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Measuring the impact of long-haul low-cost carriers on lowering fares: a quasi-experimental design to assess the pre-COVID market

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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.

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

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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 2015–2019.

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 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 the 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, 1997). Some important challenges are evaluating whether key covariates are measured satisfactory and whether balance can be achieved on key covariates (Rubin, 2008). 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 (Trethewey and Kincaid, 2005; Belobaba, 2011; Chen and Bell, 2012; Yeoman and McMahon Beattie, 2017). 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 (Stewart and O’Connell, 2019). 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 decommoditised 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 LCC 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, 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.

Kulianin 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.

Table 1 about here

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 (Doganis, 2010; Bodea and Fergurson, 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

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[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.

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 even on their transatlantic routes as a market segmentation tool to cater for the needs and expectations of price-sensitive customers. 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 the 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.

Tables 2 and 3 are about here.

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

Figure 2 shows the change in ticket sales by group based on this data. According to CAPA (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.

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

Figure 2 Sales change by treatment and control group from 2015 to 2019 on the major six North Atlantic routes

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:

$$lnfare_{hijt} = \alpha T_{jt} + \beta P_t + \gamma (T_{jt} * P_t) + \delta X_{hijt} + u_{hijt} \;\; \text{..... (eq.1)}$$

The subscripts h, i, j and t represent individual ticket, carrier, route and time. The dependent variable, $fare_{h\,ijt}$ 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 (World Bank, 2021). The treatment variable, T_{jt} is the route where Norwegian operated. The dummy variable P_t 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, $(T_{jt} * P_t)$ is an interaction term between two dummies, which captures the effect of Norwegian entry on fares in this market. Hence, the parameter γ 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 ASK), 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.

$$ATE = E(Y_1|W = 1) - E(Y_0\ |W = 0)\text{…. (eq.2)}$$

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-treated 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 Fraiser, 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:

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

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 u related 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:

$$T_{jt} = \alpha + \beta X_{ijt} + u_{ijt} \; \ldots \text{ (eq.4)}$$

X_{ijt} 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_{1i} 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 .

$$ATT = \frac{1}{n_1} \sum_{i \in I_1 \cap S_p} \left[Y_{1i} - \sum_{j \in I_0 \cap S_p} W(i,j) Y_{0j} \right] \ldots\ldots\ldots\ldots\ldots\ldots\text{(eq.5)}$$

where n_1 is the number of treated cases, and the term $\sum_{j \in I_0 \cap S_p} W(i,j) Y_{0j}$ measures the weighted average of the outcomes for all non-treated cases that match to a case i on the propensity score. In addition, $\sum_{j \in I_0 \cap S_p} W(i,j) Y_{0j}$ sums over all controls $j \in I_0 \cap S_p$. 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:

$$ATT = \frac{1}{n_1} \sum_{i \in I_1 \cap S_p} \left[Y_{1i} - \sum_{j \in I_0 \cap S_p} W(i,j) Y_{0j} \right] \ldots\ldots\ldots$$

$$= \frac{1}{n_1} \sum_{i \in I_1 \cap S_p} \left[(Y_{1ti} - Y_{1t'i}) - \sum_{j \in I_0 \cap S_p} W(i,j)\, (Y_{0tj} - Y_{0t'j}) \right] \ldots \text{ (eq.6)}$$

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 ‘adjusted 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., 2003). Therefore, GMM estimation was conducted to estimate robust standard errors to mitigate these issues (Arellano and Bond, 1991; Bertrand et al., 2003). 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 figure 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 Figure 1 shows the relatively balanced trend before the LCC entry and the fare drop after the intervention, the mean values of each 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.

After matching (one to one) and dropping the unmatched data (see table 7), the number of observations was n = 135,904 (treatment=63,782, and control=72,122). An ATT and ATE of −0.198*** was estimated, which is similar to the outputs of DIDs (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 if Norwegian didn't operate. The ATT showed the same value as the ATE.

