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Pricing effects of code-sharing in Africa

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ABSTRACT

This study investigates the impact of code-sharing (CS) agreements on airfares in Africa, a region largely overlooked in existing airline cooperation research. Analysing a comprehensive dataset covering international one-stop routes in Africa from 2017 to 2019, we examine the direct effects of CS agreements on connecting itinerary discount economy fares that swap from interline to CS. Additionally, we explore the spillover effects of airlines adopting CS on the fares of those that do not implement it. Our key findings reveal that the implementation of CS agreements results in an approximately 18% reduction in airfares for African international routes. Furthermore, we identify a negative spillover effect, demonstrating reduced airfares for interline itineraries by 12% when rival pairs adopt CS, while online and direct itineraries experience smaller reductions (around 4%).

1. Introduction

With a landmass of over 30 million square kilometres and a population of over 1.3 billion people, Africa's vast geography presents a challenge to its connectivity and integration. The airline industry has the potential to overcome these barriers by facilitating the movement of goods and people across the continent. Africa's natural resources, tourism potential, and rapidly growing economies have made it an attractive destination for foreign investment (especially from China, as discussed in Nantulya, 2019) and tourism, but without a reliable and efficient airline industry, these opportunities cannot be fully realised (Button et al., 2017). Nevertheless, the sector is lagging behind: it accounts for only 2% of world passenger and freight transport (statista, 2023). Despite efforts to improve it through liberalisation, progress has been slow due to antagonisms between nations, political instability, and ineffective negotiations, as noted by Njoya (2016).

Contrary to the trend of airlines' consolidation that characterises all other continents, Africa is still plagued by a lack of cooperation among African airlines, as well as between African airlines and major worldwide carriers and alliances (Button et al., 2022). Similar to what occurred in more developed markets in the last decades of the XX century, greater cooperation among airlines has the potential to drive network expansion, reduce costs, and increase efficiency, leading to the development and long-run sustainability of the air transport industry (AFRAA, 2022). However, theory suggests that, beside these beneficial effects, cooperation could act as coordination device thus resulting in reduced competition and higher prices (Brueckner, 2001; Ciliberto et al., 2019). We contribute to this debate by providing the first estimates of the effect of cooperation on airfares in Africa.

We focus on code-sharing (CS) as a form of airline cooperation. CS is the most widespread cooperation strategy globally and involves a marketing arrangement between two airlines where one airline's designator code is displayed on flights operated by its partner airline (Oum et al., 1996). CS typically implies a light form of coordination since it usually involves only the marketing of each other's flights, rather than the sharing of revenue and costs as it occurs instead in the case of antitrust immunity and join ventures. Nonetheless CS allows airlines to extend their network of routes and increase the load factor of their aircraft. CS has a long history in the air transport industry, with the first international CS agreement between American Airlines and Qantas dating back to 1985 (Dresner and Windle, 1996). Since then, CS has become increasingly prevalent, with about 75% of all direct and

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indirect flights between the US and Australia, as well as flights between Europe and the US, involving CS in 2018 (de Jong et al., 2022).

We investigate the impact of codesharing (CS) agreements on airfares within Africa, using a comprehensive panel data set that includes information on itineraries, monthly discount economy fares, and carriers for all one-stop international flights during the period from 2017 to 2019.² Our primary data source is the Traffic Analyzer database provided by the Official Airline Guide (OAG). This database contains data on passenger purchases, akin to the US D1B1 database.³ To study the African context, we limit the scope of our analysis to connections within Africa, including a few routes serviced by European airlines, such as British Airways and Air France, but excluding routes with European origins or destinations. Our analysis leverages the panel dimension of the data, incorporating an extensive set of fixed effects to account for unobserved heterogeneity and time-varying market characteristics. To address potential endogeneity concerns, we employ an instrumental variable (IV) approach to instrument the CS decision. This IV strategy helps mitigate the concerns of reverse causality and unobserved factors influencing the decision to engage in CS. The main result of this study reveals a substantial and statistically significant reduction in airfares if CS is introduced on itineraries with a one-stop connection, amounting to approximately 18%. notably, the magnitude of this effect exceeds that found in many previous studies, suggesting that the lack of cooperation among airlines in the region has contributed to excessively high prices due to the double markup and, potentially, also to cost inefficiencies.

Additionally, this paper presents new empirical evidence on the potential spillover effects of CS agreements. Specifically, it explores the impact of CS agreements on the airfares of carriers not directly involved in the agreement but competing with the participating airlines. In particular, this investigation focuses on three distinct types of flights to assess spillover effects: (1) connecting flights where both carriers remain independent, constituting an interline itinerary, (2) online itineraries (where the two legs of the connecting flight are operated by the same airline), and (3) direct flights operated by other airlines on the same origin-destination. We find that in all three cases the spillover effect is negative, although it is stronger (around 12%) for interline itineraries. For online and direct itineraries the effect is much smaller (about -4%) but also with weaker statistical significance. These results indicate a different degree of product differentiation between CS, interline, online and direct itineraries. CS and interline itineraries are perceived by passengers as having a high degree of substitutability, which is less strong between CS and online-direct itineraries.

Several contributions examine the effects of CS from a theoretical perspective. The majority of these contributions concurs that, when CS involves complementary legs, there is a reduction in prices and an increase in consumer surplus (e.g., Brueckner, 2001; Hassin and Shy, 2004). The intuition is that through cooperation airlines realise that, in a one stop itinerary, if they independently set prices on the leg they operate, they do not take into account the external effect on the demand for the other leg – i.e., a typical double markup effect – and this leads to higher prices. However, when one of the partners instead serves the origin–destination market with another product, such as a direct or online flight, the effect on prices is less clear, and the conclusions drawn from theoretical studies vary (e.g., Chen and Gayle, 2007). Similarly if CS involves overlapping routes the effect could be detrimental (e.g., Adler and Hanany, 2016; Heimer and Shy, 2006). Among the empirical papers, a significant portion focuses on the U.S.

market and leverages data from the Department of Transportation data bank 1B.⁴ The consensus emerging from this body of work is that CS decreases prices for connecting flights, while no effect is detectable on direct flights. While early cross-sectional studies estimate a price reduction of about 20% due to CS in connecting flights (e.g., Brueckner, 2003; Bilotkach, 2007), more recent panel data studies have found smaller price reductions, ranging from -1% to -6% (e.g., Whalen, 2007; Brueckner et al., 2011; Calzaretta et al., 2017; Brueckner and Singer, 2019).

Interestingly, some papers do not find any effect, or a positive effect of CS on fares. Gayle (2008) examines US data for the 4th quarter of 2002 and of 2003, to test the effect of the announcement made in August 2002 of Delta Airlines, Continental Airlines, and Northwest Airlines to implement CS, and he does not find any effect. Gayle (2013) presents a structural model using US data for domestic flights covering the four quarters of 2006, and explores a counterfactual analysis where a CS between carriers is transformed as a complete integration, and finds that in this case prices would decrease by 20%, concluding that CS does not eliminate double marginalisation.

Exploring the effects of CS agreements beyond the United States, with its data limitations, has been a relatively uncharted territory. Alderighi et al. (2015) gathered insights from 49 European routes between April 2003 and February 2004, using web-scraped data from the Opodo website. They observed a 10% price increase for early bookers, primarily driven by higher airfares charged by the marketing carrier. In a distinct approach, Adler and Mantin (2015) examined data from *El Al Israel Airlines* flights in March 2008 and March 2010, taking advantage of the 2009 decision by the Israeli antitrust authority to curtail cooperative agreements between *El Al Israel Airlines* and other international airlines. They found that for connecting flights where the Israeli antitrust authority decision removed CS, prices increase by 4%.

This paper makes several contributions to the existing literature. Firstly, it provides empirical evidence concerning price changes when a CS agreement is introduced for a connecting flight and the two participating airlines had previously offered an interline itinerary. Secondly, using official data covering the universe of airlines and flights, the paper provides the first evidence of the effect of CS agreements on prices in Africa. By examining the African markets, this study contributes valuable insights that can enhance our understanding of the implications and dynamics of CS agreements in a unique and understudied context. Lastly, this paper presents new empirical evidence on possible spillover effects of CS agreements. Specifically, it explores whether CS may have an indirect, second order, effect on airfares of carriers not involved in the CS agreement. The spillover analysis aims to shed light on potential market segmentation resulting from CS agreements, similar to the findings in Ito and Lee (2007).⁵

The plan of the paper is as follows. Section 2 introduces some definitions regarding the different types of air transportation services we analyse. Section 3 presents the African context, while Section 4 describes the empirical strategy. Section 5 provides information regarding data sources and variable definitions, while Section 6 shows the econometric results. Section 7 offers some conclusions.

 $^{^2}$ Discount economy tickets account for approximately 70% of total air traffic within Africa.

³ However, unlike the US D1B1, Traffic Analyzer offers only monthly data instead of individual transaction data. Additionally, it excludes airport taxes and ancillary revenues (e.g., baggage fees), covering solely the flight prices charged by each airline.

⁴ The data set provides data on a 10% sample of passengers travelling both domestic and international flights extracted from reporting carriers. Carriers are US-based (domestic) carriers, and reflect US airline and CS partner (foreign) airline routes.

⁵ They show that CS may be implemented also for market segmentation reasons. The idea is that the CS flight is perceived a lower quality product by passengers compared to an online option, since when the itinerary is operated by a different carrier than the passenger's preferred one, luggage, check-in and boarding operations may be treated differently. In our context, this may exert an influence on the change in the fare levels of the available options alternative to CS.

Different types of itineraries in the aviation sector.

