Management Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

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To cite this article:
Jun Li, Nelson Granados, Serguei Netessine (2014) Are Consumers Strategic? Structural Estimation from the Air-Travel Industry. Management Science 60(9):2114-2137. http://dx.doi.org/10.1287/mnsc.2013.1860

MANAGEMENT SCIENCE
Vol. 60, No. 9, September 2014, pp. 2114–2137
ISSN 0025-1909 (print) | ISSN 1526-5501 (online)

http://dx.doi.org/10.1287/mnsc.2013.1860

Are Consumers Strategic? Structural Estimation from the Air-Travel Industry

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Consumers often consider delaying a purchase strategically, anticipating that prices might decrease. Combining two unique data sources from the air-travel industry (posted fare data and booking data), we use a structural model to estimate the fraction of strategic consumers in the population, assuming different levels of sophistication in consumers' perception of future prices: perfect foresight and weak- and strong-form rational expectations. We find that 5.2% to 19.2% of the population is strategic across markets, measured by the first and third quartiles. Our intermarket analysis indicates that shorter trips with more attractive outside options are populated with more strategic consumers. Using a nonparametric approach, we further find that most strategic consumers arrive either at the beginning of the booking horizon or close to departure. Finally, our counterfactual analysis shows that, contrary to conventional wisdom, the presence of strategic consumers does not necessarily hurt revenues. Rather, the impact varies by market. Commitment to a nondecreasing pricing strategy is more likely to benefit business markets than leisure markets, or it could even hurt leisure markets. Intermarket analysis shows that city pairs with lower Internet penetration, higher average price, and shorter distances tend to benefit more from such commitment as well.

Keywords: econometrics; structural estimation; air travel; strategic customer behavior
History: Received October 8, 2011; accepted September 22, 2013, by Yossi Aviv, operations management. Published online in *Articles in Advance* March 20, 2014.

1. Motivation

When was the last time you passed on an immediate purchase to wait for a sale? This can be a smart choice because intertemporal price fluctuations are common across industries: fashion items are marked down several times toward the end of the season; storable goods are periodically put on sale; prices for high-tech gadgets with short life cycles dip soon after release; airlines, hotels, car rentals, and theaters regularly revise prices or launch promotions. Of course, there are also consumers who do not strategize over the timing of a purchase simply because they are not aware of the possibility that prices might decrease, they have high waiting costs, or they are not willing to forgo immediate gains in exchange for uncertain future gains. We will refer to *strategic* or *forward-looking* consumers as those who maximize long-run utility by strategically timing their purchases to obtain lower prices. We also refer to *myopic* and *nonstrategic* consumers as those who make a purchase decision immediately without strategizing over the timing of purchase.

Studying strategic consumer behavior is important for several reasons. First, very little research to date provides direct and rigorous evidence of such behavior, relying instead on anecdotal accounts. Empirical evidence of strategic consumer behavior would not only enrich our knowledge of consumer behavior, but also improve managerial decisions, such as pricing and inventory management. Second, most current demand forecasting models, including those used in airline revenue management systems, assume exogenous and intertemporally independent consumer arrivals. However, correctly incorporating intertemporal demand substitution may improve the accuracy of demand forecasting. Finally, the revenue impact of strategic consumers could be significant. The common belief is that the presence of strategic consumers shifts demand from high to low prices, thus hurting revenues, but the extent of this effect is unclear: how to price and manage seat inventory in the presence of strategic consumers continues to puzzle industry professionals.

The air-travel industry is a particularly interesting test bed to study strategic consumer behavior. Compared to price fluctuations for seasonal (e.g., apparel) or technological (e.g., electronics) products, intertemporal changes in airfares are harder to predict. It is no longer surprising to learn that your seatmate on a plane paid much less for essentially the same seat. Revenue management, the practice of bucketing airfares into multiple classes and managing seat inventory dynamically, has revolutionized pricing (Talluri and van Ryzin 2005, Boyd 2007). Airlines constantly recompute protection levels and bid prices by taking into account the current number of available seats and latest demand forecasts, which results in constant opening, closing, and reopening of fare classes. Inventory managers can also override revenue management systems based on their expertise and local knowledge of demand. Moreover, pricing departments revise fares periodically in response to changes in demand patterns, operating costs, and competitors' actions. Sometimes, pricing managers will launch temporal sales, which may trigger industry-wide price wars and further add price swings. All of this is likely to trigger fare shopping on the consumer side.

Facing this volatile nature of prices, many Web search tools have emerged to make it easier for consumers to shop. Proliferation of online travel agents (e.g., Expedia, Orbitz) and meta-search engines (e.g., Kayak, Sidestep) have made it much easier to compare prices. Microsoft's Bing Travel (formerly Farecast) even makes a suggestion to "wait" or "buy" based on the probability of prices going up or down within the next seven booking days. Using advanced machine learning systems, they claim 75% accuracy on average. Moreover, traditional off-line agencies, which have knowledge about price movements, may help consumers obtain better deals to increase customer loyalty. Based on spot checks of various travel-related online forums, travelers have reported savings of $20 to $150 (or 7% to 33%) by waiting for a better deal. Of course, consumers do not always benefit by behaving strategically—there are also cases in which travelers reported that they had to pay more since the price actually went up instead of going down.

In this paper, we merge two separate data sources to investigate just how strategic consumers really are. First, we collected information on posted rather than transacted prices. This is important because to investigate strategic consumer behavior we need to know the prices available in the market. Second, many industries where one would suspect strategic consumer behavior have fragmented distribution channels. This normally limits access to sales information across channels, creating an incomplete picture of booking behaviors. We are able to utilize booking information from global distribution systems (GDSs), which includes bookings made via online and off-line travel agents. In addition, we also use several additional data sets, such as transaction price and clickstream of online travel search, to verify our usage of data and assumptions.

We use a simple yet flexible structural model to account for the dynamics caused by strategic consumers. Unlike most other empirical papers that incorporate forward-looking behavior by assumption (e.g., Erdem and Keane 1996), our model does not impose the existence of strategic consumers a priori. Only when the estimated proportion of strategic consumers is significantly different from zero are we presenting evidence of strategic behavior. The key idea that we use to identify strategic consumers can be explained intuitively as follows. An observed increase in demand when prices fall can be attributed either to consumers strategically waiting for prices to drop or to more (myopic) consumers purchasing tickets simply because prices are more affordable. Consequently, to identify strategic consumers, the key is to first obtain an accurate measure of price sensitivity. To do so, we need an "uncontaminated" sample where demand is only affected by price sensitivity. This situation exists when prices go up or are expected to go up, since strategic consumers behave exactly like their myopic counterparts in these cases. More importantly, we need not only a measure of price sensitivity, but an *unbiased* one. We accomplish this through instrumental variables (previous prices and several variations of cumulative demand) and a panel data structure (fixed effects and autocorrelated demand shocks), which account for both static and dynamic price endogeneities.

Our methodology is also flexible enough to incorporate many extensions with respect to consumer behavior, and it allows us to examine revenue implications through counterfactual analysis. Our structural estimation results suggest that 5.2% to 19.2% of travelers are strategic across different city-pair markets, measured by the first and third quartiles. This fraction varies by the time to departure in a nonlinear fashion—most strategic consumers arrive either at the beginning of the booking horizon or close to departure. Our intermarket analysis also indicates that shorter trips with more attractive alternative options exhibit more strategic consumers. Based on the estimation results, we derive important implications for revenue management practices. Surprisingly, the presence of strategic consumers does not always hurt revenues.[1] Commitment to a nondecreasing pricing

[1] It is a common belief that strategic consumers hurt revenues (e.g., Anderson and Wilson 2003, Aviv and Pazgal 2008, Levin et al. 2009). Two recent theoretical studies (Su 2007, Cho et al. 2009) argue that strategic consumers may also boost revenues in certain scenarios, and our findings provide empirical support to this.

scheme in the presence of strategic consumers is more desirable in business markets, but not necessarily in leisure markets. Among markets benefiting from this pricing strategy, the median revenue improvement is 5.5%, and the lower and the upper quartiles are 2.9% and 8.2%, respectively. We also find evidence that markets with lower Internet penetration, higher average price, and shorter distance are more likely to benefit from such commitment.

2. Literature Review

Traditional revenue management research typically assumes an exogenous demand process (e.g., Belobaba 1989, Gallego and van Ryzin 1994). However, recently there has been a growing interest in studying operational decisions in the presence of strategic consumers (for reviews, see Shen and Su 2007, Netessine and Tang 2009). Several modeling papers have investigated the impact of strategic consumers on firms' strategies such as inventory procurement (Cachon and Swinney 2009), capacity rationing (Liu and van Ryzin 2008), and revenue management (Jerath et al. 2010), to name a few. One of the key findings is that strategic consumers may negatively impact firm revenues: Anderson and Wilson (2003), Aviv and Pazgal (2008), and Levin et al. (2009) find 7% to 20% revenue losses using simulations. Nevertheless, two recent analytical papers predict that strategic consumers can have either adverse or positive effects on revenues (Su 2007, Cho et al. 2009).

With burgeoning interest from the modeling perspective, empirical research that considers consumer choice behavior has emerged. First, a few recent empirical papers study consumer choice in revenue management settings but do not account for intertemporal substitution (Vulcano et al. 2010, Newman et al. 2014). Second, in marketing and economics there is a stream of literature that incorporates forward-looking consumer behavior, starting with Erdem and Keane (1996). More recent papers include Hendel and Nevo (2006) and Nair (2007). However, most of these papers build on the premise that consumers are forward looking a priori, and the research objective is to uncover consumer preferences rather than to empirically test the existence of strategic consumers. Third, behavioral economists have long been looking at intertemporal choices and time discounting, and recent work by Osadchiy and Bendoly (2011) examines strategic consumers in lab experiments.

To provide evidence of the existence of strategic consumers, there are at least two potential estimation approaches. The first is to estimate a discount factor (or equivalently, a waiting cost) as a continuous measure of consumer patience (e.g., Levin et al. 2009). There are two difficulties associated with this approach—identification and computational complexity. In the aforementioned empirical studies of dynamic models, utility functions cannot be identified (nonparametrically) when the discount factor is not fixed (see Rust 1994, Magnac and Thesmar 2002). Although parametric restrictions will allow utility functions and the discount factor to be identified jointly, the computational complexity usually makes it undesirable to do so. As a result, the common practice is to fix the value of the discount factor and conduct sensitivity analysis on this value, if necessary. The second approach is to segment the market into discrete consumer types—myopic and strategic (e.g., Su 2007)—and to estimate the fraction of strategic consumers. A similar idea has been applied in the latent class models in the marketing literature (Dillon and Kumar 1994). This approach greatly streamlines the estimation. Meanwhile, it is analogous to market segmentation and can be more easily understood by industry professionals, so we adopt this approach.

Given the difficulty in identifying strategic behavior and the lack of appropriate field data, so far very little research provides direct evidence of the existence of strategic consumers. To the best of our knowledge, there are only two studies that do so. Chevalier and Goolsbee (2009) test whether textbook users are forward looking by anticipating book revisions. Hendel and Nevo (2013) estimate the fraction of consumers who stockpile during temporary sales. Our work is related to theirs as we also look at aggregate data and the model bears similar structure, but we differ in three aspects. First, the research objective is different. We start out with the purpose of documenting whether consumers are strategic or not, whereas their focus is on intertemporal price discrimination as a mechanism for market segmentation. As a result, we ask different questions about strategic consumers: What market characteristics affect the presence of strategic behavior? What pricing strategies may airlines adopt in response? How does the revenue impact vary across markets? Second, prices are more volatile and harder to predict in the airline industry, and hence the existence of strategic consumers is not obvious a priori. A significant amount of price dispersion (Clemons et al. 2002, Chellappa et al. 2011) and intertemporal price fluctuations (Etzioni et al. 2003, Mantin and Gillen 2011) have been documented in the industry. Third, demand is relatively stable over time in their setting, and therefore price endogeneity is less of a concern. However, in our setting, because of the practice of revenue management, price endogeneity is an important issue that needs to be properly addressed.

