket was purchased, and trip duration at the destination) in order to categorise the nature of each of the six routes as business or leisure oriented. The two distinct booking characteristics of these two major market segments are broadly accepted by the research community, with leisure passengers generally booking their tickets longer in advance and staying longer at the destination than business passengers. While the traffic in the market between CDG—JFK seemed to be more business-oriented, with tickets sold closer to departure and passengers staying shorter periods at the destination, the market of CDG—LAX seemed to have a much bigger leisure component as passengers stayed overnight for longer periods.

We analysed the information of economy class data from six major routes by year from 2015 to 2019 (individual ticket fare, the number of sales, the number of days prior to departure that the ticket was purchased, trip duration, sales channel, departure time and day of the week, carrier, month). Carriers introduced the basic economy fare strategy

| Route Carriers operated on each route. |
|---------------------------------------|
| CDG- JFK | Air France (AF), Delta (DL), Norwegian (DY), American Airlines (AA) |
| CDG- LAX | Air France (AF), Delta (DL), Norwegian (DY) |
| FRA-JFK LAX | Delta (DL), Lufthansa (LH), Singapore Airlines (SQ) |
| AMS-JFK | Delta (DL), KLM, Norwegian (DY) |
| JFK LHR | American Airlines (AA), Delta (DL), British Airways (BA), Virgin Atlantic Airways (VS) |

¹ The total capacity of the top nine airlines between US and EU west countries in 2019 was about 61.6 M according to the OAG, while only 3.5 M by Norwegian, less than 5.6% of the total. Therefore, we chose these routes, which were operated by the top nine operators’ main routes as well as Norwegian. These routes cover more than 8.3 M seats supplied, which was 13.4% of the total US-EU. In addition, Norwegian had more than 80% of all LCCs seat capacity.
The common practice among airlines implementing the basic economy fare family was to first start with short-haul routes, both domestic and intra-Europe. Basic economy fare availability is highly dynamic, and airlines use factors such as length of stay, advance booking period, departure time and purchase day of the week to segment the market based on the evolution of the demand curve and the need to generate sales. The incumbent carriers introduced basic economy fare family along with Norwegian’s entry into their markets (see Table 3); Norwegian operated on the routes, CDG-JFK and CDG-LAX from 2016, and AMS-JFK from 2018 in this data (see Table 2).

Airfare price evolution is presented in Fig. 1 by treatment group (the routes where Norwegian operated) and others (control group). The

| Airline       | Airline code | Fare families                         | Year of introduction |
|---------------|--------------|---------------------------------------|----------------------|
| Air France    | AF           | Light – Standard – Premium            | 2017                 |
| Lufthansa     | LH           | Light – Basic – Basic Plus            | 2018                 |
| Norwegian     | DY           | Low Fare – Low Fare Plus – Flex       | 2016                 |
| American Airlines | AA       | Basic – Main Cabin – Premium          | 2018                 |
| Delta         | DL           | Basic – Main Cabin – Comfort Plus     | 2018                 |
| Singapore Airline | SQ     | Only one type Economy class           |                      |

Fig. 1. Fare evolution by treatment and control group from 2015 to 2019 on the major six North Atlantic routes.

Fig. 2. Sales change by treatment and control group from 2015 to 2019 on the major six North Atlantic routes.
seasonality trend was presented with a peak during the summertime and a drop in February on all routes. A peak trend is significantly higher before Norwegian’s entry. A parallel trend was observed for all routes before the Norwegian entry in July 2016, but a declining trend can be seen from the entry of Norwegian. In addition, the value of the treatment and control groups was almost the same from May 2018. The highest fare price for the treatment group was USD677 in July 2015, while USD658 for the control group and the lowest fare was USD339 in November 2019, USD328, respectively.

Fig. 2 shows the change in ticket sales by group based on this data. According to CAPA-Centre for Aviation (2018), the seat supply in the whole North Atlantic market was about 30 million in 2017. The ticket sales in our data were about 3 million in 2017, representing about 10% of the total market. The rapid capacity increase of the treatment group is shown, particularly in 2019.

