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International airline codesharing and consumer choice behavior: misconceptions vs. quality signals

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Abstract

We examine the impact of airline codesharing on consumer choice behavior in non-stop international route markets. Using stated preference data, we document that consumer valuation of flights by alien foreign carriers is significantly higher if these flights are offered as codeshare products by consumers' own national carrier or, to a lesser extent, a neighboring national carrier. We empirically rule out quality improvements and frequent flier programs as underlying drivers of these effects and explore two alternative explanations: misconceptions about codesharing and codesharing as a quality signal. We find that misconceptions are widespread, but that they do not cause higher valuation of codeshare products. Consistent with signaling, however, codeshare products are valued higher by more risk-averse consumers and on less familiar routes.

JEL classifications: L11, L15, L93.

Keywords: codesharing, consumer choice behavior, incomplete information, signaling, airline industry.

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1 Introduction

Codeshare agreements that allow one carrier (the 'marketing carrier') to market and sell seats on a flight operated by another carrier (the 'operating carrier') are omnipresent in today's airline industry. As codeshare agreements are a form of horizontal cooperation they have been under the scrutiny of competition authorities and the academic research community alike. There is now considerable evidence documenting that codesharing may lead to lower air fares due to efficiency gains, exploitation of economies of density and the elimination of double marginalization (e.g., Brueckner and Whalen, 2000; Brueckner, 2001, 2003). However, there also is evidence indicating that codesharing may lead to higher air fares due to the potential of collusion and increased willingness-to-pay by passengers for improved services and more convenience (e.g., Armantier and Richard, 2006; Zou et al., 2011; Gayle and Brown, 2014).[1]

Traditionally, codesharing was used to provide seamless travel on interline routes that require passengers to switch carrier during their trip. Nowadays the majority of codesharing applies to online routes that are operated by a single carrier, a practice that is known as virtual codesharing (Ito and Lee, 2005, 2007). Given this practice, part of the seats for a certain flight are sold directly by the carrier operating the flight (*pure online products*), while other seats on that same flight are sold by codesharing partners that are not involved in operating the flight (*virtual codeshare products*).

We analyze consumer choice on international routes where flights are offered as pure online as well as virtual codeshare products. Unlike previous studies on codesharing, we make use of individual-level data obtained from a stated preference experiment that resembles the booking environment at travel agency websites. Focusing on international route markets, we explicitly consider the potentially different impact of virtual codesharing by consumers' own national carrier versus a foreign carrier, and in more familiar versus less familiar route markets. This novel setup allows us to derive consumer preferences for various pure online and virtual codeshare products and to understand some of the behavioral mechanisms underlying the consumer choice process in the many international aviation markets where online and virtual products are jointly available.

The stated preference experiment is conducted amongst a representative panel of Australian air travel consumers and considers two long-haul non-stop route markets across the Pacific: Australia to South-American (Santiago, Chile) and Australia to North-America (San Francisco, United States). In these two route markets, the consumers choose between multiple alternatives: pure online flights

[1] In addition, Adler and Mantin (2015) argue that the effects may depend on the type of codeshare contract signed between airlines.

of their *own national carrier*, Qantas; pure online flights by the *neighboring national carrier*, Air New Zealand; pure online flights by a number of foreign carriers which we will refer to as *alien carriers*;[2] and virtual codeshare flights that are operated by the alien carriers but marketed and sold by alternately the own or the neighboring national carrier.

Using a discrete choice framework, we elicit the willingness-to-pay of consumers for each flight product. We find that consumers are willing to pay substantial premiums for pure online flights by their own or the neighboring national carrier over pure online flights by alien carriers. However, willingness-to-pay for flights operated by alien carriers increases substantially once these flights are offered as virtual codeshare products. This effect is particularly pronounced for the virtual codeshare products that are offered by consumers' own national carrier. Moreover, the additional willingness-to-pay for codeshared over pure online alien flights is considerably higher in the Santiago destination market, presumably reflecting the uncertainty of consumers with respect to the quality of the alien carriers in this less familiar destination market.

A standard explanation for higher willingness-to-pay due to codesharing is that codesharing leads to more convenience and better opportunities to accumulate and redeem frequent flier miles (see, e.g., Zou et al., 2011; Gayle and Brown, 2014).[3] Although codesharing may indeed increase convenience on interline routes due to coordination of flight schedules, check-in and luggage handling, such improvements do not arise on online routes like the ones we study here. With respect to frequent flier programs, respondents are instructed that they cannot earn or spend frequent flier miles on any of the available flights during the experiment. In addition, including covariates for frequent flier program membership does not alter our findings, nor do we find systematic differences in the willingness-to-pay for codeshared products among carriers that have integrated frequent flier programs versus carriers whose programs are not integrated.

We use our individual-level data to explore two alternative explanations of the willingness-to-pay for codeshare products. Both explanations deal with incomplete information on the part of the consumer. First, consumers may not be fully informed about the meaning of codesharing (Goh and Uncles, 2003).[4] To explore this explanation, we ask respondents for the definition of codesharing. While we find that there indeed are widespread misconceptions about codesharing, these misconceptions do not account for the premium on codeshared flights. Rather, causality seems to run the

[2]We use the term alien carriers to distinct these foreign carriers from Air New Zealand.

[3]Codeshare agreements typically involve the integration of frequent flier programs, which makes it easier for consumers to earn and redeem frequent flier miles across the partner carriers.

[4]This idea is often voiced in popular press, see e.g., USA Today (2016).

other way: consumers who have a strong preference for flying with a particular carrier (e.g., their own national carrier) have a stronger incentive to be informed about codesharing.

Second, consumers may be uncertain about the quality of alien carriers and perceive codesharing by familiar carriers as a signal to reduce uncertainty and risk. In particular, codesharing may signal the national carrier's confidence in the product quality of the alien carrier if consumers do not expect their national carrier to engage in horizontal agreements with low quality partners. To test this explanation, we exploit the availability of individual-level indicators of risk attitude in our data. In line with the signaling explanation, we find that more risk-averse consumers are willing to pay higher premiums for codesharing by their own national carrier than less risk-averse consumers and that this effect is particularly pronounced in less familiar route markets.

This paper contributes to a vast literature on the impact of codesharing agreements. Although the market-level fare, demand and level-of-service consequences of codesharing are well-documented, the impact of codesharing on consumer choice behavior has received limited attention. The only paper that specifically addresses consumer choice behavior with respect to codesharing is provided by Gayle (2007), who found that consumers in the US domestic airline market do not perceive a distinction between pure online and codeshared flights operated by the same carrier. Conversely, we show that in international markets many consumers perceive an otherwise identical flight operated by an alien carrier differently once it is codeshared — in particular, if their own national carrier is involved in the codeshare agreement. We also contribute to a literature on consumer preferences for domestic products and services (e.g., Nijssen and van Herk, 2009; Cosar et al., 2018; De Jong et al., 2018). In the context of international aviation, we show that such preferences may spill over to foreign partners that engage in horizontal partnerships with the domestic carrier.

This paper proceeds as follows. Section 2 presents the stated preference experiment and the data. Section 3 describes the econometric approach. Section 4 discusses the findings. Section 5 concludes.

2 Experimental setup and data

2.1 Stated preference experiment

To examine consumer choices between pure online and codeshared products, we use data collected through a stated preference experiment. The experiment covers two long-haul non-stop destination markets from Australia to Santiago, Chile (Santiago International Airport, SCL), and to San Francisco, United States (San Francisco International Airport, SFO). From the Australian consumers'

Table 1: Flight characteristics and levels

Characteristics	Destination market	Levels
Marketing-operating carriers	Santiago	QF/QF, NZ/NZ, LA/QF, AV/QF, LA/NZ, AV/NZ, LA/LA, AV/AV, AR/AR
	San Francisco	QF/QF, NZ/NZ, AA/QF, UA/QF, AA/NZ, UA/NZ, AA/AA, UA/UA, DL/DL
Travel time	Both	1700 - 1880 AUD (steps of 20 AUD)
Ticket fare	Both	13h 30 - 15h 00 (steps of 15min.)

Note(s): Carrier designator codes: QF - Qantas; NZ - Air New Zealand; LA - LATAM; AV - Avianca; AR - Aerolineas Argentinas; AA - American Airlines; UA - United Airlines; DL - Delta Air Lines.