Assembling field data to uncover intertemporal choices is a significant challenge due to the level of detail and multiple data sources required. Our data are unique in this sense because they provide a detailed dynamic view of daily available prices and realized demand. Moreover, the structural model we propose is simple yet flexible, and at the same time consistent with the aforementioned modeling literature, so our approach can be used to calibrate subsequent models. We next describe the data and the structural model.

3. Data

We use two main data sets of bookings and airfares, with millions of records for departures in the spring travel season of 2005. Sample data can be found in Table A.1 in Appendix A.

3.1. Data Description

3.1.1. Booking Data. Our booking data, Marketing Information Data Transfer (MIDT), sponsored by an airline corporate partner, includes U.S. point-of-sale reservations for all airlines serving both nonstop and connecting itineraries for selected origin–destination airport pairs. The MIDT bookings database contains reservations made by all online and off-line travel agents through GDSs, which account for roughly 70% of airline tickets sold in the United States during the period of data collection. Although this sample is representative at face value, we note that reservations made by airlines directly through their own websites or reservation offices are excluded. If the choice of booking platforms, GDS versus non-GDS, is correlated with strategic waiting, our estimates can be biased. We verify there is no sample bias for this and other potential sources in Appendix B.

Each observation in the booking data set represents economy class round-trip reservations via a travel agency for a specific departure date, booking date, airport pair, and inventory class. The departure dates are between January 1 and May 31, 2005. The booking dates go back to October 2004, that is, three months or more prior to departure. In total, we have 116 airport pairs with both domestic and international destinations. Airport pairs were selected based on two criteria: (1) catchment areas with large populations and wide geographic coverage (our data include 23 of the top 25 U.S. airports and two-thirds of the top 75 based on passenger volume) and (2) market coverage of the airline sponsor. Under the two criteria, the selected markets not only represent those where the airline sponsor has a dominant position, but also those markets where it is underrepresented. The airline holds more than 50% market share in about one-quarter of the selected markets and less than 5% market share in about half of the selected markets.

3.1.2. Fare Data. The MIDT database does not contain price information, so we priced the bookings by Web crawling fares from major online travel agency websites for the same set of airport pairs and booking dates. We crawled fares from the three largest online travel agencies: Expedia, Travelocity, and Orbitz. Together, they had an overall 22% market share and 58% eyeball share in the U.S. market. Because of constraints in our ability to Web crawl fares for the full January to May departure period, we randomly selected seven weeks of departure dates during that period. Crawling started three months before the first departure date. Every day at about noon central standard time, we extracted the three lowest round-trip fares with a seven-day length of stay for each airport pair and departure date. In total, 51,156 fares were crawled on each booking date. Each observation contains departure date, observation date, airport pair, carrier, fare amount, inventory class, and details of the itinerary such as number of stops, connecting city, and flight duration. Although these fares are proxies for the actual transaction price of each individual booking, they are close enough for one fortunate reason: online travel agency prices happen to be representative of all booking channels, because U.S. reservation systems access fares from the same source, the Airline Tariff Publishing Company.

3.2. Data Preparation

We truncated the booking history for each departure date at three months (13 weeks) prior to departure, to have a consistent longitudinal sample across departure dates. This is a representative booking date range because about 95.1% of domestic bookings and 80.0% of international bookings are made within three months prior to departure.[2] We also removed reservations with more than 20 passengers (99.9th percentile) and dropped cancelation and exchange tickets, because the paper focuses on arrival patterns and purchase decisions. In other words, we assume that needs for cancelation and rescheduling arise independently after purchase decisions are made.

We priced the remaining booking records using the Web-crawled fare records as follows. First, for both data sets, we aggregated records containing airports in the same city to obtain records at the *city-pair* level. For each city pair and departure date, booking records were aggregated by booking date. Then, each aggregated booking record was priced using the daily lowest fare for the respective city pair, departure date, and booking date. As a result, the priced bookings data set contains booking and fare information

[2] Estimates are based on bookings in our data with departures in April and May, for which we have a six-month booking history available.

Table 1 Frequency and Size of Fare Changes by Market/Departure Date/Booking Time

	Drop	No change	Rise	Average fare change if fare drops ($)	Percentage of fare change if fare drops
Daily lowest fare					
Mean	0.179	0.592	0.229	−40.8	8.6
Weekly fare (average of daily lowest fare)					
Mean	0.369	0.072	0.559	−23.6	−5.9
Range by market	[0.161, 0.518]	[0.000, 0.364]	[0.362, 0.691]	[−54.5, −4.8]	[−15.8, −2.3]
Range by departure date	[0.272, 0.425]	[0.029, 0.119]	[0.484, 0.685]	[−28.5, −18.3]	[−8.6, −5.4]
By booking week (in chronological order)					
1	0.449	0.137	0.414	−21.0	−5.6
2	0.503	0.120	0.376	−20.6	−5.7
3	0.490	0.113	0.397	−22.0	−6.2
4	0.442	0.104	0.454	−22.8	−6.9
5	0.441	0.089	0.470	−24.6	−7.9
6	0.463	0.078	0.459	−23.6	−6.7
7	0.465	0.071	0.464	−24.0	−6.8
8	0.407	0.069	0.524	−21.6	−6.7
9	0.439	0.066	0.495	−22.8	−7.3
10	0.423	0.056	0.521	−22.1	−7.1
11	0.231	0.030	0.739	−27.4	−6.9
12	0.046	0.007	0.947	−31.0	−5.4

for 114 city-pair markets (87 domestic), 45 departure dates,[3] and a three-month booking period for each departure date, for a total of 466,830 observations.

Note that our priced bookings are aggregated across multiple airlines and flight itineraries within the same city pair. We do not possess data to fully account for substitution among different itineraries and airlines, since we would need fare information for all outbound and inbound flight combinations by airline. We leave this for future research. Nevertheless, we analyzed a sample of airline-route-specific fares and found that little information is lost by aggregating fares across airlines and itineraries.[4] Plus, as we will demonstrate later, our intermarket analysis did not find market competition (as measured by the Herfindahl index) as a significant factor to explain strategic behavior, and we also examine monopoly markets separately and obtain consistent results.

[3] We dropped four departure dates because some fare records were missing.

[4] We acquired an auxiliary data set that contains all outbound and inbound flight combinations of all airlines for a selected set of markets, and we examine price paths of different flights operated by different airlines. We find that prices are set competitively, with a correlation of 0.799 between daily lowest fares across different airlines for the same departure date and a small average absolute difference of $10.5. Flights at different times of the day admit different price levels, but follow similar intertemporal trends, with an average correlation of 0.908 within the same airline. In other words, the daily lowest price follows almost exactly the same pattern as any price path on any itinerary for a given airline. Therefore, this lowest daily price path is representative of the intertemporal price trade-offs that customers face. By using a different price path, the estimate of the fraction of strategic consumers is not affected—only the intercept in the baseline demand model shifts.

Based on observed demand and price patterns, we further aggregate the data set by booking week for the following reasons. First, a common practice to construct a fare class is to require 21-/14-/7-day advance purchase. As a result, price varies more frequently from week to week than from day to day, as shown in Table 1. This aggregation level is thus consistent with industry practices and with related papers (Mantin and Gillen 2011, Hendel and Nevo 2013, Granados et al. 2012). Second, aggregation by booking week will smooth out day-of-week demand patterns over booking dates. Third, aggregation at the weekly level also reduces computational complexity, especially when estimating time-variant parameters.

3.3. Demand and Price Trends

We note several patterns from the booking data. First, demand varies significantly across city pairs and departure dates as shown in Table 2. The total number of bookings ranges from 140 to 19,693 across different city pairs, and 5,727 to 13,518 across different departure dates. Second, the demand curve over the three-month booking period follows different paths across city pairs. For example, passengers to leisure destinations book earlier than passengers to business destinations. On routes to Orlando, most bookings are made in the fourth to third week before departure, and 75% tickets are sold more than 21 days ahead of departure; on routes to Atlanta, most bookings are made in the final week before departure, and only 34% reservations are made more than 21 days before departure. Third, the demand curves jump discontinuously at 21, 14, or 7 days before departure, when advance purchase requirements bind (Li and Netessine 2013).

Table 2 **Summary Statistics of Demand and Price**

	Mean	Std. dev.	Min	Max	No. of obs.
Total passengers by market	3,913.2	4,092.9	140	19,693	114
Total passengers by departure date	9,495.0	1,613.5	5,727	13,518	45
Weekly passengers (per market per departure date)	6.4	12.6	0	280	66,690
Weekly average fare ($)	383.52	267.64	110.21	4,188.14	66,690
Weekly average fare ($)—Market L					
Overall	231.00	60.65	166.71	655.29	$N = 585$
Between departure date		49.99	186.97	425.91	$n = 45$
Within departure date		35.09	120.15	531.73	$T = 13$
Weekly average fare ($)—Market B					
Overall	231.04	56.51	167.86	577.00	$N = 585$
Between departure date		19.97	210.29	321.92	$n = 45$
Within departure date		52.94	121.55	486.12	$T = 13$

Note. Markets L and B represent city pairs to Orlando, Florida, and Atlanta, Georgia, respectively, with the same origin.

We also note a significant amount of price variation. The overall standard deviation of prices is about 80% of the mean, as shown in Table 2. Within a market, prices vary significantly both within and between departure dates. To further investigate the intertemporal component of the price variation, we summarize frequencies of price trends in Table 1. Across consecutive booking dates, the lowest fares remain the same 59.2% of the time. On the other hand, there is significant variation from week to week. Weekly fares decrease in the subsequent week with 36.9% probability, increase with 55.9% probability, and remain constant with 7.2% probability. These probabilities vary by city pair, departure date, and booking week. This intertemporal price variation underscores the uncertainty in prices faced by travelers and the opportunity to strategize on the timing of purchase. It is also this variation that drives the identification of the fraction of strategic consumers (see §5 on identification).

Note that these data are aggregated from the start because we captured daily bookings, not individual consumer arrivals and search behavior. This level of granularity is common in business. In these cases, structural estimations are more appropriate to infer strategic consumer behavior, as we illustrate in the next section.

4. The Structural Model

We use a structural model instead of reduced-form regression because the former can address price endogeneity through explicit specification of the error structure together with instrumental variables, and it also allows us to conduct counterfactual analysis of alternative pricing strategies.

4.1. The Demand Model

We first consider the decision of a consumer who desires to travel in a particular city pair and on a particular departure date. To focus on the intertemporal substitution, we assume that both the market and the day of departure are given exogenously. Although it is possible that some consumers may also consider nearby airport or adjacent departure dates, in Appendix C we show that under the condition that price histories are perfectly correlated, ignoring such substitution will not bias our estimation of the fraction of strategic consumers. In what follows, we assume that within a market and a departure date, needs for travel arise exogenously along the booking horizon. A consumer arriving at booking time t can be either strategic or myopic. Our goal is to obtain an estimate of the fraction of strategic consumers, denoted by θ, in the population.