We also conducted GMM estimation using the matched data. The DID parameter was estimated as - 0.206 (model 6) indicating a 20.6% fare reduction.

The outputs of the DID 3SLS models present a 10.1 % fare drop in the case of raw data, while 10.5% for matched data from 2015-2019. The gmm model shows a 17.2% reduction with raw data, while 20.6 % for the matched data. The outcome of PSM presents a 19.8% fare reduction. Again, as stated previously, regarding the concern SUTVA violation, particularity, the assumption of strong ignorability (conditional independence assumption (CIA) and overlap assumption) might be violated. The potential outcomes should be independent of treatment assignment, so that the average difference in outcomes between the two groups can only be attributable to treatment. However, in this case, other factors which are not included might have affected fares. Indeed, both untreated group and untreated group have a decline trend in airfare (see figure 1).

However, we also checked the balance of data before and after matching. The kdencity 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 Clump et al. (2008) 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 4 Descriptive statistics by group

Table 5 Difference in difference estimation outputs (Models 1- 3)

Table 6 Propensity score matching estimation outputs (Model 7)

Table 7 Difference in difference estimation outputs (Models 4- 6)

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 PSM and GMM 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 IVs 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 has 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.

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

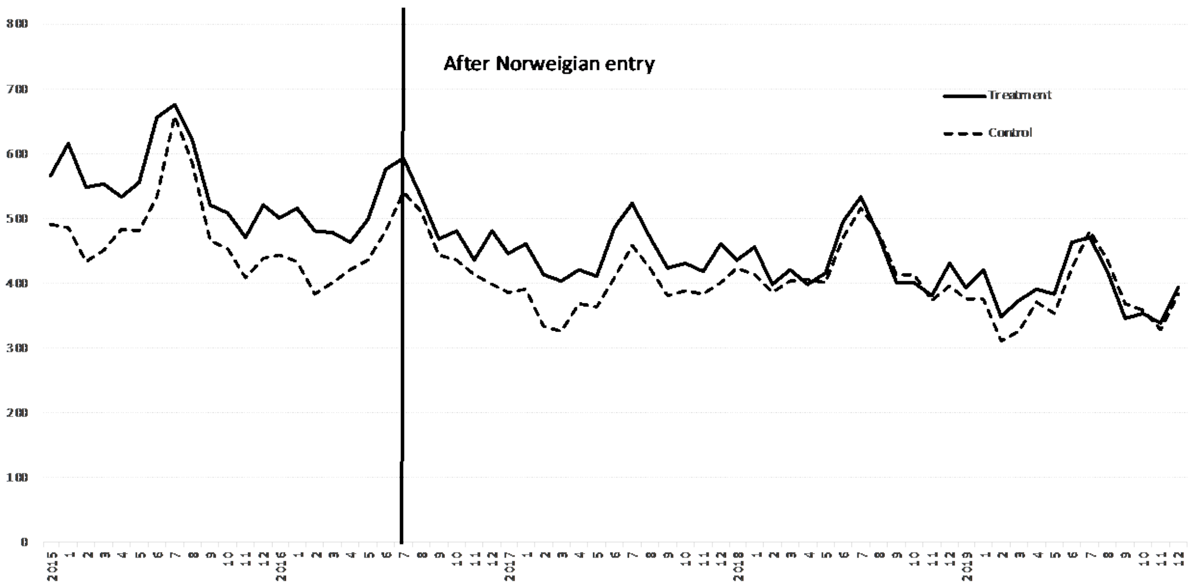

Figure 2 Sales change by treatment and control group from 2015 to 2019 on the major six North Atlantic routes