Table 2: Typology of flight products

Flight product type	Notation	Santiago flight products	San Francisco flight products
Pure online flights own national carrier	QF/QF	QF/QF	QF/QF
Pure online flights neighboring national carrier	NZ/NZ	NZ/NZ	NZ/NZ
Codeshare flights own national carrier	*/QF	LA/QF, AV/QF	AA/QF, UA/QF
Codeshare flights neighboring national carrier	*/NZ	LA/NZ, AV/NZ	AA/NZ, UA/NZ
Pure online flights alien carriers	*/*	LA/LA, AV/AV, AR/AR	AA/AA, UA/UA, DL/DL

Note(s): See footnote below Table 1 for carrier designator codes.

point of view, San Francisco represents a more familiar destination than Chile.[5] Each respondent was presented with six choice scenarios in both destination markets, although the ordering of the two destination markets varied across respondents. The process and presentation of the survey is similar to the way travel agency websites operate. Respondents first select the preferred origin airport for their trip and, subsequently, are presented with a number of flight alternatives (i.e., four in each scenario) that are characterized by the marketing-operating carrier combination of the flight, the travel time and the fare.[6]

Table 1 shows the levels of each flight characteristic. The most important characteristic for the purpose of our analysis is the marketing-operating carrier combination. This defines the type of flight product; whether it is a pure online or virtual codeshare product, and which carriers

[5]For example, the actual number of seats offered on routes from Australia to North America is about ten times larger than to South America: 2 vs 0.2 million seats in 2017 (Australian Bureau of Infrastructure Transport and Regional Economics, 2018). Moreover, it is likely that Australian consumers perceive South America as a more risky destination due to greater cultural, economic and political distance with their home country (Kraus et al., 2015).

[6]The preferred origin airports a respondent could choose from are: Sydney Airport (SYD), Melbourne Airport (MEL), Brisbane Airport (BNE), Adelaide Airport (ADL), Gold Coast Airport (OOL), Cairns Airport (CNS) and Canberra Airport (CBR). These airports cover the main Australian airports used for intercontinental flights.

are involved in operating and marketing the flight. Throughout this paper we simply refer to these marketing-operating carrier combinations as 'flight products'. We describe each flight product using the convention operating carrier code/marketing carrier code from Ito and Lee (2007).[7] Each destination market involves nine distinct flight products, which cover five broad flight product types that are summarized in Table 2.

For the other two flight characteristics, travel time and ticket fare, we choose levels that are typically observed in the considered route markets. To avoid unrealistic combinations of travel times and stopovers, all flights during the experiment are presented as non-stop flights. Moreover, respondents are informed that they cannot earn or spend frequent flier miles on any of the available flights. Consequently, the scenarios offer the trade-off between flight product type and time or monetary costs (for an example of a choice scenario, see Appendix A).

A statistically efficient experimental design was generated using Sawtooth's complete enumeration method. This method results in a heterogeneous design, meaning that there are multiple versions of the design to which respondents are randomly allocated (see Chrzan and Orme, 2000, for technical details about the design). This type of design leads to substantial gains in efficiency as compared to homogeneous designs and avoids order effects (Sándor and Wedel, 2005; Liu and Tang, 2015). Before fielding the experiment, we conducted two pilot tests using samples of Dutch undergraduate students ($n_1 = 225$ and $n_2 = 204$).[8] These pilot tests confirmed that respondents could easily relate to the choice scenarios and that the experimental design results in data that allows for efficient estimation of the effects of interest.

2.2 Codeshare (mis)conceptions and risk attitudes

In addition to the stated preference data, we collect information on respondents' (mis)conceptions of codesharing and their risk attitude. Codeshare (mis)conceptions were captured by a multiple-choice question at the end of the experiment asking respondents to select the correct definition of codesharing. The question referred back to the experiment as follows: "In the air travel choice

[7] For example, QF/QF denotes a pure-online flight by Qantas, whereas AA/QF denotes a flight operated by American Airlines and codeshared by Qantas.

[8] In these pilot studies, the stated preference scenarios were adapted to reflect flight choices in long-haul non-stop markets from Amsterdam, The Netherlands (Amsterdam Airport Schiphol, AMS) to Nairobi, Kenia (Jomo Kenyatta International Airport, NBO) and to New York (John F. Kennedy International Airport, JFK). It is noteworthy that in these different route markets the main findings were qualitatively similar to the findings in the trans-Pacific route markets presented in this paper.

experiment, it sometimes said in smaller print that a flight offered by airline A (the one shown in the logo) was operated by airline B. What do you think is meant by this?" The answer options given were: "Airlines A and B are not formally merged but known under the same airline code"; "Airlines A and B sell seats for a flight that is made in an aircraft and with a crew of airline B"; "Airlines A and B share the same landing slot at an airport"; and "I had not noticed this and/or do not know what it means". The answer options are randomized across respondents to prevent order effects. Furthermore, after seeing this question, respondents were not able to go back to the stated preference experiment to alter their choices.

Risk attitudes are captured using two types of questions. The first type asks respondents to give a global assessment of their willingness to take risks. The second type deals with the willingness to take risks in three specific domains that are relevant in our research context: finances, health/safety and recreation.[9] This way of measuring risk attitudes is in line with recent studies that show that the usual practice of measuring risk attitudes using lottery-style experiments generalizes poorly to risk behavior outside the financial realm, and that self-assessed measures of risk attitude that pertain to the specific research context often have better predictive validity (e.g., Dohmen et al., 2011; Hardeweg et al., 2013; Wolbert and Riedl, 2013). The exact wording and the scale of the risk attitude question was taken from the study by Dohmen et al. (2011).

2.3 Sample and descriptives

In June 2018, we distributed the stated preference experiment to a sample of Australian air travel consumers drawn from a representative consumer panel of market research company Pureprofile.[10] Respondents that did not reside in one of the Eastern states of Australia or had not flown in the past 12 months were excluded from the sample. A total of 502 eligible respondents completed the experiment. Table 3 provides basic descriptives of the respondents in our sample and of the Australian population in general. Most of the sociodemographics of our sample match closely with those in the general Australian population, underscoring the representativeness of our sample.[11]

[9] We choose these specific domains because in considering the risks of traveling with an alien carrier, consumers may take into account financial consequences (e.g., invalidated tickets or lost luggage), health/safety consequences (e.g., potential for accidents). Recreation and travelling are often closely connected, recreational risks are therefore also relevant.

[10] See Pureprofile (2018), for additional information on this consumer panel.

[11] This is not the case for age and university degree, although this can be attributed to the fact that individuals below 18 years are not included in the consumer panel which biases the sample means of age and university degree upwards.

Table 3: Sample descriptives

	Population	Sample			
Variable	Mean	Mean	Std. dev.	Min	Max
Socio-demographics:					
Female	0.507	0.532	0.499	0	1
Age	38.650	48.398	15.722	19	77
Australian nationality	0.824	0.892	0.310	0	1
English mother tongue	0.901	0.886	0.318	0	1
Employed	0.603	0.625	0.484	0	1
Student	0.076	0.040	0.196	0	1
University degree	0.220[a]	0.373	0.484	0	1
Air travel behavior:					
# of flights in past 12 months	N/A	2.590	3.746	1	50
international traveler	N/A	0.655	0.476	0	1
business traveler	N/A	0.175	0.381	0	1
Qantas frequent flier	N/A	0.620	0.486	0	1
Air New Zealand frequent flier	N/A	0.010	0.099	0	1

Note(s): Australian population statistics obtained from Australian Bureau of Statistics (2018). [a]the percentage of university degree in the Australian population of 15 years or older.

With respect to the statistics on air travel behavior, we document that, conditional on flying at least once, Australians fly on average 2.5 roundtrip per year. The majority of respondents flies internationally (65.5%), whereas a minority flies for business purposes (17.5%). Finally, there is a noteworthy discrepancy between membership of the frequent flier program of the own national carrier, Qantas (62.0%), and the neighboring national carrier, Air New Zealand (1.0%).

Figure 1 shows the distribution of respondents' answers to the codeshare definition answer. In line with prior literature (Goh and Uncles, 2003), we document great variation in the conceptions of codesharing across the population. The group with the correct conception of codesharing accounts for less than half of the sample (232 respondents). A substantial group (154 respondents) is aware that codesharing entails some sort of a partnership between the involved carriers, however does not know that this implies that they will be flying on an airplane and with a crew of a different carrier than the one that is selling the tickets. Another rather large group (85 respondents) concedes that they either do not know what codesharing means or had not noticed that some flights were codeshared during the experiment. Finally, a small group (31 respondents) believes that codesharing implies that two carriers share a landing slot at an airport.