Whereas the time of arrival is exogenous, the time of purchase is endogenous. Myopic consumers arriving at t immediately make a purchase-or-not decision. If a myopic consumer decides not to buy at time t, he will never come back. Strategic consumers arriving at t may decide to postpone their purchase and come back later.[5] For computational reasons, we make a conservative assumption that a strategic consumer waits for at most one period of time.[6] Should she decide to wait, she will come back later and decide whether or not to purchase the ticket. The waiting decision of a strategic consumer depends on her expectation of future prices, which we discuss later.

[5] We assume that search cost is negligible in this setting comparing to the size of price change ($23.6 on average) and considering the wide availability of travel search engines. Also note that the strategic fraction and search cost cannot be identified simultaneously.

[6] Estimation with two or more waiting periods is extremely expensive computationally. We tried allowing for (at most) two-period waiting under perfect foresight and weak-form rational expectation. We found that the amount of strategic waiting, i.e., (amount of time waiting) × (number of people waiting), is almost the same, and so are the revenue impacts in the counterfactual analysis. In other words, the model measures strategic waiting, not strategic head counts.

Similar to conventional models in the field, consumers in our model are heterogeneous along the following dimensions: (1) time of arrival (Su 2007, Aviv and Pazgal 2008), (2) strategic or myopic (Su 2007, Cachon and Swinney 2009), and (3) product valuation (Levin et al. 2009). Different valuation distributions aggregate to different forms of the baseline demand function. For example, uniform value distribution can be represented by a linear baseline demand function. Moreover, consumers who arrive early tend to be lower-value customers than those who arrive late. To incorporate this heterogeneity, we later allow price sensitivities to vary for early and late arrivals.

Knowing the consumer's problem, we model the aggregate demand observed in each booking period. The aggregate demand d_{mdt} in a city-pair market m, on departure date d, and at booking time t is composed of three subgroups: (1) myopic consumers who arrive and decide to buy at time t, (2) strategic consumers who arrive and decide to buy at time t, and (3) strategic consumers who arrive at time $t-1$ but wait for one period and decide to buy at time t. Specifically,

$$d_{mdt} = \underbrace{(1-\theta)q(p_{mdt}, X_{mdt}, t)}_{\text{myopic who purchase at } t} + \underbrace{\theta(1-z_{mdt})q(p_{mdt}, X_{mdt}, t)}_{\text{strategic who arrive and purchase at } t} + \underbrace{\theta z_{md,t-1}q(p_{mdt}, X_{md,t-1}, t-1)}_{\text{strategic who arrive at } t-1 \text{ and purchase at } t}, \quad (1)$$

where z_{mdt} equals 1 if a strategic consumer decides to wait at time t, and 0 otherwise, and $q(\cdot)$ is the *baseline demand* that one would observe if all consumers were myopic. Note that the model itself does not impose the assumption of strategic behavior: only if θ is significantly different from zero will there be evidence of strategic behavior. The baseline demand is a function of price p_{mdt}, X_{mdt} representing market-departure date characteristics, booking time polynomials, and the final booking week dummy. Note that the effective price for those consumers who arrive in the last period $t-1$ but wait until t is the current price p_{mdt} rather than the last period's price $p_{md,t-1}$. Strategic consumers who decide to wait are not obligated to buy when they return, and the decision will depend on the new price they see. Thus, the demand contribution from those who arrive in the previous period is $q(p_{mdt}, X_{md,t-1}, t-1)$ rather than $q(p_{md,t-1}, X_{md,t-1}, t-1)$.

The demand model is flexible to incorporate many alternative specifications. For example, one could allow for the fraction of strategic consumers to vary by booking week to account for the possibility that strategic consumers may choose to arrive at different stages of the booking horizon, and for heterogeneous price sensitivities to account for the possibility that consumers who arrive early may be more price sensitive than those who arrive late. In the following subsections, we discuss in more detail the modeling assumptions, alternatives, and extensions.

4.1.1. Baseline Demand Functional Form. The baseline demand $q(p_{mdt}, X_{mdt}, t)$ in Equation (1) represents the potential demand we will observe if all consumers are myopic. A common way to model demand is the *additive linear* demand model: $q(p_{mdt}, X_{mdt}, t) = \alpha_m + \beta p_{mdt} + X_{mdt}\delta + \varepsilon_{mdt}$, where ε_{mdt} is the demand shock on market m, departure date d, and booking time t.[7]

Endogeneity of price and structure of demand shocks. Even though we control for market and departure date characteristics, prices may still be endogenous in this setting. First, pricing managers who monitor the demand and prices have better knowledge about the local demand than we do as econometricians. For example, when there is a special event, such as a conference or a convention, managers might adjust prices for the corresponding departure date and destination accordingly.

Second, pricing managers adjust prices based on previously realized demand shocks, and if demand shocks are autocorrelated, prices will be correlated with contemporaneous demand shocks as well. These particular features of the air-travel industry make price endogeneity a more prominent issue than in many other industries, such as the case of consumer goods in Hendel and Nevo (2013). Failure to address these endogeneity issues will result in biased estimates of price sensitivity, and hence the fraction of strategic consumers. The direction of this bias can go both ways. If price endogeneity is not properly accounted for, as usual, price sensitivities will be underestimated. During price drops, a part of the incremental demand from the price-sensitive myopic consumers will be attributed to strategic consumers, so the fraction of strategic consumers will be overestimated. During price surges, however, the observed decrease in demand is smaller with strategic consumers than without them. Since the potential decrease in demand without strategic consumers is underestimated, the part attributed to the strategic consumers, that is, potential decrease minus observed decrease, will be underestimated. The overall effect is ambiguous. To address the endogeneity, we allow for the following structure of demand shocks:

$$\varepsilon_{mdt} = \mu_{md} + \epsilon_{mdt}, \quad \epsilon_{mdt} = \rho\epsilon_{md,t-1} + \nu_{mdt},$$

[7] The main results of this paper will be based on the linear model, but we have also experimented with the nonlinear exponential demand model with multiplicative errors, $q(p_{mdt}, X_{mdt}, t) = \exp(\alpha_m + \beta p_{mdt} + X_{mdt}\delta + \varepsilon_{mdt})$, which yields quantitatively similar estimates of the strategic fraction, but takes a significantly longer time to estimate due to the high level of nonlinearity.

where the demand shock ε_{mdt} is decomposed to a market and departure date specific shock, μ_{md}, and a serially correlated shock governed by an AR(1) process, ϵ_{mdt}. Once we allow a departure date fixed effect, there is no need to control for departure date characteristics, and we will subsequently include departure date dummies in X_{mdt}. Price p_t is allowed to be correlated with the demand shock ε_{mdt} through correlation with μ_{md} and $\epsilon_{md,t-1}$. The remaining part of the demand shock, ν_{mdt}, is an idiosyncratic shock at booking time t. For example, ν_{mdt} may include noises in arrival patterns that we are not able to capture through polynomial approximations. It is possible that airline managers receive signals of such demand shock and adjust prices in the corresponding period. Thus, p_{mdt} can be correlated with ν_{mdt}. We will use instrumental variables (previous prices and variations of cumulative demand) to address this issue. Details will be presented subsequently in the estimation section, but it is important to note up front that the above error structure is critical to ensure that cumulative demand is a valid instrument. Without it, cumulative demand will not be orthogonal to demand shock ε_{mdt} due to its intertemporal correlation.

4.1.2. Consumer Expectations. The decision to wait by strategic consumers is based on their beliefs about future prices. We do not explicitly model beliefs of stockout, but we do so implicitly using bid prices, which, operationalized as the lowest posted price in our baseline demand model, reflect the level of remaining inventory or the probability of stockout. We model consumers' waiting decision under three different circumstances with a decreasing level of consumer sophistication: perfect foresight, strong-form rational expectations, and weak-form rational expectations. Under *perfect foresight*, consumers predict future prices perfectly. Under *rational expectations*, consumers cannot predict the exact price individually, yet as a group they predict the future price distribution correctly. The distinction between strong and weak form is that under the *strong form*, consumers take into account how airlines set future prices when forming the expectation, whereas under the *weak form*, the expectation is based on historical information only.

Perfect foresight. At time t, strategic consumers know the exact future price $p_{md,t+1}$. Though unrealistic, this model can be used as a benchmark. Consider a consumer with utility of air travel denoted by ϕ. She will decide to wait if $\phi - p_{md,t+1} > \phi - p_{mdt}$, or $p_{md,t+1} < p_{mdt}$, that is, if the price drops in the next period. Note that time discounting is negligible in this setting since we are looking at relatively short time periods such as days or weeks. Moreover, utility of travel does not depend on the time of purchase: the product is always consumed on the day of departure. As a result, a consumer's waiting decision does not depend on the value of the product. Moreover, when a consumer predicts future prices perfectly, risk attitude will not be a determinant of the waiting decision either. Note that the waiting decision is solely dependent upon price projections, and we do not consider costs of waiting (e.g., costs associated with obtaining a price quote again in the future) or benefits of waiting (e.g., flexibilities associated with keeping the schedule open and committing at a later time) due to the relative short period of time that we are considering.

Weak-form rational expectation. A strategic consumer i makes a prediction of the future price $p_{md,t+1}$ at time t based on information available to her, i.e., I_{mdt} and a personal shock, i.e., o_{imt}, $\tilde{p}_{i,m,t+1} = E[p_{md,t+1} \mid I_{mdt}] + o_{i,mt}$, where $E[p_{md,t+1} \mid I_{mdt}]$ is the expectation of future prices given information set I_{mdt}. It includes, for instance, information about the particular market, departure date and historical price trend. Under the rational expectation assumption, the distribution of consumer belief $\tilde{p}_{i,m,t+1}$ is the same as that of the true conditional distribution of future price $p_{md,t+1} \mid I_{mdt}$. Therefore, assuming risk neutrality,[8] the probability that strategic consumers wait can be calculated by $\Pr(p_{md,t+1} < p_{mdt} \mid I_{mdt})$ using a logit or probit model.[9] Under either weak-form or strong-form rational expectation, once we obtain the probability of strategic consumers waiting $\Pr_{mdt}$, we can replace z_{mdt} with $\Pr_{mdt}$ in Equation (1).

Strong-form rational expectation. Consumers now consider airlines' pricing strategy when forming an expectation of future prices. Consider the following sequential game played by airlines and consumers. At the beginning of time t, airlines decide on the price p_{mdt} that they will charge for this period. Customers then arrive and observe the price. Myopic customers who arrive at t make their purchase decision based on p_{mdt}. Strategic customers who arrive at t make a purchase-or-wait decision based on the current price p_{mdt} and their *own* projection of the future price $\tilde{p}_{md,t+1}$. Strategic customers who have waited from $t-1$ to t make their purchase decision based on the new price p_{mdt}. Demand d_{mdt} is thus realized. In the next period, airlines decide on a new price $p_{md,t+1}$ taking into account the newly realized demand d_{mdt}. The game thus repeats itself. Under the rational expectation assumption, strategic consumers *collectively* anticipate the true future price distribution. Their equilibrium beliefs and probability of waiting can be found by estimating how airlines set prices, described next.

[8] Risk attitudes can be incorporated in the model with a simple adjustment. For instance, if risk-adverse strategic consumers only wait when the expected price is at least \$10 lower than the current price, then $\Pr(p_{md,t+1} < p_{mdt} - \$10 \mid I_{mdt})$.

[9] The two models yield almost identical results. We use the probit model in this paper.