Туре	Itinerary	Connection	Tickets	Security checks	Baggage claim	Frequent-flyer points	Missed connection protection
Direct	O-D	x	1 ticket for O-D	only in O	only in D	for the O-D itinerary	-
Online	O-G-D	\checkmark	1 ticket for O-D	only in O	only in D	for the O-G and G-D itineraries	\checkmark
Codeshare	O-G-D	\checkmark	1 ticket for O-D	only in O	only in D	for the O-G and G-D itineraries	\checkmark
Interline	O-G-D	\checkmark	1 ticket for O-D	only in O	only in D	only for the leg operated by the airline passenger is associated to	\checkmark
Self Connecting	O-G-D	~	2 tickets 1 for O-G and 1 for G-D	both in O and in G	both in G and in D	only for the leg operated by the airline passenger is associated to	×

2. Definition of air transportation services

Before examining the impact of CS agreements on fares in Africa, it is important to provide clear definitions of key terms relating to itineraries and CS types. First, a distinction must be made between direct and connecting flights. A direct flight connects two airports without any intermediate stops. A connecting flight, on the other hand, facilitates travel between an origin airport (O) and a destination airport (D), but with at least one stop at an intermediate airport known as a gateway (G). It is common for many international itineraries to include connecting flights, particularly due to the hub-and-spoke system of full service carriers (FSCs) that is prevalent in the aviation industry.

Another important distinction concerns connecting flights, where it is necessary to distinguish between self-connecting, interline and online itineraries. In the case of self-connecting itineraries, passengers purchase two separate tickets. The first ticket takes the passenger from O to G (i.e. the first leg of the connecting flight), the second ticket covers the journey from G to D. The two legs are operated and sold by different airlines. If the itinerary is interline, the passenger buys a single ticket, usually from a travel agency, where the two legs of the flight, O-G and G-D, are operated by different airlines. The flight from O to G is operated by airline A_1 , while the flight from G to D is operated by the other airline A_2 . Check-in, baggage claim and security checks are only carried out at O, and baggage claim is only carried out at D. If the flight between O and G is delayed, the passenger is protected if he or she misses the next flight. In an online itinerary instead, both legs O-G and G-D are operated by a single airline. Passengers buy a single ticket either from a travel agent or from the airline's website. They go through check-in, baggage claim and security only at O, and collect their baggage only at D. Protection is provided in the event of delays, and passengers can earn points for both legs and benefit from an optimal coordination in scheduling. Clearly, from the passenger point of view, the online itinerary offers the best experience, followed by the interline itinerary and finally the self-connecting itinerary. Table 1 summarises the main differences between itinerary types.

The CS agreement introduces an important change and gives rise to a new type of itinerary. In the case of connecting flights, when airlines enter into CS, a distinction is made between the carrier that operates and sells the ticket (the operating carrier) and the carrier that only sells the ticket (the marketing carrier). A CS agreement allows the marketing carrier to sell tickets on the flights it does not operate.⁶ In a CS itinerary, the passenger purchases a single ticket from the marketing carrier that may not operate (at least part of) the itinerary. The passenger goes through check-in, baggage claim and security at the origin airport O and only collects baggage at D. Protection is provided and frequent flyer points can be collected for both legs. A CS itinerary is therefore somewhere between an interline and an online one. This is also reflected, on the airline side, in term of pricing. Indeed, in interline (and self-connecting) itineraries, the two operating airlines set ticket prices to maximise their individual profits, resulting in a double marginalisation effect. This phenomenon does not occur in online itineraries, where there is only one profit to be maximised. Finally, although airlines do not jointly set their prices in a CS agreement, carriers experience some coordination and information sharing allowing them to internalise part of the double marginalisation, as largely agreed in the industrial organisation literature.

Also, CS arrangements can be divided into two main types: traditional and virtual. The former is implemented when each carrier operates one leg of the connecting route and can also sell on the leg it does not operate.⁷ The latter applies instead when an airline does not operate any of the O-G-D segments but only markets some of the tickets.

As shown by Adler and Mantin (2015) and by Adler and Hanany (2016), there are several factors that may induce airlines to sign a CS agreement, ranging from network expansion, increasing perceived flight frequency, stimulating demand by eliminating double marginalisation, price discrimination through market segmentation (Ito and Lee, 2007), cost reduction through economies of density and scope (the airline can open new routes without operating an aircraft and benefit from more passengers at the hub airport), higher load factors through better listing in reservation systems. A further incentive may be to raise prices through cooperation. The aim of this paper is to determine whether CS is a factor that reduces prices in African aviation as the effect of a number of factors, including the limitation of double marginalisation. Furthermore, by analysing the spillover effects of CS on interline, online and direct routes, the paper provides some evidence on whether CS can be used for market segmentation: for example, if airlines offering online itineraries react to the introduction of CS by competitors by reducing the price less than airlines offering (non-CS) interline itineraries, then this implies that a CS itinerary is a close substitute for an interline itinerary and a less close substitute for an online itinerary.

3. Air transportation in Africa

Africa offers immense potential for the development of air services due to its demographic characteristics (approximately 15% of

⁶ The right to sell tickets on the flight operated by the other CS member may vary under different specifications. In a free-sale CS, seats on the aircraft operating the route are not allocated to the marketing carrier, which can directly access the operating carrier's reservation system and sell tickets. In a hard-block CS agreement, the marketing carrier buys some seats from the operating carrier and sells them independently.

 $^{^7}$ In a traditional CS, it is sufficient that at least one leg involves an operating and different marketing carrier.

the world's population, spread over more than 50 countries) and geographical factors (vast distances and growing urban concentrations). In addition, the underdevelopment of alternative modes of transport further enhances the prospects for aviation growth in Africa (Button et al., 2015; Abate, 2016; Lubbe and Shornikova, 2017). However, despite these favourable conditions, the African continent's aviation markets remain relatively underdeveloped, accounting for only about 2% of global air traffic. Moreover, the market is concentrated in a few countries, and many airlines - particularly those in sub-Saharan Africa - exhibit a local focus and inefficiency (Martini et al., 2023). As a result, African airlines face challenges in realising the benefits of economies of scope and density. In addition, they often face significant political interference, which further hampers their efficiency (Button et al., 2022). Several additional factors contribute to the high costs and operational challenges faced by African airlines. These include the high cost of financing aircraft purchases, limited connectivity and liberalisation, expensive jet fuel and high aviation taxes and charges. As a result, air fares in Africa are significantly higher than in more developed regions such as Europe and the United States. When the average income of a country is taken into account, the 'real cost' of air travel in Africa becomes even more burdensome. It is estimated that the average African middle-class citizen can afford only one air trip per year, whereas their European and North American counterparts can afford approximately 26 and 33 air trips per year, respectively (The Africa Logistic, 2022).

The financial difficulties of African airlines and their inability to offer competitive fares are major obstacles to the development of the aviation industry in many African countries. For example, African airlines in the past 17 years have made profits only once, compared with 7 times for airlines in Latin America and 13 times for airlines in North America, Europe and Asia (IATA, 2023). In order to overcome these challenges, it is essential to prioritise the liberalisation of African airspace. Over the past three decades, various efforts have been made to improve connectivity and remove the rigid bilateral constraints that hamper the industry. The Yamoussoukro Decision (YD) of 1999 is an important agreement in this regard (Scotti et al., 2017). Despite these efforts, progress in liberalising African air transport has been insufficient (Button et al., 2022). However, the establishment of the Single African Air Transport Market (SAATM) in 2018 represents a clear and committed step towards the full implementation of the Yamoussoukro Decision. The African Airlines Association (AFRAA) emphasises that liberalisation is crucial not only to improve connectivity, but also to create an enabling environment for airlines to enter into cooperative arrangements that provide the necessary commercial and operational flexibility. The global airline industry has seen remarkable benefits from commercial cooperation, particularly through membership of strategic alliances and CS agreements. However, such cooperation is currently lacking among African airlines (Button et al., 2022). Njoya (2016) attributes part of the failure of past liberalisation efforts to the lack of cooperation between African airlines and airlines from other regions. Promoting commercial cooperation is therefore seen as a key strategy for making travel within Africa more convenient and affordable. It can lead to lower fares and increased revenues for African airlines, ultimately making intra-Africa travel more accessible and viable.

4. The empirical strategy

This section presents the econometric model used to investigate the impact of CS agreements on air fares in Africa. The analysis has two main objectives: (1) to examine the price changes following the introduction of CS on specific routes, and (2) to examine the spillover effects of the introduction of CS on the same set of routes under different circumstances (e.g. direct, online, etc.). Two different empirical approaches will be used to achieve these objectives. For the first objective, a fixed effects econometric model is implemented as follows, exploiting the panel dimension of the dataset:

$$\log FARE_{prt} = \gamma CS_{prt} + \alpha_{pr} + \alpha_{rt} + \epsilon_{prt}$$
(1)

where FARE_{prt} is the average fare charged by the pair of operating carriers p on the (one-stop) route r with origin in O and destination in D during the period t (month-year), expressed in logarithm. We can also denote the connection O-D as market r. An origin-destination route O-D corresponds to our relevant market, regardless of the location of the gateway G. CS_{prt} is a dummy variable equal to 1 if the two operating carriers have a CS agreement on the market r in period t, and 0 otherwise. One element that distinguishes this paper from what is available in the literature is that the dummy variable CS becomes 1 during the observed time period. It therefore always starts at a level of 0, hence no CS on the route. This makes it possible to study the effect of the introduction of CS, not just its presence as in previous papers. α_{pr} is the carrier pair-route fixed effect, α_{rt} is the route-period fixed effect and ϵ_{pmt} is a standard error term. The model is applied to pairs of operating carriers on connecting routes with at least six observations (i.e. a semester).