Figure 2 shows the distribution of answers to the risk indicators. Respondents rated their willingness to take risks on a scale from 0 to 10, where 0 meant "not at all willing to take risks" and 10 "very willing to take risks". For the purpose of our analysis, we reverse coded the scale such

Figure 1: Distribution of codeshare (mis)conceptions

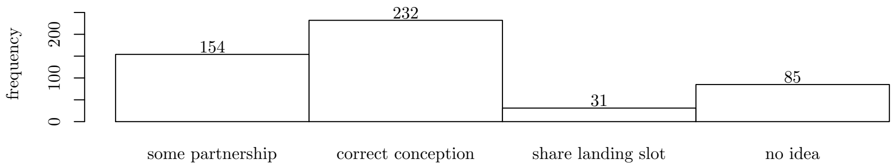
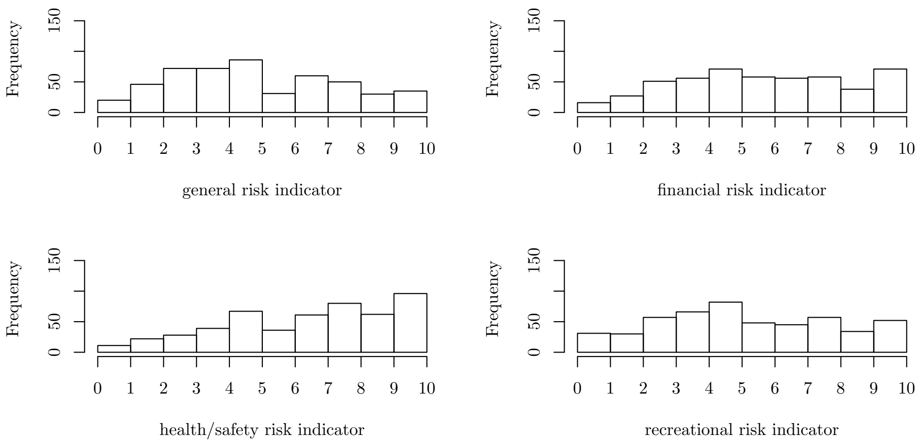


Figure 2: Distribution of risk indicators



that higher scores imply more risk-aversion. Overall, the distributions show that there is substantial variation in risk attitude across the respondents. General and recreational risk attitude are more normally distributed, whereas financial and health/safety risk attitude are slightly more right-skewed — implying more risk-aversion in these domains. It is also noteworthy that the risk indicators are not perfectly correlated, although pair-wise correlations are generally high at 0.57 - 0.77 (see Appendix B for the correlation matrix). This is in line with the literature and warrants the use of domain-specific risk indicators (Dohmen et al., 2011; Wolbert and Riedl, 2013).

3 Econometric approach

We use a discrete choice framework to elicit consumer valuations for the flight products that appear during the stated preference experiment. We start with multinomial logit models that estimate average differences in willingness-to-pay between the different flight products. Subsequently, we specify panel mixed logit models that correct for the panel structure of the data and allow for unobserved preferences for flight products across consumers. To examine codeshare (mis)conceptions and risk-aversion as two behavioral mechanisms underlying choice behavior, we specify a hybrid panel mixed logit model in the spirit of, among others, Ben-Akiva et al. (2002) and Ashok et al. (2002). This model links individuals' codeshare (mis)conceptions and risk-aversion to their valuation of each flight product, while explicitly taking into account that risk attitude is unobserved and therefore contains substantial measurement error.[12] To reveal differences in choice behavior between less and more familiar markets, all models are estimated separately for the Santiago and San Francisco destination markets.

3.1 Multinomial and panel mixed logit

In line with random utility theory (McFadden, 1974), we assume that the utility that individual n derives from flight alternative i in choice scenario t can be decomposed into a deterministic component that depends on observed characteristics of the alternatives (i.e., the type of flight product, travel time and ticket fare) and a stochastic component that captures unobserved idiosyncrasies:

$$U_{nit} = V_{nit}(d_{lnit}, t_{nit}, p_{nit}) + \varepsilon_{nit}, \tag{1}$$

where d_{lnit} is a vector of L dummies for flight products; and t_{nit} and p_{nit} are the travel time and ticket fare, respectively.

Following Train and Weeks (2005) and Scarpa et al. (2008) we use a specification in willingness-to-pay space for the deterministic component of utility:

$$V_{nit} = \gamma(\alpha_{ln} d_{lnit} + \beta t_{nit} - p_{nit}), \tag{2}$$

where the parameters of main interest, α_{ln}, provide the willingness-to-pay for flight products; β provides the willingness-to-pay for a one unit change in travel time; and γ is the cost parameter which incorporates scale and hence has no direct interpretation (Train and Weeks, 2005).[13]

[12] We acknowledge that codeshare (mis)conceptions may also be measured with some error. However, as (mis)conceptions are measured using a multiple-choice type of question (instead of an arbitrary scale) measurement error is presumably of much less concern.

[13] In most of our specifications, the willingness-to-pay space transformation is formally equivalent to the more usual preference space specification. In a robustness check that allows for random cost parameters, the willingness-to-pay space transformation enables us to directly specify the distribution of willingness-to-pay. This typically leads to more reasonable distributions, compared with distributions that are derived *post-hoc* from the coefficients of a specification in preference space (Train and Weeks, 2005).

Assuming utility-maximizing behavior and an independent, identically extreme value distribution for the error term, ε_{nit}, leads to the well-known logit choice probability of individual n choosing flight alternative i:

$$P_n(i) = \frac{e^{\gamma(\alpha_{ln} d_{lnit} + \beta t_{nit} - p_{nit})}}{\sum_{j=1}^{J} e^{\gamma(\alpha_{ln} d_{lnjt} + \beta t_{njt} - p_{njt})}},\ i \in J, \tag{3}$$

which can be estimated using standard likelihood procedures.

To correct for the panel structure of the data and allow for unobserved preferences for flight products, we include a random term to the flight product parameters: $\alpha_{ln} = \alpha_{l0} + \alpha_{l\sigma}\psi_{ln}$, where ψ_{ln} is an individual-specific standard normally distributed random term; and $\alpha_{l\sigma}$ is the random scale parameter to be estimated.

This addition leads to the panel mixed logit probability of individual n making the sequence of flight choices $\mathbf{i} = \{i_1, ..., i_T\}$:

$$P_n(\mathbf{i}) = \int \prod_{t=1}^{T} \left[\frac{e^{\gamma(\alpha_{ln} d_{lnit} + \beta t_{nit} - p_{nit})}}{\sum_{j=1}^{J} e^{\gamma(\alpha_{ln} d_{lnjt} + \beta t_{njt} - p_{njt})}} \right] f(\psi)\, d\psi,\ i \in J, \tag{4}$$

which can be estimated by simulated maximum likelihood procedures (see, e.g., Train, 2009).[14]

3.2 Hybrid panel mixed logit

To examine codeshare misconceptions and risk-aversion as two behavioral mechanisms underlying choices between pure online and codeshared flight products, we rewrite the flight product parameters as follows: $\alpha_{ln} = \alpha_{l0} + \alpha_{l1} msc_n + \alpha_{l2} rsk_n^* + \alpha_{l\sigma}\psi_{ln}$, where msc_n is a dummy equal to one for individuals with a misconception of codesharing and zero otherwise; rsk_n^* represents each individuals (latent) risk attitude; α_{l0} gives the baseline flight product valuation; and α_{l1} and α_{l2} give the variations in flight product valuations related to codeshare misconceptions and risk attitude.[15]

As risk attitude is latent it is not directly observed, but characterized by a structural equation:

$$rsk_n^* = \theta_v s_{nv} + \theta_\sigma \omega_n \tag{5}$$

[14] Our initial specification assumes independence between individuals' unobserved preferences for specific flight products. This assumption is relaxed in a robustness checks where we allow for correlations between an individual's unobserved preference for pure online products and codeshared products offered by the same carrier.

[15] Due to the coding of msc_n and rsk_n, the baseline flight product parameters represent the valuation of individuals that have a misconception of codesharing and an average risk attitude (i.e., neither risk-averse nor risk-seeking); the parameter associated with msc_n represents the difference in carrier preferences between individuals that have the wrong and correct conception of codesharing; and the parameter associated with rsk_n^* yields the changes in carrier preferences for a one standard deviation increase in (latent) risk attitude.

where s_{nv} is a vector of V sociodemographics; θ_v is a vector of associated parameters to be estimated; ω_n is an individual-specific standard normally distributed random term; and θ_σ is the scale parameter.[16]

Information about (latent) risk attitude is obtained from the risk indicators. The relationship between (latent) risk attitude and the R risk indicators is given by the following measurement equation:

$$I_{rn} = \delta_{r0} + \delta_{r1} rsk_n^* + \delta_{r\sigma}\eta_{rn} \tag{6}$$

where δ_{r0} and δ_{r1} are parameters to be estimated; and η_{rn} is an error term.

