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26 July 2022

Online at https://mpra.ub.uni-muenchen.de/113960/
MPRA Paper No. 113960, posted 03 Aug 2022 14:04 UTC

Discount opportunities in hub-and-spoke networks: The determinants of hidden-city ticketing*

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July 26, 2022

Abstract

We offer a comprehensive empirical study on hidden-city ticketing (HCT), a pricing phenomenon in the airline industry that occurs when the fare for a nonstop trip from A to B is more expensive than a connecting trip from A to B and B to C. Exploiting a unique panel of over 772 thousand fares for flights departing between October 1$^{\text{st}}$, 2019 and February 29$^{\text{th}}$, 2020, we find that HCT depends on route competition (both on A-B and A-C routes), largely occurs in the last week to departure, and primarily occurs on carriers that operate large hub-and-spoke networks (e.g., American, Delta, and United).

JEL classification: L11, L13, L93, D40.

Keywords: advance-purchase, airline pricing, competition, hidden-city ticketing, price discrimination.

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*We are grateful to Graziano Abrate, Jan Brueckner, Branko Bubalo, Marcella Nicolini, and to the participants of the 2021 International Transportation Economics Association conference and the 2021 TEM workshop for helpful comments. All errors are our own. The author's affiliation with The MITRE Corporation is for identification purposes only, and is not intended to convey or imply MITRE's concurrence with, or support for, the positions, opinions, or viewpoints expressed by the author. ©2022 The MITRE Corporation. ALL RIGHTS RESERVED. Approved for Public Release; Distribution Unlimited. Public Release Case Number 22-2465.

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1 Introduction

Hidden-city ticketing (HCT) is a pricing phenomenon in the airline industry that occurs when the price for a nonstop trip from A to B is more expensive than the price for a connecting trip from A to C that connects at B (i.e., the "hidden city").[1] When this phenomenon occurs, passengers traveling from A to B can save money by purchasing the connecting A-B-C trip. These HCT passengers would take the first flight from A to B, then deliberately forego the trip's second flight from B to C.

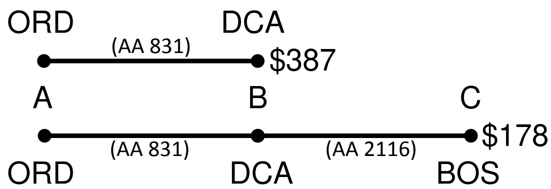
Figure 1 presents an example of HCT on American Airlines. In this example, the A-B route is a nonstop trip from Chicago O'Hare to Reagan National (DCA) in Washington, D.C. The A-C route is a connecting trip from Chicago O'Hare (city A) to Boston (city C) that connects at DCA (i.e., "hidden-city" B). In this instance, the price of the connecting A-B-C trip ($178) is $209 cheaper than the price of the nonstop A-B trip ($387). Hence, passengers whose final destination is Washington, D.C. will save money if they purchase the connecting Chicago to Boston trip and then, after deplaning at DCA, ending their journey by not boarding the second flight to Boston.

Although passengers can save money by purchasing hidden-city tickets, only one-way passengers are eligible to take advantage of these opportunities. For instance, failure to show up for the second flight on the outbound portion of a roundtrip will result in the cancellation of the rest of the roundtrip ticket. In addition, only passengers with carry-on luggage may engage in HCT because checked luggage will not be transferred to baggage claim at the connecting city on a hidden-city ticket.

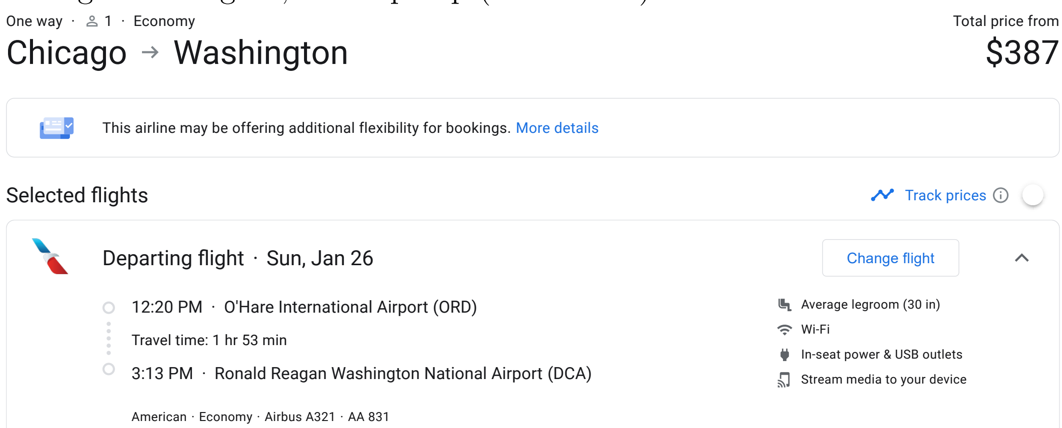
There is another key risk that prospective HCT passengers should be aware of. Specifically, most airlines prohibit HCT in their contract of carriage (e.g., American, Delta, and United explicitly state that a passenger must complete all segments of a purchased ticket).

[1] HCT is also referred to as "skiplagging". For a comprehensive review on different aspects of HCT, see Meire and Derudder (2022). For some theory behind the cause and impact of HCT, see Wang and Ye (2016) and Oh and Huh (2022).

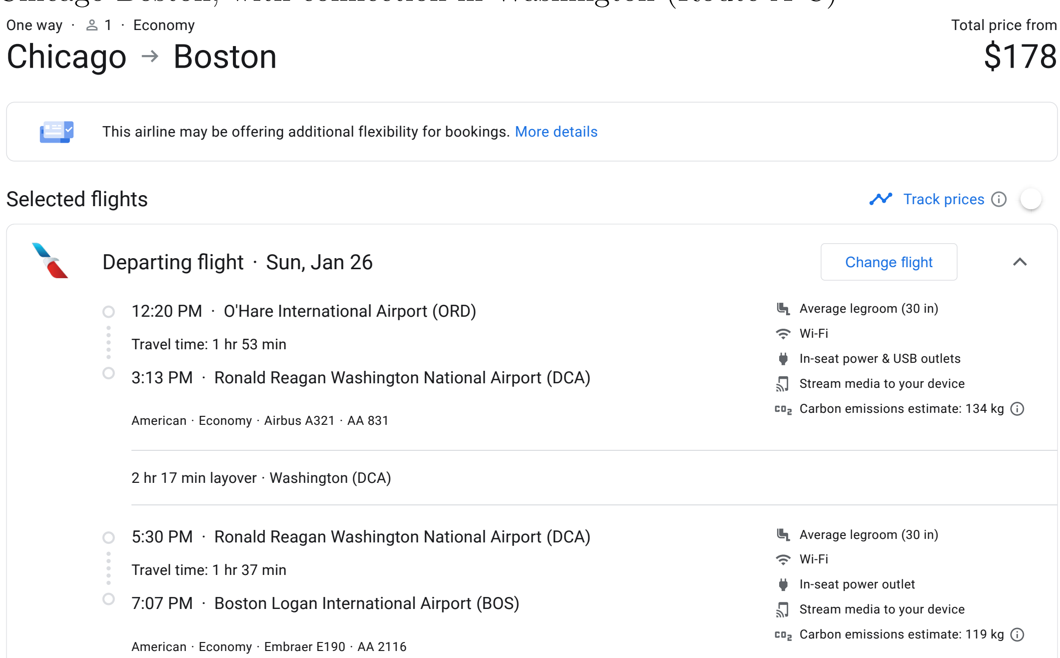
Figure 1: Example of Hidden-City ticketing



Chicago-Washington, nonstop trip (Route A-B)



Chicago-Boston, with connection in Washington (Route A-C)



As a result, passengers engaging in HCT may suffer retaliatory consequences including receiving a lifetime ban from the airline or having their frequent flyer membership revoked. In rare instances, airlines have even sued HCT passengers.[2]

Even though there are risks associated with HCT, the focus of this article is on the potential factors (e.g., network, route, and ticket characteristics) that contribute to the existence of HCT opportunities. One obvious factor is the extensive hub-and-spoke network structure of the large full-service carriers (e.g., American, Delta, and United). By funneling passengers through a hub, carriers are able to exploit economies of traffic density, resulting in a lower cost per passenger (Caves et al., 1984; Brueckner et al., 1992; Brueckner and Spiller, 1994). However, by controlling a large fraction of flights and gates at their hubs, carriers are also able to exercise market power and charge a "hub premium" to passengers who originate or terminate their trips at the hub (Borenstein, 1989; Lederman, 2008; Ciliberto and Williams, 2010; Escobari, 2011; Bilotkach and Pai, 2016). In other words, fares for A-B trips may be high due to the hub premium while fares for A-B-C trips may be low due to the density savings that are passed on to passengers who connect or "flow through" the hub.

A second factor that likely contributes to the existence of HCT opportunities is an airline's yield management strategy.[3] For example, airlines employ a variety of mechanisms (e.g., advance-purchase requirements and other ticket restrictions such as Saturday night stay, minimum stay, and non-refundability) to segment passengers with different price elasticities of demand.[4] All else equal, HCT opportunities will likely arise if passengers on the A-C route are more price-elastic (i.e., have a higher price elasticity of demand) than passengers on the A-B route.

In the sections that follow, we examine how various route and ticket characteristics affect the prevalence of HCT opportunities. Related to the first factor mentioned above, we hypothesize that the level of competition within an airline's hub-and-spoke network is a key

[2]For example, Lufthansa sued a passenger in 2019 for missing the last leg of his ticketed journey. See `https://www.cnn.com/travel/article/lufthansa-sues-passenger-scli-intl/index.html`.

[3]For background on airline yield management practices, see Talluri et al. (2004) and Belobaba (2009).

[4]For specific examples of price discrimination in the airline industry, see Dana (1998), Stavins (2001), Bischoff et al. (2011), Puller and Taylor (2012), Aslani et al. (2014), Escobari and Jindapon (2014), Wang and Ye (2016), Escobari et al. (2019), and Luttmann (2019b), among others.

driver of HCT. In particular, the level of competition on A-B and A-C routes should have countervailing effects on the frequency of HCT opportunities. Since HCT occurs when the nonstop A-B fare is more expensive than the connecting A-C fare (i.e., $\text{Fare}_{\text{AB}} > \text{Fare}_{\text{AC}}$), additional competition on A-C routes should decrease Fare_{AC}, increasing the likelihood that $\text{Fare}_{\text{AB}} > \text{Fare}_{\text{AC}}$ holds. In contrast, additional competition on A-B routes should decrease Fare_{AB}, decreasing the likelihood that $\text{Fare}_{\text{AB}} > \text{Fare}_{\text{AC}}$ holds.