3.2. Methodology

The DID method is typically used to estimate the effect of a specific intervention or treatment, which in this case is ‘the entry of Norwegian (LH LCC)’ in the market by comparing the changes in outcomes over time between a population that is enrolled in the intervention group and a population that is in the control group. It estimates the average treatment effect or the causal effect in the population. In this paper, first, we estimated the DID parameter for fares on the North Atlantic market, as expressed below:

\[ \text{Infare}_{ijt} = \alpha T + \beta P + \gamma (T \times P) + \delta X_{ijt} + u_{ijt} \]  \hspace{1cm} (eq.1)

The subscripts h, i, and t represent individual ticket, carrier, route and time. The dependent variable, fare\_\text{ijt}, is the individual ticket price for basic economy class fare, route/carrier/flight basis, which is deflated by the average yearly CPI (2010 = 100) for both countries of origin and destination (The World Bank, 2021). The treatment variable, T, is the route where Norwegian operated. The dummy variable P represents the time when Norwegian operated. They started their operation in July 2016. This dummy variable takes the value of one if the routes were in their operation period, and zero otherwise. Another independent variable, (T \times P), is an interaction term between two dummies, which captures the effect of Norwegian entry on fares in this market. Hence, the parameter \( \gamma \) is the DID estimator, as it measures the effect of the treatment on the average outcome of the dependent variables (Wooldridge, 2002).

The model includes a vector of control variables, X (e.g., number of ticket sales, number of days booked ahead of departure, average real GDP [USD] and GDP per capita between two countries on the route, average population between two cities, adjusted fuel cost ([USD] per AKS), trip duration [hour], and distance [km] between origin and destination). All variables were expressed in natural log form. In addition, airline’s dummy, sales channel dummy variables (direct or indirect) and monthly dummy variables are included to capture the seasonal effects.

The estimation of treatment effects at the population level uses the averages below as standard estimator.

\[ \text{ATE} = E[Y_1 | W = 1] - E[Y_0 | W = 0] \]  \hspace{1cm} (eq.2)

Let W = 1 denote the receipt of treatment, W = 0 is nonreceipt, and Y_i is the measured outcomes. In this case, W = 1 is the market where Norwegian operated, and W = 0 is others. \( E[Y_1 | W = 1] \) denotes the mean outcomes of the individuals in the treatment group, while \( E[Y_0 | W = 0] \) denotes the mean outcomes of the individuals in the non-treatment group. Distinguishing the type of treatment effects is also important as we cannot observe both potential outcomes such as outcomes under the treatment condition and non-treatment condition; we then rely on the group average to evaluate counterfactuals (Guo and Fraser, 2015). A counterfactual is the outcome that would have occurred if something different had happened. Causality can be defined as the difference between actual outcomes and counterfactual outcomes. The researchers and policymakers might be interested in explicitly evaluating the effect of the intervention on those who actually received the intervention, but not that on those among whom the intervention was never intended (Wang et al., 2017).

We were also interested in how the market was affected within the treated group and how differed from the overall effectiveness. The average treatment effects for the treated (ATT) is expressed as follows:

\[ E[(Y_1 - Y_0) | X, W = 1] \]  \hspace{1cm} (eq.3)

The ATT is the difference between the outcomes of treated and the outcomes of the treated observations which had not been treated.

The ATE is the average difference between the outcomes of the treated and control observations. When all the strict assumptions are satisfied, both ATE and ATT are equivalent. This is efficient for a random experiment; however in observational studies, it might be biased if the treated and control observations are not similar (Guo and Fraser, 2015; Fukui, 2019). The fundamental assumption for consistency of those estimators was that the error terms were unrelated to regressors, and errors were often heteroskedastic. In addition, for estimating any causal effect, the stable unit treatment value assumption (SUTVA) is required, which is usually violated when there is interference between data (Rubin, 1986). SUTVA is often violated due to the spill over or displacement which derived from communications, social comparisons and competition (Gerber and Green, 2010). Therefore, it is necessary to balance the data and variances among data. Propensity score analysis was therefore conducted, and the outcomes examined.

Propensity score analysis is a statistical method for estimating treatment effects with non-experiential or observational data. The propensity score is the probability of treatment assignment conditional on observed baseline characteristics, which allows one to design and analyse an observational (non-randomised) study so that it mimics some of the particular characteristics of a randomised controlled trial (Austin, 2011). The following model is regressed with logistic regression to estimate the probability of treatment assignment, that is the propensity scores:

\[ T = \alpha + \beta X_{ij} + u_i \]  \hspace{1cm} (eq.4)

\( X_{ij} \) is a vector of explanatory variables, which are the potential confounders. The key objective of PSM is to balance the data, and we need propensity scores that balance the two groups on the observed covariates. The first step of PSM is to estimate the conditional probability of receiving treatment, to seek for the best conditioning variables or covariates which might cause an imbalance between the treatment group and the control group. Logistic regression is used to estimate the propensity scores to identify the covariates affecting the bias and specify a function form of the covariates for the PSM model. The propensity score is a balancing score which is predicted probability by logistic regression.