Assuming a normal distribution for the error term of the measurement equation, η_{rn}, the conditional probability of observing the sequence of risk indicators $\mathbf{I} = \{I_1, ..., I_R\}$ is:

$$P_n(\mathbf{I}|\omega) = \prod_{r=1}^{R} \left[\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(I_{rn}-(\delta_{r0}+\delta_{r1} rsk_n^*))^2}{2\sigma^2}} \right] \tag{7}$$

The probability of each individual (i.e., joint probability of the sequences of choices and risk indicators per individual) can than be expressed as:

$$\begin{aligned} P_n(\mathbf{i}, \mathbf{I}) = \int\int \prod_{t=1}^{T} & \left[\frac{e^{\gamma(\alpha_{ln} d_{lnit} + \beta t_{nit} - p_{nit})}}{\sum_{j=1}^{J} e^{\gamma(\alpha_{ln} d_{lnjt} + \beta t_{njt} - p_{njt})}} \right] \\ \times \prod_{r=1}^{R} & \left[\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(I_{rn}-(\delta_{r0}+\delta_{r1} rsk_n^*))^2}{2\sigma^2}} \right] f(\omega) f(\psi)\, d\omega\, d\psi, \end{aligned} \tag{8}$$

which can be estimated using simulated maximum likelihood estimation.

To estimate hybrid choice models, the latent variable needs to be normalized. Two common approaches are normalizing the parameters of one of the measurement equations, or normalizing the variance of the structural equation error term (Vij and Walker, 2016). We opt for the latter approach, as it has been shown to lead to parameter estimates that are closer to the underlying data generation process (Raveau et al., 2012). An additional advantage of this normalization is that the latent variable parameter in the choice model can be interpreted as the change in flight product valuations for a one standard deviation in (latent) risk attitude.[17]

[16]In search of a parsimonious specification, we started with including all sociodemographics listed in Table 3 and maintained only those that were significantly related to (latent) risk attitude (i.e., gender, age, university degree, employment status).

[17]We note here that we estimated our preferred model specification with the other normalization approach which led to very similar results. These model estimation results are available upon request.

In simulated maximum likelihood estimation, the choice of good starting values is critical. We follow the practice of Hess and Train (2017) by first estimating restricted versions of the model and then using the obtained estimates as starting values for more extended versions. In particular, the estimates of the multinomial logit are used as starting values for the panel mixed logit. Starting values for the hybrid panel mixed logit are obtained by first estimating the choice and the measurement/structural component separately (Bierlaire, 2016a).

4 Model estimation results

4.1 Multinomial and panel mixed logit results

Table 4 provides the multinomial and mixed logit results. Columns (1) and (2) provide the parameter estimates for the multinomial (Eq. 3) and mixed logit specifications (Eq. 4) in the Santiago destination market, whereas columns (3) and (4) provide the estimates for these models in the San Francisco destination market. In all estimation results reported in the main text, we consider the five broad types of flight products described in section 2: pure online flights by Qantas (QF/QF), pure online flights by Air New Zealand (NZ/NZ), codeshared flights by Qantas (*/QF), codeshared flights by Air New Zealand (*/NZ) and pure online flights by alien carriers (*/*).[18] Pure online flights by alien carriers represents the reference category. Consequently, the reported parameter estimates associated with the flight products (i.e., the α-parameters) should be interpreted as the additional willingness-to-pay in Australian dollars (AUD) relative to the alien pure online product.

In terms of model fit, the panel mixed logit model offers a significant improvement over the multinomial logit model in the Santiago destination market ($\chi^2 = 278.97$, $df = 4$, $p < .01$), as well as in the San Francisco destination market ($\chi^2 = 282.72$, $df = 4$, $p < .01$). This underlines the importance of correcting for the panel structure of the data and justifies our focus on the parameter estimates obtained from the panel mixed logit model.[19]

In both destination markets, the baseline flight product parameters are large in magnitude and highly statistically significant. This implies that, on average, consumers have substantial willingness-

[18] In initial model specifications, we considered each distinct combination of operating and marketing carrier as a separate product category (see Appendix C for the estimation results). The parameter estimates of these specifications indicated that there are no substantial and robustly significant differences in consumers' valuation of the flight products by the different alien carriers. This suggests that consumers regard these carriers more or less as perfect substitutes and allows us to aggregate the alien carriers in a single flight product category.

[19] It should be added that the parameter estimates from the multinomial logit are not widely different from those in the panel mixed logit.

Table 4: Multinomial and panel mixed logit estimation results

Parameters	Santiago destination market (1)		(2)		San Francisco destination market (3)		(4)	
QF/QF baseline	147.70**	(5.53)	134.33**	(6.18)	98.08**	(4.64)	86.84**	(5.71)
QF/QF random scale			80.32**	(6.75)			82.26**	(6.96)
NZ/NZ baseline	97.90**	(5.31)	83.31**	(5.42)	62.44**	(4.70)	50.88**	(5.33)
NZ/NZ random scale			52.23**	(7.00)			57.49**	(7.04)
*/QF baseline	108.96**	(4.65)	96.09**	(5.15)	76.83**	(3.95)	68.28**	(4.61)
*/QF random scale			70.33**	(5.22)			65.08**	(4.70)
*/NZ baseline	73.06**	(4.53)	62.91**	(4.50)	40.42**	(3.99)	33.22**	(4.17)
*/NZ random scale			44.58**	(5.53)			44.05**	(5.18)
Travel time	-0.92**	(0.05)	-0.91**	(0.04)	-0.88**	(0.04)	-0.90**	(0.04)
Cost parameter	0.02**	(0.00)	0.02**	(0.00)	0.02**	(0.00)	0.02**	(0.00)
Observations (choice)	3002		3002		3002		3002	
Individuals	502		502		502		502	
Parameters	6		10		6		10	
Draws (MLHS)	-		500		-		500	
Log likelihood	-2831.693		-2692.209		-2935.407		-2794.046	

Note(s): All models are estimated using BIOGEME (Bierlaire, 2016b). Draws in panel mixed logit are according to Modified Latin Hybercube Sampling (MLHS, see, Hess et al., 2006). Standard errors in parentheses. *p<0.05; **p<0.01

to-pay for pure online as well as codeshared flight products offered by Qantas and Air New Zealand, relative to pure online flight products offered by alien carriers. Consumers are willing to pay the highest premium for the pure online products by their own national carrier, Qantas, at 134 AUD (87 AUD) or approximately 8.5% (5.5%) of the average ticket fare in the Santiago (San Francisco) destination market. Interestingly, consumers are also willing to pay a substantial premium for codeshared products offered by Qantas. This premium equals 96 AUD (68 AUD) or approximately 6% (4.5%) in the Santiago (San Francisco) destination market. Pure online and codeshared products by Air New Zealand command somewhat lower, although still considerable, premiums of respectively 83 and 63 AUD (51 and 33 AUD) or approximately 5 and 4% (3 and 2%) in the Santiago (San Francisco) destination market.[20]

The random scale parameters are also highly statistically significant, indicating that there is substantial heterogeneity in willingness-to-pay for each flight product across consumers. Using the baseline and random scale parameters, we estimate the distribution of willingness-to-pay for each flight product. From these distributions, we derive that the share of the population with a positive

[20] Moreover, our results imply a value of travel time savings of about 53 AUD per hour, which is broadly consistent with values of air travel time savings found in other countries (see, e.g., Shires and de Jong, 2009; Wardman et al., 2016).

willingness-to-pay in the Santiago (San Francisco) destination market, is equal to 95.5% (85.5%) for pure online products by Qantas, 94.5% (81%) for pure online products by Air New Zealand, 91.5% (85.5%) for codeshare products by Qantas and 92% (77.5%) for codeshare products by Air New Zealand. Thus, although the magnitude of the premiums varies a lot across consumers, the vast majority of the population has a positive willingness-to-pay for pure online and codeshared flight products by Qantas and Air New Zealand, relative to pure online products by alien carriers.

Table 5 provides the results of three additional panel mixed logit estimations in the Santiago and San Francisco destination market, respectively. Columns (1) and (4) report the parameter estimates of a specification that includes a large range of covariates, including Qantas frequent flier program membership.[21] The other covariates that are included are: gender, age, Australian nationality, trip frequency and whether the respondents frequently travels internationally and/or for business purposes.[22] Inclusion of these covariates leads to parameter estimates that are virtually identical to those in the specifications of columns (2) and (4) in Table 4. Most importantly, this rules out frequent flier program membership as an explanation for the differences in valuation of the flight products in our analysis.