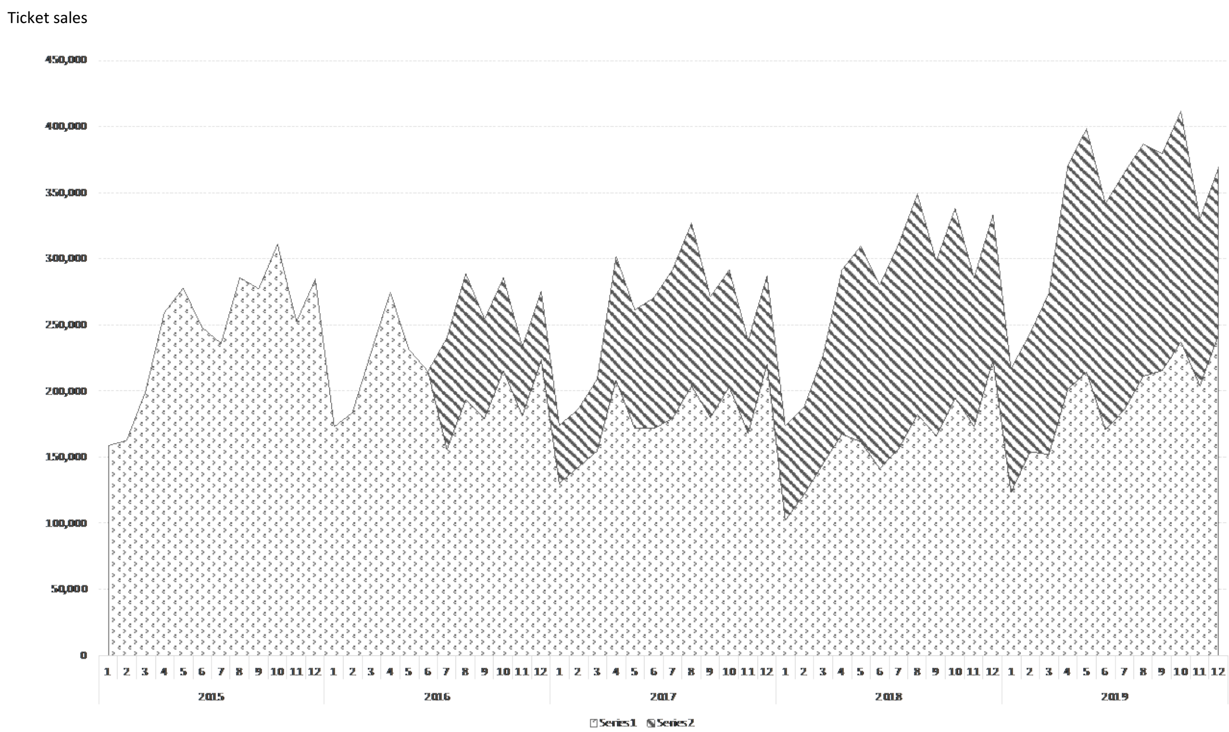

Table 1 Examples of previous studies about the impact assessment on fares in the air transport market

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 Vacation Route	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 Hub destinations	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	Service class Fare type Distance GDP HHI	A fare decrease of around Euro 55 because of LCC entry.
Fageda and Fernandez Villadangos (2009)	Spain domestic	Demand data from AENA	2001-2007	2SLS-IV	Demand Distance GDP Population	On oligopoly routes due to the presence of low-cost carriers is 6.5%.
Chi and Koo (2009)	US domestic	DB1B (quarterly fares)	Two years of data (2000 and 2005)	FGLS	Fare Frequency Capacity Load factor HHI Market Share	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	Fare Market share Seat availability HHI Distance Presence of LCC	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 OTA website UK CAA	Jun 2003-Dec 2004	RE	Fare Market share HHI Booking day Dep time Distance	Fares are higher in the British–Irish concentrated city-pair markets, or in markets with firms with high market shares.