In this model, we employed PSM by nonparametric regression with kernel based matching estimators, which were developed from nonparametric regression for curve smoothing. This enabled us to perform one to many matching by computing the weighted average of the outcome variable for all nontreated cases and then comparing that weighted average with the outcomes of the treated group.

The average treatment effect for the treated group as ATT is expressed in the following equation:

Where I_0 and I_1 denote as the set of indices for controls and all samples, while Y_0 and Y_1 are as the outcomes of control cases and treated cases, respectively. Each treated case i \( \in I_1 \). Outcome Y_{ij} can be compared with an average of the outcome Y_{0j} for the matched case j \( \in I_0 \) in the untreated group to estimate a treatment effect for each treated case i.
Table 4
Descriptive statistics by group.

|                          | Treatment | Control | Treatment | Control |
|--------------------------|-----------|---------|-----------|---------|
|                          | Mean      | Mean    | Difference| Mean    | Mean    | Difference| Mean    | Mean    | Difference|
| Fare (USD)               | 443.4     | 640.28  | -196.8    | 455.6   | 570.8   | -115.2    | 2019 (original data) | 2015 (matched data) |
| GDP (USD trillions)      | 7270      | 9314    | -2044     | 10634   | 8580    | 2054      |                      |                      |
| Fuel cost (USD/ASK)      | 1.73      | 1.29    | 0.44      | 1.07    | 1.21    | -0.14     |                      |                      |
| Trip duration (hours)    | 512.8     | 675.1   | -162.3    | 566.1   | 676     | -109.1    |                      |                      |
| Days sold before the departure | 73.94 | 83.4   | -9.46     | 101.7   | 115.5   | -9.46     |                      |                      |
| Distance (km)            | 6557.8    | 9344    | -2806.2   | 7421    | 9344    | -1923     |                      |                      |
| Direct channel           | 0.54      | 0.64    | -0.1      | 0.40    | 0.63    | -0.23     |                      |                      |
| No. of observations      | 3,673,914 | 126,156 | 63,782    | 72,122  | 135,904 | 2019 (original data) | 2015 (matched data) |

\[ ATT = \frac{1}{n_{1}} \sum_{t, j, \bar{p}_{i}} \left[ Y_{0i} - \sum_{j \in \bar{p}_{i}} W(i,j)Y_{0j} \right] \quad (eq.5) \]

where \( n_{1} \) is the number of treated cases, and the term \( \sum_{j \in \bar{p}_{i}} W(i,j)Y_{0j} \) measures the weighted average of the outcomes for all non-treated cases that match to a case \( i \) on the propensity score. In addition, \( \sum_{j \in \bar{p}_{i}} W(i,j)Y_{0j} \) sums over all controls \( j \in I_{q} \cap \bar{p}_{i} \). The estimator forms a weighted average by weighting the propensity scores differentially or using different weights of \( W(i,j)Y_{0j} \). \( W(i,j) \) is the weight on propensity score between \( i \) and \( j \).

When \( t \) denotes a time point after treatment (Norwegian operation) and \( t' \) is before the operation, equation (3) can be:

\[ ATT = \frac{1}{n_{1}} \sum_{t, j, \bar{p}_{i}} \left[ Y_{0i} - \sum_{j \in \bar{p}_{i}} W(i,j)Y_{0j} \right] \]

\[ = \frac{1}{n_{1}} \sum_{t, j, \bar{p}_{i}} \left[ Y_{i} - Y_{0i} \right] - \frac{1}{n_{1}} \sum_{t, j, \bar{p}_{i}} W(i,j) \left( Y_{0j} - Y_{0j} \right) \quad (eq.6) \]

This measures the average change in outcome resulting from treatment for a treated case \( i \in I_{1} \).

The scores are then used to match treated observations and observations in the control group by choosing the matched data. We used a user developed STATA programme (Leuven and Sianesi, 2003) to implement PSM analysis for estimating a treatment effect for the treated with local linear regression matching in this study.