The inclusion of a rich set of fixed effects allows us to parsimoniously control for many sources of unobserved heterogeneity. In particular, the airline pair-route fixed effect captures time-invariant factors associated with the interaction between two airlines in a given market. It controls for any persistent characteristics or differences between pairs of airlines operating on the same route that might affect ticket prices. The route-period fixed effect, on the other hand, accounts for time-varying factors that may affect ticket prices in a given market during a given period. These include factors such as seasonal variations, unique characteristics of country pairs and competitive dynamics on the route. The dummy variable CS captures the switch from interline to CS. The coefficient γ in Eq. (1) is identified using only the variation in fares in the same route and period between pairs that are in CS and those that are not, as well as the variation within pairs and routes before and after the switch to CS. It is therefore possible to interpret γ as the DiD effect: the difference in fares charged in route *r* between pairs of airlines operating in CS and those operating in interline, before and after CS is introduced.8

The potential endogeneity of the CS dummy variable in the Eq. (1) model is an important concern, as airlines may strategically select routes on which to adopt CS agreements based on unobserved factors that may be correlated with the error term. This correlation may pose a challenge in identifying the causal effect of CS adoption on ticket prices. To address this endogeneity issue, we use an instrumental variable approach. Similar to Ciliberto et al. (2021), we use "gateway characteristics" to construct an instrument. Ciliberto et al. (2021) study the airline's decision to enter a market (i.e. a route) and need an instrument for the entry variable to study its effect on airfares. They use a potential entrant instrument given by the number of non-stop flights of a given airline from the destination airport. Their exclusion restriction is based on the intuition that passengers only care about the network available at the origin airport. Similarly, in our context, we exploit a characteristic of the gateway airport given by the number of direct flights departing from it that are operated under a CS agreement. This variable can be considered as a potential CS instrument, as it is likely that a higher number of direct CS flights from gateway G corresponds to a higher likelihood of compliance with a CS agreement also on the O-G-D route, but it is related to cooperation on other routes. The prevalence of CS agreements in G serves as an indicator of

⁸ Including route-period and route-pair fixed effects means that to identify γ we use only those routes where there are at least two pairs of airlines operating on different legs where at least one of them switches from CS = 0 to CS = 1.

its importance as a gateway for connecting flights. Consequently, we define the instrumental variable *CSPROPENSITY* as follows:

$$CSPROPENSITY_{prt} = \sum_{k \neq r} \sum_{a \notin p} \left(CSDIRECT_{ap_{-j}kt} + CSDIRECT_{ap_{-i}kt} \right),$$
(2)

where *k* is a non-stop route departing from the gateway *G* of the 1stop connection *r*, *a* is an airline different from those belonging to pair *p* that provides a direct flight from *G* with destination different from the endpoints in route *r*, and $CSDIRECT_{ap_{-j}kt}$ is a variable equal to 1 if airline *a* operates the route *k* in CS with airline *i* of the pair *p* (and $CSDIRECT_{ap_{-j}kt}$ similarly with airline *j* in pair *p*).⁹ Our exclusion restriction is based on the assumption that airlines' pricing strategies for the O-D itinerary are influenced solely by the characteristics of that specific trip. In other words, consumers choosing a flight between O and D are not influenced by the characteristics of non-stop flights departing from gateway G to destinations other than D. Our instrument, *CSPROPENSITY*, captures the propensity of an airline pair to enter into CS agreements for flights departing from gateway G at a given time *t*.

We test the robustness of the impact of CS agreements on interline flight prices in Africa using an alternative instrument. This instrument is a three-month lagged variable of *CSPROPENSITY*, defined as *LAGCSPROPENSITY*. Our alternative exclusion restriction is based on the premise that the propensity to codeshare on different routes and with different partners influences prices charged on route *r* three months later – after various market demand conditions, such as seasonal demand or the entry of new competitors, have presumably changed – only through the impact it has on the codesharing decision of pair *p* on route *r*. Since the instrument is lagged, the *CS* variable in the first stage of the 2SLS also incorporates the same time gap.

To further test the robustness of our findings, we evaluate the sign and statistical significance of the CS variable using an additional instrumental variable. We use the dummy variable DIRECTOD, which is set to 1 if at least one of the airlines in the *p*-pair also operates a direct flight on route *r*. The existence of a direct connection on route *r* provides the operating airline with valuable information about the effects of internalising demand between the endpoints of route *r*. In contrast, for an interline itinerary, each airline only considers the demand for its own segment. Thus, DIRECTOD acts as an instrument for *CS* without directly affecting the price of the interline itinerary *r*, as it pertains to a different demand segment. However, the limited number of observations for DIRECTOD restricts its use, so we employ it solely to validate the robustness of the sign and significance of *CS*.

Our second objective is to assess whether the adoption of CS by an airline pair in a given market affects the prices of alternative itineraries – namely direct, interline and online services – within the same market. To achieve this, we construct three separate samples, each tailored to a specific itinerary type (interline, online and direct), and use the following econometric models for estimation:

interline sample : log FARE_{prt}

$$= \lambda CSMARKET_{rt} + X'_{rt}\beta + \alpha_{pr} + \alpha_{rm} + \nu_{prt}$$
(3)

direct and online samples :
$$\log FARE_{irt}$$

= $\lambda CSMARKET_{rt} + X'_{rt}\beta + \alpha_{ir} + \alpha_{rm} + v_{irt}$ (4)

In the interline example, Eq. (3), $log FARE_{prt}$ represents the interline fare charged by pair *ij* in market *r* at time *t*, and *CSMARKET* is a dummy variable equal to 1 if at least one pair of airlines other than *p* adopt a CS agreement in this market *r* in a period *t*. The set of

fixed effects is slightly different from the one used to estimate the main model (Eq. (1)). Specifically, α_{pr} is the airline pair-route fixed effect, which absorbs any time-invariant characteristics of airline pairs in specific markets, while α_{rm} is the route times month of year fixed effect, which captures route characteristics that vary seasonally. Due to collinearity with our variable of interest, $CSMARKET_{rt}$, we cannot include route-period fixed effects; instead, we add standard controls for time-varying factors affecting demand and supply on a given route. The vector X includes the product of the GDP of the two countries where the origin and the destination airports are located, the product of the population of these two countries, the average of their political stability indices, and the number of operating carriers offering any type of service in market r six months earlier. This variable captures the level of market competition. Given its potential endogeneity we include lagged values, as in Bilotkach and Hüschelrath (2019).¹⁰ In the model designed to analyse the spillover effects of CS adoption on fares of the direct and online connections, Eq. (4), the main difference with Eq. ((3)) is that in these cases the connection is served by the same airline, so $FARE_{irt}$ represents the fare charged by airline *i* on route *r* at time *t*, and pair-route fixed effects are replaced by airline-route fixed effects,

To better understand the rationale behind Eq. (3) and (4), let us consider an airline pair that currently operates an interline itinerary in market r (or an airline that serves market r with a direct flight or an online itinerary). If another airline pair initiates a CS agreement, the dummy variable *CSMARKET* takes the value of 1 from the CS introduction period τ onwards. Hence, the objective of these specifications is to isolate and assess the impact of CS agreements initiated by competing carriers on the fares charged by non-CS carriers within a given market. This analysis seeks to determine how these non-CS carriers react to the introduction of CS agreements.

5. Data and variables

This section presents the datasets used in the analysis to assess the impact of CS agreements on air fares in Africa. The primary dataset covers a 36-month period from 2017 to 2019, and includes all intra-Africa international itineraries during this period. We derive our baseline dataset, which includes interline itineraries (which either remain interline or become CS) except those with a gateway outside Africa. In addition, we derive two further subsamples: the first consisting of non-stop (direct) flights and the second consisting of online (connecting) itineraries.

Data for airfares and bookings are taken from the OAG Traffic Analyser, which provides monthly average traffic data for ticket sales at both airline and route level. As mentioned in the Introduction airfares are not posted but comes from actual purchases, are reported in US dollars and exclude fees for seat assignment, baggage, priority boarding, in-flight food and beverages, taxes, airport charges and surcharges (as detailed in Dresner et al., 2021). The datasets also include codes for operating and marketing airlines.

To ensure data quality and relevance, we applied standard data cleaning procedures. First, we exclude observations that did not report airfares, as they are likely due to misreporting or missing data. We decide not to trim minimum ticket prices to avoid information loss. Nevertheless, we conduct robustness checks and test different thresholds for airfares, as very low fares may be associated with frequent flyer programs or discounted cabin crew fares. Second, we exclude airline pair-route combinations that occurred infrequently, less than six times in our dataset, whether consecutive or not. This is essential to address the challenges of accurately assessing changes in CS agreements when dealing with infrequent cases. Similarly, to obtain a clearer pattern

⁹ In the rare cases where an airline pair p operates the same interline route through different gateways, this number is calculated as an average across the gateways.

¹⁰ Bilotkach and Hüschelrath (2019) use the lagged value of passenger volume as instrument for market concentration.

Example of the activation of CS.

t	OC_1	MC_1	OC_2	MC_2	CS
1	A_1	A_1	A2	A_2	0
2	A_1	A_1	A_2	A_2	0
23	A_1	A_1	A_2	A_2	0
24	A_1	A_1	A_2	A_1	1
Т	A_1	A_1	A_2	A_1	1

for our model application, we exclude pairs of airlines that alternated between having and not having CS agreements on the same route. Robustness checks were performed using different thresholds, which did not significantly change the final estimates.