In addition to competition, we hypothesize that advance-purchase requirements are another key driver of HCT. Assuming that passengers who purchase tickets closer to departure are more price-inelastic and have higher search costs than passengers who book further in advance, then HCT opportunities are expected to be more frequent closer to departure. In other words, passengers who purchase tickets further in advance are more likely to seek out HCT opportunities given their low search costs and high price elasticity. In contrast, passengers who purchase tickets closer to departure are less likely to seek out these opportunities given their high search costs and low price elasticity. Armed with this knowledge of the customer base, airlines may respond by ensuring that HCT opportunities are scarce during the early booking period.

Although HCT opportunities may be common in hub-and-spoke networks,[5] the lack of sufficient data has likely been the reason why few empirical studies have previously been conducted on this topic.[6] For instance, the Airline Origin and Destination Survey (DB1B) released by the United States Department of Transportation has been used in several previous empirical studies of the airline industry.[7] However, the DB1B currently does not include information on the specific flight(s) purchased or the exact purchase and departure dates

[5]For example, a study conducted by Hopper in 2015 found that HCT opportunities exist in 26% of U.S. domestic routes. See `https://media.hopper.com/research/hidden-city-ticket-opportunities-common-think`.

[6]To the best of our knowledge, two recent empirical studies have examined HCT. Liu (2020) examines HCT on a single departure date (April 6$^{\text{th}}$, 2016), with corresponding fares collected two months prior to departure (February 6$^{\text{th}}$, 2016). Sun et al. (2022) conduct a data-driven analysis to identify spatial regions and temporal periods of HCT using data from 2010 to 2021.

[7]For example, see Brueckner et al. (1992), Gerardi and Shapiro (2009), Brueckner et al. (2013), or Dai et al. (2014), among others.

(only the quarter of travel is reported). As a result, the DB1B cannot be used to examine how factors such as advance-purchase requirements affect the frequency of HCT opportunities.

To examine *when* and *why* HCT opportunities occur, we rely on a unique panel of over 772 thousand published fares collected over a seven-month period from a major online travel agency. Flights in our sample depart between October 1st, 2019 and February 29th, 2020 and encompass many of the most densely traveled routes across the continental United States. Notably, because we track the price of both nonstop (A-B trips) and connecting trips (A-B-C trips) in the sixty-day period before departure, we are able to examine how advance-purchase requirements affect HCT opportunities.

We have three primary findings. First, the level of competition on both A-B and A-C routes are key determinants of HCT. Consistent with expectations, we find that an additional carrier providing nonstop service on the A-C route increases the likelihood of HCT by 1.6%-3.6% while an additional nonstop carrier on the A-B route decreases the likelihood of HCT by 3.5%.[8]

Second, we find that advance-purchase requirements are another key determinant of HCT. In particular, HCT opportunities are more frequent in the last week before departure because nonstop A-B fares increase at a higher rate than connecting A-C fares during this period. As we previously discussed, one possible explanation for this result is related to passenger heterogeneity during the booking period. Because most passengers purchasing tickets a few days before departure are price-inelastic customers with high search costs, airlines may be less concerned about passengers seeking out HCT opportunities during this period.

Third, we find that the major full-service carriers (i.e., American, Delta, and United) are responsible for majority of HCT, while HCT opportunities are relatively rare on low-cost carriers (e.g., Frontier, JetBlue, Spirit, and Sun Country). As alluded to earlier, the hub-

[8] As we mentioned earlier, HCT occurs when the nonstop A-B fare is more expensive than the connecting A-C fare (i.e., $\text{Fare}_{\text{AB}} > \text{Fare}_{\text{AC}}$). Therefore, additional competition on A-C routes should decrease Fare_{AC}, increasing the likelihood that $\text{Fare}_{\text{AB}} > \text{Fare}_{\text{AC}}$ holds. In contrast, additional competition on A-B routes should decrease Fare_{AB}, decreasing the likelihood that $\text{Fare}_{\text{AB}} > \text{Fare}_{\text{AC}}$ holds.

and-spoke network structure provides passengers with more opportunities to exploit HCT. In contrast, the business models of low-cost carriers typically do not involve funneling passengers through large connecting hubs.

Although the focus of this article is on the airline industry, we believe our results are applicable to variety of other industries that operate using hub-and-spoke networks. Obvious candidates are other passenger transport modes such as bus and rail (especially in Europe and Asia). In addition, companies involved in cargo, container shipping, electricity generation, freight, manufacturing, and warehousing may also have interest in our findings considering that many companies in these sectors employ hub-and-spoke networks to distribute and/or manufacture their goods.

The rest of this article is structured as follows. Section 2 describes the data sources used in the analysis. Section 3 presents a descriptive analysis of HCT. Section 4 conducts the econometric investigation of HCT. Finally, Section 5 provides concluding remarks.

2 Data

The data we use are obtained from several sources. However, the data underlying our main empirical results are obtained from two sources: fare and itinerary information from a major online travel agency (OTA) and supplementary airline data from the United States (U.S.) Department of Transportation (DOT). Section 2.1 describes our primary source of fare and itinerary data, Section 2.2 the data sources used to construct instrumental variables, and Section 2.3 the source of our transacted fare data. Finally, Appendix Table A1 provides summary statistics and a brief description of the variables included in our empirical analysis.

2.1 Fare and Itinerary Data

Our primary source of fare and itinerary data information comes from a major OTA.[9] From the OTA, one-way economy-class fare quotes for both nonstop and connecting trips were obtained for flights departing between October 1st, 2019 and February 29th, 2020.[10] Our data encompasses over 100 of the most densely traveled routes in the continental U.S.[11] For each route, the lowest observed economy-class fare for each of the next sixty travel days were collected. This data collection procedure allows us to track the evolution of economy fares for an individual flight (or pair of flights for connecting trips) over the sixty-day period before departure.

To determine if HCT occurs within an airline-route combination on a given day, we matched the fare for each of our one-stop connecting trips (A-B-C trips) with the corresponding nonstop fare (A-B trips) for the first segment of the connecting trip. Our resulting dataset contains 772,635 fare observations. The airlines included in our sample include four full-service carriers (Alaska, American, Delta, and United) and four low-cost carriers (Frontier, JetBlue, Spirit, and Sun Country).[12] The total number of A-B routes in our sample is 101. Figure 2 presents a visual representation of the these routes (see Table 2 in Section 3 for the complete list).

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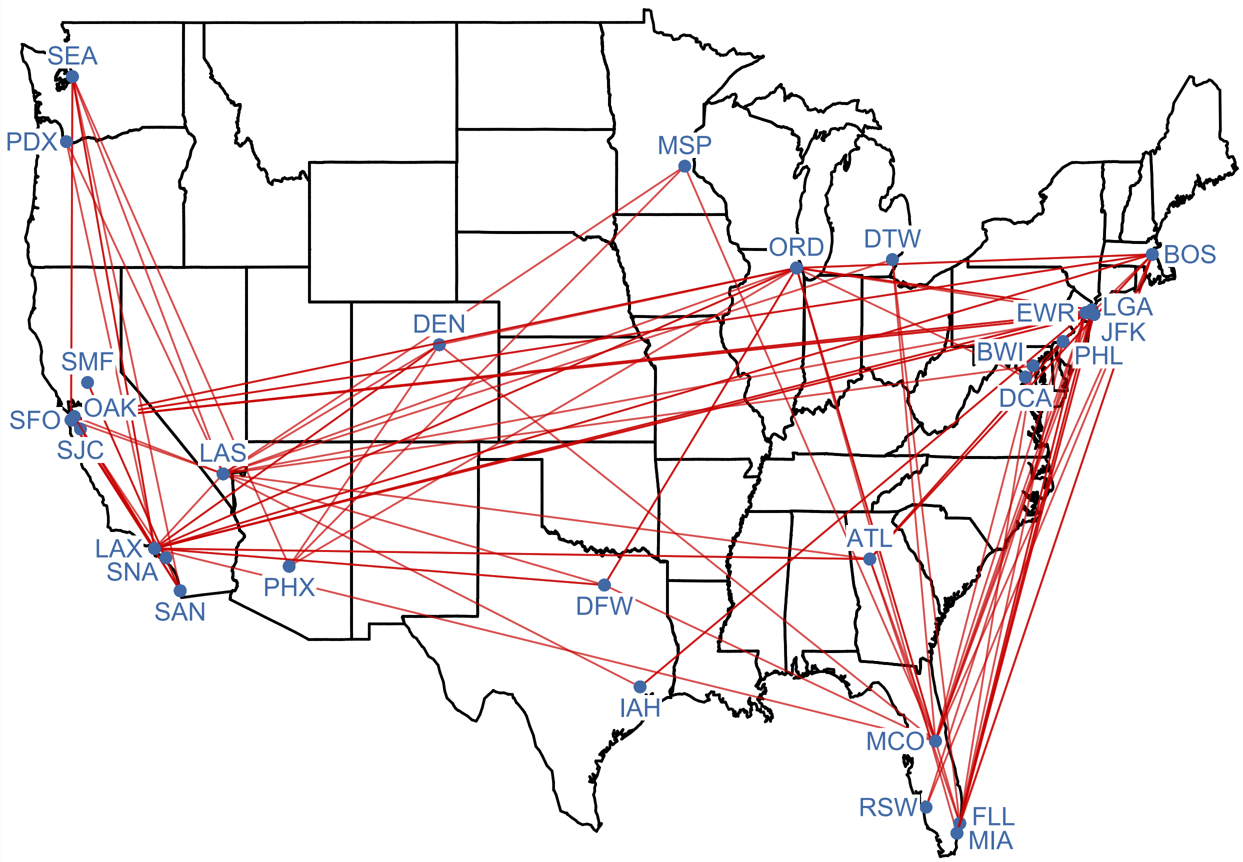
[9]Major OTAs include Expedia, Google Flights, Kayak, and Priceline. Several previous studies have relied on data from a major OTA. Among others, see Bergantino and Capozza (2015), Bilotkach et al. (2015), Escobari (2012), Gaggero and Piga (2010), Gaggero and Piga (2011), Koenigsberg et al. (2008), and Luttmann (2019a).

[10]Roundtrips are not included because only one-way passengers can take advantage of HCT opportunities. Because our analysis sample ends on February 29th, 2020, the COVID-19 pandemic has a negligible impact on our results. In the U.S., COVID-19 was declared a national emergency on March 13th, 2020. Moreover, California became the first state to issue a statewide stay-at-home order on March 19th, 2020.