4. Estimated results and interpretations

First, the outputs of the DID models are discussed (see Table 5). Both OLS and 3SLS estimations were conducted. Parameters included the characteristics of each ticket purchased. In the fare equation, ‘adjusted fuel unit cost’, ‘ticket sales’, ‘distance (km) between origin and destination’ and ‘adjusted average GDP of each country’ were entered in log form. The dummy variables to express flight schedule (the travel day of the week, and departure time) were also included. The demand equation considered the parameters of ‘adjusвет fuel fare’, ‘the number of days sold before the departure’, ‘GDP per capita between two countries on the route’, ‘average population between two countries on the route’ in log form, and ‘the ticket sold channel (direct or not)’ as a dummy variable. This is based on the assumptions that people who usually take an economy class don’t book the long-haul flight ticket (basic economy fare) in a last minute, and book and purchase the ticket online. Therefore, these factors might affect in a positive way to the total ticket sales. In addition, the effect of airlines and time variables year and month were captured by dummy variables.

As expected, all signs for the variables, ‘treatment’, ‘post’ and ‘DID parameter’ were negative with statistically significant in the results of the 3SLS estimations. The DID parameters in Columns 2 and 3 were \(-0.006\) for OLS (Model 1) and \(-0.101***\) for 3SLS (Model 2). All 3SLS outputs were statistically significant. The OLS models detected endogeneity problems after assessing the variance inflation factor test. In addition, heteroskedasticity issues were found after conducting Breusch-Pagan test for all OLS outputs, so, we adopted the estimation outputs of the DID parameter by 3SLS estimation and as discussed below.

All ticket sales show a negative sign, while ‘fuel cost’, ‘distance’, and ‘GDP’ variables present a positive sign as expected (e.g., Dresner et al., 1996; Oliveira and Huse, 2009; Soyk et al., 2021). The positive sign for the afternoon departure parameter makes sense because the convenient time of the departure’s fare is more expensive. Departure between 15:00 and 21:00 showed the positive values. In demand equation, the Norwegian dummy variable presents strong positive signs (1.235***), which makes sense. However, the positive parameter of the direct sales’ channel on the number of sales (0.03****) is strange as the share of direct online sales is less than non-direct channel (more than 60% according to data). The positive sign for the number of days sold the ticket before departure parameter (0.0967****) implies that more people buy tickets in advance. The positive signs for the departure month dummy (April, May, July, August, and October) show the larger traffic during the high seasons.

However, there were issues of heteroskedasticity in OLS and 3SLS in general, and the estimators were inconsistent (Cameron and Trivedi, 2005), although this could be solved (Bertrand et al., 2004). Therefore, GMM estimation was conducted to estimate robust standard errors to mitigate these issues (Arellano and Bond, 1991; Bertrand et al., 2004). For brevity, only the result of model 3 (GMM- original data) is discussed when comparing the outputs of the 3SLS models.

The ticket sales variable (model 3) shows a strong negative sign (\(-0.185***\)), while ‘fuel cost’, ‘distance’, and ‘GDP’ variables present the positive sign, as in the 3SLS (model 2). There was a positive sign for afternoon departure parameters, except for the time period between 18:00 and 21:00, with a significant small parameter (\(-0.004***\)) in model 3 and \(-0.003***\) for model 5 (matched data 3SLS).

The strong positive sign for the Norwegian dummy variable (0.35****) is shown in demand equation. The negative year 2018 sign (\(-0.0498***\)) indicates a traffic drop in 2018 in a certain level, as in model 2 (3SLS) (\(-0.128**\)). This is because of the large capacity drop of the control group, but the rapid and aggressive increase in 2019 (reference year) for both markets (see Fig. 2). The direct sales’ channel on the number of sales (\(-0.0492***\)) shows the negative sign in GMM model, which makes sense. However, the parameter of fare variable (\(-4.018**\)) seems too large.

The DID parameter of the GMM model (model 3) is \(-0.172***\), which is larger than that of 3SLS (\(-0.101***\)), indicating that fares dropped on the route where Norwegian operated by 17.2% on average during 2015 and 2019 after their entry, compared to what it would have happened without Norwegian’s entry.