In our main analysis, the basic unit of observation is an airline pair operating a one-stop route. This airline pair is defined as the combination of the airlines responsible for the first and second leg of the route. A route, also referred to as a market, is defined as a one-way flight between two airports, regardless of any intermediate connection. This means that routes from origin to destination (O-D) and from destination to origin (D-O) are treated as separate routes, following a common practice in the literature based on the same data source (e.g. Dresner et al., 2021). The primary dataset consists of two groups of airline pairs. The first group consists of pairs that enter into a codeshare (CS) agreement at some point in time, while the airlines in the second group never enter into a CS agreement. To be included in the first group, a pair of airlines must operate an interline route for at least three periods and then switch to CS for the following months. It is worth noting that in our dataset there are a few cases of virtual CS, which we categorise as interline. These virtual CS observations represent less than 0.8% of the total number of records and do not significantly affect the estimates when treated differently. Table 2 visualises the structure of the dataset in a case where one airline pair in a route initiates a CS agreement. OC_1 (OC_2) is the operating carrier in leg 1 (leg 2) and MC_1 (MC_2) is the marketing carrier in leg 1 (leg 2). From period 1 to period 23 we have that OC_1 is airline A_1 and OC_2 is airline A_2 . These two airlines are also the marketing airlines in leg 1 and leg 2 respectively (i.e. $MC_1 = A_1$ and $MC_2 = A_2$). Therefore, the dummy variable *CS* is equal to 0 in all periods until t = 23. In period 24, we observe a change in leg 2: airline A_1 becomes MC_2 , i.e. it sells the tickets in the second leg even if it does not operate it. This means that the two airlines A_1 and A_2 enter into a CS agreement and the dummy variable CS takes the value 1. There is no further change on this route until the last period, *T*, and so from period 24 the dummy variable *CS* takes the value 1.

Our primary dataset comprises 1008 one-stop unidirectional routes served by 83 carriers, including 6 LCCs such as *Safair* and *Mango*, as well as prominent European and Gulf carriers such as *Air France, British Airways* and *Emirates*. This results in a final dataset of 2061 unique carrier-pair-route combinations, with a total of 31,085 observations.¹¹ Table 3 shows the top 10 connecting routes with interline itineraries in Africa, ranked by bookings within our dataset. The first route is between Cape Town (South Africa) and Mauritius, jointly operated by *South African Airways* and *Air Mauritius*. The second is between Gaborone (Botswana) and Nairobi (Kenya), operated by *Air Botswana* and *Kenya Airways*. The third link is between Durban (South Africa) and Mauritius, served by *South African Airways* and *Air Mauritius*. Many of these top routes are popular with tourists, particularly those from South Africa, and some are also served by European legacy carriers.¹² Table 4 provides some summary statistics for the variables used in our empirical models. We split the descriptive analysis between the baseline sample (*Panel A*) and the different sub-samples for the spillover analyses. *Panel B* includes pure interline routes, where airline pairs never adopt CS. *Panel C* is the sub-sample including online itineraries, while *Panel D* is the sub-sample of direct (non-stop) observations. In *Panel A* there are 1008 routes and 2061 airline pairs-routes combinations, *Panel C* there are 878 routes and 1862 airline pairs-routes combinations, while *Panel D* there are 455 routes and 616 airline pairs-routes combinations.

In the baseline sample (Panel A), the average connecting fare is about 215 US dollars and the CS agreement (CS) is active in 4% of the airline pair-route-month observations. The average value of CSPROPENSITY, the instrumental variable representing the propensity of the airline pair from each specific gateway to sign a CS agreement, is about 1.5, i.e., at the gateway airport, the two airlines that adopt a CS agreement have about 2 direct connections (not to O or D) that are already operated under a CS agreement LAGCSPROPENSITY is the three-month lagged value of CSPROPENSITY that we generate as an alternative instrument for CS, and its mean is equal to 1.3 direct connections from the gateway, just smaller than CSPROPENSITY. DIRECTOD, a further instrument to conduct a robustness check for the sign and significance of the CS effect, has an average of 0.01, i.e., the number of interline routes that also have a direct connection from either airline in the *p* pair is low, about 1.5 percent. Therefore we use this variable as a check on the sign and significance of CS rather than its magnitude.

The average of *DOMLEG*, a dummy variable equal to 1 if at least one of the two segments is domestic (i.e. it connects two points within the same country), has an average equal to 0.50, implying that half of the observations in *Panel A* have a domestic leg. *KEYGTW* is a continuous variable between 0 and 1 that measures the importance of the gateway for the pair of airlines. This importance is measured as the percentage of destinations in the network of the two airlines (forming the pair of the observed route) that can be reached with a direct flight from the gateway. This is a proxy measure for the importance of the gateway in a possible hub-and-spoke network, which we consider important to control for.¹³ In the primary sample, on average, the gateway is often a key airport for the pair of airlines in 66% of the observations.

Panel B has 27,959 observations. It consists of routes that remain interline throughout the analysis period, i.e. routes operated by pairs of airlines that never codeshare on these routes. The average figures are quite similar to those characterising the routes in *Panel A* in terms of fares, proportion of routes with a domestic leg and gateway importance. The key variable here is *CSMARKET*. On average, it is equal to about 3%.

Panel C consists of itineraries that remain online throughout the analysis period. It contains 19,729 observations. The average fare is lower than that observed in Panels A-B (194 US dollars). We also observe a higher proportion (7%) of itineraries where the operating airline faces competition from at least one pair of airlines participating in a CS agreement. The observed gateway importance is also higher (about 88%), while the share of itineraries with a domestic leg is much lower (27%). Panel D focuses on the subsample of direct flights and has 9299 observations. As expected, we observe the lowest average fare (around 176 US dollars). A CS agreement occurs in 5% of the itineraries.

¹¹ Before applying the cutoffs described above, we had 6580 markets and 128 carriers. The distribution in terms of carrier identity was similar.

 $^{^{12}\,}$ Our study focuses on itineraries within Africa, and there are a few cases where European carriers serve one of the two legs. Those observations account for about 4% of the total.

¹³ We consider the maximum of the percentages of the two airlines forming the pair. This means that a value of one corresponds to the case where at least one of the two airlines provides direct services between that particular gateway and all destinations served.

Top 10 connecting routes in Africa.

Airport pair code	Airport pair name	Airline pair code	Airline pair name
CPT-MRU	Cape Town-Mauritius	SA-MK	South African Airways-Air Mauritius
GBE-NBO	Gaborone-Nairobi International Apt	BP-KQ	Air Botswana-Kenya Airways
DUR-MRU	Durban International Apt-Mauritius	SA-MK	South African Airways-Air Mauritius
JNB-SLI	Johannesburg Tambo International-Solwezi	SA-P0	South African Airways-Proflight Commuter Services
BLZ-LUN	Blantyre-Lusaka	3W-ET	Malawian Airlines-Ethiopian Airlines
ZNZ-JNB	Zanzibar-Johannesburg Tambo International	PW-SA	Precision Air Services Plc-South African Airways
PLZ-MRU	Port Elizabeth-Mauritius	BA-MK	British Airways-Air Mauritius
BLZ-NBO	Blantyre-Nairobi International Apt	3W-ET	Malawian Airlines-Ethiopian Airlines
EBB-MBA	Entebbe-Mombasa	KQ-JM	Kenya Airways-Jambojet
NKC-ABJ	Nouakchott-Abidjan	L6-AF	Mauritanian Airlines International-Air France

Table 4

Descriptive	statistics	of	econometric	variables.