[11]In lieu of collecting published fares for all possible routes in the U.S. market, we relied on the DOT's Airline Origin and Destination Survey from the third and fourth quarters of 2018 to identify the major airport-pairs within the continental U.S. ranked by total passenger traffic. A market in our analysis is defined as a directional pair of origin and destination airports. Therefore, Los Angeles (LAX)-New York City (JFK) and JFK-LAX are treated as separate markets.

[12]Although fare quotes for Southwest Airlines are not available from any of the major OTAs, the presence of Southwest is accounted for in our empirical analysis when we construct any variable controlling for the number of carriers serving a given route.

Figure 2: Hidden-City routes (i.e., A-B routes) in our analysis sample



2.2 Instrumental Variables

In general, measures of market concentration such as the number of competitors or the Herfindahl–Hirschman Index are endogenous in analyses of airline pricing. For instance, markets with high fares may be attractive for new entrants. At the same time, these markets may be unattractive if high fares are a direct result of entry barriers such as limited slot or gate access at the endpoint airports. Accordingly, the potential simultaneity bias that results from an airline's decision to enter or exit a given route may bias coefficient estimates in regressions of airline pricing. To correct for this potential endogeneity, we employ an instrumental variables strategy (see Section 4 for specific details).

To construct our instruments, we rely on data from the U.S. DOT and the U.S. Census

Bureau. From the U.S. DOT's T-100 Domestic Segment database, we retrieved the total number of nonstop passengers on each route and month between October 2018 and February 2019. From the U.S. Census Bureau, we obtained yearly population measures at the metropolitan statistical area for each endpoint airport in our analysis sample.

2.3 Transacted Fare Data

There exists substantial uncertainty regarding whether passengers actually exploit HCT in the U.S. domestic market. To demonstrate that a subset of passengers are likely engaging in HCT, we rely on transacted fare data from the U.S. DOT's Airline Origin and Destination Survey (DB1B). These data are released quarterly and represent a 10% random sample of tickets purchased for domestic air travel. To capture approximately the same time period as our published fare data, we rely on DB1B data from the fourth quarter of 2019.[13]

3 Descriptive Analysis

As discussed in Section 2.1, we are able to identify if a HCT opportunity occurs on a given day by matching an airline's connecting A-B-C fare with the airline's nonstop fare for the first segment of the connecting trip (A-B segment). HCT occurs if the fare for the connecting A-B-C trip is cheaper than the nonstop fare for the A-B trip on the same airline.

Table 1 displays the probability of observing HCT across the four full-service and four low-cost carriers in our sample. Across all carriers, HCT occurs 15.4% of the time (23.8% on full-service carriers and 3.8% on low-cost carriers). This finding is consistent with a U.S. Government Accountability Office report from 2001. Analyzing fare data for six major U.S. airlines across 2,302 markets, GAO (2001) found that HCT opportunities occur approximately 17% of the time.

In Table 1, the three largest full-service carriers (American Airlines, Delta, and United) are responsible for the majority of HCT, as they jointly account for almost 89% of the

[13]We excluded the first quarter of 2020 because this quarter includes the entire month of March (i.e., the beginning of the COVID-19 pandemic in the U.S.).

instances of HCT observed in our sample. Notably, we find that HCT rarely occurs on Frontier or JetBlue and almost never occurs on Sun Country (a small low-cost carrier). Nevertheless, these findings are expected. HCT opportunities are more likely to occur on carriers that operate large hub-and-spoke networks (e.g., American, Delta, and United) while they are less likely to occur on carriers that operate point-to-point networks (e.g., Frontier, JetBlue, Spirit, and Sun Country).

Table 1: Probability of HCT by airline

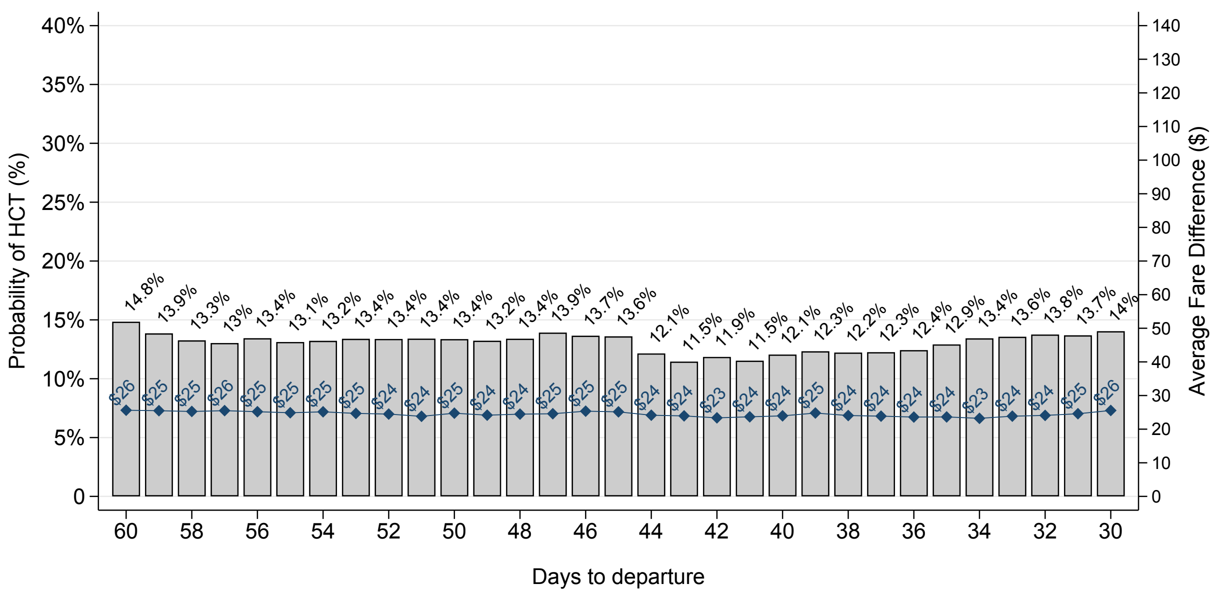
Airline	Type of airline	HCT	Total observations
Alaska	Full-service	2.8%	45,068
American Airlines	Full-service	22.3%	193,244
Delta	Full-service	32.1%	78,706
Frontier	Low-cost	2.6%	35,402
JetBlue	Low-cost	2.2%	31,863
Spirit	Low-cost	4.2%	254,150
Sun Country	Low-cost	0.1%	2,647
United	Full-service	28.2%	131,555
Overall Full-service		23.8%	448,573
Overall Low-cost		3.8%	324,062
Overall All carriers		15.4%	772,635

To illustrate how the probability of observing HCT evolves in the sixty-day period before departure, Figure 3 displays the probability of observing HCT (denoted by a gray bar) and, when HCT occurs, the average difference between the nonstop A-B fare and the connecting A-B-C fare (denoted by the connected solid blue line). The number above each gray bar indicates the probability of observing HCT while the number above the solid blue line indicates the average fare difference. For example, the gray bar at 60 days to departure in the top panel of Figure 3 indicates that the probability of HCT occurring 60 days before departure is 14.8% and the solid blue line indicates that the average fare difference is $26. Similarly, the gray bar at 29 days to departure in the bottom panel of Figure 3 indicates that the probability of HCT occurring 29 days before departure is 11.4% and the solid blue line indicates that the average fare difference is $24.

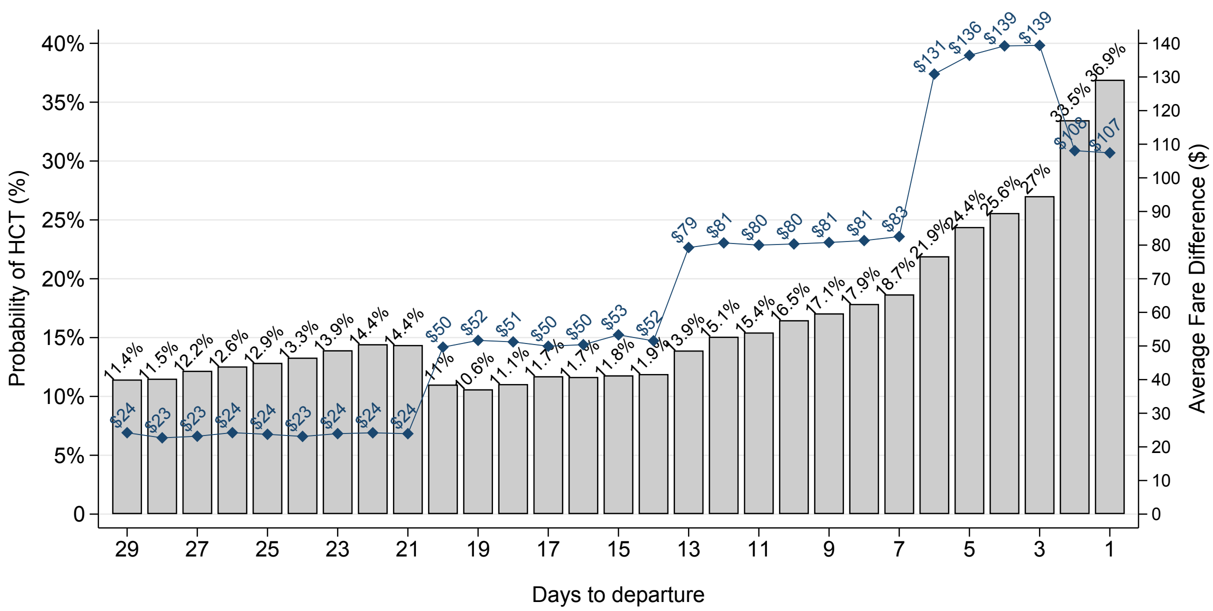
As depicted in the top panel of Figure 3, the probability of observing HCT is relatively

Figure 3: Probability of HCT and average fare difference during the booking period

(a) Early booking period



(b) Late booking period



Notes: The Average Fare Difference is the difference between the average nonstop fare from A to B and the average connecting fare from A to C with a connection at B. This difference is computed only under HCT instances (i.e., when Nonstop Fare_{AB} > Connecting Fare_{AC}).

unchanged during the early booking period, ranging from 11.5% to 14.8%. The likelihood of observing HCT remains relatively stable until two weeks before departure, when the probability of observing HCT begins to increase monotonically from 11.9% fourteen days before departure to 36.9% one day before departure.