Although Fig. 1 shows the relatively balanced trend before the LCC entry and the fare drop after the intervention, the mean values of each
### Table 5
DID estimation outputs with original data.

| (1) | (2) | (3) |
|-----|-----|-----|
| OLS lnfare | 3SLS lnfare | GMM |
| Treatment | 0.151*** | -0.0799*** | -0.00867*** |
| Post | -0.0224*** | -0.0931*** | -0.147*** |
| DID estimator | 0.00603 | 0.101*** | 0.172*** |
| Ticket sales | -0.0022*** | -0.0238*** | -0.185*** |
| Fuel cost | 0.0771*** | 0.00736*** | 0.00376*** |
| Distance | 0.470*** | 0.446*** | 0.241*** |
| GDP | 0.217*** | 0.131*** | 0.00837*** |
| The number of Days before the departure | -0.121*** | 27.94 | 29.69 |
| Population | -0.248*** | 0.3044 *** | 0.3044 *** |
| Online booking | 0.0273*** | 51.32 | 51.32 |
| AA | 0.0899*** | 74.84 | 74.84 |
| AF | 0.148*** | 167.68 | 167.68 |
| DL | 0.0500*** | 285.30 | 285.30 |
| Norwegian | 0.249*** | 176.23 | 176.23 |
| Y2015 | 0.462*** | 118.00 | 118.00 |
| Y2016 | 0.467*** | 61.51 | 61.51 |
| Y2017 | 0.214*** | 39.50 | 39.50 |
| Y2018 | 0.0874*** | 101.59 | 101.59 |
| Jan | 0.00485*** | 3.48 | 3.48 |
| Feb | -0.201*** | -139.84 | -139.84 |
| March | -0.134*** | -100.45 | -100.45 |
| April | -0.0425*** | -33.56 | -33.56 |
| May | -0.0407*** | -33.23 | -33.23 |
| June | 0.118*** | 97.49 | 97.49 |
| July | 0.221*** | 182.58 | 182.58 |
| Aug | 0.160*** | 131.47 | 131.47 |
| Sep | -0.0627*** | -51.33 | -51.33 |
| Oct | -0.0666*** | -53.98 | -53.98 |
| Nov | -0.157*** | -119.88 | -119.88 |
| Travel day on Mon | -0.0391*** | -0.0371*** | -0.00837*** |
| Tue | -0.0675*** | -0.0673*** | -0.0160*** |
| Wed | -0.0685*** | -0.0723*** | -0.0166*** |
| Thu | -0.0405*** | -0.0396*** | -0.0113*** |
| Fri | 0.000537 | -0.00135 | -0.00194*** |
| Sat | 0.0117*** | -0.00224* | -0.00234*** |

(continued on next page)
group differ, which indicates the sample might not be randomly segmented into groups (see Table 2). In addition, the descriptive statistics shows the large mean difference of key variables between the treatment group and control group. For example, mean fare of the treatment group is USD443, while USD640 for the control group (see Table 4). The DID design is not a perfect substitute for randomised experiments, but it often represents a feasible way to learn about causal relationships (Wing et al., 2018). However, as explained in the previous section, SUTVA is often violated due to spillovers or displacements derived from communications, social comparisons and competition. A concern with DID models is that the programme and intervention groups may differ in ways that would affect their trends over time, or their compositions may change over time (Stuart et al., 2014).

A PSM strategy was thus used to balance the data, and multiple quasi-experimental techniques may be important. The estimation outputs are presented in Table 6. The probability of treatment assignment was estimated by logit model with a vector of covariates: the number of ticket sales, distance (km), population, adjusted fuel cost (USD) per ASK, GDP, adjusted GDP per capita, the number of days purchased in advance, carrier, month and year dummy variables, and a direct booking dummy variable. All variables were in log form. Then, a local linear regression matching method was used to estimate the ATT and ATE.

| (1) | (2) | (3) |
|-----|-----|-----|
| OLS lnfare | 3SLS lnfare | GMM |

The number of days before the departure

(8.25)

Population

−13.08***

(50.71)

GDP per capita

−1.793***

(71.23)

Trip duration

0.978***

(172.80)

AA

−0.434***

(149.32)

AF

−0.230***

(82.06)

DL

−0.0904***

(19.87)

DY

0.350***

(79.24)

Y2015

1.823***

(185.40)

y2016

2.172***

(141.60)

Y2017

0.821***

(77.03)

Y2018

−0.0498***

(19.87)

online

−0.0492***

(38.11)

Jan

0.101***

(30.68)

Feb

0.0839***

(19.47)

March

0.0897***

(24.80)

April

0.156***

(51.06)

May

0.128***

(43.31)

June

0.154***

(46.06)

July

0.0641***

(15.60)

August

0.0752***

(20.95)

Sep

−0.00547

(1.83)

Oct

0.0106***

(3.46)

Nov.