4.2. The Price Process

To estimate the demand model under the strong-form rational expectations, we need to specify how airlines set prices, also known as the *price process*. In the airline industry, this decision is complex and involves coordination from several departments. Typically, the pricing department will determine how many fare classes to offer and the associated fare levels, and both may change over time. In turn, the inventory management department will determine optimal seat inventory by fare class based on demand forecasts. Therefore, a complete supply model would *at least* require specifications of fare classes and associated fare levels, demand forecast updates of *each* fare class, and a dynamic inventory control model (or a dynamic inventory game in the case of a competitive market). Such a model is far too complex to be amenable both analytically and computationally within the scope of this paper. More importantly, putting competition aside, this approach would invoke assumptions about airlines' demand forecasting algorithm by fare class, which would likely be misspecified since little is known about them. Consequently, we take an empirical approach to approximate the price process, as many other papers do (e.g., Nair 2007). One drawback is that such a model cannot be used in simulations with alternative demand patterns, because the empirical pricing model only describes the *current* equilibrium.

To approximate the price process empirically, we identify three key determinants of short-term price fluctuations in the airline industry: unsold capacity, time to departure, and demand forecast (based on past demand patterns and departure date characteristics). We approximate unsold capacity using cumulative demand, because the total capacity within a city-pair market is largely fixed in the short term, and our estimation is done market by market. Note that short-term price fluctuations in the airline industry do not depend on costs, because fixed route planning costs are sunk and marginal costs are minimal. We also assume that airlines' price process does not account for strategic consumers, which is reasonable given that the current generation of revenue management systems are not designed to account for this behavior. We adopt a backward elimination procedure (exit level 0.2) to select variables from a broad set of candidates along these three dimensions: cumulative demand, booking time polynomials, lagged prices and demands, weekly and within-week price volatility, and departure date dummies. The resulting model is described as follows, which explains about 90% of the price variations for more than 70% of our markets:

$$p_{md,\,t+1} = \gamma_p p_{mdt} + \gamma_d \sum_{s=1}^{t} d_{mds} + X_{md,\,t+1}\gamma + \omega_{md,\,t+1}, \quad (2)$$

$$\omega_{md,\,t+1} \sim N(0, \sigma_{md,\,t+1}),$$

where $X_{md,\,t+1}$ includes booking time polynomials and departure date dummies, and $\omega_{md,\,t+1}$ is a random supply shock, which includes, for example, pricing adjustments by revenue managers, sporadic fare wars or fare hikes, or special promotions. After controlling for the lagged price, we do not find evidence of serial correlation in the supply residuals. However, we do find evidence of heteroscedasticity in the residuals over booking time, which we allow in our model.

It is important to briefly summarize how seat capacity is accounted for in the price process and demand models. In the price process, as we see above, unsold capacity is accounted for using cumulative demand. Because our estimation is conducted separately for each city pair, cumulative demand is highly correlated with unsold inventory, with some variations in flight offerings on different days of the week or different seasons. In the demand model, unsold seat capacity is best reflected through bid prices, which we approximate using lowest prices. As a matter of fact, because our demand data structure is broken down by origin–destination city pair, knowing capacity by flight or leg would not help much unless we take into account airline route networks, which is beyond the scope of this paper.

5. Identification and Estimation

5.1. Identification

As we outlined earlier, there is a significant amount of intertemporal price fluctuation across departure dates and booking weeks. The identification of the fraction of strategic consumers θ is based on the variation of price trends. More precisely, because the estimation is conducted for each market separately, the identification is based on the variation of price trajectories across booking periods and departure dates within a city-pair market.

We would observe different demand levels with and without strategic consumers only when the price falls or is expected to fall. Otherwise, strategic consumers behave in the same way as their myopic counterparts, and variations in demand are attributed only to price sensitivity. However, in the case of price reductions, variations in demand can be attributed to both price sensitivity and strategic consumers. If we are able to quantify the changes in demand induced by price sensitivity, the extra variation in demand can be attributed to strategic consumers. The question is, how do we identify price sensitivities and the fraction of strategic consumers separately? To illustrate this more precisely, recall the model under perfect foresight (Equation (1)) and consider the following cases described by price trends $z_{md,t-1}$ and z_{mdt}:

Case 1. $z_{md,t-1}=0$,
$z_{mdt}=0 \;\Rightarrow\; d_{mdt}=q(p_{mdt}, X_{mdt}, t)$;

Case 2. $z_{md,t-1}=0$,
$z_{mdt}=1 \;\Rightarrow\; d_{mdt}=(1-\theta)q(p_{mdt}, X_{mdt}, t)$;

Case 3. $z_{md,t-1}=1$,
$z_{mdt}=0 \;\Rightarrow\; d_{mdt}=q(p_{mdt}, X_{mdt}, t) + \theta q(p_{mdt}, X_{mdt}, t-1)$;

Case 4. $z_{md,t-1}=1$,
$z_{mdt}=1 \;\Rightarrow\; d_{mdt}=(1-\theta)q(p_{mdt}, X_{mdt}, t) + \theta q(p_{mdt}, X_{mdt}, t-1)$.

In Case 1, the price keeps rising from time $t-1$ to t and to $t+1$, so the observed sales consist only of the baseline demand, $d_{mdt}=q(p_{mdt}, X_{mdt}, t)$. Thus, $q(\cdot)$ can be identified; that is, price sensitivities are identified using instances of consecutive increasing prices. Once the baseline demand function is identified, each of the other three cases can help identify the fraction θ. In sum, it is the variation in z, i.e., the price *trend* (rather than price level), that identifies the fraction of strategic consumers. Note, however, that the fraction θ is overidentified, since we can solve the parameters with any two cases. This means that we can actually identify more parameters, for example, time-variant fraction of strategic consumers and heterogeneous price sensitivities.

So far, we have discussed the identification for models under perfect foresight. In fact, the same logic also carries over to models under rational expectations since the only difference is that z_{mdt} becomes a probability rather than a dichotomous variable. The variation in z (now Pr) still serves as the source of identification for θ. In summary, we obtain the identification because strategic consumers behave differently under different expectations of future prices.

5.2. Estimation

Note that our demand model is nonlinear in its *parameters* $(\theta, \beta, \Delta, \rho)$, where Δ denotes a set of parameters including the intercept α, departure date dummies (one dropped), the final booking week dummy, and booking week polynomials δ. We use a nonlinear generalized method of moments (GMM) with moment conditions $E[Y'\nu(\theta, \beta, \Delta, \rho)]$ for estimation, where Y is the set of instruments to be discussed shortly. There are two key challenges in this nonlinear GMM estimation: (1) finding the global optimum to the nonlinear minimization problem with high dimensions and (2) accounting for fixed effects and serial correlations in error terms. We design an algorithm that greatly reduces the dimensionality and accounts for fixed effects and serial correlation via panel data partial differencing. The exact procedure is described in Appendix D, which also derives asymptotic variance of the proposed estimator in our particular context. Briefly, the key idea is to first transform the nonlinear problem into a linear problem to estimate a partial set of parameters and address the error structure given other parameters, and then minimize over these parameters.

We perform estimation for each city-pair market since each market demonstrates significantly different patterns of time trends, seasonality, day-of-week effects, and price sensitivities. Pooling all markets together would result in misspecification of the baseline demand model, which would further bias the estimation of the fraction of strategic consumers. To mitigate this effect we would need hundreds of market-specific coefficients. Instead, the estimation is more accurate and efficient when it is performed for each market separately.

5.2.1. Variables. The baseline demand includes the following factors.

(1) *Price.* At the daily booking level, we use the lowest price as a representative price. This is a good approximation since we care most about strategic consumers who are price-sensitive. Also, on most booking days, there is no obvious deviation between the lowest price and the alternative average of the three lowest prices, hence the estimation results we observe are very similar. To aggregate daily price points to the weekly level, there are at least two options—the minimum and the average of the lowest daily prices within a week. Significant differences mostly appear in the final week before departure, when prices may change rapidly from day to day. For this reason we use the average of the lowest daily prices as the measure of the weekly price.

(2) *Booking time.* We use a dummy for the final booking week before departure, and booking week t, t^2, t^3; the incremental explanatory power is minimal when including higher polynomial terms.

(3) *Departure date dummies.* Demand varies with departure date greatly. For example, during the vacation seasons, leisure destinations experience many more travelers than they normally do. Also, departures tend to cluster around weekdays in business markets, and around weekends in leisure markets.

Both weak- and strong-form rational expectation models include booking time and departure date variables. The weak-form model also includes previous price trends, fall(s) and rise(s), to predict future price changes. Note that the effect can be different over the booking horizon, early versus late, and across markets, leisure versus business.[10]

[10] We also considered including lagged prices and within-week or weekly price volatilities. We found little incremental explanatory power of these variables on top of controlling for previous price trends.

5.2.2. Instrumental Variables. Recall that we decompose the demand shock into a fixed effect component, a serially correlated component, and an idiosyncratic shock ν_{dmt} at booking time t. The concern is that p_{dmt} can be correlated with ν_{dmt}. Therefore, we need to find instruments that are correlated with p_{dmt}, but not with the current idiosyncratic demand shock ν_{dmt}.

A valid instrument in this context should vary with the booking period, which makes commonly used instruments invalid in our setting. For example, cost-based supply shifters, such as fuel prices and labor costs, are not valid because short-term prices (weekly or daily prices) do not depend on these factors. They only affect prices in the long run. Neither can we use Hausman-style instruments at the firm level because our model and estimation are at the market level rather than firm level; thus an airline-specific shock is not useful in our setting. Finally, instrumental variables commonly used in studies of airline industry, such as distance and demographics (Borenstein and Rose 1994, Granados et al. 2012), are not applicable either since they are time-invariant market-level variables.

One advantage of the specified error structure is that it allows us to find valid instruments. As we remove fixed effects and serial correlations from the demand shock, the remaining shock ν_{dmt} is thus uncorrelated with previous prices and demand. At the same time, previous prices and demands, especially cumulative demand, which is a proxy for inventory level in given a market, is correlated with current prices thanks to revenue management practices. Consequently, we are able to construct the following moment conditions:

$$E[p_{mds}\nu_{mdt}] = 0, \quad s < t,\ t = 2, 3, \ldots, T; \tag{3}$$

$$E\left[\left(\sum_{s=1}^{t-1} d_{mst}\right)\nu_{mdt}\right] = 0, \quad t = 2, 3, \ldots, T. \tag{4}$$

Thus, we have $T-1$ moment conditions based on previous prices and one moment condition based on cumulative demand, and two parameters (θ, β) to be identified. As we discussed in the section Identification, this overidentification can also be used to identify time-variant fractions of strategic consumers or heterogeneous price sensitivities.

There are multiple ways to construct instruments based on cumulative demand. One is to compute cumulative demand only with booking data but without accounting for cancellations. Alternatively, one could compute cumulative demand accounting for cancellations. Cancellations affect price decisions because they increase unsold seats, but they are not likely to affect demand, because cancellations can be largely viewed as an independent process from the arrival process.[11] Third, one could predict prices based on previous price and cumulative demand accounting for cancellations (i.e., the price process in §4.2), and use predicted price $\hat{p}_{mdt}$ as an instrument for p_{mdt}. Because $\hat{p}_{mdt}$ is based on information up to $t-1$, it is uncorrelated with demand shock ν_{dmt}. We test all three variations of instruments in estimation. We expect $\hat{p}_{mdt}$ to be more efficient because it combines multiple sources of information and mimics airlines' pricing decisions more closely.