Variable Obs Mean Std. Dev. Min Max FARE (US \$) 31,085 215.26 127.11 10 1,892 CS (#) 31,085 0.04 0 56 CS (POPENSITY (#) 31,085 1.52 5.31 0 56 LAGCSPROPENSITY (#) 29,024 1.33 4,94 0 56 DIRECTOD (#) 31,085 0.50 0 1 DOMLEC (#) 31,085 0.50 0 1 DOPDP (# 10 ²) 31,085 62.99 92.47 0.47 584.85 DIDPDSTAB (# 10 ²) 31,085 -0.49 -0.48 -1.90 0.92 Variable Obs Mean Std. Dev. Min Max FARE (US \$) 27,959 0.03 - 0 1 CSMARKET (#) 27,959 0.52 0 1 0 CSMARKET (#) 27,959 0.56 9.389 0.47 584.84 DOPOLEG (#10 ¹⁰)	P	anel A: main sample	e, interline adopting	CS and not adopting	it	
CS (#) 31,085 0.04 0 1 CSPROPENSITY (#) 31,085 1.52 5.31 0 56 DRECTOD (*) 31,085 0.01 0 1 DOMLEG (#) 31,085 0.50 0 1 DOMLEG (#) 31,085 0.50 0 1 DOPOP (# 10 ¹²) 31,085 0.66 0.36 0 1 DDOP (# 10 ¹²) 31,085 1.679 2,760 0.12 22,524 DDOD (# 10 ⁰) 31,085 -0.49 -0.48 -1.90 0.92 Variable Obs Mean Std. Dev. Min Max FARE (US \$) 27,959 0.03 0 1 1 CSMARET (#) 27,959 0.52 0 1 6 CSMARET (#) 27,959 0.66 2,805 0.12 22,524 ODGDP (# 10 ¹⁰) 27,959 0.660 2,805 0.12 22,524 ODGDP (# 10 ¹⁰) 27,959 <t< td=""><td>Variable</td><td>Obs</td><td>Mean</td><td>Std. Dev.</td><td>Min</td><td>Max</td></t<>	Variable	Obs	Mean	Std. Dev.	Min	Max
CSPROPENSITY (#) 31,085 1.52 5.31 0 56 LAGCSPROPENSITY (#) 29,024 1.33 4.94 0 56 DIRECTOD (#) 31,085 0.01 0 1 DOMLEG (#) 31,085 0.50 0 1 CSPROPENSITY (#) 31,085 0.66 0.36 0 1 DOPDO (#) 31,085 62.99 92.47 0.47 584.85 ODPDO (#) 31,085 62.99 92.47 0.47 584.85 ODPDO (#) 31,085 62.99 92.47 0.47 584.85 ODPOD (#) 31,085 0.49 -0.48 -1.90 0.92 Parel B: interline sub-sample not adopting CS 0 1 0 1 Variable Obs Mean Std. Dev. Min Max CSMARKET (#) 27,959 0.52 0 1 6 CSWARKET (#) 27,959 0.56 93.89 0.47 584.84	FARE (US \$)	31,085	215.26	127.11	10	1,892
LAGCSPROPENSITY (#) 29,024 1.33 4.94 0 56 DRECTOD (#) 31,085 0.01 0 1 CMUEG (#) 31,085 0.66 0.36 0 1 KEYGTW (%) 31,085 1,679 2,760 0.12 22,524 ODGDP (# 10 ⁴) 31,085 62.99 92.47 0.47 584.85 ODPOLSTAB (#) 31,085 -0.49 -0.48 -1.90 0.92 Variable Obs Mean Std. Dev. Min Max FARE B: interline sub-sample not adopting CS Variable Obs Mean Std. Dev. Min Max FARE (US \$) 27,959 0.03 0 1 6 CSMARKET (#) 27,959 0.65 39.89 0.47 25,24 ODGDP (# 10 ¹²) 27,959 1.660 2,805 0.12 2,524 ODEDP (# 10 ¹⁰) 27,959 65.63 9.38.9 0.47 56.16 Std. Dev<	CS (#)	31,085	0.04		0	1
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DOMLEG (#) 31,085 0.50 0 1 KEYGTW (%) 31,085 0.66 0.36 0 1 ODDPO (# 10 ⁶) 31,085 1,679 2,760 0.12 22,524 ODDPO (# 10 ⁶) 31,085 62.99 92.47 0.47 584.85 ODPOLSTAB (#) 31,085 -0.49 -0.48 -1.90 0.92 Variable Obs Mean Std. Dev. Min Max FARE (US \$) 27,959 210.15 122.55 10 1,892 CSMARKET (#) 27,959 0.52 0 1 1 DOMLEG (#) 27,959 0.52 0 1 6 KEYGTW (ODPOP (# 10 ¹²) 27,959 1.660 2,805 0.12 22,524 ODDP (# 10 ⁶) 27,959 0.563 93.89 0.47 584.84 ODPOLSTAB (#) 19,729 0.7 0 1 SCMARKET (#) 19,729 0.27 0 1 ODALEG	LAGCSPROPENSITY (#)	29,024	1.33	4.94	0	56
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$\begin{array}{c c c c c c c c c c c c c c c c c c c $	KEYGTW (%)	31,085	0.66	0.36	0	1
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Panel B: interline sub-sample not adopting CS Variable Obs Mean Std. Dev. Min Max FARE (US \$) 27,959 210.15 122.55 10 1,892 CSMARKET (#) 27,959 0.03 0 1 DOMLEG (#) 27,959 0.52 0 1 DOMLEG (#) 27,959 1.660 2,805 0.12 22,524 ODGDP (# 10 ¹²) 27,959 1.660 2,805 0.47 584.84 ODPOLSTAB (#) 27,959 -0.44 0.55 -2.15 1.00 Fanel C: online sub-sample Variable Obs Mean Std. Dev. Min Max FARE (US \$) 19,729 194.25 118.18 10 1,523 CSMARKET (#) 19,729 0.27 0 1 1 DOMLEG (#) 19,729 2.31 1.00 1 6 DDGDP (# 10 ¹²) 19,729 2.31 0.047 56.93 <t< td=""><td>ODGDP (# 10⁶)</td><td>31,085</td><td>62.99</td><td>92.47</td><td>0.47</td><td>584.85</td></t<>	ODGDP (# 10 ⁶)	31,085	62.99	92.47	0.47	584.85
VariableObsMeanStd. Dev.MinMax $FARE$ (US \$)27,959210.15122.55101,892 $CSMARKET$ (#)27,9590.0301 $DOMLEG$ (#)27,9590.5201 $TOTCOMP$ (#)27,9592.080.9116 $KEYGTW$ (ODPOP (# 10 ¹²)27,9591,6602,8050.1222,524 $ODGDP$ (# 10°)27,959-0.440.55-2.151.00Dente C: online sub-sampleVariableObsMeanStd. Dev.MinMaxFARE (US \$)19,729194.25118.18101,523CSMARKET (#)19,7290.0701DOMLEG (#)19,7290.2701ODPO (# 10 ¹²)19,7290.880.1701DOMLEG (#)19,7291,6382,4890.3220,174ODPOP (# 10 ¹²)19,7291,6382,4890.3220,174ODPOP (# 10 ¹²)19,72942.7965.930.47560.17ODED Fareet D: direct sub-sampleVariableObsMeanStd. Dev.MinMaxPanel D: direct sub-sampleVariableObsMeanStd. Dev.MinMaxODPOP (# 10 ⁶)19,7292,311.0016ODPOP (# 10 ⁶)<	ODPOLSTAB (#)	31,085	-0.49	-0.48	-1.90	0.92
FARE (US \$)27,959210.15122.55101,892CSMARKET (#)27,9590.0301DOMLEG (#)27,9590.5201TOTCOMP (#)27,9592.080.9116KEYGTW (ODPOP (# 10 ¹²)27,9591,6602,8050.1222,524ODGDP (# 10 ⁵)27,95965.6393.890.47584.84ODPOLSTAB (#)27,959-0.440.55-2.151.00Panel C: online sub-sampleVariableObsMeanStd. Dev.MinMaxFARE (US \$)19,729194.25118.18101,523CSMARKET (#)19,7290.07011DOMLEG (#)19,7290.27011DOMLEG (#)19,7290.880.17016ODPOP (# 10 ¹²)19,7291,6382,4890.3220,174ObsMeanStd. Dev.MinMaxFanel D: direct sub-sampleVariableObsMeanStd. Dev.MinMaxODPOP (# 10 ¹²)19,7291,6382,4890.3220,174ODGDP (# 10 ⁶)19,729-0.560.54-2.151.00ObsMeanStd. Dev.MinMaxFarel U: direct sub-sampleVariableObsMeanStd. Dev.MinMaxOD		Panel B: int	erline sub-sample no	ot adopting CS		
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KEYGTW (OPOPO (# 10 ¹²) 27,959 1,660 2,805 0.12 22,524 ODGDP (# 10 ⁶) 27,959 65.63 93.89 0.47 584.84 ODPOLSTAB (#) 27,959 -0.44 0.55 -2.15 1.00 Panel C: online sub-sample Variable Obs Mean Std. Dev. Min Max FARE (US \$) 19,729 194.25 118.18 10 1,523 CSMARKET (#) 19,729 0.07 0 1 100 1 DOMLEG (#) 19,729 0.27 0 1 <t< td=""><td>DOMLEG (#)</td><td>27,959</td><td>0.52</td><td></td><td>0</td><td>1</td></t<>	DOMLEG (#)	27,959	0.52		0	1
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Panel C: online sub-sampleVariableObsMeanStd. Dev.MinMaxFARE (US \$)19,729194.25118.18101,523CSMARKET (#)19,7290.0701DOMLEG (#)19,7290.2701TOTCOMP (#)19,7292.311.001ODOPOP (# 10 ¹²)19,7291,6382,4890.3220,174ODGDP (# 10 ¹²)19,72942.7965.930.47560.17ODPOLSTAB (#)19,729-0.560.54-2.151.00Panel D: direct sub-sampleVariableObsMeanStd. Dev.MinMaxFARE (US \$)9,299176.48104.85141,319CSMARKET (#)9,2992.320.9616ODPOP (# 10 ¹²)9,2992.320.9616ODPOP (# 10 ¹²)9,2991.7063,1110.1222,524ODGDP (# 10 ⁶)9,29951.5276.220.85584.84	$ODGDP (# 10^{6})$	27,959	65.63	93.89	0.47	584.84
VariableObsMeanStd. Dev.MinMaxFARE (US \$)19,729194.25118.18101,523CSMARKET (#)19,7290.0701DOMLEG (#)19,7290.2701CSMARKET (#)19,7290.880.1701TOTCOMP (#)19,7292.311.0016ODPOP (# 10 ¹²)19,7291,6382,4890.3220,174ODGDP (# 10 ⁶)19,729-0.560.54-2.151.00Panel D: direct sub-sampleVariableObsMeanStd. Dev.MinMaxFARE (US \$)9,299176.48104.85141,319CSMARKET (#)9,2992.320.9616ODPOP (# 10 ¹²)9,2991,7063,1110.1222,524ODGDP (# 10 ¹²)9,29951.5276.220.85584.84	ODPOLSTAB (#)	27,959	-0.44	0.55	-2.15	1.00
FARE (US \$)19,729194.25118.18101,523CSMARKET (#)19,7290.0701DOMLEG (#)19,7290.2701KEYGTW (%)19,7290.880.1701TOTCOMP (#)19,7292.311.0016ODPOP (# 10 ¹²)19,7291,6382,4890.3220,174ODGDP (# 10 ⁶)19,729-0.560.54-2.151.00Panel D: direct sub-sampleVariableObsMeanStd. Dev.MinMaxFARE (US \$)9,2990.05016ODPOP (# 10 ¹²)9,2992.320.9616ODPOP (# 10 ¹²)9,2991.7063,1110.1222,524ODGDP (# 10 ¹⁶)9,29951.5276.220.85584.84		Pa	nel C: online sub-sa	mple		
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Variable	Obs	Mean	Std. Dev.	Min	Max
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	FARE (US \$)	19,729	194.25	118.18	10	1,523
KEYGTW (%) 19,729 0.88 0.17 0 1 TOTCOMP (#) 19,729 2.31 1.00 1 6 ODPOP (# 10 ¹²) 19,729 1,638 2,489 0.32 20,174 ODGDP (# 10 ⁶) 19,729 1,638 2,489 0.47 560.17 ODPOLSTAB (#) 19,729 -0.56 0.54 -2.15 1.00 Panel D: direct sub-sample Variable Obs Mean Std. Dev. Min Max FARE (US \$) 9,299 176.48 104.85 14 1,319 CSMARKET (#) 9,299 0.05 0 1 1 TOTCOMP (#) 9,299 2.32 0.96 1 6 ODPOP (# 10 ¹²) 9,299 1,706 3,111 0.12 22,524 ODGDP (# 10 ⁶) 9,299 51.52 76.22 0.85 584.84	CSMARKET (#)	19,729	0.07		0	1
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	DOMLEG (#)	19,729	0.27		0	1
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	KEYGTW (%)	19,729	0.88	0.17	0	1
ODGDP (# 10 ⁶) 19,729 42.79 65.93 0.47 560.17 ODPOLSTAB (#) 19,729 -0.56 0.54 -2.15 1.00 Panel D: direct sub-sample Variable Obs Mean Std. Dev. Min Max FARE (US \$) 9,299 176.48 104.85 14 1,319 CSMARKET (#) 9,299 0.05 0 1 TOTCOMP (#) 9,299 2.32 0.96 1 6 ODPOP (# 10 ¹²) 9,299 1,706 3,111 0.12 22,524 ODGDP (# 10 ⁶) 9,299 51.52 76.22 0.85 584.84	TOTCOMP (#)	19,729	2.31	1.00	1	6
ODPOLSTAB (#) 19,729 -0.56 0.54 -2.15 1.00 Panel D: direct sub-sample Variable Obs Mean Std. Dev. Min Max FARE (US \$) 9,299 176.48 104.85 14 1,319 CSMARKET (#) 9,299 0.05 0 1 TOTCOMP (#) 9,299 2.32 0.96 1 6 ODPOP (# 10 ¹²) 9,299 1,706 3,111 0.12 22,524 ODGDP (# 10 ⁶) 9,299 51.52 76.22 0.85 584.84	ODPOP (# 10 ¹²)	19,729	1,638	2,489	0.32	20,174
Panel D: direct sub-sample Variable Obs Mean Std. Dev. Min Max FARE (US \$) 9,299 176.48 104.85 14 1,319 CSMARKET (#) 9,299 0.05 0 1 TOTCOMP (#) 9,299 2.32 0.96 1 6 ODPOP (# 10 ¹²) 9,299 1,706 3,111 0.12 22,524 ODGDP (# 10 ⁶) 9,299 51.52 76.22 0.85 584.84	ODGDP (# 10 ⁶)	19,729	42.79	65.93	0.47	560.17
Variable Obs Mean Std. Dev. Min Max FARE (US \$) 9,299 176.48 104.85 14 1,319 CSMARKET (#) 9,299 0.05 0 1 TOTCOMP (#) 9,299 2.32 0.96 1 6 ODPOP (# 10 ¹²) 9,299 1,706 3,111 0.12 22,524 ODGDP (# 10 ⁶) 9,299 51.52 76.22 0.85 584.84	ODPOLSTAB (#)	19,729	-0.56	0.54	-2.15	1.00
FARE (US \$)9,299176.48104.85141,319CSMARKET (#)9,2990.0501TOTCOMP (#)9,2992.320.9616ODPOP (# 10 ¹²)9,2991,7063,1110.1222,524ODGDP (# 10 ⁶)9,29951.5276.220.85584.84		Pa	nel D: direct sub-sa	mple		
CSMARKET (#) 9,299 0.05 0 1 TOTCOMP (#) 9,299 2.32 0.96 1 6 ODPOP (# 10 ¹²) 9,299 1,706 3,111 0.12 22,524 ODGDP (# 10 ⁶) 9,299 51.52 76.22 0.85 584.84	Variable	Obs	Mean	Std. Dev.	Min	Max
TOTCOMP (#) 9,299 2.32 0.96 1 6 ODPOP (# 10 ¹²) 9,299 1,706 3,111 0.12 22,524 ODGDP (# 10 ⁶) 9,299 51.52 76.22 0.85 584.84	FARE (US \$)	9,299	176.48	104.85	14	1,319
ODPOP (# 10 ¹²) 9,299 1,706 3,111 0.12 22,524 ODGDP (# 10 ⁶) 9,299 51.52 76.22 0.85 584.84	CSMARKET (#)	9,299	0.05		0	1
ODGDP (# 10 ⁶) 9,299 51.52 76.22 0.85 584.84	TOTCOMP (#)	9,299	2.32	0.96	1	6
	ODPOP (# 10 ¹²)	9,299	1,706	3,111	0.12	22,524
ODPOLSTAB (#) 9,299 -0.58 0.54 -2.07 0.88	ODGDP (# 10 ⁶)	9,299	51.52	76.22	0.85	584.84
	ODPOLSTAB (#)	9,299	-0.58	0.54	-2.07	0.88