−0.0218***

(5.85)

CONS

287.0***

(56.56)

N

2814830

2814830

2814830

The number of days sold before the departure

0.8507***

(99.12)

Adjusted fare (USD)

−1.875***

(26)

Fuel cost (USD)/ASK

1.136***

(24.04)

Distance

−1.53***

(39.44)

GDP

0.674*

0.41

The number of days sold before the departure

−0.2768***

(57.99)

Population

0.1196*

(0.26)

GDP per capita

1.182*

2.13

Online booking

2.887***

(49.74)

AA

5.46***

(195.54)

AF

2.943***

(179.32)

DL

2.698***

(128.51)

DY

1.708***

(63.65)

Y2015

−15.64***

(128.29)

Y2017

−5.791***

(66.65)

Y2018

−7.308***

(193.46)

Feb

−7.102***

(186.02)

March

−6.645***

(196.9)

May

−6.787***

(202.0)

June

−6.35***

(198.42)

July

−0.1734***

(6.99)

August

−0.2733

(1.10)

September

0.4591***

(18.29)

October

0.0212

(0.84)

November

−0.14***

(5.01)

Constant

4.3908

1753634

chi2 (24)

1359242

p

0.000

ATT

−0.1979***

t statistics in parentheses.

* p < 0.05, ** p < 0.01, *** p < 0.001.

Z statistics in parentheses.

* p < 0.05, ** p < 0.01, *** p < 0.001.

C. Miyoshi and J. Rubio Molina-Prados
|                  | (4)                | (5)                | (6)                |
|------------------|--------------------|--------------------|--------------------|
|                  | OLS lnfare         | 3SLS lnfare        | gmm                |
| Treatment        | -0.0811***         | -0.0875***         | -0.0917***         |
|                  | (-16.27)           | (-21.35)           | (-4.46)            |
| Post             | -0.0104            | 0.196***           | -0.0994            |
|                  | (-1.32)            | (21.95)            | (-0.77)            |
| DID estimator    | -0.0400***         | -0.105***          | -0.206             |
|                  | (-6.53)            | (-14.41)           | (-1.64)            |
| Ticket sale      | -0.108***          | -0.110***          | -0.0525***         |
|                  | (-61.05)           | (-33.68)           | (0.65)             |
| Distance         | 0.573***           | 0.751***           | 0.445***           |
| GDP              | 0.569***           | 0.217***           |                   |
| The number of date before the departure | -0.0802*** |                   |                   |
|                  | (-85.69)           |                   |                   |
| GDP per capita   |                    |                    |                   |
| Trip duration    | 0.0439***          | (3.54)             |                   |
| Online booking   | -0.0212***         | (-7.40)            |                   |
| AA               | -0.0507***         | (-6.75)            |                   |
| AF               | 0.0758***          | (19.79)            |                   |
| DL               | 0.202***           | (41.78)            |                   |
| DY               | -0.0241*           | (-2.52)            |                   |
| Y2015            | Y2016              |                    |                   |
| y2016            | 0.310***           | (22.12)            |                   |
| Y2017            |                    |                    |                   |
| Y2018            | Jan                |                    |                   |
|                  | 0.0430***          | (6.64)             |                   |
| Feb              | -0.154***          | (-22.70)           |                   |
| March            | -0.0983***         | (-15.04)           |                   |
| April            | -0.0301***         | (-4.70)            |                   |
| May              | 0.0101             | (1.38)             |                   |
| June             | 0.114***           | (17.89)            |                   |
| July             | 0.289***           | (44.61)            |                   |
| August           | 0.252***           | (38.69)            |                   |
| Sep              | -0.0243***         | (-3.64)            |                   |
| Oct              | -0.0118            | (-1.70)            |                   |
| Nov.             | -0.108***          | (-14.32)           |                   |
| Travel day       |                    |                    |                   |
| Mon              | -0.0266***         | -0.0197***         | -0.0779***         |
|                  | (-7.34)            | (-5.35)            | (-4.03)            |
| Tue              | -0.0463***         | -0.0376***         | -0.0680***         |
|                  | (-12.12)           | (-10.05)           | (-6.29)            |
| Wed              | -0.0702***         | -0.0592***         | -0.0838***         |
|                  | (-19.62)           | (-16.21)           | (-9.99)            |
| Thu              | -0.0313***         | -0.0377***         | -0.0445***         |
|                  | (-4.87)            | (-10.05)           | (-6.29)            |
| Fri              | 0.0132***          | 0.00325            | 0.0130             |
|                  | (3.72)             | (0.90)             | (1.57)             |
| Sat              | 0.0159***          | -0.00186           | -0.0188*           |
|                  | (4.72)             | (-0.55)            | (-2.20)            |
| dp0300           | -0.0706            | -0.0670            | -8.688***          |
|                  | (-1.28)            | (-1.20)            | (-4.50)            |
| dp0600           | -0.152**           | -0.239**           | 49.37***           |