Similarly, the average fare difference between the nonstop A-B fare and the connecting A-B-C fare, which is computed only under HCT and depicted by the connected solid blue line in the figure, is generally constant in the early part of the booking period, hovering around $24 until three weeks to departure. Then, the average fare difference increases to $50-$53 between two and three weeks to departure, and continues to increase until reaching a maximum of $139 three days before departure.

To provide a comprehensive summary of the hidden-city routes in our sample, Table 2 reports each A-B route (first column) with the probability of observing HCT on the route (second column). The last column of the table, displays the final destination(s) of the A-B-C tickets sorted in descending order by the percentage of HCT observed for each destination C on the given A-B route. For example, EWR-MIA, the last entry in the first panel of Table 2, may be the first leg of a connecting trip to Los Angeles (LAX), Orlando (MCO), Chicago (ORD), or San Francisco (SFO). Considering all fare observations from Newark (EWR) to one of these four destinations with a connection in Miami (MIA), the probability of observing HCT on EWR-MIA is 11%. However, if we only consider MCO (i.e., we only select the trips from EWR to MCO with connection in MIA), the probability of observing HCT is 52%. In particular, no instances of HCT are observed for connecting trips from EWR via MIA to the other three destinations of LAX, ORD, and SFO.

The most common hidden-city route in our sample is Chicago O'Hare to Reagan National in Washington, D.C. (ORD-DCA). HCT occurs 91% of the time on ORD-DCA, and within this route, Boston is the most likely final destination on a hidden-city ticket. However, this finding is not entirely surprising considering that DCA is a slot-controlled airport and a hub for American Airlines.

Table 2: A-B routes and probability of HCT

A-B routes	HCT	Final destinations C, sorted by percentage instances of HCT within each final destination in parentheses
ATL-BOS	0%	LAS(0%), LAX(0%), LGA(0%)
ATL-FLL	0%	MCO(3%), BOS(0%), LGA(0%), LAS(0%), LAX(0%)
ATL-LAS	8%	FLL(66%), LAX(8%)
ATL-LAX	52%	LAS(52%)
ATL-LGA	40%	BOS(40%), FLL(0%)
ATL-MCO	18%	FLL(48%), BOS(2%), LGA(1%), LAS(0%), LAX(0%)
BOS-ATL	24%	DCA(54%), ORD(53%), RSW(33%), FLL(25%), MIA(22%), MCO(20%), SFO(7%), LAX(2%)
BOS-DCA	14%	ORD(44%), MCO(16%), MIA(16%), RSW(10%), LAX(8%), ATL(4%), SFO(2%), FLL(2%)
BOS-FLL	7%	ORD(29%), ATL(7%), MCO(6%), SFO(1%), LAX(0%), DCA(0%)
BOS-LAX	29%	SFO(29%)
BOS-MCO	13%	ORD(21%), FLL(19%), ATL(5%), DCA(0%), LAX(0%)
BOS-MIA	17%	ATL(50%), MCO(45%), LAX(0%), SFO(0%)
BOS-ORD	4%	RSW(16%), ATL(7%), SFO(5%), FLL(2%), MIA(2%), LAX(1%), MCO(0%)
BOS-RSW	0%	ORD(0%)
BOS-SFO	57%	LAX(57%)
BWI-FLL	8%	MCO(10%), LAS(6%)
BWI-LAS	25%	FLL(25%)
BWI-MCO	1%	FLL(1%), LAS(0%)
DEN-LAS	5%	PHX(15%), LAX(7%), MCO(0%)
DEN-LAX	60%	LAS(62%), PHX(45%)
DEN-MCO	0%	LAS(0%)
DEN-PHX	45%	LAS(54%), LAX(27%)
DFW-LAS	16%	LAX(17%), ORD(8%), MCO(4%)
DFW-LAX	19%	ORD(73%), LAS(19%), MCO(0%)
DFW-MCO	38%	ORD(56%), LAS(0%), LGA(0%)
DFW-ORD	24%	LGA(32%), LAS(3%), MCO(1%), LAX(0%)
DTW-FLL	9%	MCO(9%), LAS(0%)
DTW-LAS	4%	FLL(6%), MCO(0%)
DTW-MCO	1%	FLL(1%), LAS(1%)
EWR-FLL	5%	MCO(7%), LAX(6%), IAH(5%), ORD(3%), SFO(1%)
EWR-IAH	9%	RSW(67%), SFO(30%), MCO(15%), LAX(7%), FLL(2%), ORD(2%), MIA(0%), PBI(0%)
EWR-LAX	15%	SFO(15%)
EWR-MCO	5%	ORD(15%), FLL(5%), IAH(2%), LAX(0%), SFO(0%)
EWR-MIA	11%	MCO(52%), LAX(0%), ORD(0%), SFO(0%)

Continuing

Table 2 Cont.

A-B routes	HCT	Final destinations C, sorted by percentage instances of HCT within each final destination in parentheses
EWR-ORD	20%	IAH(51%), PBI(43%), RSW(37%), FLL(25%), MCO(16%), MIA(14%), SFO(8%), LAX(5%)
EWR-RSW	17%	ORD(17%)
EWR-SFO	15%	LAX(15%)
IAH-EWR	25%	LAS(25%)
IAH-LAS	1%	EWR(1%)
JFK-FLL	0%	MCO(0%), LAS(0%), LAX(0%), SFO(0%)
JFK-LAS	26%	SFO(40%), LAX(22%)
JFK-LAX	30%	LAS(31%), SFO(23%)
JFK-MCO	1%	FLL(1%), LAX(1%), LAS(0%)
JFK-MIA	17%	MCO(17%), LAS(0%), SFO(0%)
JFK-SFO	13%	LAX(18%), LAS(12%)
LAX-ATL	44%	DFW(100%), LAS(100%), BOS(82%), EWR(72%), MCO(60%), ORD(49%), JAX(39%), JFK(33%)
LAX-BOS	10%	JFK(40%), EWR(0%), JAX(0%), ATL(0%), MCO(0%), ORD(0%)
LAX-DEN	13%	DFW(42%), SFO(39%), EWR(20%), BOS(20%), ATL(14%), MCO(10%), ORD(6%), JAX(3%), SEA(2%), LAS(0%), OAK(0%)
LAX-DFW	11%	LAS(100%), ORD(39%), BOS(20%), MCO(18%), JFK(16%), ATL(14%), EWR(8%), JAX(7%), DEN(0%), OAK(0%), SEA(0%)
LAX-EWR	53%	ORD(100%), ATL(88%), MCO(80%), BOS(52%), JAX(8%)
LAX-JFK	20%	BOS(79%), MCO(55%), ATL(50%), JAX(4%)
LAX-LAS	3%	OAK(8%), SEA(5%), DFW(4%), JFK(2%), DEN(1%), ORD(1%), JAX(1%), ATL(0%), BOS(0%), EWR(0%), MCO(0%), SFO(0%)
LAX-MCO	6%	JFK(13%), ATL(8%), EWR(1%), BOS(0%), DEN(0%), JAX(0%)
LAX-OAK	0%	LAS(0%), ORD(0%)
LAX-ORD	23%	LAS(100%), DEN(64%), BOS(34%), MCO(30%), ATL(27%), EWR(12%), DFW(9%), JAX(4%), JFK(2%), OAK(0%), SEA(0%)
LAX-SEA	3%	ATL(83%), ORD(38%), DEN(34%), MCO(32%), BOS(3%), OAK(0%), DFW(0%), EWR(0%), JFK(0%)
LAX-SFO	4%	LAS(39%), DFW(30%), SEA(9%), ATL(3%), ORD(1%), MCO(1%), BOS(0%), EWR(0%), DEN(0%), JAX(0%), JFK(0%)
LGA-ATL	22%	MCO(34%), MIA(23%), FLL(10%), ORD(0%)
LGA-FLL	24%	ORD(36%), ATL(25%), MCO(20%)
LGA-MCO	10%	ORD(57%), FLL(2%), ATL(2%), MIA(0%)
LGA-MIA	28%	ATL(31%), MCO(27%), ORD(0%)
LGA-ORD	12%	FLL(35%), MCO(15%), MIA(14%), ATL(3%)
MSP-LAS	0%	PHX(0%), MCO(0%)
MSP-MCO	13%	LAS(13%)
MSP-PHX	23%	LAS(23%)
OAK-LAS	2%	LAX(3%), SAN(1%), BUR(0%), SNA(0%)
OAK-LAX	2%	LAS(2%), SAN(0%)

Continuing

Table 2 Cont.

A-B routes	HCT	Final destinations C, sorted by percentage instances of HCT within each final destination in parentheses
ORD-BOS	0%	LGA(4%), FLL(0%), DCA(0%), DEN(0%), DFW(0%), LAS(0%), LAX(0%), MCO(0%), MIA(0%), PHX(0%), SFO(0%)
ORD-DCA	91%	BOS(99%), LGA(91%), MCO(86%), MIA(85%), FLL(69%), SFO(60%)
ORD-DEN	7%	PHX(31%), LAX(13%), MCO(8%), DFW(5%), LAS(4%), MIA(2%), LGA(2%), SFO(1%), DCA(1%), FLL(0%)
ORD-DFW	36%	MIA(64%), SFO(55%), LAX(48%), DEN(45%), MCO(43%), LAS(42%), FLL(30%), PHX(14%), BOS(10%), DCA(0%), LGA(0%)
ORD-FLL	10%	MCO(13%), BOS(10%), DEN(6%), LGA(4%), DCA(0%), DFW(0%), LAS(0%), LAX(0%), PHX(0%), SFO(0%)
ORD-LAS	18%	LAX(22%), PHX(13%), DFW(6%), DEN(6%), FLL(5%), MCO(0%), SFO(0%)
ORD-LAX	13%	LAS(18%), PHX(18%), SFO(10%), DFW(0%)
ORD-LGA	36%	BOS(77%), MCO(34%), MIA(31%), DCA(29%), DFW(19%), FLL(15%), DEN(0%)
ORD-MCO	13%	MIA(41%), DEN(11%), BOS(8%), DCA(6%), FLL(2%), DFW(1%), LAS(0%), LGA(0%), PHX(0%)
ORD-MIA	14%	MCO(32%), DCA(0%), DEN(0%), LAS(0%), LGA(0%), PHX(0%), SFO(0%)
ORD-PHX	67%	LAX(79%), LAS(72%), SFO(48%), DFW(0%)
ORD-SFO	53%	LAS(65%), LAX(39%), PHX(20%), DEN(0%)
PDX-LAS	1%	LAX(7%), FLL(0%)
PDX-LAX	5%	LAS(23%), FLL(0%)
PHL-FLL	14%	MCO(14%)
PHL-MCO	6%	FLL(6%), SNA(0%)
SAN-SFO	37%	SMF(37%)
SAN-SMF	0%	OAK(0%), SJC(0%)
SEA-LAS	8%	LAX(14%), SAN(1%), SFO(1%), PHX(0%)
SEA-LAX	65%	SAN(81%), LAS(68%), PHX(63%), SFO(37%)
SEA-PHX	27%	SAN(36%), SFO(35%), LAS(26%), LAX(7%)
SEA-SAN	0%	SFO(0%)
SEA-SFO	46%	SAN(53%), PHX(46%), LAX(39%), LAS(38%)
SFO-BOS	24%	EWR(27%), JFK(3%), ORD(0%)
SFO-EWR	26%	BOS(26%), ORD(0%)
SFO-JFK	23%	BOS(23%), ORD(11%)
SFO-LAS	1%	SEA(1%), ORD(0%), LAX(0%), BDL(0%), BOS(0%), EWR(0%), JFK(0%), SAN(0%)
SFO-LAX	5%	LAS(40%), SAN(8%), SEA(6%), JFK(3%), BDL(1%), BOS(1%), ORD(0%), EWR(0%)
SFO-ORD	24%	EWR(52%), BOS(49%), JFK(41%), BDL(13%)
SFO-SAN	0%	BDL(0%), BOS(0%), EWR(0%), ORD(0%), SEA(0%)
SFO-SEA	1%	ORD(1%), BOS(1%), BDL(0%), EWR(0%), JFK(0%), LAS(0%), SAN(0%)
SJC-SAN	0%	SNA(0%)
SMF-SAN	0%	BUR(0%), SNA(0%)
SNA-SJC	0%	MCO(0%)