To provide an additional check on the potential influence of frequent flier programs, we consider in columns (2) and (5) the difference in valuation of codeshare products involving operating and marketing carriers that in reality share their frequent flier program. If willingness-to-pay for codeshared products is due to frequent flier programs, the valuation of codeshared products should be larger for codeshared products among carriers that in reality have integrated programs. We find that the virtual codeshare product that is marketed by Qantas and operated by American Airlines (AA/QF) is valued higher than the codeshare product that is marketed by Qantas and operated by United Airlines (UA/QF). However, the effect is rather small. Moreover, in the destination market where the willingness-to-pay for codeshare products is highest (Santiago), we do not find that virtual codesharing among carriers with integrated programs is higher. This finding is in line with the aforementioned finding: frequent flier programs do not seem to play a prominent role in the estimated willingness-to-pay.[23]

[21] Inclusion of Air New Zealand frequent flier program membership was not feasible due to the small share of respondents that are member of this program.

[22] To constrain the computational burden associated with the large number of additional parameters to be estimated, we start with an initial run of a multinomial logit model including all covariates and drop all interaction terms that are not statistically significant at the 10% confidence level from the subsequent panel mixed logit model estimation. Parameter estimates on the covariates are available upon request.

[23] Recall that we tried to preclude the effect of frequent flier programs in the experiment by explicitly telling

Table 5: Additional panel mixed logit estimation results

	Santiago destination market						San Francisco destination market					
Parameters	(1)		(2)		(3)		(4)		(5)		(6)	
QF/QF mean	135.57**	(6.10)	134.33**	(6.17)	143.58**	(6.98)	87.00**	(5.66)	86.80**	(5.70)	91.79**	(6.67)
QF/QF scale	77.18**	(6.57)	80.27**	(6.74)	102.63**	(7.11)	79.61**	(6.94)	82.09**	(6.95)	108.46**	(7.58)
NZ/NZ mean	84.53**	(5.36)	83.45**	(5.42)	87.16**	(5.94)	51.18**	(5.28)	50.61**	(5.33)	53.49**	(5.87)
NZ/NZ scale	50.05**	(7.08)	52.33**	(6.98)	73.56**	(7.04)	56.56**	(6.84)	57.62**	(7.02)	80.97**	(7.26)
*/QF mean	97.23**	(5.06)	98.60**	(5.50)	106.97**	(5.84)	69.01**	(4.57)	62.86**	(5.15)	76.40**	(5.17)
*/QF shared program			-6.60	(5.03)					10.51*	(4.50)		
*/QF scale	66.98**	(5.13)	70.16**	(5.20)	83.76**	(5.87)	63.80**	(4.68)	65.05**	(4.70)	78.78**	(5.36)
*/NZ mean	64.10**	(4.46)	61.36**	(5.12)	68.53**	(4.81)	33.77**	(4.10)	32.51**	(4.84)	38.01**	(4.49)
*/NZ shared program			3.12	(4.96)					1.23	(4.82)		
*/NZ scale	43.51**	(5.47)	44.59**	(5.52)	56.11**	(5.52)	41.67**	(5.26)	44.25**	(5.18)	56.30**	(5.30)
Travel time	-0.90**	(0.04)	-0.91**	(0.04)	-0.92**	(0.04)	-0.90**	(0.04)	-0.90**	(0.04)	-0.90**	(0.04)
Cost parameter	0.02**	(0.00)	0.02**	(0.00)	0.02**	(0.00)	0.02**	(0.00)	0.02**	(0.00)	0.02**	(0.00)
cor(QF/QF, */QF)					0.82**	(0.04)					0.83**	(0.04)
cor(NZ/NZ, */NZ)					0.81**	(0.07)					0.91**	(0.07)
Observations (choices)	3002		3002		3002		3002		3002		3002	
Individuals	502		502		502		502		502		502	
Parameters	31		12		6		23		12		6	
Draws (MLHS)	500		500		500		500		500		500	
Log likelihood	-2774.179		-2821.723		-2742.416		-2885.374		-2923.141		-2794.046	

Note(s): All models are estimated using BIOGEME (Bierlaire, 2016b). Draws are according to Modified Latin Hybercube Sampling (MLHS, see, Hess et al., 2006). Standard errors in parentheses. *p<0.05; **p<0.01

Finally, in columns (3) and (6), we extend our specification by allowing for correlations in individuals unobserved preferences for pure online and codeshare products offered by the same carrier. Specifically, the parameter ρ_1 captures correlation between pure online and codeshare products by Qantas, while ρ_2 captures correlation between pure online and codeshare products by Air New Zealand. These correlations are highly statistically significant and very strong (>0.8) in both destination markets, indicating that, not surprisingly, consumers who have a strong unobserved preference for pure online products by Qantas (Air New Zealand) generally also have a strong unobserved preference for its virtual codeshare products.

4.2 Hybrid panel mixed logit results

Table 6 provides the estimation results of the hybrid panel mixed logit models that links individuals' (mis)conceptions about codesharing and risk attitude to their valuations of the flight products. Columns (1) and (3) provide the parameter estimates of the standard hybrid panel mixed logit specification (Eq. 8), for respectively the Santiago and San Francisco destination markets. Columns (2) and (4) provide the parameter estimates of extensions in which risk attitude is allowed to have an increasing or decreasing impact over its range.[24]

To assess model fit of the hybrid panel mixed logit models, we factor out the portion of the log likelihood that relates to the choice component of the hybrid panel mixed logit models (see, e.g., Hess and Beharry-Borg, 2012).[25] This shows that the hybrid panel mixed logit yields a significant improvement in model fit as compared with the panel mixed logit (χ^2 = 62.86, df = 12, $p < .01$ in the Santiago destination market; and χ^2 = 27.25, df = 12, $p < .01$ in the San Francisco destination market). The inclusion of a non-linear impact of risk attitude results in a further improvement in model fit in the Santiago destination market (χ^2 = 13.90, df = 4, $p < .01$), but not in the San Francisco destination market (χ^2 = 4.88, df = 4, $p > .05$).

The estimates of the misconception parameters in Table 6 represent the difference in the premium that consumers with the correct versus wrong conception of codesharing are willing to pay for each

respondents that they could not earn or spend frequent flier programs on any of the flight products. Our findings regarding the impact of frequent flier program membership suggests that this instruction was effective.

[24]Here we only show the estimates of the parameters in the discrete choice component of the hybrid panel mixed logit model. The parameter estimates for the measurement and structural components are provided in Appendix C.

[25]Comparing the total log likelihood of the hybrid panel mixed logit models to that of the panel mixed logit models is otherwise not informative, as the models are not estimated on the same data (i.e., the panel mixed logit is estimated on the choice observations only, while the hybrid panel mixed logit is estimate on both the choice observations and risk indicators).