(continued on next page)
After matching (one to one) and dropping the unmatched data, the number of observations was n = 135,904 (treatment = 63,782, and control = 72,122) (see Table 4). An ATT and ATE of −0.198*** was estimated, which is similar to the outputs of DDIs (model 3: GMM, −0.172***). It indicated that fares dropped by 19.8% on average where Norwegian operated during 2015 and 2019 after their entry, compared to what it would have happened without Norwegian’s entry. This supports the significant economy fare reduction in the market where Norwegian operated by their aggressive expansion via large and rapid investment by 2019. This is our contribution to the literature, because two previous two studies (Kuljanin et al., 2021; Soyk et al., 2021) presented the average fare reduction on the overall market (11–18% reduction), although the data used were different.

Analysis of the impact on fare and traffic has been an important area for air transport researchers and policymakers, as well as for industry strategic implications. It is necessary to use a large number of observed data, and the selected data are not always randomly chosen. The study of causal inference is challenging, and regression estimation with Instrumental variables has been widely used to investigate impact analysis in air transport studies.

We investigated the impact of LH LCC on airfares taking a different approach from previous studies by using a combination of DID and PSM. Quasi-experimental research designs can be an effective way to learn about causal relationships when researchers actively decide which possible imperfect comparison groups are likely to best satisfy the assumptions of a particular technique (Wing et al., 2018). There are still some limitations in our study, such as the weakness of the internal validity due to the data, which might involve other interventions not included in the model. It is challenging to find the effective instrumental variables in the models, and imbalanced data might have caused the overestimation of parameters. Reducing the sample size after matching the data might also have caused inefficiency (King and Nielsen, 2019).

Another potential limitation is the effect of reverse causality. Due to the introduction of the basic economy fare among FSCs, the environment may have been suitable for LH LCC entry and lower fare prices, and vice versa. We have not investigated and presented this point clearly in this paper, but it should be considered for further study.

We aimed to contribute to the field, however, because it is important to assess the market reaction using several methods to validate the estimation outputs. An LH LCC, Norwegian, could not survive in the market as a result, because the combination of several factors might have caused their failure, such as aggressive and rapid growth involving too large a strategic investment, B737 issues, and the COVID-19 traffic disruption. This inference is beyond the scope of our study. However, a certain level of viability as an LH LCC and a significant reduction in fares have been supported based on this study. This output can be used for the airline’s strategic decision making and policy proposition, particularly when LCCs expand into longer routes after the COVID recovery, probably like Wizzair and JetBlue. Frequent and specific (detailed) assessments by market and period are imperative.

However, we also checked the balance of data before and after matching. The kdensity distribution of matched data looks well fit by treatment and non-treatment groups (Figure A-2) compared to the original data (Figure A-1). In addition, the propensity score’s kdensity distribution fits satisfactory (Figure A-3). In addition, as Crump et al. (2009) suggest, propensity scores range between 0 and 1, showing the issue of limited overlapping assumption is handled by trimming data. Figure A-4 presents a standardised mean difference, and the variance ratio of matched data is balanced compared to raw data.