4 Econometric Analysis

We aim to accomplish two primary objectives with our econometric analysis. Foremost, we wish to understand the main drivers of HCT (Section 4.2). Second, we would like to determine the possible savings that a passenger gains from HCT, but also the potential loss that an airline incurs if a passenger engages in HCT (Section 4.3). Before doing so, we first show that passengers are likely exploiting HCT opportunities in the U.S. market (Section 4.1).[14]

4.1 Exploitation of HCT

To determine if a subset of U.S. passengers are likely taking advantage of HCT opportunities during our sample period, we rely upon transacted fare data provided in the DOT's DB1B database. As discussed in Section 2.3, these data are released quarterly and represent a 10% random sample of all airline tickets purchased for travel in the domestic U.S. market. For the best correspondence of the DB1B with the time period of our published fare and itinerary data (October 2019–February 2020), we use DB1B data from the fourth quarter of 2019.[15]

Although the DB1B does not provide information on the specific date each ticket was purchased and, more importantly, the actual flight(s) each passenger boarded, it is still possible to test for potential exploitation of HCT by passengers. Specifically, we assume that a passenger cannot exploit HCT on a roundtrip ticket, since failure to show up for the second leg of the outbound portion of the trip typically results in cancellation of the rest of the roundtrip ticket. Therefore, to exploit HCT, a roundtrip passenger would need to purchase two separate one-way tickets.

[14] We are grateful to Jan Brueckner for this insightful suggestion.

[15] We do not include the first quarter of 2020 because this time period includes March 2020, where the normal practices of airline pricing are drastically altered by the outbreak of COVID-19 (Gaggero and Luttmann, 2022). Moreover, to prevent outliers from affecting results, we exclude tickets with prices below the 5^{th} and above the 95^{th} percentiles.

Based on this idea, we estimate the following regression,

$$HCT\%_{rca} = \beta_0 + \beta_1 \cdot AveragePriceDifference_{rca} + \delta_a + \epsilon_{rca} \tag{1}$$

where the main independent variable of interest is the average price difference (*AveragePriceDifference*$_{rca}$), computed as the difference between the average one-way nonstop fare on route r and airline a (i.e., A-B routes) and airline a's average one-way connecting fare that uses route r to a given final destination c (i.e., A-B-C routes).[16] The dependent variable ($HCT\%_{rca}$) is the percentage of tickets on route r, airline a, and final destination c that were purchased on a one-way basis, so as to exploit HCT.[17] Note that a positive coefficient on β_1 would indicate that an increase in the difference between the average one-way nonstop fare and the average one-way connecting fare is associated with an increase in the number of tickets purchased on a one-way basis (i.e., an increase in the number of passengers potentially exploiting HCT). Airline fixed effects (δ_a) are included as controls.[18]

The results of estimating equation (1) are reported in Table 3. The first column displays ordinary least squares (OLS) estimates while the second column displays fractional logit estimates. Because the dependent variable is a percentage that is bounded between zero and one, our preferred estimates are the fractional logit estimates in column (2).

The positive and statistically significant coefficient on *AveragePriceDifference* in both Table 3 columns indicate that passengers are likely exploiting HCT in the U.S. domestic market. Furthermore, consistent with our Table 1 findings, the positive coefficients on American,

[16]For example, ORD-DCA-BOS and ORD-DCA-MIA trips on American constitute two separate observations. In this example, ORD-DCA is the "A-B" route (i.e., route r) and ORD-DCA-BOS and ORD-DCA-MIA are two separate "A-C" routes that use route r (i.e., rc routes). Because *AveragePriceDifference* is intended to measure the savings from HCT, *AveragePriceDifference* is set to zero in the case of negative values (i.e., when HCT does not occur).

[17]Specifically, $HCT\%_{rca} = \frac{One{-}Way\ Tickets_{rca}}{(One{-}Way\ Tickets_{rca} + One{-}Way\ Tickets_{ra})}$.

[18]The coefficient on the *AveragePriceDifference* may suffer from simultaneity bias. However, any resulting bias will decrease the magnitude of the *AveragePriceDifference* coefficient (i.e., we would underestimate the effect of the average price difference on the fraction of tickets purchased on a one-way basis). Additionally, we are only interested in the correlation between *AveragePriceDifference* and *HCT%*. We are not attempting to make any causal statements.

Table 3: Test for exploitation of HCT with DB1B data

	(1)	(2)
Estimator:	OLS	Fractional Logit
Dependent variable:	HCT%	HCT%
Average Price Difference	0.0003***	0.004***
	(0.000)	(0.000)
Alaska	-0.016***	-0.506***
	(0.006)	(0.172)
American Airlines	0.025***	0.533***
	(0.006)	(0.154)
Delta	0.022***	0.498***
	(0.006)	(0.150)
Hawaiian	-0.015***	-0.533***
	(0.006)	(0.191)
United	0.004	0.172
	(0.006)	(0.154)
Frontier	-0.019***	-0.705***
	(0.005)	(0.155)
JetBlue	-0.026***	-1.048***
	(0.006)	(0.210)
Spirit	-0.022***	-0.855***
	(0.005)	(0.153)
Southwest	-0.012**	-0.348**
	(0.005)	(0.149)
Allegiant	-0.018***	-0.682***
	(0.005)	(0.159)
R^2 or Pseudo-R^2	0.081	0.031
Observations	162,889	162,889

Notes: Data are from the DOT's DB1B database for the fourth quarter of 2019. Sun Country is the omitted airline fixed effect. Standard errors are clustered at the route A-B level. Constant is included but not reported. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Delta, and United indicate that HCT typically arises on full-service carriers that operate large hub-and-spoke networks (although the coefficient on United is statistically insignificant).[19]

Having established that passengers are likely exploiting HCT opportunities, we now turn our attention to examining the main drivers of HCT in Section 4.2 and the potential savings that passengers may obtain from engaging in HCT in Section 4.3.

4.2 Determinants of HCT

4.2.1 Probability of Observing HCT

To determine how various route and ticket characteristics affect the prevalence of HCT opportunities, we model the probability of observing HCT as a function of route-level competition (both on A-B and A-C routes), advance-purchase requirements, ticketing carrier, and other itinerary-specific characteristics such as the month-of-departure, day-of-the-week-of-departure, and the time-of-day-of-departure.

Specifically, we estimate equation (2) below,

$$\Pr(HCT_{ircdat} = 1) = f(Competition A\text{-}B_{ird}, Competition A\text{-}C_{icd}, DaysToDeparture_{it}, Airline_{ia}, \delta_{id}) \tag{2}$$

where the subscript i indexes the itinerary, r the A-B route, c the final destination for the itinerary that uses route r (i.e., the A-C route), d the departure date, a the airline, and t the time dimension, measured in the number of days to departure (i.e., how far in advance the itinerary is booked). Competition on A-B and A-C routes (*CompetitionA-B* and *CompetitionA-C*) are measured by the number of nonstop carriers serving the route on the itinerary's departure date. To account for nonlinear fare changes that occur during the booking period, we follow Gaggero and Luttmann (2020, 2022) and split the days to departure variable into five categories: 1 to 2, 3 to 6, 7 to 13, 14 to 20, and 21 to 60; the indicator for 21 to 60 days to departure serves as the reference category. The ticketing carrier for each itinerary is represented by a separate indicator (*Airline*) with Sun Country serving

[19] The omitted airline fixed effect is Sun Country, a small low-cost carrier.

as the reference category (Table 1 indicates that HCT opportunities are least prevalent on Sun Country). Finally, δ is a matrix of fixed effects that control for each itinerary's month-of-departure, day-of-week-of-departure, and time-of-departure.

We recognize that there may exist some unobserved factor that is correlated with both the number of carriers serving A-B and/or A-C routes and the prevalence of HCT opportunities. To correct for the possible endogeneity of *CompetitionA-B* and *CompetitionA-C*, we employ a two-stage least squares (2SLS) approach with six instruments: (i) the number of nonstop passengers on route A-B during the same month of the previous year, (ii) the number of nonstop passengers on route A-C during the same month of the previous year, (iii) the natural logarithm of the arithmetic mean of the metropolitan statistical area (MSA) populations of the endpoint cities on route A-B, (iv) the natural logarithm of the arithmetic mean of the MSA populations of the endpoint cities on route A-C, (v) the natural logarithm of the geometric mean of the MSA populations of the endpoint cities on route A-B, and (vi) the natural logarithm of the geometric mean of the MSA populations of the endpoint cities on route A-C. These instruments are similar to those used in Gerardi and Shapiro (2009) and Dai et al. (2014).

In our baseline specification, we estimate equation (2) using 2SLS with standard errors that are clustered at the A-B route level. However, because our dependent variable is a binary indicator taking the values of zero or one, we also estimate equation (2) using instrumental variables (IV) probit.