Fageda et al. (2011)	Spain domestic	Biannual from AENA	2003-2009	2SLS	Demand Distance GDP Population Number of tourist per capita	An average price reduction of about 45–50 euros due to LCC.
Alderighi et al. (2012)	Intra-Europe	Booking data from GDS	April 2001-July 2003	OLS/2SLS	Service class Fare type Distance GDP HHI	An average fare decrease in the business and leisure classes of, respectively, of €258 and €111 with respect to the monopoly case.
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	Tickets were aggregated by channel (à la carte, traditional), travel purpose (business, leisure), branded bundle sold, advance purchase week, OD city-pair, and booking year. This aggregation produced 17,920 unique records.	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-Sep22, 2010) over a 28-day booking horizon. 7522 bookings total	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	2008-2010	GMM	Fare Fuel unit cost HHI Proportion of closed fares LCC entry Total seats	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	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

Notes: OLS refers Ordinary least Squires, 2SLS for two stage least squires, IV for instrumental variable, GMM for generalised method of moments, 3SLS for three stage least squires, RE for random effect estimation model.

Table 2 Carriers operated on each route

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

Table 3 Fare family structure on the North Atlantic routes

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	

Table 4 Descriptive statistics by group

	2015-2019 (original data)			2015-2019 (matched data)		
	Treatment	Control		Treatment	Control	
	Mean	Mean	Difference	Mean	Mean	Difference
Fare (USD)	443.4	640.28	-196.88	455.6	570.8	-115.2
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)	6537.8	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	
No. of observations			3,800,070			135,904

Table 5 DID estimation outputs with original data

	(1)	(2)	(3)
	OLS. lnfare	3SLS lnfare	GMM
main			
Treatment	-0.151***	-0.0789***	-0.00867***
	(-47.49)	(-47.32)	(-5.65)
post	-0.0224***	-0.0931***	-0.147***
	(-5.30)	(-27.99)	(-71.03)
DID parameter	0.00603	-0.101***	-0.172***
	(1.41)	(-30.42)	(-83.15)
Ticket sales	-0.0622***	-0.0238***	-0.185***
	(-151.25)	(-41.87)	(-729.12)
Fuel cost	0.0771***	0.00736***	0.00376***
	(52.23)	(5.16)	(4.78)
Distance	0.470***	0.446***	0.241***
	(188.05)	(308.65)	(186.08)
GDP		0.217***	0.131***
		(91.73)	(60.38)
The number of Days.	-0.121***		
	(-507.42)		
population			
gdp per capita	-0.248***		
	(-21.69)		
Trip duration	0.0345***		
	(13.89)		
Online	0.0273***		
	(51.32)		
AA	0.0899***		
	(74.84)		
AF	0.148***		
	(167.68)		
DL	0.300***		
	(285.30)		
Norwegian	0.249***		
	(176.23)		
Y2015	0.462***		
	(118.00)		
Y2016	0.467***		
	(61.51)		
Y2017	0.214***		
	(39.50)		
Y2018	0.0874***		
	(101.59)		
Jan	0.00483***		
	(3.48)		
Feb	-0.201***		
	(-139.84)		