6. Results

6.1. The effect of CS agreements on fares

This section uses the econometric model outlined in Eq. (1) to investigate the causal relationship between CS and fare levels. The results are summarised in Table 5. Column (1) of Table 5 presents the Ordinary Least Squares (OLS) estimates capturing the association between the activation of a CS agreement and the logarithm of fares. These estimates are conditioned on airline pair-route and route-month fixed effects. The coefficient of *CS* indicates the percentage change in fares charged by a pair of airlines on a given route after the activation of a CS agreement. This is compared to the fares charged by pairs that remain interline on the same route and to their fares before the introduction of a CS agreement. The results show that the conditional correlation is small, positive and statistically insignificant. This suggests that, on average, within a given route, the prices charged by airlines do not change after the implementation of the CS agreement.

Building on the discussion in Section 4, where carriers are expected to strategically select routes for CS operations in order to maximise expected profits, the variable CS is likely to be endogenous. The estimated effect obtained from a simple OLS regression may be biased. To mitigate this, we use an instrumental variable approach to estimate the causal effect of the introduction of CS on fares. Column (2) presents the results of the first stage, where the dummy variable CS is the

Impact of CS agreement on airfares in African interline itineraries.

Independent variable	Dependent variable						
	(1)	(2)	(3)	(4) LFARE			
	LFARE	CS	LFARE				
	(OLS)	(First stage)	(2SLS)	(2SLS)			
CS	0.038		-0.202***				
	(0.041)		(0.059)				
CSPROPENSITY		0.011***					
		(0.003)					
LAGCSPROPENSITY				-0.246***			
				(0.060)			
Observations	31,085	31,085	31,085	29,024			
Adj. R-Squared	0.84	0.50	-	-			
F-stat (Cragg-Donald Wald)			1,102.03	1,095.95			
OPERATING PAIR × ROUTE FEs	~	\checkmark	~	~			
ROUTE \times TIME FEs	\checkmark	\checkmark	\checkmark	\checkmark			

Standard errors, clustered at the route level, in parentheses.

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

dependent variable. The estimated coefficient for *CSPROPENSITY* suggests that the instrument is strong, as it is statistically significant and positive (equal to 0.011). This implies that a higher number of segments operated in CS by the two carriers from the gateway (excluding those connecting the gateway to the origin and destination of the specific route) increases the likelihood of having a CS agreement on the observed route.

Column (3) presents the results obtained using Two-Stage Least Squares (2SLS) estimation, with *CSPROPENSITY* as the instrument for *CS*. The estimated coefficient, denoted γ , is now negative and statistically significant (equal to -0.202). This suggests that pairs of airlines that switch to CS reduce their fares on a given route by about 18% compared to the fares charged by airlines that continue to offer interline itineraries.

Column (4) shows the 2SLS results obtained using the alternative instrumental variable *LAGCSPROPENSITY*, introduced earlier in Section 5. These findings confirm our previous results, as the sign remains negative and the coefficient is statistically significant. Moreover, its magnitude (-0.246) closely aligns with that of *CS*.

The comparison between the OLS and 2SLS estimates indicates that airlines tend to strategically select routes for CS agreements, and failing to account for this effect leads to biased estimates of the *CS* coefficient.¹⁴ The magnitude of the effect is substantial and slightly larger than that found in the existing literature analysing CS agreements on intercontinental or US domestic routes.¹⁵ This difference could be attributed to the underdevelopment of the African aviation sector.

In order to assess the robustness of our results, we perform several checks, the results of which are summarised in Table 6. First, we introduce two additional control variables that could explain both the propensity to enter into CS agreements and lower fares. The dummy variable *DOMLEG* takes a value of one if the gateway is located in either the origin or destination country, helping to control for any effects related to domestic legs of the journey. In addition, we add the variable *KEYGTW*, which serves as a proxy for the importance of the gateway in the network of the pair of airlines, mitigating confounding factors associated with the presence of a hub. As shown in row (1) of

estimated coefficient for the variable *CS*. Second, we perform our estimation using a different instrumental variable. Specifically, row (2) in Table 6 reports the results of the *CS* estimated coefficient when instead of *CSPROPENSITY* we use

Table 6 (additional controls), we find no significant difference in the

CS estimated coefficient when instead of *CSPROPENSITY* we use *DIRECTOD* as instrumental variable. The sign of the estimated coefficient is negative and statistically significant, as for *CS*. Hence, the negative effect of the adoption of a CS agreement in interline itineraries within Africa seems to be sufficiently robust. The magnitude of the estimated coefficient is higher (in absolute terms) with *DIRECTD*: -0.811. This corresponds to a reduction in fares of about 55%, much higher than before. This is due to a small number of observations (1.5%) where there is, in a given interline route *r*, both the adoption of a CS agreement and a direct itinerary on the same O-D. Moreover, interline fares are always lower if there is also a direct flight.