The regression results are reported in Table 4. To ensure that the linear estimates of columns (1) and (2) are directly comparable with the output from the probit regressions, columns (3) and (4) report the marginal effects. The corresponding probit coefficients are reported in Appendix Table A2. The last two columns of Table A2 also report the first-stage estimates for *CompetitionA-B* and *CompetitionA-C*, respectively.[20]

[20] The first-stage regressions for the 2SLS and IV probit models are identical (i.e., linear first-stage estimated by OLS with the same six instruments).

Table 4: Probability of observing HCT

	(1)	(2)	(3)	(4)
Estimator:	OLS	2SLS	Probit	IV-Probit
Dependent variable:	HCT	HCT	HCT	HCT
	Estimated coefficients	Estimated coefficients	Marginal effects	Marginal effects
Competition A-B	-0.022**	-0.035**	-0.023**	-0.002
	(0.009)	(0.016)	(0.011)	(0.015)
Competition A-C	0.031***	0.036***	0.030***	0.016**
	(0.008)	(0.008)	(0.007)	(0.007)
DaysToDeparture 1-2	0.199***	0.197***	0.195***	0.198***
	(0.049)	(0.048)	(0.037)	(0.037)
DaysToDeparture 3-6	0.088**	0.088**	0.086**	0.085**
	(0.043)	(0.043)	(0.037)	(0.037)
DaysToDeparture 7-13	0.018	0.018	0.021	0.019
	(0.026)	(0.026)	(0.023)	(0.023)
DaysToDeparture 14-20	-0.020	-0.021	-0.017	-0.017
	(0.016)	(0.016)	(0.014)	(0.014)
Alaska	0.058*	0.067	0.033**	0.036**
	(0.034)	(0.043)	(0.017)	(0.018)
American Airlines	0.231***	0.234***	0.212***	0.204***
	(0.048)	(0.051)	(0.034)	(0.030)
Delta	0.359***	0.369***	0.366***	0.370***
	(0.089)	(0.095)	(0.104)	(0.093)
United	0.271***	0.271***	0.244***	0.253***
	(0.053)	(0.054)	(0.040)	(0.045)
Frontier	0.020	0.033	0.019***	0.019***
	(0.033)	(0.043)	(0.004)	(0.006)
JetBlue	0.046	0.054	0.023	0.017
	(0.039)	(0.047)	(0.017)	(0.014)
Spirit	0.061**	0.066**	0.047***	0.048***
	(0.027)	(0.033)	(0.008)	(0.009)
R^2	0.148	0.146		
Observations	772,635	772,635	772,635	772,635

Notes: All specifications include month-of-year, day-of-week, and time-of-day-of-departure fixed effects. Sun Country is the omitted airline fixed effect. Columns (3) and (4) report the marginal effects for the Probit regressions. Probit coefficient estimates are reported in Appendix Table A2. The endogenous variables in columns (2) and (4) are *Competition A-B* and *Competition A-C* and the corresponding first-stage regressions are reported in Appendix Table A2. Standard errors are clustered at the route A-B level. Constant is included but not reported. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

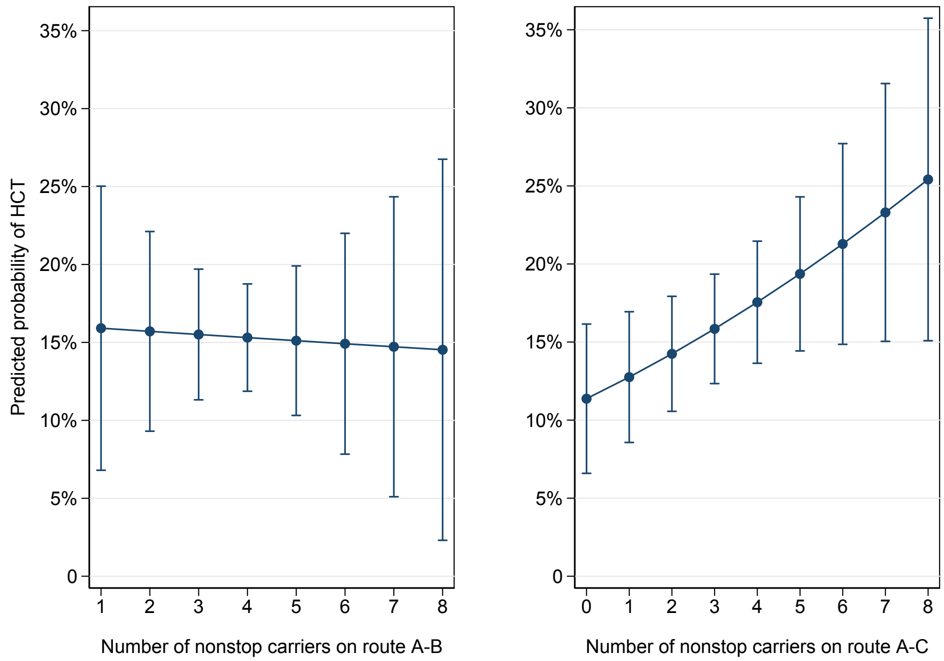
As the Table 4 results indicate, competition is one of the primary drivers of HCT, especially on A-C routes. An additional nonstop carrier serving the A-C route increases the likelihood of HCT by 3.1%-3.6% under the linear estimates and by 1.6%-3.0% under the probit estimates. The effect of *CompetitionA-B* on HCT is slightly less pronounced, as the marginal effect is statistically insignificant in column (4). Considering only the statistically significant estimates, an additional nonstop carrier serving the A-B route decreases the likelihood of HCT by 2.2%-3.5% in the linear model and by 0.2% in the probit model.

The signs on both competition variables are consistent across all Table 4 specifications and in line with expectations of a negative effect of *CompetitionA-B* and a positive effect of *CompetitionA-C* on the likelihood of observing HCT. For instance, standard economic theory predicts that additional competition should result in lower market prices. Because HCT occurs when $\text{Fare}_{\text{AB}} > \text{Fare}_{\text{AC}}$, additional competition on A-C reduces Fare_{AC}, thereby increasing the likelihood that this inequality holds (expected positive sign on *CompetitionA-C*). In contrast, additional competition on A-B reduces Fare_{AB}, decreasing the likelihood that $\text{Fare}_{\text{AB}} > \text{Fare}_{\text{AC}}$ holds (expected negative sign on *CompetitionA-B*).

Using the IV-Probit estimates, Figure 4 depicts the predicted probability of HCT as competition increases on A-B routes (left diagram) and A-C routes (right diagram). The bars stemming from the point estimates represent the 95% confidence interval. As the figure illustrates, the predicted probability of HCT monotonically increases as the number of nonstop carriers serving route A-C increases, in line with expectations. In contrast, as the number nonstop carriers serving the A-B route increases, the overall probability of HCT decreases. However, the slope of the line connecting the predicted probabilities is not very steep, pointing towards a relatively lower impact of *CompetitionA-B* on HCT, as already suggested by column (4) of Table 4.

The coefficient on the airline fixed effects are consistent with the findings in Table 1, where HCT opportunities were found to be more prevalent on American, Delta, and United, the major full-service carriers in the U.S. domestic market. Relative to Sun Country, the omitted

Figure 4: Predicted probability of HCT as competition increases with 95% conf. interval



airline fixed effect in the regressions, HCT opportunities are approximately 21% more likely on American, 37% more likely on Delta, and 25% more likely on United. A smaller effect is found for Alaska. However, our sample excludes routes to Alaska (see Figure 2). In addition, Alaska's hubs are confined to cities on the west coast instead of being dispersed across the continental U.S. like the hub networks for American, Delta, and United.[21]

We believe the dispersed hub-and-spoke network structure of the three major full-service carriers provides passengers with more opportunities to exploit HCT. In contrast, HCT opportunities are less likely on low-cost carriers because their business models do not involve operating large connecting hubs. Consistent with this story, the coefficients for the low-cost carriers (Frontier, JetBlue, and Spirit) are substantially lower in magnitude (and statistical significance) than the coefficients for American, Delta, and United.

Finally, the coefficients on the *DaysToDeparture* variables indicate that HCT oppor-

[21] Alaska currently has hubs at Anchorage (ANC), Los Angeles (LAX), Portland (PDX), San Francisco (SFO), and Seattle (SEA).

tunities are more prevalent in the last week before departure, consistent with the pattern previously displayed in Figure 3. The coefficients in Table 4 indicate that, relative to trips booked 21 to 60 days in advance, the likelihood of observing HCT increases by 9% between three and six days before departure, and by about 20% in the last two days to departure. This finding may result from different pricing patterns of A-B and A-C fares as the departure date approaches, with a possible steeper trajectory for A-B fares. We investigate this presumption further in the next subsection.

4.2.2 Fare Regressions

To test the conjecture that the increased probability of observing HCT closer to the departure date is due to the steeper increase of nonstop A-B fares relative to connecting A-C fares, we regress the natural logarithm of fare on the same set of regressors deployed in the HCT regressions (i.e., we estimate equation (2) with the natural logarithm of fare as the dependent variable). Because the dependent variable is in logs, the estimated coefficients on the *DaysToDeparture* dummies represent the percentage change in fare relative to *DaysToDeparture 21-60*, the omitted days to departure category in the regressions.[22]

Due to the potential endogeneity of the competition variables (see Section 2.2), we estimate our fare regressions using 2SLS with the same set of instruments used in equation (2). Table 5 reports results when the natural logarithm of the A-B fare (column 1) and A-C fare (column 2) are the dependent variables. Comparing the *DaysToDeparture 1-2* and *DaysToDeparture 3-6* coefficients across columns, both coefficients are larger in magnitude when $\log(\text{Fare}_{\text{AB}})$ is the dependent variable. This finding implies that A-B fares increase at a higher rate than A-C fares, supporting the presumption that the increased likelihood of observing HCT in the last week before departure is driven by a steeper growth rate of the nonstop A-B fare relative to the connecting A-C fare.

[22]Since the dependent variable is in logs and the *DaysToDeparture* variables are indicators, marginal effects are interpreted as the $100 \times (e^{\beta} - 1)$% change in fare.