March	-0.134***		
	(-100.45)		
April	-0.0425***		
	(-33.56)		
May	-0.0407***		
	(-33.23)		
June	0.118***		
	(97.49)		
July	0.221***		
	(182.58)		
August	0.160***		
	(131.47)		
Sep	-0.0627***		
	(-51.33)		
Oct	-0.0666***		
	(-53.98)		
Nov	-0.157***		
	(-119.88)		
Travel day			
Mon	-0.0391***	-0.0371***	-0.00837***
	(-43.43)	(-37.34)	(-16.91)
Tue	-0.0676***	-0.0673***	-0.0160***
	(-73.54)	(-66.49)	(-30.55)
Wed	-0.0685***	-0.0723***	-0.0166***
	(-76.54)	(-73.34)	(-32.33)
Thu	-0.0405***	-0.0396***	-0.0113***
	(-44.96)	(-39.84)	(-22.78)
Fri	-0.000537	-0.00135	-0.00194***
	(-0.61)	(-1.39)	(-4.09)
Sat	0.0117***	-0.00224*	-0.00324***
	(13.36)	(-2.31)	(-6.83)
dp0300	-0.0429***	-0.0268***	0.0180***
	(-7.38)	(-4.20)	(5.76)
dp0600	-0.163***	-0.225***	0.123***
	(-4.93)	(-6.17)	(6.92)
dp0900	-0.0115***	-0.0361***	-0.000194
	(-7.71)	(-22.49)	(-0.24)
dp1500	0.0229***	0.0252***	0.0184***
	(27.94)	(28.60)	(42.14)
dp1800	0.00341***	0.00351***	-0.00398***
	(5.17)	(4.86)	(-11.23)
dp2100	0.00364***	0.0108***	0.0105***
	(5.52)	(14.91)	(29.69)
_cons	4.567***	0.383***	3.095***
	(39.26)	(14.14)	(122.42)
Ticket sales			
Fare price		-0.0692***	
		(-11.34)	
The number of days		0.0967***	
		(116.48)	
population		-35.24***	

	(-307.75)	
GDP per capita	-0.846***	
	(-69.90)	
Trip duration	0.0661***	
	(20.23)	
AA	-0.970***	
	(-586.00)	
AF	-0.662***	
	(-431.27)	
DL	-0.231***	
	(-101.28)	
DY	1.235***	
	(570.16)	
Y2015	-0.0611***	
	(-15.14)	
Y2016	0.407***	
	(57.64)	
Y2017	0.127***	
	(25.25)	
Y2018	-0.125***	
	(-99.38)	
online	0.0310***	
	(40.45)	
Jan	-0.0188***	
	(-9.44)	
Feb	0.0263***	
	(11.02)	
March	-0.0116***	
	(-5.60)	
April	0.142***	
	(77.71)	
May	0.0196***	
	(11.04)	
June	-0.0191***	
	(-10.01)	
July	0.0860***	
	(39.23)	
August	0.134***	
	(66.68)	
Sep	-0.0481***	
	(-26.81)	
Oct.	0.0431***	
	(23.52)	
Nov.	-0.0213***	
	(-10.06)	
_cons	682.8***	
	(299.92)	
xb2		
Fare price		-4.018***
		(-302.47)
The number of		

days			0.0141***
			(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***
			(-17.30)
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

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

.

Table 7 DID estimation outputs with matched data

	(4) OLS lnfare	(5) 3SLS lnfare	(6) gmm
main			
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)	(-7.13)
Fuel cost	0.330***	-0.173***	0.126
	(11.76)	(-6.11)	(0.65)
Distance	0.573***	0.751***	0.445***
	(34.97)	(75.56)	(31.51)
gdp		0.569***	0.217***
		(15.22)	(17.18)
The number of dats	-0.0802***		
	(-85.69)		
Gdp per capita			
Trip duration	0.0439***		
	(3.54)		
online	-0.0212***		
	(-7.40)		
AA	-0.0507***		
	(-7.65)		
AF	0.0758***		
	(19.79)		
DL	0.202***		
	(41.78)		
DY	-0.0241*		
	(-2.52)		
Y2015			
y2016	0.310***		
	(21.22)		
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		
	(1.58)		
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)	(-9.70)	(-7.48)
Wed	-0.0702***	-0.0592***	-0.0838***
	(-19.62)	(-16.21)	(-9.09)
Thu	-0.0313***	-0.0377***	-0.0445***
	(-8.47)	(-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	-8.698***
	(-1.28)	(-1.20)	(-4.50)
dp0600	-0.152**	-0.239***	49.37***
	(-2.65)	(-4.09)	(5.25)
dp0900	-0.0719***	-0.0167	-0.820***
	(-6.00)	(-1.38)	(-24.58)
dp1500	0.0500***	0.105***	0.0839***
	(14.46)	(30.46)	(12.54)