Table 6: Hybrid panel mixed logit estimation results

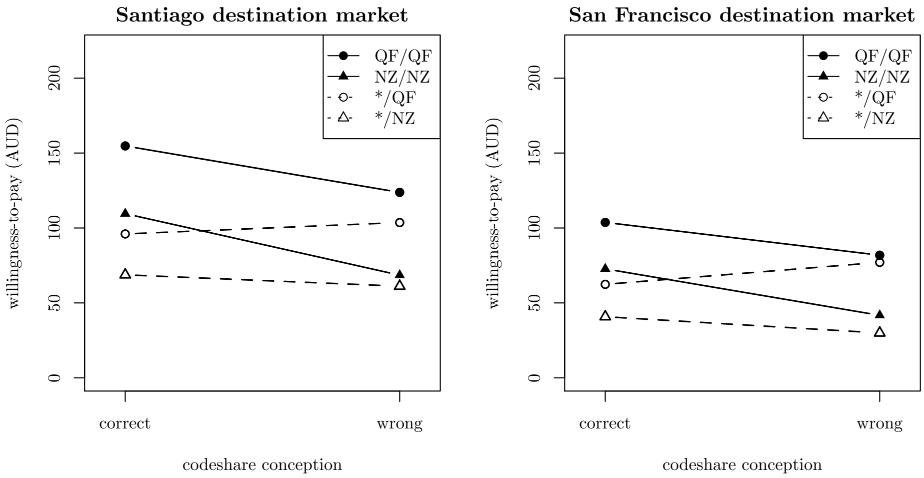
Parameters	Santiago destination market (1)		(2)		San Francisco destination market (3)		(4)	
QF/QF baseline	154.75**	(9.17)	164.38**	(10.60)	103.73**	(8.57)	99.71**	(9.71)
QF/QF misconception	-31.00**	(11.20)	-27.97*	(11.30)	-21.89*	(10.90)	-23.75*	(11.00)
QF/QF risk attitude	25.86**	(5.76)	21.39**	(6.38)	15.86**	(5.56)	17.63**	(6.17)
QF/QF risk attitude^2			-10.21	(5.67)			4.13	(5.02)
QF/QF random scale	76.61**	(6.85)	75.66**	(6.88)	78.80**	(7.10)	78.64**	(7.07)
NZ/NZ baseline	109.56**	(7.65)	122.94**	(9.08)	72.74**	(7.01)	76.47**	(8.06)
NZ/NZ misconception	-41.03**	(9.72)	-37.73**	(9.81)	-31.01**	(9.45)	-29.50**	(9.52)
NZ/NZ risk attitude	17.81**	(5.00)	13.47*	(5.87)	10.01*	(5.01)	8.19	(5.62)
NZ/NZ risk attitude^2			-14.02**	(5.14)			-4.94	(4.77)
NZ/NZ random scale	40.76**	(7.80)	39.91**	(8.05)	46.87**	(7.30)	47.38**	(7.29)
*/QF baseline	96.01**	(7.63)	96.80**	(8.98)	62.39**	(6.86)	54.69**	(7.85)
*/QF misconception	7.63	(9.61)	8.37	(9.68)	14.67	(8.92)	11.50	(8.88)
*/QF risk attitude	18.58**	(4.94)	16.57**	(5.13)	7.05	(4.73)	11.68*	(5.43)
*/QF risk attitude^2			-1.63	(5.01)			9.39*	(4.32)
*/QF random scale	67.06**	(5.15)	66.78**	(5.15)	64.14**	(4.76)	62.90**	(4.77)
*/NZ baseline	68.75**	(6.64)	77.11**	(7.77)	40.81**	(5.99)	44.77**	(6.88)
*/NZ misconception	-7.59	(8.49)	-5.84	(8.62)	-10.84	(7.82)	-9.83	(7.87)
*/NZ risk attitude	7.19	(4.43)	3.83	(4.98)	4.64	(4.09)	2.27	(4.65)
*/NZ risk attitude^2			-9.05*	(4.29)			-4.76	(3.81)
*/NZ random scale	42.55**	(5.54)	43.25**	(5.49)	38.49**	(5.56)	38.91**	(5.55)
Travel time	0.02**	(0.00)	0.02**	(0.00)	0.02**	(0.00)	0.02**	(0.00)
Cost parameter	-0.91**	(0.04)	-0.92**	(0.04)	-0.90**	(0.04)	-0.90**	(0.04)
Observations (choice)	3002		3002		3002		3002	
Individuals	502		502		502		502	
Parameters	35		39		35		39	
Draws (MLHS)	500		500		500		500	
Log likelihood	-6824.158		-6818.552		-6949.672		-6943.664	
Log likelihood (choice)	-2660.78		-2653.83		-2780.42		-2777.98	

Note(s): All models are estimated using BIOGEME (Bierlaire, 2016b). Draws are according to Modified Latin Hybercube Sampling (MLHS, see, Hess et al., 2006). Standard errors in parentheses. *p<0.05; **p<0.01

flight product type. Consumers with a misconception of codesharing are willing to pay a lower premium for pure online products by Qantas and Air New Zealand, relative to consumers with the correct conception of codesharing. This premium is approximately 31 and 41 AUD (22 and 31 AUD) lower for, respectively, Qantas and Air New Zealand in the Santiago (San Francisco) destination market. Interestingly, there is no significant impact of codeshare misconceptions on the premium for codeshared flights by Qantas and Air New Zealand. In other words, codeshare misconceptions do not lead to differences in the willingness-to-pay for codeshared over pure online alien flights.

These effects are illustrated in Figure 3, which show the willingness-to-pay for each flight product relative to pure online alien products (y-axis) for consumers with the correct and wrong conception of codesharing (x-axis). Consumers that are well-informed about codesharing, on the right hand side

Figure 3: Willingness-to-pay for carriers by codeshare (mis)conception



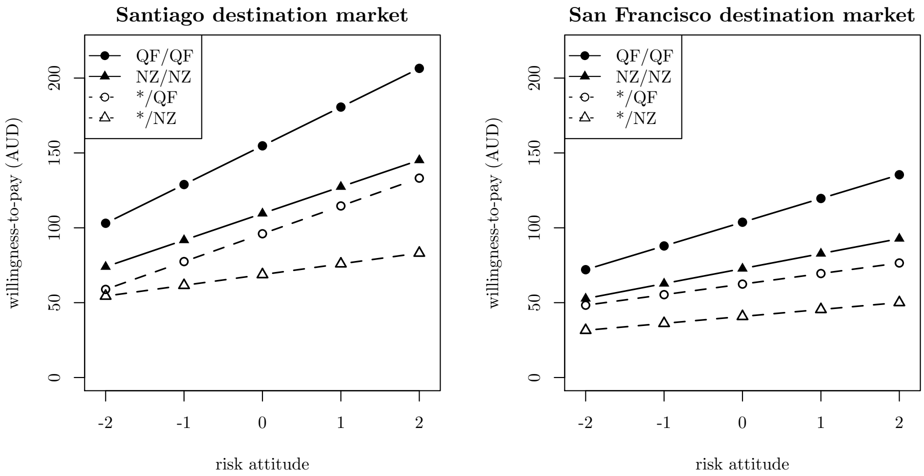
of the diagrams, are willing to pay a virtually identical premium for codeshared flight products by Qantas and Air New Zealand (dashed lines) as the wrongly-informed consumers on the left hand side of the diagram. Thus, our data do not support the hypothesis that the increase in willingness-to-pay for alien flights that are codeshared by the own or the neighboring national carrier are caused by codeshare misconceptions.

At the same time, Figure 3 shows that the premium for pure online products by Qantas and Air New Zealand (solid lines) is strictly higher for the well-informed consumers. It seems unlikely that this higher willingness-to-pay for pure online products by Qantas or Air New Zealand over pure online alien products, is the causal effect of having the correct conception of codesharing: neither of these product types involve codesharing. Rather, this pattern suggests that consumers who have a strong preference for flying with a specific carrier (e.g., their own national carrier) might have a stronger incentive to be informed of the true meaning of codesharing.[26]

The estimates of the risk attitude parameters in columns (1) and (3) of Table 6, represent the change in the premium for each product type over pure online products by alien carriers, for a one standard deviation increase in (latent) risk attitude. In the Santiago destination market, such a one standard deviation increase in risk attitude leads to a significantly higher premium for pure online flights by Qantas (26 AUD) and Air New Zealand (18 AUD), as well as alien flights codeshared

[26]The importance of the causal direction is not without practical consequence for carriers. They should not hope or expect that by better informing travelers of the true meaning of codesharing, the willingness-to-pay for their pure online flights compared to alien pure online flights increases.

Figure 4: Willingness-to-pay for carriers by risk-aversion

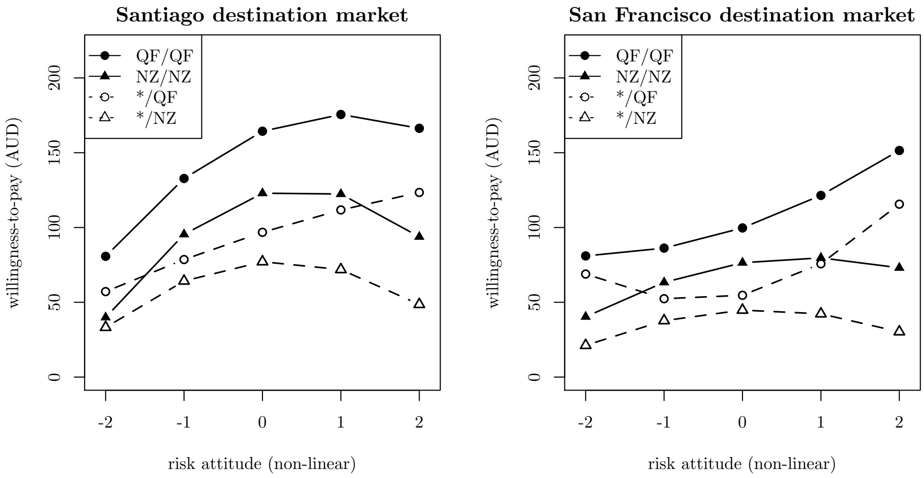


by Qantas (19 AUD). Although the signs on these parameters are similar in the San Francisco destination market, the parameters are only significant for the pure online products (16 AUD for pure online products by Qantas; and 10 AUD for pure online products by Air New Zealand).