Table 5: Fare regressions

	(1)	(2)
Estimator:	2SLS	2SLS
Dependent variable:	$\log(\text{Fare}_{\text{AB}})$	$\log(\text{Fare}_{\text{AC}})$
Competition A-B	-0.090***	0.010
	(0.024)	(0.017)
Competition A-C	-0.056***	-0.127***
	(0.020)	(0.017)
DaysToDeparture 1-2	0.924***	0.769***
	(0.051)	(0.039)
DaysToDeparture 3-6	0.536***	0.497***
	(0.058)	(0.031)
DaysToDeparture 7-13	0.217***	0.239***
	(0.051)	(0.026)
DaysToDeparture 14-20	0.048**	0.080***
	(0.023)	(0.016)
Alaska	0.365***	0.625***
	(0.097)	(0.111)
American Airlines	0.546***	0.359***
	(0.073)	(0.088)
Delta	0.854***	0.412***
	(0.200)	(0.099)
United	0.611***	0.398***
	(0.084)	(0.104)
Frontier	0.097	0.223**
	(0.096)	(0.089)
JetBlue	0.497***	0.406***
	(0.130)	(0.125)
Spirit	0.024	0.094
	(0.093)	(0.098)
R^2	0.496	0.448
Observations	772,635	772,635

Notes: All specifications include month-of-year, day-of-week, and time-of-day-of-departure fixed effects. Sun Country is the omitted airline fixed effect. The endogenous variables in columns (1) and (2) are *Competition A-B* and *Competition A-C*. Standard errors are clustered at the route A-B level. Constant is included but not reported. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Two additional findings emerge from Table 5. First, fares on full-service carriers are generally higher than on low-cost carriers, with the exception that JetBlue fares are similar to full-service carrier fares. In contrast, the statistically insignificant Spirit coefficients indicate that Spirit fares are similar to Sun Country fares, the excluded airline fixed effect in Table 5. Since Spirit and Sun Country are both ultra-low-cost carriers, this result is consistent with expectations.

Second, in addition to the expected result that additional competition on route A-B (A-C) decreases A-B (A-C) fares, we observe that *CompetitionA-B* is statistically insignificant in the $\log(\text{Fare}_{\text{AC}})$ regression, while *CompetitionA-C* is negative and significant in the $\log(\text{Fare}_{\text{AB}})$ regression. We believe that A-C fares are less directly related to the extent of competition on A-B routes than the A-B fare is to competition on A-C routes. The rationale is that the effect of A-B competition on the A-C fare should be minimal, because the relevant competition measure for A-C routes is broader, not only involving route A-B, but all other routes that start in A, terminate at C, and connect at airports other than B.

4.3 Savings from HCT

The analysis thus far has shown *when* and *why* HCT is more likely to occur. Our next step is to examine the price differential due to HCT, which represents the possible savings that a passenger may accrue from engaging in HCT, or, alternatively, the airline's potential revenue loss from a HCT passenger. To do so, we construct a new variable, *PriceDifference*, which is set equal to the difference between Fare_{AB} and Fare_{AC}. If this difference is negative (i.e., HCT does not occur), *PriceDifference* is set equal to zero. Because *PriceDifference* is nonnegative and censored at zero, we estimate a Tobit model. We use the same set of regressors described in equation (2), as well as the same set of instruments to correct for the potential endogeneity of the competition variables. In other words, we estimate equation (2) using a Tobit model with *PriceDifference* as the dependent variable.

Table 6: Determinants of *PriceDifference*

	(1)	(2)
Estimator:	Tobit	IV-Tobit
Dependent variable:	PriceDifference	PriceDifference
Competition A-B	-10.713	-20.856**
	(7.413)	(9.599)
Competition A-C	13.507***	17.336***
	(3.441)	(3.599)
DaysToDeparture 1-2	117.948***	117.878***
	(32.893)	(32.932)
DaysToDeparture 3-6	88.265***	89.176***
	(31.762)	(32.025)
DaysToDeparture 7-13	33.192*	34.348*
	(19.576)	(20.217)
DaysToDeparture 14-20	1.192	1.230
	(13.645)	(13.782)
Alaska	154.976***	157.429***
	(35.382)	(35.038)
American Airlines	275.971***	273.871***
	(43.386)	(41.422)
Delta	353.732***	358.961***
	(83.333)	(87.751)
United	288.400***	285.703***
	(43.522)	(42.465)
Frontier	119.926***	128.512***
	(24.072)	(25.189)
JetBlue	134.274***	136.522***
	(42.243)	(39.627)
Spirit	175.078***	176.564***
	(31.992)	(31.068)
Observations	772,635	772,635

Notes: The dependent variable (*PriceDifference*) is equal to max(0, $\text{Fare}_{\text{AB}} - \text{Fare}_{\text{AC}}$). All specifications include month-of-year, day-of-week, and time-of-day-of-departure fixed effects. Sun Country is the omitted airline fixed effect. The endogenous variables in column (2) are *Competition A-B* and *Competition A-C*. Standard errors are clustered at the route A-B level. Constant is included but not reported. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

The Tobit results are presented in Table 6. The signs on the competition variables are consistent with expectations. In the same manner that additional competition on A-B routes decreases the likelihood of HCT, additional competition on A-B routes also decreases the price difference due to HCT. Furthermore, consistent with how additional competition on A-C routes increases the likelihood of HCT, additional A-C competition also increases the HCT price difference.

Considering the estimates in column (2) of Table 6, an additional nonstop carrier on route A-C increases the average price difference by more than $17, while an additional nonstop carrier on route A-B decreases the average price difference by almost $21. In addition, the price difference due to HCT is higher on the major full-service carriers: Delta has the largest average price difference, followed by United, and then American.

The magnitude on the $DaysToDeparture$ indicators are also plausible because the HCT price difference increases as the departure date approaches. Consistent with Figure 3, the peak of the price difference occurs in the last two days to departure. Relative to trips booked 21 to 60 days in advance, the HCT price difference increases by almost $118 in the last two days to departure.

Finally, a robustness check based on a different dependent variable (the percentage price difference) and model (fractional logit) yield similar qualitative results to Table 6. These results are not reported here, but are available in Appendix Table A3.

5 Conclusion

This article has offered a comprehensive empirical analysis of hidden-city ticketing (HCT), which, to the best of our knowledge has never been conducted before. HCT is a pricing phenomenon that occurs when the fare for a nonstop trip from A to B (i.e., A-B routes) is more expensive than a connecting trip from A to C that connects at B (i.e., the "hidden city"). Exploiting a unique panel of over 772 thousand fares collected over a seven-month period (flights in our sample depart between October 2019 and February 2020), we find that HCT opportunities arise approximately 15% of the time. In particular, the major U.S. carriers that operate large hub-and-spoke networks (i.e, American, Delta, and United) account for the majority of HCT.

Analyzing the determinants of HCT, we find that competition is one of the primary drivers, especially on A-C routes. An additional nonstop carrier on route A-C increases the likelihood of HCT by 1.6%-3.6% while an additional nonstop carrier on route A-B decreases the likelihood of HCT by 3.5%. These findings are consistent with standard economic theory that predicts that additional competition results in lower market prices. Because HCT occurs when $\text{Fare}_{\text{AB}} > \text{Fare}_{\text{AC}}$, additional competition on A-C should reduce Fare_{AC}, thereby increasing the likelihood that $\text{Fare}_{\text{AB}} > \text{Fare}_{\text{AC}}$ holds. Conversely, additional competition on A-B reduces Fare_{AB}, decreasing the likelihood that $\text{Fare}_{\text{AB}} > \text{Fare}_{\text{AC}}$ holds.

We also find that advance-purchase requirements are another key driver of HCT, with HCT opportunities more likely closer to the date of departure. In particular, HCT is more prevalent in the last week to departure because nonstop A-B fares increase at a higher rate than connecting A-C fares during this period. One possible interpretation of this finding is related to the heterogeneity of passengers during the booking period. Because early purchasers are typically price-sensitive passengers with low search costs, they are more likely to seek out HCT opportunities. Accordingly, airlines may respond by ensuring that HCT opportunities are rare during the early booking period. In contrast, most passengers purchasing tickets a few days before departure are price-insensitive customers with high search costs (i.e., late purchasers who are less likely to seek out HCT opportunities). For this reason, airlines may decide to extract additional surplus by raising nonstop A-B fares at a higher rate than connecting A-C fares in the final week because they are less concerned about passengers taking advantage of HCT opportunities during this period.

In addition to examining the determinants of HCT, we also quantify the savings that a passenger receives from engaging in HCT. We find that an additional nonstop carrier serving the A-B (A-C) route leads to a $21 reduction ($17 increase) in average savings. Moreover, average savings from HCT increase by $89 and $118 for trips purchased three to six and one to two days before departure, respectively.

As internet search engines become more sophisticated, they are increasingly helping consumers quickly identify HCT opportunities. However, HCT is clearly detrimental to airline operations and profits. In addition to the revenue loss that results from lower fares paid by HCT passengers, HCT may also delay the departure of the B-C flight if the airline waits in vain for HCT passengers (Skorupski and Wierzbińska, 2015). There is also an opportunity cost associated with reserving a seat on the B-C flight for a HCT passenger when that seat could instead be sold to another customer.

It is also worth mentioning that if all connecting A-C passengers were HCT passengers at connecting city B, the B-C flight would fly empty. This is obviously an extreme and unlikely outcome, but it clearly demonstrates that HCT could have important environmental consequences that should be considered by regulators (Kang et al., 2022). In other words, HCT passengers are unnecessary polluters that should not only be discouraged by airlines, but also discouraged by regulatory authorities.

An interesting extension to the analysis presented in this article would be to examine whether airlines attempt to circumvent HCT by applying differential pricing for one-ways and roundtrips that connect through attractive intermediate cities. To circumvent HCT, it is expected that the usual one-way premium would be higher for trips connecting at attractive destinations (e.g., Los Angeles, New York, Miami) than for trips connecting at relatively unattractive destinations (e.g., Atlanta, Houston, or Phoenix). In other words, airlines may raise one-way fares that connect in attractive cities, so that the gain from exploiting HCT on these routes is diminished.

More generally, future research could extend the present analysis to other countries or continents. The U.S. domestic market is quite consolidated, but elsewhere it is not. For example, the airline industry is at an earlier stage of consolidation in Europe, with almost every European country having its own flag carrier and few steps taken towards consolidation (e.g., the Air France/KLM merger in 2004 and the British Airways/Iberia merger in 2011). The European market is characterized by differences in airline network structures, with full-service carriers spatially operating around a small number of central hubs and low-cost carriers evenly spreading flights across their networks (Bubalo and Gaggero, 2021). Given these differences, it would be interesting to test whether the results we find on route competition also extend to the European airline market.

Furthermore, the present analysis could be extended to other industries that, like airlines, operate using hub-and-spoke networks. Examples include passenger rail and long-distance bus, to see if these industries, which started applying rudimentary yield management techniques by offering discounted fares to early purchasers, has HCT opportunities. Other candidate industries include cargo, container shipping, freight, and warehousing since a large number of companies in these sectors employ hub-and-spoke networks to distribute their goods.