dp1800	0.00681**	-0.00328	-0.0188***
	(2.89)	(-1.40)	(-5.03)
dp2100	-0.00183	0.0452***	-0.0290***
	(-0.57)	(14.23)	(-3.63)
_cons	0.925***	-5.692***	0.382
	(7.68)	(-13.92)	(.)
Ticket sales			
Fare		-0.618***	
		(-22.19)	
The number of Days		0.0835***	
		(29.13)	
population		-55.86***	
		(-68.39)	
Gdp per capita		-3.113***	
		(-40.04)	
Trip duration		-0.0131	
		(-0.76)	
AA		-1.318***	
		(-160.39)	
AF		-0.425***	
		(-66.36)	
DL		-0.371***	
		(-38.54)	
DY		0.558***	
		(38.11)	
Y2015			
Y2016		0.703***	
		(38.45)	
Y2017			
Y2018			
online		0.110***	
		(24.44)	
Jan		-0.000767	
		(-0.08)	
Feb		-0.00308	
		(-0.29)	
March		0.0102	
		(1.03)	
April		0.0571***	
		(6.01)	
May		0.0462***	
		(4.81)	

June	0.0455***	
	(4.44)	
July	0.187***	
	(14.55)	
August	0.218***	
	(18.24)	
Sep	0.101***	
	(10.00)	
Oct.	0.0777***	
	(7.37)	
Nov.	-0.0362**	
	(-3.06)	
_cons	1105.0***	
	(67.53)	
xb2		
Fare		-0.0700
		(-0.98)
The number of days		0.0961***
		(12.35)
population		-35.24***
		(-436.00)
Gdp per capita		-0.846***
		(-8.03)
Trip duration		0.0656
		(1.27)
AA		-1.885***
		(-84.87)
AF		-0.498***
		(-21.63)
DL		-0.0254
		(-0.83)
DY		9.686***
		(42.04)
Y2015		
y2016		0.411***
		(8.85)
Y2017		
Y2018		
online		0.0533***
		(3.37)
Jan		-0.107*

			(-2.15)
Feb			-0.104
			(-1.95)
March			-0.0728
			(-1.41)
April			0.119*
			(2.38)
May			0.0281
			(0.55)
June			0.0465
			(0.92)
July			0.172***
			(3.29)
August			0.253***
			(4.71)
Sep			-0.0597
			(-1.09)
Oct			-0.353***
			(-6.13)
Nov.			-0.961***
			(-15.45)
_cons			682.7
			(.)
N	127564	127564	127564

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 6 Propensity score matching estimation outputs

	Model 7
	2015-2019
Dependent Variable	Treatment
Tickets sold	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	2.887***
	(149.74)
AA	5.46***
	(195.54)
AF	2.943***
	(179.32)
DL	2.698***
	(128.51)
DY	1.708***
	(63.65)
Y2015	-
Y2016	-15.64***
	(128.29)
Y2017	-5.791***
	(-66.65)
Y2018	-
Jan	-7.308***
	(-193.46)
Feb	-7.102***
	(-186.02)
March	-6.645***
	(-196.9)
April	-6.7878***
	(-202.0)
May	-6.35***
	(-198.42)
June	-6.0357***
	(-194.67)
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
N	1753634
chi2 (24)	1359242
p	0.000
ATT	-0.1979***

Z statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix

Figure A-1 Kdencity distribution by treatment and non-treatment group (original data)