6. Results

Our estimations provide consistent findings of strategic consumers across markets under various model specifications. We first illustrate these findings using different model specifications for two representative markets, and then we summarize them across all markets. The representative markets are a leisure market, labeled L, with Orlando, Florida, as the destination, and a business market, labeled B, with Atlanta, Georgia, as the destination (the origins of both markets are disguised for confidentiality). We estimate the price elasticity of market L to be 1.89 (using $\beta = -0.254$ from Table 3), and that of market B to be 0.375. Incidentally, these elasticity values fall within the range of elasticities of 0.181 to 2.01 across 85 air-travel demand studies (Gillen et al. 2003), and they are also roughly in line with the average cross-channel price elasticities for leisure and business travel of 1.45 and 0.62 (excluding opaque agencies) in Granados et al. (2012).

6.1. Results Under Different Moment Conditions

In Table 3 we report results under perfect foresight for the following moment conditions: (1) current price and previous prices, (2) only previous prices, (3) cumulative demand without accounting for cancellations and previous prices, (4) cumulative demand accounting for cancellations and previous prices, and (5) predicted prices and previous prices. Predicted prices are estimated using the price process model. All five models allow for departure date fixed effects and serial correlation in demand shocks. Table 3 shows that all models lead to similar estimates of the fraction of strategic consumers, between 18.5% and 25.1%. Comparing the results of model (1), which assumes current price is orthogonal to residual demand shocks, with models (2)–(5), which instead use instruments for current price, we find that, as expected, price sensitivity is underestimated in the former. The price sensitivity is estimated to be -0.179

[11] One may also want to use *cancellations* directly as an instrument. However, it turned out to be a weak instrument in many markets due to its small amount of variation by nature. Cumulative demand accounting for cancellations, however, does not suffer from this problem.

Table 3 Comparison of Moment Conditions Under Perfect Foresight—Market L

Moments	(1) Current and previous prices	(2) Previous prices	(3) Cumulative demand w/o cancellation and previous prices	(4) Cumulative demand w/ cancellation and previous prices	(5) Predicted price based on (4) and previous prices
Fraction	0.185***	0.232***	0.244***	0.248***	0.251***
	(0.048)	(0.068)	(0.060)	(0.057)	(0.057)
Price	−0.179***	−0.269***	−0.291***	−0.275***	−0.254***
	(0.022)	(0.058)	(0.048)	(0.047)	(0.044)
Booking time t	−2.649	−3.267	−3.536	−3.532	−3.431
	(2.848)	(3.029)	(3.047)	(3.040)	(3.095)
t^2	1.248**	1.297**	1.327**	1.330**	1.328**
	(0.500)	(0.530)	(0.533)	(0.532)	(0.542)
t^3	−0.070***	−0.070***	−0.071***	−0.071***	−0.072***
	(0.025)	(0.027)	(0.027)	(0.027)	(0.028)
Final week	7.961	13.375**	14.734**	14.064**	13.225**
	(5.032)	(5.709)	(5.815)	(5.816)	(5.915)
Departure date fixed effects	Yes	Yes	Yes	Yes	Yes
Serial correlation	Yes	Yes	Yes	Yes	Yes
No. of observations	585	585	585	585	585

**$p < 0.05$; ***$p < 0.01$.

in model (1) and −0.291 to −0.254 in the subsequent models. In this particular market, the orthogonality assumption leads to an underestimation of the fraction of strategic consumers, with 18.5% in model (1) versus 23.2% to 25.1% in the other models. In some markets, we observe overestimation of the fraction.

All models with instruments for current price yield very similar estimates, with models (3)–(5) using both previous prices and cumulative demand being slightly more efficient. We will use model (5) with $\hat{p}_{dmt}$ as an instrument for subsequent analysis, because it shows a slight improvement in efficiency (smaller standard errors) for the majority of markets. Note that using cumulative demand as an instrument provides very similar results.

6.2. Results Under Different Consumer Expectation Models

Next we compare the estimated strategic fractions under different assumptions of price expectations: perfect foresight and rational expectations (weak and strong). We first discuss the results of price prediction models for rational expectations and then we discuss the fraction of strategic consumers under the different models.

6.2.1. Predicting Prices. Columns (1)–(4) in Table 4 show results for weak-form rational expectation. Similar to what we have shown for price fluctuations in Table 1, the probability of future prices falling is affected by departure dates and booking time, and in addition, by the trajectory of historical prices. We tested two models under weak-form rational expectation using different lengths of price history: the first model (columns (1) and (3)) uses only the most recent price change, and the second model (columns (2) and (4)) uses the two most recent price changes.

Results in columns (1) and (3) show that a price drop is likely to be followed by another price drop. However, for different types of markets, leisure versus business, this effect occurs in different booking periods. In leisure markets, an early price drop in the booking horizon is likely to be followed by another drop, whereas for business markets this case of consecutive fare drops is more likely closer to departure.[12] Intuitively, in business markets where prices are more likely to increase toward the departure date, a price drop would be a *stronger* signal of low demand for that particular date and is thus more likely to be followed by another drop.

We then add more historical price trends into the prediction model. Columns (2) and (4) show that if we have more knowledge about the recent price trajectory, our prediction will improve by a small amount. Results from these two columns also show that it is unlikely that two consecutive price drops (or rises) will be followed by a third drop (or rise). The fitted models show reasonable improvements from the null model (with only intercept), as indicated by a likelihood ratio index (pseudo-R^2) ranging from 0.170 to 0.195. The percentage of price changes correctly predicted ranges from 65.4% to 73.9%. These goodness-of-fit statistics suggest sizable predictive power of the covariates, which is also comparable to the 75% accuracy claimed by Bing Travel.

Although we show this result in two representative markets, the patterns are consistent across all markets.

[12] Here early stage is defined as at least 21 days ahead of departure. We also tried using 45, 14, and 7 days, and we observed the same phenomenon, but at different significance levels.

Table 4 Models Predicting Future Prices and Trends—Markets L and B

	Weak rational expectation probit model				Strong rational expectation pricing process	
	Market L		Market B		Market L	Market B
	(1)	(2)	(3)	(4)	(5)	(6)
Drop ∗ early stage	0.696*** (0.150)		0.120 (0.146)			
Drop ∗ late stage	0.263 (0.295)		0.787** (0.337)			
Drop–drop		Omitted		Omitted		
Rise–drop		1.171*** (0.209)		0.614*** (0.185)		
Rise–rise		1.672*** (0.221)		0.538*** (0.191)		
Drop–rise		0.953*** (0.192)		0.553*** (0.176)		
Previous price					0.827*** (0.042)	0.563*** (0.052)
Cumulative demand w/ cancellation					0.097*** (0.021)	0.193** (0.083)
Booking time t	−1.800*** (0.383)	−2.780*** (0.663)	−1.596*** (0.386)	−2.214*** (0.659)	14.463*** (3.526)	44.814*** (4.835)
t^2	0.310*** (0.062)	0.455*** (0.098)	0.295*** (0.064)	0.368*** (0.099)	−3.665*** (0.620)	−9.768*** (0.854)
t^3	−0.016*** (0.003)	−0.023*** (0.005)	−0.017*** (0.003)	−0.019*** (0.005)	0.226*** (0.031)	0.596*** (0.045)
Departure date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	585	585	585	585	585	585
Likelihood ratio index (Pseudo-R^2)	0.195	0.260	0.170	0.188		
Correctly predicted (%)	69.8	73.9	65.4	67.2		
Adjusted R^2					0.868	0.729

Notes. Columns (1) and (3): Price drops are predicted based on most recent price change—drop or rise. "Early stage" is defined as at least 21 days ahead of departure, and "late stage" otherwise. Columns (2) and (4): Price drops are predicted based on the trend of recent price changes—drop–drop, drop–rise, rise–drop, or rise–rise.
$^{**}p < 0.05$; $^{***}p < 0.01$.

In summary, price changes are predictable to a certain extent: destination type, departure date, booking time, and price trajectory all carry information to predict future price changes. The first three elements are common knowledge to travelers. The price trajectory may not be as transparent, but it is more likely to be transparent to consumers who are strategic, such as those who visit sites like Bing Travel or Kayak.com for historical fare charts. Columns (5) and (6) show results under strong-form rational expectation, i.e., the price process. Both previous price and cumulative demand are additional predictors of future price.

6.2.2. Strategic Consumers Across Models. Table 5 shows the fraction of strategic consumers under different consumer expectations for market L. We find persistent evidence of strategic consumers regardless of the assumptions about expectations of future prices. Under perfect foresight, the fraction is 25.1%. Under rational expectations, the estimates are higher: 35.8% and 30.8% under weak form, and 28.3% under strong form. All estimates are statistically significant.

In market L, the estimated fraction of strategic consumers is smaller under perfect foresight. In some other markets, it is the opposite. This is reasonable because when prices drop (or more so than rise), all strategic consumers wait under perfect foresight, whereas only a fraction waits under rational expectation. Thus, with the same amount of demand shift observed in the data, we would estimate more underlying strategic consumers under rational expectation. But when prices rise (or more so than drop), no strategic consumer waits under perfect foresight, whereas a fraction of all strategic consumers still waits under rational expectation. In this case, with the same lack of demand shift observed in the data, we would estimate less strategic consumers under rational expectation. Which one of the above dominates can differ across markets as demand and price trends vary.[13]

[13] To see this mathematically, let's consider a simplified two-period problem with total demand d. Suppose we observe demand data d_1

Table 5 Fraction of Strategic Consumers Under Different Consumer Expectations—Market L

	(1) Perfect foresight	(2) Weak-form rational	(3) Weak-form rational	(4) Strong-form rational
Fraction	0.251***	0.358***	0.308***	0.283***
	(0.057)	(0.064)	(0.065)	(0.067)
Price	−0.254***	−0.232***	−0.238***	−0.252***
	(0.044)	(0.050)	(0.048)	(0.051)
Booking time t	−3.431	−3.271	−3.444	−1.648
	(3.095)	(2.996)	(2.954)	(2.879)
t^2	1.328**	1.346**	1.364***	1.028**
	(0.542)	(0.525)	(0.518)	(0.505)
t^3	−0.072***	−0.075***	−0.075***	−0.057**
	(0.028)	(0.027)	(0.026)	(0.026)
Final week	13.225**	13.323**	12.621**	11.133**
	(5.915)	(5.490)	(5.418)	(5.055)
Departure date fixed effects	Yes	Yes	Yes	Yes
Serially correlated demand shock	Yes	Yes	Yes	Yes
No. of observations	585	585	585	585

Notes. Column (2): Price drops are predicted based on the most recent price change—drop or rise. Column (3): Price drops are predicted based on the trend of recent price changes—drop–drop, drop–rise, rise–drop, or rise–rise.
$^{**}p < 0.05$; $^{***}p < 0.01$.

6.2.3. Heterogeneous Price Sensitivities. In the airline industry, one common belief is that consumers who arrive late are also less price sensitive. As we see in the identification section, estimations of price sensitivity and of the fraction of strategic consumers are closely related to each other. Therefore, there may be a concern that the fraction of strategic consumers we identify could be partially driven by the restriction of homogeneous price sensitivity throughout the booking period. To test this, we now allow different price sensitivities for early and late arrivals, and the results are shown in Table 6. Although varying price sensitivities in only two periods is still restrictive, the results are consistent under several alternative specifications of late arrivals. Alternatively, we also allow strategic and nonstrategic consumers to have different price sensitivities, and the results are again similar.