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Appendix Tables

Table A1: Summary statistics and a brief description of the variables included in the analysis

	Description	Mean	Std. Dev.	Min	Max
DEPENDENT VAR.					
HCT%†	$\frac{One\text{−}Way\ Tickets_{rca}}{(One\text{−}Way\ Tickets_{rca} + One\text{−}Way\ Tickets_{ra})}$	0.055	0.094	0.000	0.907
HCT	Dummy=1 in case of Hidden-City Ticketing	0.154	0.361	0.000	1.000
$\log(\text{Fare}_{\text{AB}})$	Fare A-B, nonstop flight, in logs	4.644	0.633	2.708	7.955
$\log(\text{Fare}_{\text{AC}})$	Fare A-C with layover in B, in logs	5.081	0.536	3.555	7.901
PriceDifference	$\max(0, \text{Fare}_{\text{AB}} - \text{Fare}_{\text{AC}})$	9.342	40.049	0.000	2,277
PriceDifference%	$\max\left(0, \frac{\text{Fare}_{\text{AB}} - \text{Fare}_{\text{AC}}}{\text{Fare}_{\text{AB}}}\right)$	0.034	0.105	0.000	0.880
REGRESSORS					
AveragePriceDifference†	$\max(0, \text{Average Fare}_{\text{AB}} - \text{Average Fare}_{\text{AC}})$	30.905	60.011	0.000	600.000
Competition A-B	Number of nonstop carriers serving route A-B on the flight's day of departure	3.921	1.320	1.000	8.000
Competition A-C	Number of nonstop carriers serving route A-C on the flight's day of departure	2.493	1.638	0.000	8.000
DaysToDeparture 1-2	Dummy=1 if DaysToDeparture $\in [1, 2]$	0.044	0.205	0.000	1.000
DaysToDeparture 3-6	Dummy=1 if DaysToDeparture $\in [3, 6]$	0.095	0.294	0.000	1.000
DaysToDeparture 7-13	Dummy=1 if DaysToDeparture $\in [7, 13]$	0.141	0.348	0.000	1.000
DaysToDeparture 14-20	Dummy=1 if DaysToDeparture $\in [14, 20]$	0.118	0.322	0.000	1.000
DaysToDeparture 21-60	Dummy=1 if DaysToDeparture $\in [21, 60]$, omitted category in the regressions	0.602	0.489	0.000	1.000
Alaska	Dummy=1 for Alaska	0.058	0.234	0.000	1.000
American Airlines	Dummy=1 for American Airlines	0.250	0.433	0.000	1.000
Delta	Dummy=1 for Delta	0.102	0.302	0.000	1.000
United	Dummy=1 for United	0.170	0.376	0.000	1.000
Frontier	Dummy=1 for Frontier	0.046	0.209	0.000	1.000
JetBlue	Dummy=1 for JetBlue	0.041	0.199	0.000	1.000
Spirit	Dummy=1 for Spirit	0.329	0.470	0.000	1.000
Sun Country	Dummy=1 for Sun Country, omitted category in the regressions	0.003	0.058	0.000	1.000
INSTRUMENTS					
Passengers A-B	Monthly number of nonstop passengers on route A-B, in thousands	84.206	31.805	19.194	168.542
Passengers A-C	Monthly number of nonstop passengers on route A-C, in thousands	49.482	33.049	0.000	168.542
$\log(\sqrt{PopA * PopB})$	Geometric mean of population of A and B, in logs	15.699	0.445	14.480	16.588
$\log(\sqrt{PopA * PopC})$	Geometric mean of population of A and C, in logs	15.619	0.470	14.480	16.588
$\log(\frac{PopA+PopB}{2})$	Arithmetic mean of population of A and B, in logs	15.805	0.451	14.687	16.606
$\log(\frac{PopA+PopC}{2})$	Arithmetic mean of population of A and C, in logs	15.778	0.451	14.687	16.606

Notes: Number of observations is 772,635, except 162,889 for the variables marked with † (DB1B data).

Table A2: Estimated probit coefficients and first-stage regressions for Table 4

	(1)	(2)	(3)	(4)
Estimator:	Probit	IV-Probit	OLS	OLS
Dependent variable:	HCT	HCT	Comp. A-B	Comp. A-C
Competition A-B	-0.121**	-0.190**		
	(0.057)	(0.077)		
Competition A-C	0.155***	0.200***		
	(0.037)	(0.037)		
DaysToDeparture 1-2	0.806***	0.792***	-0.040	0.102*
	(0.135)	(0.131)	(0.039)	(0.059)
DaysToDeparture 3-6	0.404***	0.400***	-0.020	-0.045
	(0.154)	(0.151)	(0.036)	(0.040)
DaysToDeparture 7-13	0.108	0.109	0.035	-0.030
	(0.116)	(0.118)	(0.027)	(0.028)
DaysToDeparture 14-20	-0.098	-0.100	-0.004	0.025
	(0.085)	(0.084)	(0.016)	(0.017)
Alaska	1.441***	1.432***	-0.962**	-1.432***
	(0.270)	(0.263)	(0.476)	(0.415)
American Airlines	2.544***	2.495***	-0.752	-1.371***
	(0.175)	(0.157)	(0.455)	(0.428)
Delta	3.031***	3.050***	-0.581	-1.331***
	(0.299)	(0.322)	(0.559)	(0.438)
United	2.656***	2.591***	-0.690	-0.623
	(0.180)	(0.155)	(0.520)	(0.480)
Frontier	1.191***	1.206***	-0.384	-1.003**
	(0.171)	(0.148)	(0.547)	(0.501)
JetBlue	1.269***	1.272***	-0.137	-1.570***
	(0.358)	(0.339)	(0.542)	(0.443)
Spirit	1.611***	1.591***	-0.642	-1.105**
	(0.150)	(0.119)	(0.453)	(0.457)
Passengers A-B			0.026***	0.000
			(0.004)	(0.002)
Passengers A-C			0.002	0.041***
			(0.002)	(0.002)
$\log\left(\sqrt{PopA * PopB}\right)$			-5.706***	0.793**
			(1.293)	(0.363)
$\log\left(\sqrt{PopA * PopC}\right)$			-0.670	0.030
			(0.418)	(0.450)
$\log\left(\frac{PopA+PopB}{2}\right)$			4.678***	-0.344
			(1.266)	(0.358)
$\log\left(\frac{PopA+PopC}{2}\right)$			0.814*	-0.554
			(0.448)	(0.416)
R^2			0.656	0.659
Wald χ^2 test		12.691***		
Observations	772,635	772,635	772,635	772,635

Notes: All specifications include month-of-year, day-of-week, and time-of-day-of-departure fixed effects. Sun Country is the omitted airline fixed effect. Standard errors are clustered at the route A-B level. Constant is included but not reported. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Online Appendix

As a robustness check, we replicate the analysis reported in Table 6 using, in place of *PriceDifference*, the price difference in percentage, i.e., *PriceDifference%*$= \max\left(0, \frac{\mathrm{Fare_{AB}} - \mathrm{Fare_{AC}}}{\mathrm{Fare_{AB}}}\right)$. We then estimate a fractional logit model (see Table A3).

The potential endogeneity of the competition variables is accounted for using a control function approach described in Wooldridge (2001), where each endogenous variable (i.e., *Competition A-B* and *Competition A-C*) is first regressed on the instruments and the exogenous variables to obtain the residuals, $\widehat{v}_{AB}$ and $\widehat{v}_{AC}$, which are then included as additional regressors in fractional logit model to produce unbiased estimates.[23]

[23]Because the residuals are used as regressors in the second-stage, standard errors are bootstrapped.

Table A3: Determinants of *PriceDifference%*

	(1)		(2)	
Estimator	Fractional logit		Fractional logit	
Dependent variable	PriceDifference%		PriceDifference%	
	Estimated coefficients	Marginal effects	Estimated coefficients	Marginal effects
Competition A-B	-0.185	-0.006	-0.320***	-0.010***
	(0.168)	(0.005)	(0.004)	(0.000)
Competition A-C	0.226**	0.007**	0.294***	0.009***
	(0.089)	(0.003)	(0.003)	(0.000)
DaysToDeparture 1-2	1.379***	0.056***	1.373***	0.056***
	(0.266)	(0.017)	(0.012)	(0.001)
DaysToDeparture 3-6	1.239***	0.047***	1.242***	0.047***
	(0.276)	(0.016)	(0.009)	(0.000)
DaysToDeparture 7-13	0.686***	0.020**	0.692***	0.020***
	(0.257)	(0.010)	(0.011)	(0.000)
DaysToDeparture 14-20	0.064	0.001	0.060***	0.001***
	(0.329)	(0.007)	(0.013)	(0.000)
Alaska	4.458***	0.005**	4.517	0.005***
	(0.744)	(0.002)	(3.543)	(0.000)
American Airlines	6.659***	0.044***	6.667*	0.042***
	(0.621)	(0.011)	(3.544)	(0.000)
Delta	7.577***	0.100**	7.732**	0.109***
	(0.719)	(0.046)	(3.543)	(0.001)
United	6.832***	0.052***	6.821*	0.049***
	(0.598)	(0.012)	(3.544)	(0.000)
Frontier	3.986***	0.003***	4.125	0.004***
	(0.673)	(0.001)	(3.541)	(0.000)
JetBlue	3.771***	0.003	3.863	0.003***
	(0.865)	(0.002)	(3.542)	(0.000)
Spirit	4.753***	0.007***	4.812	0.007***
	(0.588)	(0.001)	(3.543)	(0.000)
$\widehat{v}_{AB}$			0.312***	
			(0.005)	
$\widehat{v}_{AC}$			-0.153***	
			(0.004)	
Pseudo-R^2	0.155		0.159	
Observations	772,635		772,635	

Notes: The dependent variable (*PriceDifference%*) is equal to $\max\left(0, \frac{\text{Fare}_{\text{AB}} - \text{Fare}_{\text{AC}}}{\text{Fare}_{\text{AB}}}\right)$. All specifications include month-of-year, day-of-week, and time-of-day-of-departure fixed effects. Sun Country is the omitted airline fixed effect. Model (1) originates from a standard fractional logit regression. Model (2) originates from a fractional logit regression with a control function approach, where each endogenous variable (*Competition A-B* and *Competition A-C*) is first regressed on the instruments and the exogenous variables to obtain the residuals, $\widehat{v}_{AB}$ and $\widehat{v}_{AC}$, which are then included as additional controls in the fractional logit model to produce unbiased estimates (Wooldridge, 2001). Standard errors are clustered at the route A-B level in Model (1) and bootstrapped in Model (2). Constant is included but not reported. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.