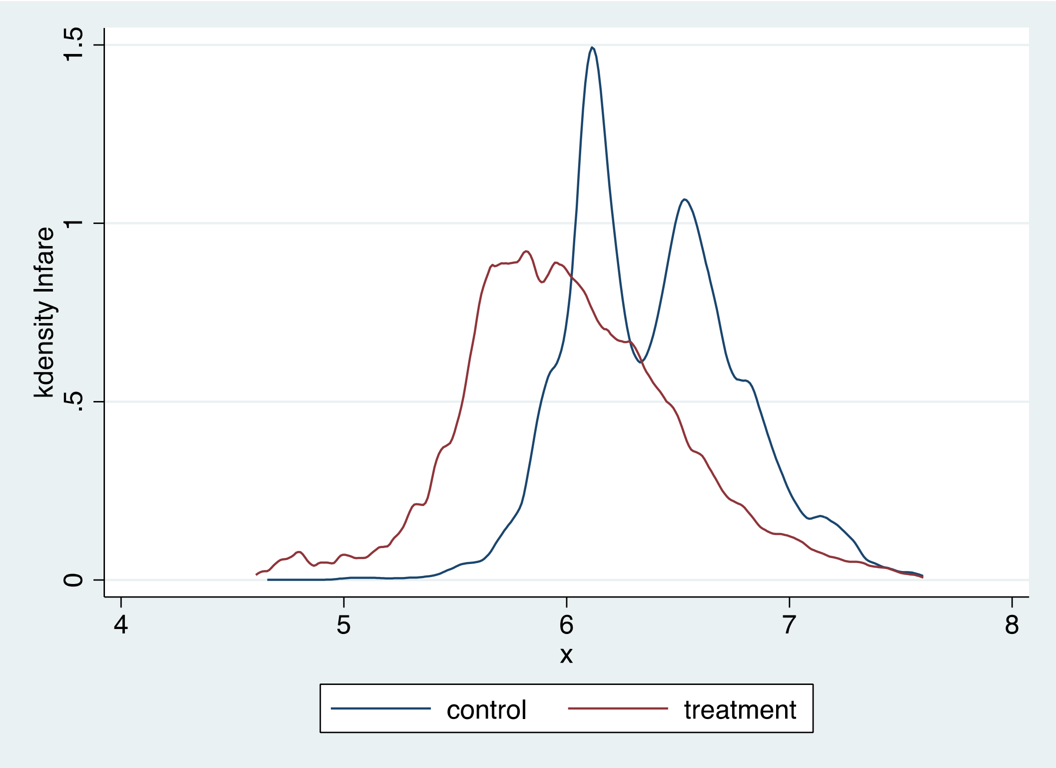

Figure A-2 Kdencity distribution by treatment and non-treatment group (matched data)