6.3. Fraction of Strategic Consumers Across Markets

We summarize the estimation results across markets in Table 7. For each market in our data, we estimate both perfect foresight and strong-form rational expectation models (results are similar to weak-form rational expectation). We obtain on average 12.1% strategic consumers under the former and 12.7% under the latter. We also find a sizable heterogeneity across markets, with standard deviations of 7.4% and 8.9%, respectively.

6.3.1. Intermarket Analysis. To see how the fraction of strategic consumers is correlated with market characteristics, we use stepwise regressions with backward elimination (exit level 0.2) to identify significant predictors among multiple factors (see Table 8 for details). We find that consumers traveling on shorter routes are more likely to be strategic, perhaps because they have alternate modes of ground transportation. Markets with higher average prices also exhibit a higher fraction of strategic consumers, possibly because the stakes are higher. Also, markets with higher price volatilities will have more strategic consumers, because consumers have more chances to be strategic.

6.4. Fraction of Strategic Consumers over Time

To investigate the arrival pattern of strategic consumers across the booking horizon, we estimate nonparametrically a time-variant vector of the fractions of strategic consumers. Figure 1 shows the fraction of strategic consumers in the 13-week period before departure under the strong-form rational expectation. We group city pairs by destination because the results are similar. We separate international and domestic destinations since their arrival patterns are likely to be different. Interestingly, based on *estimated* price sensitivities, three clusters appear within domestic destinations, with β smaller than −0.001, between −0.01 and −0.1, and above −0.1, respectively. We

and $d-d_1$ for the two periods when the price rises, and d_1', $d-d_1'$ when the price falls. Under perfect foresight, $d_1 = N_1 + S$, $d_1' = N_1$, where N_1 denotes the total number of nonstrategic consumers arriving in the first period, and S denotes the strategic consumers arriving in the first period. Since there are only two stages, no strategic consumers arrive in the second stage. Under rational expectation, $d_1 = N_1 + \phi S$, $d_1' = N_1 + \phi' S$, where ϕ, ϕ' denote probabilities of prices rise in each case, and $\phi > \phi'$. We are interested in $\theta = S/N_1$. We solve that under prefect foresight, $\theta_p = (d_1 - d_1')/d_1$; under rational expectation, $\theta_r = (d_1 - d_1')/(d_1 + (\phi d_1' - \phi' d_1))$. Thus, when $\phi d_1' \geq \phi' d_1$, we have $\theta_r \geq \theta_p$; when $\phi d_1' < \phi' d_1$, we have $\theta_r < \theta_p$.

Table 6 Price Sensitivities of Early vs. Late Arrivals—Market L

	Less than 1.5 months		Less than 21 days		Less than 7 days	
Late arrival[a]	Perfect foresight (1)	Strong-form rational (2)	Perfect foresight (3)	Strong-form rational (4)	Perfect foresight (5)	Strong-form rational (6)
Fraction	0.224***	0.297***	0.247***	0.240***	0.223***	0.216*
	(0.067)	(0.095)	(0.073)	(0.083)	(0.082)	(0.118)
Early arrivals	−0.270***	−0.211***	−0.223***	−0.202***	−0.225***	−0.216***
	(0.066)	(0.070)	(0.057)	(0.059)	(0.072)	(0.080)
Late arrivals	−0.282***	−0.248***	−0.265***	−0.229***	−0.251***	−0.245***
	(0.059)	(0.061)	(0.049)	(0.055)	(0.064)	(0.070)
No. of observations	585	585	585	585	585	585

Notes. The fraction of strategic consumers is not statistically significant in market B, but the point estimates are again similar: 8.9% without heterogeneous price sensitivities, and 7.4%, 8.4%, and 5.2% with heterogeneous price sensitivities under rational expectation.

[a]Late arrivals are defined by the time left to departure.

*$p < 0.1$; ***$p < 0.01$.

Table 7 Fraction of Strategic Consumers Across Markets

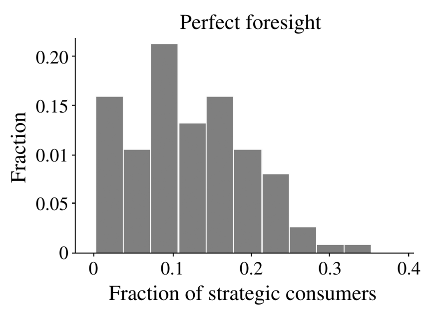
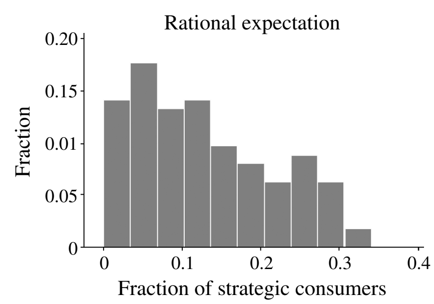
	Perfect foresight		Rational expectation (strong)	
Percentile	Strategic fraction (%)	Histogram	Strategic fraction (%)	Histogram
5%	1.1		0.7	
25%	6.3		5.2	
50%	11.6		11.2	
75%	16.8		19.2	
95%	24.4		28.3	
Mean	12.1		12.7	
Std. dev.	7.4		8.9	

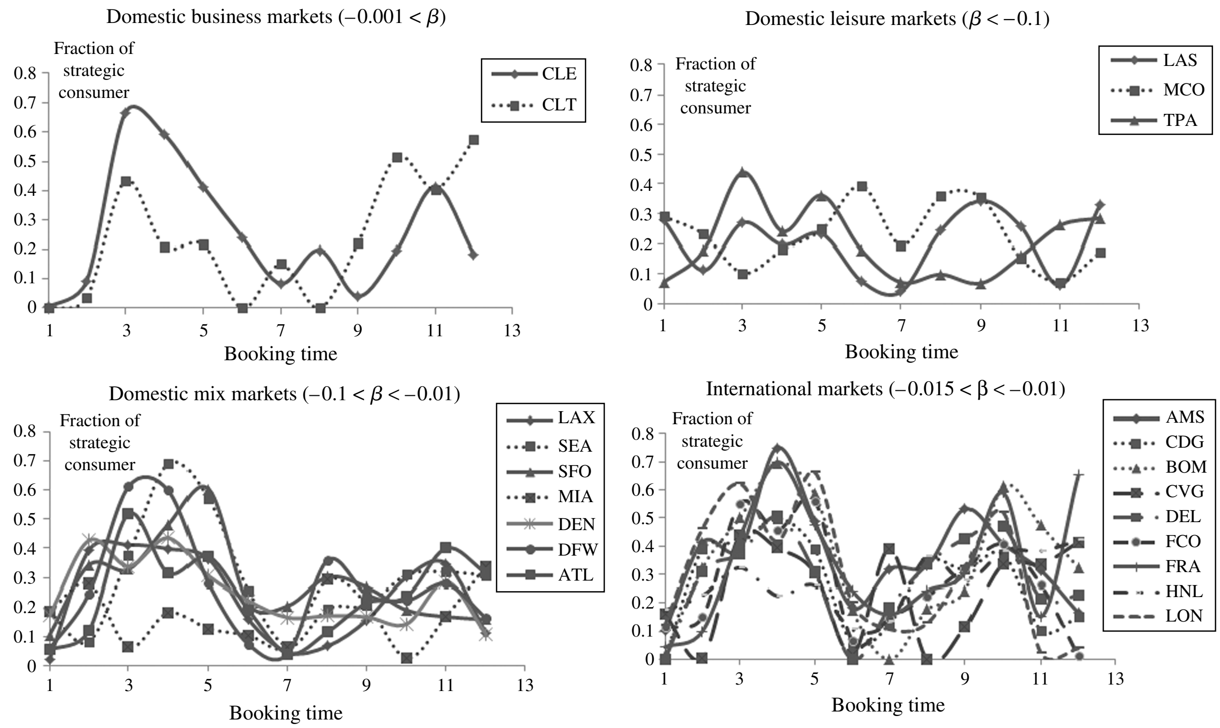
Table 8 Explaining the Fraction of Strategic Consumers with Market Characteristics

	(1) Perfect foresight	(2) Rational expectation (strong)
ln(distance)	−0.035**	−0.036**
	(0.015)	(0.018)
Avg. market price	0.048*	0.062*
	(0.026)	(0.034)
Price volatility (coefficient of variation)		0.123*
		(0.065)
Low-cost carrier market share		0.132
		(0.096)
Constant	0.101	−0.039
	(0.086)	(0.107)
No. of observations	114	114
Adjusted R-square	0.0293	0.0305

Notes. Results are based on stepwise regressions (backward selection with exit level 0.2). Candidate variables include the following: estimated price sensitivity, distance, international destination, origin and destination demographics (population and income), hub indicators, market competition (Herfindahl index), low-cost carrier market share, load factor (average of all direct and connecting flights weighted by passenger volume), average market price, price volatility (standard deviation and coefficient of variation), online market share (percentage of tickets distributed online), and opaque market share (percentage of tickets distributed through online opaque channels, i.e., Priceline and Hotwire).

*$p < 0.1$; **$p < 0.05$.

Figure 1 **Fraction of Strategic Consumers Varying with Booking Time (Grouped by Destination)**



label the three groups business markets, mix markets, and leisure markets, respectively. The breakdown follows intuition. For example, Charlotte, North Carolina, and Cleveland, Ohio, are in the business group, whereas Orlando, Tampa, and Las Vegas are in the leisure group. Destinations such as New York, San Francisco, and Seattle are in the middle group (mix). Another interesting observation is that price sensitivities of international destinations fall between the domestic business and leisure groups, with values between −0.01 to −0.015.

Figure 1 shows that the fraction of strategic consumers has two modes over the booking horizon. One is around week 3 to week 5 (two months before departure), when the risk and cost of waiting is lower because typically there is still a good amount of unsold seats; the other mode is week 9 to week 11 (roughly three weeks to departure), when strategic consumers are likely in search of last-minute deals. This bimodal distribution is consistently observed for all types of destinations, although it is less prominent in popular leisure markets such as Las Vegas (LAS) and Orlando (MCO). In these popular leisure destinations, there is less price dispersion throughout the booking period because there is a more steady offer of leisure level fares throughout the booking curve, which results in steady arrivals of strategic consumers.

7. Counterfactual Analysis: Nondecreasing Price Commitment

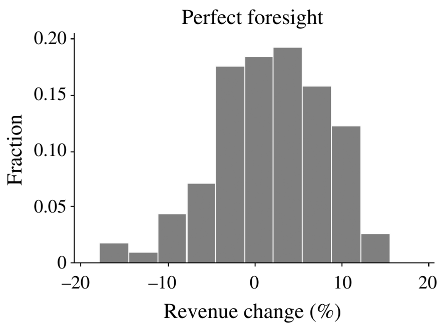
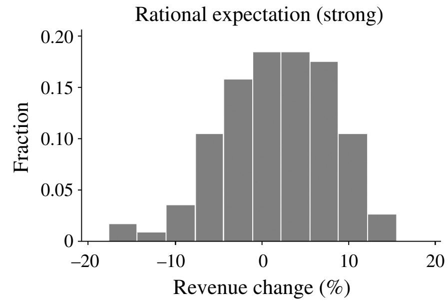
Now that we have robust evidence of strategic consumers, what are the revenue implications? What pricing strategy should airlines take in response? How should the strategy vary by market?

One common approach to eliminate strategic waiting is to commit to fixed or nondecreasing price paths (e.g., Aviv and Pazgal 2008), which happens to be the practice used by many low-cost carriers. They often have an everyday-low-price strategy where prices go up close to departure as the seats for sale become scarce. The question is: would it be better for airlines to commit to nondecreasing prices? Computing the optimal nondecreasing price path is itself a question requiring separate analytical efforts beyond the scope of this paper. Rather, we examine the impact of a heuristic nondecreasing price scheme that adds a small twist to the current pricing strategy. We start from the current initial prices and predict a candidate price point for the next period using the current pricing strategy.[14] We set the future price as the maximum of this candidate price and the current price to guarantee the nondecreasing property.