### Table 7 (continued)

|       | (4)  | (5)  | (6)  |
|-------|------|------|------|
| OLS Infare | 3SLS Infare | gmm  |
| AA    | -1.885** | -1.885** | -1.885** |
| AF    | -0.498*** | -0.498*** | -0.498*** |
| DL    | -0.0254 | -0.0254 | -0.0254 |
| DY    | 9.686*** | 9.686*** | 9.686*** |
| Y2015 | 0.411*** | 0.411*** | 0.411*** |
| Y2016 | (8.85) | (8.85) | (8.85) |
| Y2017 | 0.0533*** | 0.0533*** | 0.0533*** |
| online| (3.37) | (3.37) | (3.37) |
| Jan   | -0.107* | -0.107* | -0.107* |
| Feb   | -0.104 | -0.104 | -0.104 |
| March | -0.0728 | -0.0728 | -0.0728 |
| April | 0.119* | 0.119* | 0.119* |
| May   | 0.0281 | 0.0281 | 0.0281 |
| June  | 0.0465 | 0.0465 | 0.0465 |
| July  | 0.172*** | 0.172*** | 0.172*** |
| August| 0.253*** | 0.253*** | 0.253*** |
| Sep   | -0.0597 | -0.0597 | -0.0597 |
| Oct   | -0.353*** | -0.353*** | -0.353*** |
| Nov.  | -0.961*** | -0.961*** | -0.961*** |
| cons  | 682.7 | 682.7 | 682.7 |
| N     | 127564 | 127564 | 127564 |

**p < 0.05, ***p < 0.01, **p < 0.001.

### 5. Discussion and conclusions

We attempted three strategies to present the competitive pre-COVID market situation by evaluating the impact of LH LCC on the market employing DID and PSM estimation. Each methodology has strengths and weaknesses based on the assumptions required to support each method.

The result of the DID showed a 17.2% reduction in fares on the overall market and 20.6% with the matched data in the case of GMM estimation, while 10.1% for 3SLS. The outcomes of the FSS and PSM with matched data indicate that fares dropped by 19.8–20.6% on average where Norwegian operated during 2015 and 2019 after their entry, compared to what it would have happened without Norwegian’s entry. This supports the significant economy fare reduction in the market where Norwegian operated by their aggressive expansion via large and rapid investment by 2019. This is our contribution to the literature, because two previous two studies (Kuljanin et al., 2021; Soyk et al., 2021) presented the average fare reduction on the overall market (11–18% reduction), although the data used were different.

Analysis of the impact on fare and traffic has been an important area for air transport researchers and policymakers, as well as for industry strategic implications. It is necessary to use a large number of observed data, and the selected data are not always randomly chosen. The study of causal inference is challenging, and regression estimation with Instrumental variables has been widely used to investigate impact analysis in air transport studies.

We investigated the impact of LH LCC on airfares taking a different approach from previous studies by using a combination of DID and PSM. Quasi-experimental research designs can be an effective way to learn about causal relationships when researchers actively decide which possible imperfect comparison groups are likely to best satisfy the assumptions of a particular technique (Wing et al., 2018). There are still some limitations in our study, such as the weakness of the internal validity due to the data, which might involve other interventions not included in the model. It is challenging to find the effective instrumental variables in the models, and imbalanced data might have caused the overestimation of parameters. Reducing the sample size after matching the data might also have caused inefficiency (King and Nielsen, 2019).

Another potential limitation is the effect of reverse causality. Due to the introduction of the basic economy fare among FSCs, the environment may have been suitable for LH LCC entry and lower fare prices, and vice versa. We have not investigated and presented this point clearly in this paper, but it should be considered for further study.

We aimed to contribute to the field, however, because it is important to assess the market reaction using several methods to validate the estimation outputs. An LH LCC, Norwegian, could not survive in the market as a result, because the combination of several factors might have caused their failure, such as aggressive and rapid growth involving too large a strategic investment, B737 issues, and the COVID-19 traffic disruption. This inference is beyond the scope of our study. However, a certain level of viability as an LH LCC and a significant reduction in fares have been supported based on this study. This output can be used for the airline’s strategic decision making and policy proposition, particularly when LCCs expand into longer routes after the COVID recovery, probably like Wizzair and JetBlue. Frequent and specific (detailed) assessments by market and period are imperative.
Windle, Robert, Dresner, Martin, 1999. Competitive responses to low cost carrier entry. 
Transport. Res. Part E: Logist. Transp. Rev. 35 (1), 59–75.

Wing, C., Simon, K., Bello-Gómez, 2018. Designing difference in difference studies: best 
practices for public health. Annu. Rev. Publ. Health 39, 453–469.

Wooldridge, J., 2002. Introductory Econometrics: A Modern Approach. South-Western 
College Publishers, Cincinnati, OH.

Yeoman, I., Wheatley, C., McMahon-Beattie, U., 2016. Trends in retail pricing: a 
consumer perspective. J. Revenue Pricing Manag. 16 (2), 174–200.