These effects are illustrated in Figure 4, which plots the willingness-to-pay for each flight product relative to pure online alien products (y-axis) over the range of risk attitude (x-axis). As shown by the positive slopes for the pure online products (solid lines), more risk-averse consumers tend to avoid flying with alien carriers. Consistent with codesharing as a signaling phenomenon, the slopes associated with the codeshare products (dashed lines) are also positive, although only significantly so for the codeshare product offered by Qantas in the Santiago destination market. Thus, these diagrams do provide evidence for the signaling explanation of the codesharing premium, although it only seems to apply to codeshare products that are offered by the own national carrier and in markets where consumers are presumably more uncertain about the quality of alien carriers.

The estimates of the non-linear impact of risk attitude reported in column (2) and (4) of Table 6 and illustrated in Figure 5. They provide additional insights into the impact of risk attitude on the valuation of each flight product. As revealed by the highly convex line associated with the codeshare product of Qantas in the San Francisco destination market, codesharing does seem to exhibit a signaling effect in less familiar markets as well, although strictly for those consumers that are highly risk-averse. Moreover, as shown by the concave lines of all product types offered by Air New Zealand, highly risk-averse consumers tend to also avoid flight products of Air New Zealand in

Figure 5: Willingness-to-pay for carriers by risk-aversion (non-linear)



addition to those of alien carriers.[27]

Overall, our findings regarding risk attitude are consistent with the story that at least some consumers are willing to pay high premiums to their own national carrier to avoid uncertainty and risks that they perceive with alien carriers. Interestingly, this risk premium also applies to alien flights that are codeshared by the own national carrier, which suggests that consumers regard codesharing by their own national carrier as a quality signal.

To ensure the robustness of our findings regarding codeshare misconceptions and risk attitude, we estimated a number of alternative specifications that: (1) include additional covariates, (2) allow for taste correlation and (3) include random cost parameters. The estimation results for these robustness checks are provided in Appendix C. Overall, the estimation results show that our findings are robust with respect to these more flexible specifications.

5 Conclusion

This paper investigates consumer choices between pure online and virtual codeshare flight products in international air transport markets. Our main result indicates that consumer valuation of flights by alien foreign carriers increases significantly once these flights are offered as codeshare products by consumers' own national carrier. The same holds, but to a lesser extent, for alien flights that are codeshared by a neighboring national carrier. Specifically, we find that Australian consumers

[27] However, while both destination markets show a concave line, concavity is only statistically significant in the Santiago destination market.

in trans-Pacific route markets are willing to pay premiums of, on average, 4.5 - 6% for alien flights that are codeshared by Qantas, and 2 - 4% for alien flights that are codeshared by Air New Zealand, over pure online alien flights.

These premiums occur for virtual codeshare products offered on non-stop routes where codesharing does not lead to quality improvements. Moreover, the premiums are shown not to be related to frequent flier programs. This sets our findings apart from the increases in willingness-to-pay due to advantages of traditional codesharing studied in the extant literature, among others, improvements in connecting services and new opportunities to earn and redeem frequent flier miles.

Our analysis focuses on two alternative explanations of the willingness-to-pay increases associated with virtual codesharing. We find no support for the common belief that unawareness among consumers about the meaning of codesharing leads to higher willingness-to-pay for codeshare products. Instead, the evidence suggest a reverse relationship: consumers with a strong preference for a specific carrier (e.g., the own national carrier) are more likely to be aware of the meaning of codesharing. We do however find that the willingness-to-pay for codesharing is especially pronounced for more risk-averse consumers and in less familiar route markets. These findings are consistent with idea that consumers perceive codesharing by a familiar carrier as a signal about the product quality of a carrier that is alien to them. This, in turn, raises willingness-to-pay for flights operated by that alien carrier.

Interestingly, our findings are in sharp contrast to those of Gayle (2007), who established that consumers in the US domestic market do not perceive a distinction between pure online and codeshared flights operated by the same carrier. However, if quality signals are indeed the main driver of the willingness-to-pay differences identified by our analysis, it is plausible that the effect disappears in domestic route markets, where consumers have less uncertainty in evaluating the quality of the available carriers. This assessment is corroborated by the highest willingness-to-pay for codeshared products occurring in the Santiago destination market, which is the least familiar and most culturally different destination market studied in our paper. In this light, it would be interesting if further research could generalize our findings to an array of international route markets that vary in terms of cultural, institutional and political distances.

Although this paper focuses on virtual codeshare agreements, we expect the signaling mechanism to also play a role in consumer valuation of products offered under traditional codeshare agreements and other forms of horizontal partnerships between airlines in international markets (e.g., global airline alliances). While such horizontal partnership unquestionably bring a host of other advantages to airlines, the signaling mechanism constitutes a novel, additive benefit that seems especially relevant on international route markers where consumers have to deal with uncertainty about the quality of alien carriers.

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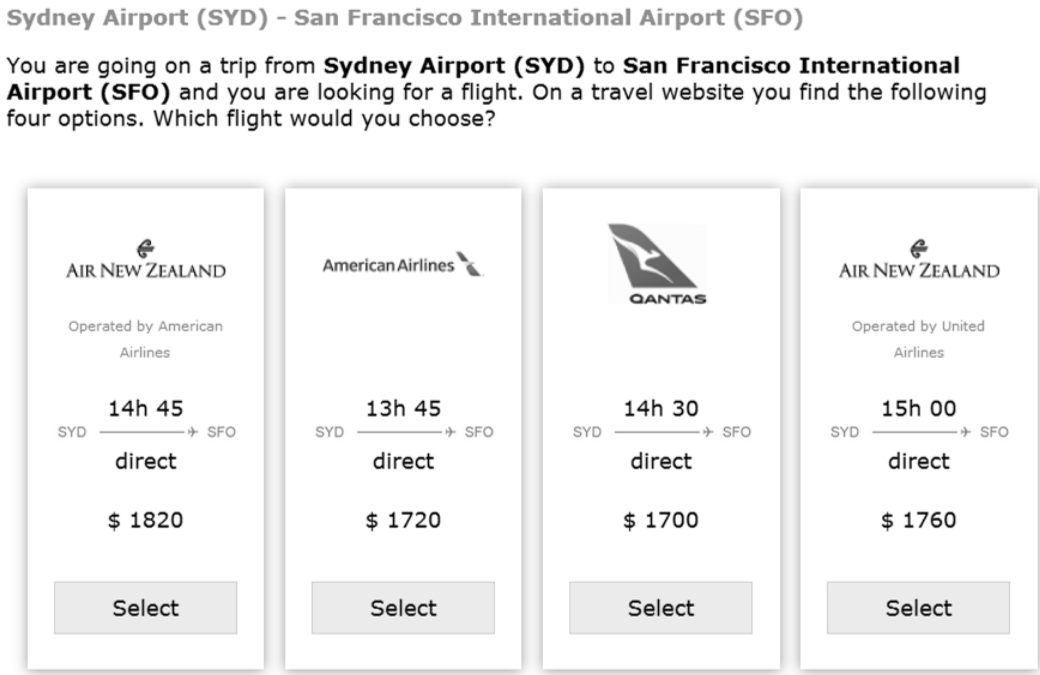
A Example of stated preference choice task

Figure 6: Example of stated preference choice task



B Correlation matrix risk indicators

Table 7: Correlation matrix risk indicators

	general risk	financial risk	health/safety risk	recreational risk
general risk	1			
financial risk	0.715	1		
health/safety risk	0.628	0.574	1	
recreational risk	0.772	0.653	0.653	1

C Supplementary estimation results

Table 8: Measurement and structural models estimation results

	Santiago destination market		San Francisco destination market	
Parameters	(1)		(2)	
Structural parameters:				
Gender	0.34**	(0.09)	0.26**	(0.10)
Age	0.01**	(0.00)	0.01*	(0.00)
University degree	-0.32**	(0.09)	-0.29**	(0.10)
Employed	-0.32**	(0.11)	-0.39**	(0.12)
Student	-0.68**	(0.25)	-0.79**	(0.24)
Measurement parameters:				
General risk attitude constant	5.62**	(0.23)	5.82**	(0.25)
General risk attitude latent variable	2.16**	(0.08)	2.17**	(0.09)
General risk attitude scale	1.15**	(0.06)	1.17**	(0.06)
Financial risk attitude constant	6.37**	(0.21)	6.55**	(0.23)
Financial risk attitude latent variable	1.95**	(0.09)	1.96**	(0.10)
Financial risk attitude scale	1.62**	(0.06)	1.63**	(0.06)
Health/safety risk attitude constant	7.08**	(0.20)	7.25**	(0.22)
Health/safety risk attitude latent variable	1.79**	(0.10)	1.80**	(0.10)
Health/safety risk attitude scale	1.76**	(0.06)	1.77**	(0.06)
Recreational risk attitude constant	5.91**	(0.23)	6.13**	(0.26)
Recreational risk attitude latent variable	2.21**	(0.09)	2.24**	(0.10)
Recreational risk attitude	1.37**	(0.06)	1.34**	(0.06)
Observations (indicators)	2008		2008	
Individuals	502		502	
Log likelihood (joint model)	-6824.158		-6949.672	