Each simulation involves computing a new set of demands and prices according to the nondecreasing

[14] We also randomize the initial prices based on its empirical distribution. The simulated revenues deviate no more than 0.5%, and the results from the intermarket analysis are consistent.

Table 9 Counterfactual Analysis Across All Markets

	Perfect foresight		Rational expectation (strong)	
Percentile	ΔRevenue (%)	Histogram	ΔRevenue (%)	Histogram
5%	−9.0		−8.3	
25%	−1.5		−2.1	
50%	2.2		1.8	
75%	6.7		6.8	
95%	10.9		10.9	
Mean	2.1		2.0	
Std. dev.	6.3		6.3	

price heuristic and that no consumer behaves strategically because airfares can only increase over time. The results of simulating nondecreasing price commitment across markets are summarized in Table 9. The impact on revenues across markets had mixed results, with some markets incurring revenue gains and others markets incurring revenue losses. The ranges of the revenue changes are $[-1.5\%, 6.7\%]$ under perfect foresight and $[-2.1\%, 6.8\%]$ under rational expectations, as measured by the first and third quartiles.

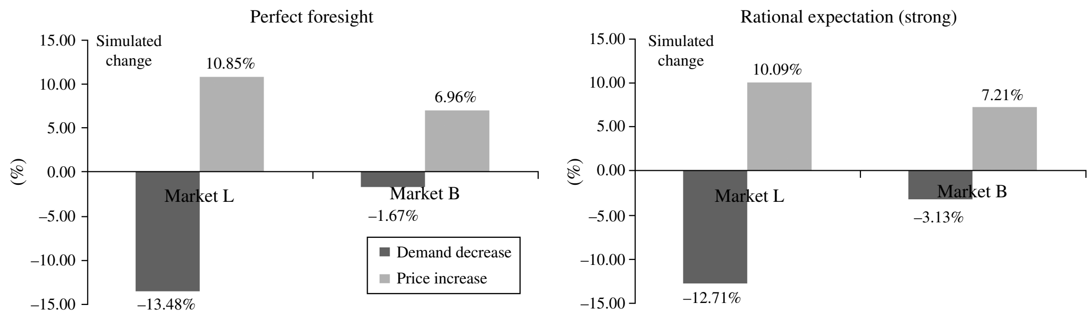
These mixed results can be explained by examining the simulations for the representative markets L and B. Table 10 shows results of the counterfactual analysis based on 1,000 simulations under perfect foresight and strong-form rational expectation for markets L and B. For the business market B, commitment to nondecreasing prices leads to 3.85% to 5.17% revenue increases. However, in the leisure market L, revenues decrease by 3.91% to 4.10%. These revenue changes have a low standard deviation across simulations. More generally, this pattern is not specific to the representative markets, but it holds in general for business and leisure markets.

To explain this counterintuitive phenomenon, consider the two effects of strategic consumers as illustrated in Figure 2 using the simulated results: the price-reduction effect and the demand-increasing effect. Strategic consumers drive down prices. Airlines thus gain lower revenue from high-value customers who would otherwise pay a higher fare. Yet strategic consumers also drive up demand. First, market demand is higher since prices are lower. Second,

Table 10 Counterfactual Analysis for Markets L and B

	(1) Current	(2) Nondecreasing price commitment	(2) − (1) Percentage of change	Std. dev. (%)
		Market L		
Perfect foresight				
Revenue ($1,000 per departure day)	97.540	93.548	−4.10	(0.52)
Demand (per departure day)	408.586	353.516	−13.48	(0.89)
Price (weighted) ($)	238.725	264.623	10.85	(0.84)
Price ($)	234.949	253.451	7.88	(0.56)
Rational expectation (strong)				
Revenue ($1,000 per departure day)	98.012	94.182	−3.91	(0.49)
Demand (per departure day)	406.728	355.029	−12.71	(0.90)
Price (weighted) ($)	240.977	265.281	10.09	(0.83)
Price ($)	236.142	254.217	7.66	(0.58)
		Market B		
Perfect foresight				
Revenue ($1,000 per departure day)	51.297	53.949	5.17	(0.47)
Demand (per departure day)	184.585	181.501	−1.67	(0.10)
Price (weighted) ($)	277.906	297.239	6.96	(0.55)
Price ($)	235.668	260.087	10.36	(0.55)
Rational expectation (strong)				
Revenue ($1,000 per departure day)	51.044	53.011	3.85	(0.43)
Demand (per departure day)	183.784	178.037	−3.13	(0.20)
Price (weighted) ($)	277.739	297.750	7.21	(0.59)
Price ($)	235.595	259.997	10.36	(0.55)

Figure 2 **Demand and Price Changes with Nondecreasing Price Commitment**



strategic customers who would otherwise walk away end up buying because they can time their purchase to buy at a lower fare. By eliminating strategic consumers, airlines can increase prices but lose demand. The overall effect of eliminating strategic consumers thus depends on which of the above two effects dominates, and this is further determined by heterogeneity in the composition of high- and low-value customers in the market. In business markets with proportionally more high-value customers, the price-increasing effect dominates, whereas in leisure markets with proportionally more low-value customers, the demand-decreasing effect dominates.

7.1. Intermarket Analysis

To see what market characteristics affect revenue impacts of nondecreasing price commitment, we again use stepwise regression with backward elimination (exit level 0.2) to identify significant predictors among various market characteristics, including both the *estimated* fraction of strategic consumers and price sensitivities, and other variables constructed using auxiliary data from the Department of Transportation for the corresponding period. The results are shown in Table 11. Columns (1) and (2) show that markets with larger β (less price sensitive) are likely to see more benefits from such commitment, holding the fraction of strategic consumers constant. This is consistent with our finding above that market B benefits from a nondecreasing price commitment but market L does not. Holding price sensitivity constant, markets with more strategic consumers will benefit more (or suffer less) from such commitment. Columns (3) and (4) find that markets with lower online penetration, which are typically more businesslike, benefit more from nondecreasing price commitment. Markets with higher price volatility, offering more chances for consumers to be strategic, benefit more as well. Short-haul routes also benefit. Recall these routes also exhibit a higher fraction of strategic consumers.

7.2. Nondecreasing Price Commitment in Monopoly Markets

Note that in markets with multiple airlines, a nondecreasing price is sustained only if all airlines commit to it. However, without specifying a complete dynamic game from the airlines side, which is out of scope of this paper, we do not know whether such commitment

Table 11 **Explaining Revenue Impacts of Nondecreasing Price Commitment with Market Characteristics**

	(1) Perfect foresight	(2) Strong rational expectation		(3) Perfect foresight	(4) Strong rational expectation
Strategic fraction	0.142**	0.108*	Online market share	−0.140***	−0.153***
	(0.065)	(0.064)		(0.038)	(0.042)
Price sensitivity	0.190**	0.230**	Price volatility	0.122**	0.083
	(0.094)	(0.097)	(coefficient of variation)	(0.060)	(0.062)
			ln(distance)	−0.012**	−0.012**
				(0.006)	(0.006)
			Load factor		0.147
					(0.110)
Constant	0.015	0.025**	Constant	0.118**	0.074
	(0.012)	(0.011)		(0.049)	(0.058)
No. of observations	114	114	No. of observations	114	114
Adjusted R-square	0.0691	0.0541	Adjusted R-square	0.1455	0.1159

Notes. Results in columns (3) and (4) are based on stepwise regressions (backward selection with exit level 0.2). Candidate variables include the following: sensitivity, distance, international destination, origin and destination demographics (population and income), hub indicators, market competition (Herfindahl index), low-cost carrier market share, load factor (average of all direct and connecting flights weighted by passenger volume), average market price, price volatility (standard deviation and coefficient of variation), online market share (percentage of tickets distributed online), and opaque market share (percentage of tickets distributed through online opaque channels, i.e., Priceline and Hotwire).

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

can be sustained in a competitive equilibrium. What we show so far is a *potential* for earning higher or lower revenues. To see whether our general insight is immune to the effects of competition, we examine the 19 monopoly markets identified in our sample. Here monopoly markets are defined as those with one airline holding more than 90% market share. Although this sample is not large enough to conduct an intermarket regression, we note the following observations. We again observe heterogeneity in revenue impacts of nondecreasing price commitment. The ranges are $[-3.3\%, 8.8\%]$ and $[-3.7\%, 8.8\%]$ under perfect foresight and rational expectation, respectively. The five markets (with destinations such as Las Vegas and Seattle) that see a negative impact have an average price sensitivity of -0.027, whereas those (with destinations such as Buffalo, New York, and London) with positive impact have an average price sensitivity of -0.0014. This validates our previous findings that markets with lower price sensitivities benefit more from a nondecreasing price path.

8. Conclusions and Discussions

We provide evidence of strategic consumers in the air-travel industry, and this evidence is robust to various modeling assumptions. We obtain an estimate of 5.2% to 19.2% of strategic consumers on average across markets under the rational expectation assumption, as measured by the first and third quartiles. Contrary to the predominant belief, our counterfactual analysis shows that using nondecreasing price commitment to eliminate strategic behavior is not always preferable. In business markets, where a large proportion of consumers are relatively less price sensitive, the presence of strategic consumers tends to drive down the total revenue through lower prices. Eliminating these consumers will yield higher prices with a relatively smaller reduction in demand, for a net gain. However, in leisure markets, the presence of strategic consumers increases revenues by inducing higher demand. After commitment to nondecreasing prices, lost demand cannot be fully compensated by price increases, and hence the overall revenue is lower.

Our results have important implications for both theory and practice. In many industries with significant price fluctuations over time, it is important to account for consumers' intertemporal choices when modeling demand, and we propose a structural model for this purpose. Failing to do so can result in suboptimal pricing or inventory decisions. Our empirical approach to identifying the presence of strategic consumers allows airline managers to improve demand forecasts and the estimates of price sensitivity, which will in turn improve pricing decisions. They can also assess the revenue impacts of strategic consumers and decide whether it is desirable to inhibit or encourage strategic behavior. Our approach can also be applied in many other industries to identify the presence of strategic consumers and derive the managerial implications.

Naturally, our study is not free of limitations, which offer avenues for future research. As we discussed earlier, we do not model details of interfirm competition, which merits a separate paper, although our simple controls for competition through the Herfindahl index were insignificant in the estimation of the fraction of strategic consumers. A competitive model can also provide insights on whether the potential to increase revenues through a nondecreasing price commitment can effectively materialize if all airlines commit. Another restriction in our methodology is the discrete, two-point distribution of strategic consumer behavior (rather than a continuous distribution). We also conducted only limited counterfactual analysis: a separate study might attempt to devise a new optimization algorithm to maximize revenues considering strategic behavior. These extensions will inevitably run into computational difficulties, and resolving them will be part of the challenge. Last, with the recent growth of e-commerce, social media, metasearch sites like Kayak, and fare prediction engines like Bing Travel, it will be interesting to study how strategic behavior evolves over time (Mantin and Rubin 2013).