Third, we conduct additional analyses to address potential concerns related to the composition of the sample and to examine the impact of specific choices made during the construction of the dataset. Given the unique characteristics of the African air transport network, which in the North African region tends to be more influenced by European airlines, with the existence of some open sky agreements between African countries (e.g. Morocco) and the European Union, it is reasonable to assume that the effect of CS on fares may differ between North Africa and the rest of the continent. To explore this possibility, we exclude routes with origins and destinations in North African Mediterranean countries and focus only on sub-Saharan Africa. The estimated coefficient of CS is shown in row (3) of Table 6. Similarly, driven by the same concern, we analyse African airline pairs only (row 4). In both cases we observe a significant increase in the magnitude of the CS coefficient. If we consider only the sub-Saharan sub-sample, the estimated coefficient is -0.333, while if we restrict the observations to African airlines, it is -0.328. These results provide further evidence that, compared to their interline counterparts, airline pairs that switch to CS achieve a substantial reduction in fares, estimated at around 30%. In row (5), we exclude pairs involving low-cost carriers (LCCs) from the sample, as they operate under a different business model compared to fullservice carriers. The estimated coefficient remains consistent with that obtained in the baseline analysis, indicating that the presence of LCCs does not significantly affect the observed CS effect. Rows (6) and (7) modify the sample by varying the cutoffs for acceptable fare levels and the time we observe the pair in the sample, respectively. In row (6) we exclude observations with fares below 50 US dollars. This adjustment results in a slightly stronger effect, with an estimated fare reduction of -23%. In row (7) we refine the sample by excluding airline pairsroutes that have been in the data set for less than one year. Compared to the baseline cut-off of six months, this change yields slightly lower coefficients, indicating a fare reduction of about -15%.

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¹⁴ There are many possible reasons—unobservable by the researchers regarding this route selection, mainly related to carrier pair and period effects that we do not consider in our estimation. For instance, differences over time in efficiency levels among airlines or other operational dimensions.

¹⁵ Among others, Brueckner (2003) finds a reduction in fares of 8%–17%, Ito and Lee (2007) compare the CS case with the online case and find a similar sign and magnitude. In Brueckner et al. (2011), the estimated effect is about a 4% reduction in fares compared to the interline case.

Robustness checks of the effects of CS agreement on fares in Africa.

	Dependent variable: LFARE	
	CS estimated coefficient (2SLS)	Observations
Specification		
Additional controls		
(1) DOMLEG, KEYGTW	-0.192***	31,085
	(0.059)	
Alternative IV		
(2) DIRECTOD	-0.811***	31,085
	(0.230)	
Sample		
(3) Sub-Saharan Africa	-0.333***	28,741
	(0.072)	
(4) African carriers only	-0.328***	24,149
•	(0.055)	
(5) Excluding LCC	-0.201***	31,066
	(0.059)	
(6) $FARE >= 50$	-0.264***	30,330
	(0.054)	
(7) $T \ge 12$	-0.160**	23,226
	(0.058)	
SE correction		
(8) Operating pair and Route	-0.202***	31,085
	(0.059)	,
(9) Operating pair \times Time and Route	-0.202***	31,085
	(0.059)	,
(10) Operating pair and Route \times Time	-0.202***	31,085
	(0.061)	-
OPERATING PAIR \times ROUTE FES	\checkmark	
ROUTE \times TIME FEs	\checkmark	

Standard errors, clustered at the route level, in parentheses.

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

Finally, we examine the impact of different ways of clustering the standard errors, using three different methods to account for potential correlation in the error term. First, we use double clustering at the operating pair and route level (row 8). In row 9, we cluster the errors at the operating pair-month and route level, while in row 10 we cluster them at the operating pair-route and month level. Despite these differences in clustering, there is no change in the sign and significance of the *CS* estimated coefficient.

Overall, these exercises assure us that our results are robust and that switching to a CS agreement leads to lower fares for the airline pairs involved. This result is consistent with previous studies on cooperative pricing (see, e.g., Brueckner, 2003; Ito and Lee, 2007), which consistently show that CS leads to lower fares compared to the interline case, although they find a smaller effect. In our case, the observed effect of CS is stronger in the African air transport market, which is in line with expectations given that air transport in this continent has not yet exploited all possible improvements.

6.2. Spillover effects

We now shift our focus to examining the spillover effects of the adoption of a CS agreement — in particular, the impact of a mild form of cooperation between rivals on non-cooperating carriers. The previous section shows that interline itineraries on which CS agreements are implemented tend to have significantly lower fares than interline itineraries without CS on the same route. We therefore examine whether CS has a pro-competitive effect on the fares charged by non-cooperating airlines operating on the same route.

To explore this, we analyse three categories of itineraries that may be affected by the introduction of CS. First, we examine the impact of CS on interline itineraries. To do this, we restrict the sample to airline pairs that interline on routes connecting origin and destination via a gateway airport and never implement a CS agreement. We compare the fares charged by these airline pairs on routes where CS is introduced by competing airline pairs with the fares charged on routes where CS is not introduced. As mentioned above, the main explanatory variable of Eq. (3), i.e. *CSMARKET*, is an indicator that takes a value of 1 if some carrier pairs (other than those included in the sample) operate CS on that route in that period. In this analysis, the variable *CSMARKET* varies at the route-time level.

In Table 7, the coefficient CSMARKET provides a comparison of fares before and after the introduction of CS between routes with and without CS. Column (1) of Table 7 presents the results of this analysis using the OLS method. When CS is introduced on interline routes by a competing pair, the prices charged by the non-implementing pair fall by around 12% on average, as the estimated coefficient is negative, statistically significant and equal to -0.13. This effect is not negligible. This effect is not negligible and implies a significant impact on the dynamics of fares in the interline market. Column (2) of Table 7 presents the results for the sample of online itineraries, while column (3) presents the results for the sample of direct flights. The estimated coefficients (equal to -0.044 in column (2) and 0.037 in column (3)) have a weak statistical significance, suggesting that when competing airlines in the same market reduce their prices on the interline route due to the CS agreement, the prices of other types of routes also fall by around 4%. Although these results are weakly significant, they highlight interesting findings. On the one hand, online and direct flights are often perceived as distinct products from interline flights and therefore may not experience the same impact of increased competition observed in the interline market. On the other hand, even if they are differentiated products, increased competitive pressure on the route could still have some effect. In Africa, the latter factor seems to prevail, highlighting that codeshare, online and direct routes are perceived as substitute products, at least to some degree.

To ensure the robustness of our spillover results, we conducted a series of sensitivity checks, mirroring the approach taken for the main results. The results of these checks are presented in Table 8. The estimated coefficients are consistently of similar magnitude across

Spillover effect of CS adoption in interline, online and direct itineraries.

Independent variable	Dependent variable: LFARE					
	(1)	(2)	(3)			
	INTERLINE	ONLINE	DIRECT			
	(OLS)	(OLS)	(OLS)			
CSMARKET	-0.130***	-0.044*	-0.037*			
	(0.033)	(0.025)	(0.021)			
Observations	11,143	10,069	5,660			
Adj. <i>R</i> -squared	0.75	0.74	0.87			
OPERATING PAIR/CARRIER \times ROUTE FES	✓	×	✓			
ROUTE \times MONTH FES	✓	×	✓			

Standard errors, clustered at the route level, in parentheses.

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

Table 8

Robustness of the CS spillover effect in interline, online and direct itineraries.

	INTERLINE ONLINE				DIRECT				
	CSMARKET	Obs.	Adj. R-Squared	CSMARKET	Obs.	Adj. R-Squared	CSMARKET	Obs.	Adj. R-Squared
Specification									
(1) Add. controls (DOMLEG, KEYGTW)	-0.130*** (0.033)	11,143	0.75	-0.042* (0.024)	10,069	0.74			
(2) Add. controls (CSOTHER)	-0.08*** (0.017)	11,143	0.75	-0.045* (0.025)	10,069	0.74	-0.037* (0.021)	5,660	0.87
Sample									
(3) Sub-Saharan Africa	-0.129*** (0.032)	10,694	0.76	-0.049** (0.025)	9,652	0.74	-0.037* (0.021)	5,120	0.87
(4) African carriers only	-0.137*** (0.029)	7,806	0.71	-0.046 (0.029)	9,702	0.71	-0.030 (0.026)	5,374	0.87
(5) Excluding LCCs	-0.130*** (0.033)	11,140	0.75	-0.044* (0.025)	10,069	0.74	-0.037* (0.021)	5,618	0.87
(6) $FARE >= 50$	-0.116*** (0.025)	10,832	0.73	-0.047** (0.024)	9,681	0.72	-0.026 (0.022)	5,282	0.85
(7) $T >= 12$	-0.132*** (0.033)	10,421	0.75	-0.044* (0.025)	9,845	0.74	-0.037* (0.021)	5,626	0.87
Clustering									
(8) Route and Time	-0.130*** (0.036)	11,143	0.75	-0.044* (0.024)	10,069	0.74	-0.037* (0.021)	5,660	0.87
(9) Operating pair/carrier \times Route and Time	-0.130*** (0.031)	11,143	0.75	-0.044 (0.028)	10,069	0.74	-0.037 (0.030)	5,660	0.87
(10) Operating pair/carrier and Route \times Time	-0.130*** (0.026)	11,143	0.75	-0.044 (0.029)	10,069	0.74	-0.037 (0.027)	5,660	0.87
OPERATING PAIR/CARRIER X ROUTE FES ROUTE X MONTH FES	✓ ✓			✓ ✓			✓ ✓		

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

p < 0.01, p < 0.05, p < 0.1.

the table. While the significance levels remain stable for the interline sample, they show a slightly higher sensitivity to the choice of clustering in the online and direct samples. In particular, the coefficient on CSMARKET becomes marginally insignificant when two-way clustering is used (rows (9) and (10)). Noteworthy is the introduction of an additional control variable, CSOTHER, in row (2). This variable takes the value 1 if one of the airlines in the pair (or the airline operating the route in the online and direct samples) has a CS agreement with another airline on the same route. We introduce this variable to ensure that the observed effect is not driven by the fares charged by carriers with CS agreements within the same market. The inclusion of this control increases the magnitude of the effect on interline routes, suggesting that carriers involved in CS agreements reduce the fare charged on interline itineraries without CS to a lesser extent than for pairs whose carriers do not offer an alternative CS product. Overall, these analyses confirm the robustness of the pro-competitive effect of CS agreements on other routes, particularly in the interline context.