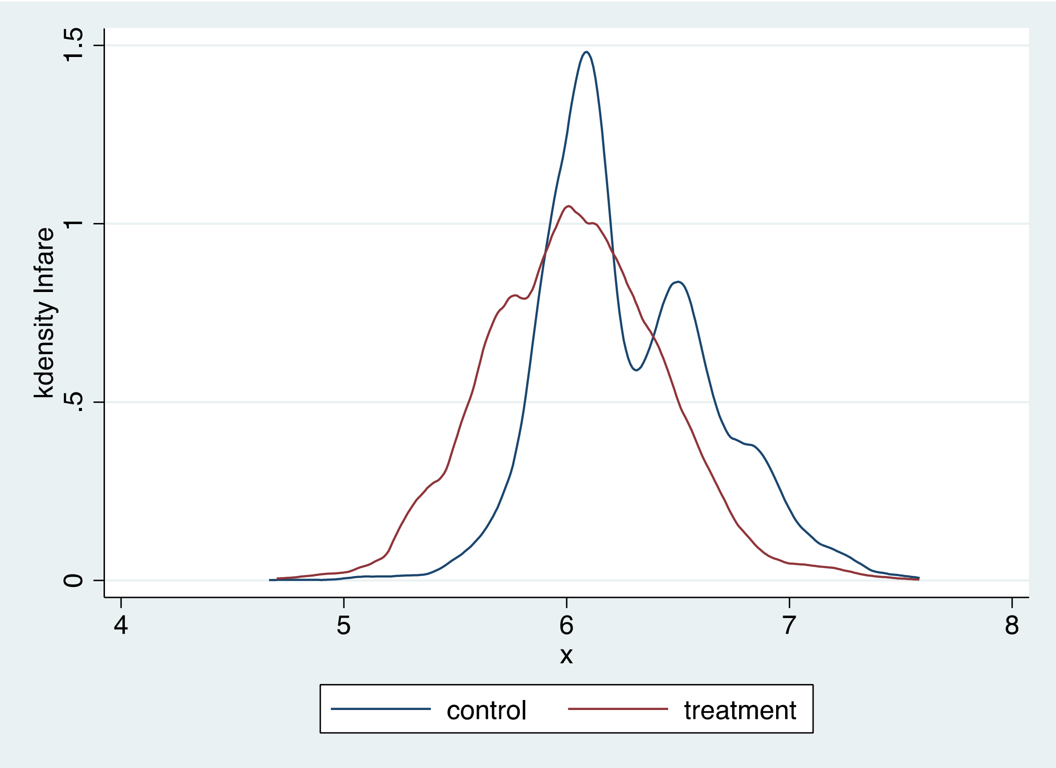

Figure A-3 Kdencity distribution of propensity score by treatment and non-treatment group

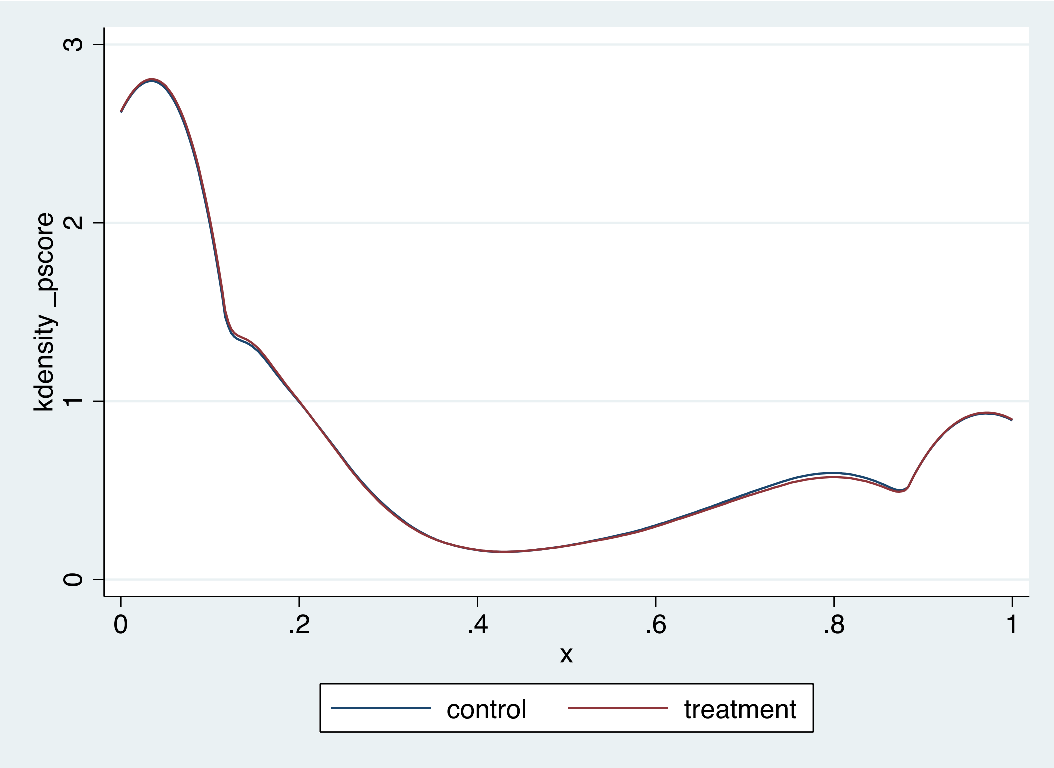

Figure A-4 Standardised mean difference and variance ratio by raw and matched data