Note(s): All models are estimated using BIOGEME (Bierlaire, 2016b). These measurement and structural parameter estimates correspond to those obtained from the baseline hybrid panel mixed logit specification of column (1) and (3) in Table 6. *p<0.05; **p<0.01

Table 9: Initial multinomial and panel mixed logit estimation results

	Santiago destination market				San Francisco destination market			
Parameters	(1)		(2)		(3)		(4)	
QF/QF baseline	146.90**	(7.28)	130.61**	(7.18)	108.60**	(6.23)	94.75**	(6.63)
QF/QF rnd. scale			73.18**	(6.62)			73.25**	(6.55)
NZ/NZ baseline	97.18**	(7.18)	80.90**	(6.84)	72.49**	(6.22)	60.67**	(6.27)
NZ/NZ rnd. scale			53.09**	(6.96)			50.27**	(7.33)
LA/QF - AA/QF baseline	105.89**	(7.13)	90.58**	(6.59)	92.85**	(6.23)	81.82**	(6.03)
LA/QF - AA/QF rnd. scale			48.54**	(6.91)			48.83**	(6.48)
AV/QF - UA/QF baseline	110.52**	(7.14)	95.02**	(6.72)	81.59**	(6.23)	69.71**	(6.18)
AV/QF - UA/QF rnd. scale			55.50**	(6.75)			53.27**	(6.42)
LA/NZ - AA/NZ baseline	70.93**	(7.15)	62.49**	(6.29)	50.82**	(6.31)	46.48**	(5.59)
LA/NZ - AA/NZ rnd. scale			-9.24	(22.00)			-7.34	(19.20)
AV/NZ - UA/NZ baseline	73.77**	(7.10)	64.36**	(6.48)	50.81**	(6.30)	45.38**	(6.56)
AV/NZ - UA/NZ rnd. scale			24.62*	(12.40)			23.42	(23.30)
LA/LA - AA/AA baseline	-5.32	(8.16)	-36.23**	(12.40)	15.95*	(6.69)	-0.30	(7.80)
LA/LA - AA/AA rnd. scale			75.57**	(13.40)			57.97**	(9.75)
AV/AV - UA/UA baseline	2.72	(7.98)	-13.36	(9.97)	15.22*	(6.70)	2.99	(7.42)
AV/AV - UA/UA rnd. scale			53.62**	(12.20)			46.54**	(9.95)
Travel time	0.02**	(0.00)	0.02**	(0.00)	0.02**	(0.00)	0.02**	(0.00)
Cost parameter	-0.92**	(0.05)	-0.92**	(0.04)	-0.88**	(0.04)	-0.88**	(0.04)
Observations (choices)	3002		3002		3002		3002	
Individuals	502		502		502		502	
Parameters	10		18		10		18	
Draws (MLHS)	-		500		-		500	
Log likelihood	-2830.621		-2742.072		-2929.176		-2837.589	

Note(s): All models are estimated using BIOGEME (Bierlaire, 2016b). Draws in panel mixed logit are according to Modified Latin Hybercube Sampling (MLHS, see, Hess et al., 2006). Standard errors in parentheses. *p<0.05; **p<0.01

Table 10: Hybrid panel mixed logit robustness checks

	Santiago destination market						San Francisco destination market					
Parameters	(1)		(2)		(3)		(4)		(5)		(6)	
QF/QF baseline	154.29**	(8.89)	158.20**	(9.92)	157.04**	(9.12)	102.96**	(8.44)	108.75**	(9.57)	93.83**	(6.14)
QF/QF misconception	-28.93*	(11.30)	-25.62*	(12.60)	-35.06**	(11.10)	-22.17*	(11.00)	-25.19*	(12.50)	-15.53	(8.32)
QF/QF risk-aversion	17.48**	(6.02)	24.27**	(6.14)	27.08**	(5.76)	11.79*	(5.60)	14.26*	(5.95)	10.53**	(3.34)
QF/QF random scale	75.16**	(6.82)	100.13**	(7.25)	71.58**	(6.91)	76.64**	(7.02)	106.34**	(7.65)	80.01**	(5.34)
NZ/NZ baseline	110.05**	(7.58)	116.51**	(8.70)	110.27**	(7.39)	72.06**	(6.93)	76.30**	(7.96)	58.84**	(6.40)
NZ/NZ misconception	-41.48**	(9.80)	-44.82**	(11.00)	-43.69**	(9.12)	-32.13**	(9.44)	-36.69**	(10.90)	-18.82*	(8.49)
NZ/NZ risk-aversion	13.19*	(5.34)	18.94**	(5.35)	18.84**	(4.63)	7.17	(5.05)	11.18*	(5.63)	15.67**	(4.45)
NZ/NZ random scale	40.45**	(7.87)	68.14**	(7.14)	34.73**	(7.37)	46.83**	(7.27)	72.99**	(6.75)	52.55**	(5.77)
*/QF baseline	95.59**	(7.46)	105.09**	(8.24)	99.95**	(8.00)	62.99**	(6.79)	71.06**	(7.48)	56.60**	(4.97)
*/QF misconception	8.58	(9.63)	4.95	(10.50)	0.56	(9.34)	14.60	(8.93)	12.06	(9.86)	14.33*	(7.13)
*/QF risk-aversion	12.51*	(5.09)	18.94**	(5.15)	21.01**	(4.58)	6.16	(4.66)	6.48	(4.81)	-2.60	(3.32)
*/QF random scale	64.50**	(5.10)	80.47**	(5.75)	68.68**	(5.55)	62.93**	(4.72)	80.06**	(5.53)	64.13**	(3.42)
*/NZ baseline	69.33**	(6.53)	76.98**	(7.20)	67.25**	(6.39)	40.44**	(5.96)	48.16**	(6.59)	34.46**	(4.59)
*/NZ misconception	-7.45	(8.37)	-9.78	(9.16)	-5.35	(7.84)	-10.31	(7.80)	-16.33	(8.75)	-4.22	(6.21)
*/NZ risk-aversion	4.69	(4.58)	8.48	(4.43)	7.98*	(3.83)	3.54	(4.07)	5.58	(4.40)	2.73	(3.25)
*/NZ random scale	40.21**	(5.56)	54.87**	(5.86)	41.54**	(5.11)	37.63**	(5.69)	54.70**	(5.30)	28.21**	(4.68)
Travel time	0.02**	(0.00)	0.02**	(0.00)	-3.42**	(0.07)	0.02**	(0.00)	0.02**	(0.00)	-3.25**	(0.08)
Cost parameter	-0.91**	(0.04)	-0.93**	(0.04)	-0.92**	(0.06)	-0.90**	(0.04)	-0.90**	(0.04)	-0.83**	(0.05)
cor(QF/QF, */QF)			0.83**	(0.04)					0.87**	(0.04)		
cor(NZ/NZ, */NZ)			0.89**	(0.07)					1.00^{a}	(0.00)		
Observations (choice)	3002		3002		3002		3002		3002		3002	
Individuals	502		502		502		502		502		502	
Parameters	57		37		37		46		36		37	
Draws (MLHS)	500		500		500		500		500		500	
Log likelihood	-6788.644		-6738.882		-6731.668		-6922.136		-6849.231		-6843.611	
Log likelihood (choice)	-2630.68		-2580.82		-2558.2		-2754.6		-2688.43		-2660.72	

Note(s): All models are estimated using BIOGEME (Bierlaire, 2016b). Draws are according to Modified Latin Hybercube Sampling (MLHS, see, Hess et al., 2006). Standard errors in parentheses. [a]this parameter could not be identified in the hybrid panel mixed logit specification and is therefore fixed to one, implying perfect correlation between the unobserved preference for pure online and codeshare products by Air New Zealand. $^{*}p<0.05$; $^{**}p<0.01$