7. Conclusions

This study adds an additional contribution to the existing literature on cooperation agreements in the airline industry, in particular by examining their applicability in underdeveloped markets, with a focus on the African aviation sector. While most studies have focused on well-established markets such as the US and the North Atlantic, little research has examined regions in the early stages of development, such as Africa. The core objective of this paper is to examine whether key findings from the established literature are applicable to these emerging regions, thus addressing a critical gap in current research.

Our analysis focuses on international connecting flights within Africa and seeks to understand whether cooperation, particularly through codeshare agreements, can mitigate the issue of excessively high prices observed in the region. To achieve this, we use a comprehensive dataset covering the entire universe of international connecting routes in Africa, spanning the years 2017 to 2019.

Our main finding, which is robust to several alternative specifications, is that codeshare, when introduced by a pair of airlines switching from interline service, leads to a substantial reduction in airfares, about -18%. This magnitude exceeds observations in many previous studies, highlighting the significant impact of double mark-ups in the African aviation market and the high potential for economic efficiency.

Furthermore, our analysis reveals significant spillover effects on interline routes and, to a lesser extent, on online and direct routes. This suggests that airlines operating in the same market with different itineraries (i.e., interline, online or direct) respond to the introduction of codeshare by other airline pairs by lowering their fares. This effect is particularly relevant in interline itineraries, and lighter in online and direct itineraries. We interpret the lower fare sensitivity of online and direct itineraries as evidence of product differentiation, because these products are perceived by passengers as less close substitutes for codeshare itineraries. In contrast, the degree of substitutability between interline and codeshare itineraries is very high.

In conclusion, our findings suggest that increased cooperation between airlines has the potential to drive significant growth in the African aviation market. The observed reduction in airfares with the introduction of CS agreements is not only consistent with the recommendations of the African Airlines Association (AFRAA, 2022), but also highlights the potential for increased demand for air transport in Africa. Our paper focuses on the price effects of CS agreements on connecting flights and provides a significant contribution to understanding the dynamics of cooperation in underdeveloped markets. Some room is left for future research. Firstly, in addition to the double mark-up limitation, other factors, such as cost reductions passed on to passengers, may have contributed to the observed decrease in prices. It would be interesting to quantify the different contributions. Secondly, further research is needed to investigate the impact of CS on frequencies and single leg fares.

CRediT authorship contribution statement

Andrea Gualini: Writing – original draft, Investigation, Data curation. Laura Ogliari: Writing – review & editing, Supervision, Methodology, Investigation. Gianmaria Martini: Writing – review & editing, Supervision, Methodology, Conceptualization. Davide Scotti: Writing – review & editing, Supervision, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data. They were purchased for a fee from OAG.

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References

- Abate, M., 2016. Economic effects of air transport market liberalization in africa. Transp. Res. A 92, 326–337.
- Adler, N., Hanany, E., 2016. Regulating inter-firm agreements: The case of airline codesharing in parallel networks. Transp. Res. B 84, 31–54.
- Adler, N., Mantin, B., 2015. Government and company contracts: The effect on service and prices in international airline markets. Econ. Transp. 4 (3), 166–177.
- AFRAA, 2022. Better skies for africa: Afraa's actions for the recovery and sustainability of the air transport industry.

- Alderighi, M., Gaggero, A.A., Piga, C.A., 2015. The effect of code-share agreements on the temporal profile of airline fares. Transp. Res. A 79, 42–54.
- Bilotkach, V., 2007. Price effects of airline consolidation: evidence from a sample of transatlantic markets. Empir. Econ. 33 (3), 427–448.
- Bilotkach, V., Hüschelrath, K., 2019. Balancing competition and cooperation: Evidence from transatlantic airline markets. Transp. Res. A 120, 1–16.
- Brueckner, J.K., 2001. The economics of international codesharing: an analysis of airline alliances. Int. J. Ind. Organ. 19 (10), 1475–1498.
- Brueckner, J.K., 2003. International airfares in the age of alliances: The effects of codesharing and antitrust immunity. Rev. Econ. Stat. 85 (1), 105–118.
- Brueckner, J.K., Lee, D.N., Singer, E.S., 2011. Alliances, codesharing, antitrust immunity, and international airfares: do previous patterns persist? J. Compet. Law Econ. 7 (3), 573–602.
- Brueckner, J.K., Singer, E., 2019. Pricing by international airline alliances: A retrospective study. Econ. Transp. 20, 100139.
- Button, K., Brugnoli, A., Martini, G., Scotti, D., 2015. Connecting african urban areas: airline networks and intra-sub-saharan trade. J. Transp. Geogr. 42, 84–89.
- Button, K., Martini, G., Scotti, D., 2017. The Economics and Political Economy of African Air Transport. Routledge.
- Button, K., Porta, F., Scotti, D., 2022. The role of strategic airline alliances in africa. J. Transp. Econ. Policy (JTEP) 56 (2), 272–294.
- Calzaretta, Jr., R.J., Eilat, Y., Israel, M.A., 2017. Competitive effects of international airline cooperation. J. Compet. Law Econ. 13 (3), 501–548.
- Chen, Y., Gayle, P.G., 2007. Vertical contracting between airlines: An equilibrium analysis of codeshare alliances. Int. J. Ind. Organ. 25 (5), 1046–1060.
- Ciliberto, F., Murry, C., Tamer, E., 2021. Market structure and competition in airline markets. J. Polit. Econ. 129 (11), 2995–3038.
- Ciliberto, F., Watkins, E., Williams, J.W., 2019. Collusive pricing patterns in the US airline industry. Int. J. Ind. Organ. 62, 136–157.
- de Jong, G., Behrens, C., van Herk, H., Verhoef, E., 2022. Airfares with codeshares:(why) are consumers willing to pay more for products of foreign firms with a domestic partner? J. Econ. Behav. Organ. 193, 1–18.
- Dresner, M., Gualini, A., Martini, G., Valli, M., 2021. Airline competition and LCCs in the North Atlantic market. J. Transp. Econ. Policy (JTEP) 55 (4), 261–282.
- Dresner, M.E., Windle, R.J., 1996. Alliances and code-sharing in the international airline industry. Built Environ. (1978-) 201–211.
- Gayle, P.G., 2008. An empirical analysis of the competitive effects of the delta/continental/northwest code-share alliance. J. Law Econ. 51 (4), 743–766.
- Gayle, P.G., 2013. On the efficiency of codeshare contracts between airlines: is double marginalization eliminated? Am. Econ. J. Microecon. 5 (4), 244–273.
- Hassin, O., Shy, O., 2004. Code-sharing agreements and interconnections in markets for international flights. Rev. Int. Econ. 12 (3), 337–352.
- Heimer, O., Shy, O., 2006. Code-sharing agreements, frequency of flights, and profits under parallel operation. Compet. Policy Antitrust.
- IATA, 2023. Chart of the week, regional financial performance recovering, but still varied.
- Ito, H., Lee, D., 2007. Domestic code sharing, alliances, and airfares in the US airline industry. J. Law Econ. 50 (2), 355–380.
- Lubbe, B., Shornikova, S., 2017. The development of African air transport. In: The Economics and Political Economy of African Air Transport. Routledge, pp. 16–39.
- Martini, G., Porta, F., Scotti, D., 2023. Persistent and transient productive efficiency in the African airline industry. J. Prod. Anal. 1–20.
- Nantulya, P., 2019. Implications for Africa from China's one belt one road strategy. Afr. Cent. Strateg. Stud. 22.
- Njoya, E.T., 2016. Africa's single aviation market: The progress so far. J. Transp. Geogr. 50, 4–11.
- Oum, T.H., Park, J.-H., Zhang, A., 1996. The effects of airline codesharing agreements on firm conduct and international air fares. J. Transp. Econ. Policy 187–202.
- Scotti, D., Martini, G., Leidi, S., Button, K.J., 2017. The African air transport network. In: The Economics and Political Economy of African Air Transport. Routledge, pp. 40–60.
- statista, 2023. Global air cargo market share in 2019, by region.
- The Africa Logistic, 2022. Collaboration and strategic partnerships hold much promise for the African air transport industry.
- Whalen, W.T., 2007. A panel data analysis of code-sharing, antitrust immunity, and open skies treaties in international aviation markets. Rev. Ind. Organ. 30 (1), 39–61.