Acknowledgments

The authors thank the review team for helpful comments on earlier drafts of this paper. They also thank the following people (listed in alphabetical order) for comments and suggestions: Gérard Cachon; Anindya Ghose; Karan Girotra; Lorin Hitt; Raghuram Iyengar; Stephen Leider; Benny Mantin; Antonio Moreno; Aviv Nevo; Marcelo Olivares; Nikolay Osadchiy; Amine Ouazad; Sergei Savin; Nicos Savva; Katja Seim; Xuanming Su; Robert Swinney; Gabriel Weintraub; conference participants at the Behavioural Operations Conference, the Revenue Management and Pricing Conference, the MSOM Society Annual Conference, the Workshop on Empirical Research in Operations Management, and the Workshop on Information Systems and Economics; and seminar attendees at University College London, London School of Business, Michigan Ross School of Business, Columbia Business School, Stanford Graduate School of Business, Dartmouth Tuck Business School, MIT Sloan School of Management, NYU Stern School of Business, Purdue Krannert School of Management, Georgia Institute of Technology Scheller College of Business, Duke Fuqua School of Business, Northwestern Kellogg School of Business, Chicago Booth School of Business, Cornell Johnson School of Management, UNC Kenan-Flagler Business School, and the New Economic School. The authors also thank the corporate sponsor for making the data available, and Wharton INSEAD Alliance and Penn Lauder CIBER for financial support. Nelson Granados thanks Pepperdine University for funding through the Julian Virtue Professorship.

Appendix A. Sample Data

Table A.1 Sample Data

Booking data								
Origin	Destination	Carrier	Inventory class	Agency ID	Agency group	Departure date	Booking date	Pass count
XXX	ATL	AB	K	xxxx	Expedia	25-Jan-05	3-Jan-05	1
XXX	ATL	CD	U	xxxx	Off-line	23-Jan-05	3-Jan-05	1

Fare data								
Origin	Destination	Carrier	Website	Departure date	Booking date	Fare	Base code 1	Base code 2
XXX	ATL	AB	Expedia	21-Jan-05	5-Oct-04	$178	Txxxx	Txxxx
XXX	ATL	EF	Orbitz	21-Jan-05	5-Oct-04	$178	Lxxxx	Lxxxx

Departure route	Return route	Departure flight	Return flight
12:22–15:43	7:10–9:05	xxxx	xxxx
xxxx	xxxx	xxxx	xxxx

Appendix B. Data Representativeness

GDS-Based Bookings

We believe that the choice of a GDS versus non-GDS channel is unaffected by strategic waiting for the follow reasons: (1) GDSs are booking platforms that operate in the background, and the typical traveler is not aware whether the booking is done via a GDS or not, and (2) the GDS and non-GDS channels have almost exactly the same or perfectly correlated prices over the booking horizon. Therefore, consumers do not explicitly select the booking platform, and the timing of purchase is not influenced by the booking platform used.

Nevertheless, using an alternate data set, we verified a stricter sufficient condition that the probability to book via GDS is constant over the booking horizon. To verify the usage of GDS booking data, we acquired a sample of online air-travel transactions from comScore through Wharton Research Data Service. It spans 2008 to 2011 with 50,000 randomly selected households in each year. This sample includes both GDS and non-GDS bookings. The estimated daily GDS-based booking share is relatively stable at 68.8% (standard deviation 4.7%) across 90 days before departure.

Three Lowest Fares

Our posted fare data consist of three lowest round-trip fares with a seven-day stay for each airport pair and each departure date. These fares are scraped on a daily basis for three months before each departure date from three major online travel agencies: Expedia, Travelocity, and Orbitz. We find a high correlation of 0.960 of prices across travel agencies for the same city pair, departure date, booking date, and inventory class. The slight differences arise mainly due to differences in the algorithms to construct and price itineraries.

We extracted only the three lowest fares based on a pilot study in which we extracted the lowest fare of each airline serving a given airport pair. We found that since a common airline pricing strategy is to match each other's fare levels, there is an average correlation of 0.799 in price paths for a given departure date across major airlines with at least 10% market share.

Fares for Seven-Day Length of Stay

We picked a seven-day length of stay because it is widely used in the industry (for example, by Infare) and other papers (Etzioni et al. 2003, Mantin and Gillen 2011). We verified how representative the fares are compared to other lengths of stay. We crawled a 30-day fare history from Bing Travel for two representative markets, one business and one leisure, and two representative departure dates, one weekend and one weekday. Correlations of price histories are displayed in Table B.1. The average correlation is as high as 0.89 with a narrow range, suggesting price variations are mainly driven by departure dates, but not return dates. We also note that Saturday night stay and two- to three-night stay requirements were discontinued by all major U.S. carriers during January 2005 to May 2008.

Posted Fares

To assess the overall representativeness of our posted fare data compared to the actual transaction fares, we acquired actual transaction prices for tickets sold by the corporate sponsor and matched them with the respective Web-crawled fare for each airport pair, departure date, and booking date. We observed a significantly high correlation of 0.860 between the daily lowest fares and actual transaction fares from the corporate sponsor.

Appendix C. Substitution Across Adjacent Departure Dates

To evaluate the potential impact of demand substitution across adjacent departure dates, we first acquired auxiliary data from an anonymous online travel agency to examine the extent to which travelers are flexible in departure dates. We randomly selected 1,000 users who purchased air tickets during 2009 to 2010, and 84.5% of the 5,000 associated searches for these users had a fixed departure date. Only 7.0% were flexible within a ±1 day range, and 1.8% were flexible within a ±2 day range. Note that 84.5% is a conservative estimate for the overall market because proportionally more leisure travelers choose to search online, whereas most business travels, which are usually fixed in terms of travel dates, are arranged by off-line travel agents. The fact

Table B.1 Correlation of Fare Histories for Trips with Different Lengths of Stay

Length of stay	Return date	Thu 8/9/2012	Fri 8/10/2012	Sat 8/11/2012	Sun 8/12/2012	Mon 8/13/2012	Tues 8/14/2012	Wed 8/15/2012	Mean
				XXX to Atlanta, GA, departure on 8/8/2012, Wed					
1	8/9/2012								0.937[a]
2	8/10/2012	1.000							0.937
3	8/11/2012	0.981	0.981						0.930
4	8/12/2012	0.994	0.994	0.990					0.938
5	8/13/2012	0.992	0.992	0.989	0.997				0.937
6	8/14/2012	0.871	0.871	0.875	0.877	0.879			0.892
7	8/15/2012	0.859	0.859	0.865	0.862	0.862	0.960		0.886
8	8/16/2012	0.865	0.865	0.831	0.853	0.847	0.909	0.938	0.872
				XXX to Orlando, FL, departure on 8/8/2012, Wed					
1	8/9/2012								0.910
2	8/10/2012	0.960							0.900
3	8/11/2012	0.702	0.708						0.724
4	8/12/2012	0.901	0.925	0.784					0.889
5	8/13/2012	0.924	0.869	0.714	0.888				0.891
6	8/14/2012	0.960	0.944	0.738	0.919	0.950			0.927
7	8/15/2012	0.967	0.943	0.719	0.911	0.948	0.991		0.923
8	8/16/2012	0.954	0.950	0.700	0.898	0.941	0.983	0.983	0.916

Length of stay	Return date	Sat 8/11/2012	Sun 8/12/2012	Mon 8/13/2012	Tues 8/14/2012	Wed 8/15/2012	Thu 8/16/2012	Fri 8/17/2012	Mean
				XXX to Atlanta, GA, departure on 8/10/2012, Fri					
1	8/11/2012								0.898
2	8/12/2012	0.995							0.900
3	8/13/2012	0.992	0.997						0.897
4	8/14/2012	0.879	0.882	0.881					0.906
5	8/15/2012	0.869	0.870	0.868	0.962				0.913
6	8/16/2012	0.860	0.861	0.858	0.933	0.965			0.914
7	8/17/2012	0.840	0.841	0.835	0.897	0.923	0.957		0.898
8	8/18/2012	0.854	0.855	0.850	0.906	0.933	0.964	0.996	0.908
				XXX to Orlando, FL, departure on 8/10/2012, Fri					
1	8/11/2012								0.698
2	8/12/2012	0.835							0.874
3	8/13/2012	0.707	0.886						0.868
4	8/14/2012	0.659	0.883	0.937					0.893
5	8/15/2012	0.659	0.883	0.938	1.000				0.893
6	8/16/2012	0.657	0.878	0.930	0.999	0.999			0.890
7	8/17/2012	0.682	0.880	0.893	0.919	0.920	0.909		0.852
8	8/18/2012	0.688	0.874	0.789	0.851	0.849	0.856	0.761	0.810

[a]0.937 is the average price correlation of a one-day-stay price with the prices of all other lengths of stay.

that a large majority of travelers are set with one specific departure date indicates that it is reasonable to assume departure dates are given exogenously.

Nevertheless, we still investigate the potential impact of flexibility in departure dates on the model. We proved in the following condition under which the fraction of strategic consumers can be estimated consistently without accounting for substitution across different departure dates. Intuitively, this holds because when prices of alternative departure dates follow the same intertemporal trend along the booking time axis, (1) a strategic consumer's waiting decision is unaffected by the alternative price trend, and (2) the baseline demand function can be casted in the same structure.

Theorem 1. *Suppose consumers choose to travel on either departure date 1 or date 2, and let p_{1t}, p_{2t} denote air ticket prices for departure dates 1 and 2, respectively, at booking time t. If p_{1t} and p_{2t} are perfectly correlated, then the fraction of strategic consumers can be consistently estimated using a model that does not account for departure date substitution.*

Proof of Theorem 1. Since p_{1t} and p_{2t} are perfectly correlated, p_{2t} can be written as a linear function of p_{1t}. Let,

$$p_{2t} = \alpha_0 + \alpha_1 p_{1t}.$$

Baseline demand function is now a function of both p_{1t} and p_{2t},

$$q_1(p_{1t}, p_{2t}, X_{1t}, t) = \alpha + \beta_1 p_{1t} + \beta_{12} p_{2t} + X_{1t}\delta + \varepsilon_{1t},$$
$$q_2(p_{1t}, p_{2t}, X_{2t}, t) = \alpha + \beta_2 p_{2t} + \beta_{21} p_{1t} + X_{2t}\delta + \varepsilon_{2t},$$

where q_j denotes baseline demand on departure date j, $j = 1, 2$; β_j, $j = 1, 2$, denotes self-price sensitivities; β_{12} and β_{21}

denote cross-price sensitivities; And X_{jt}, $j = 1, 2$, denotes other covariates just as before.

If there are no strategic consumers, the observed demands will be the same as q_1 and q_2. However, when there are strategic consumers, the observed demands will also depend on strategic consumers' expectation of the joint evolution of p_{1t} and p_{2t}. Suppose strategic consumer i believes that prices in the next booking period will be $\tilde{p}_{i,1,t+1}$, $\tilde{p}_{i,2,t+1}$. At time t, he decides to choose from the following two options: (1) departing on date 1 at price $\min\{p_{1t}, \tilde{p}_{i,1,t+1}\}$ or (2) departing on date 2 at price $\min\{p_{2t}, \tilde{p}_{i,2,t+1}\}$. Trade-offs between these two options depend both on current and anticipated prices and on his intrinsic preferences on the two departure dates. If his decision corresponds to a departure date for which he anticipates the price to fall, he waits. Thus, modeling strategic consumers' waiting decision is, in general, complex.

However, under the condition that $p_{2t} = \alpha_0 + \alpha_1 p_{1t}$, a strategic consumer only needs to form one price expectation, since the two price series will follow exactly the same trend. Thus, a strategic consumer will wait if $p_{1t} > \tilde{p}_{i,1,t+1}$. This is the exact same waiting condition defined for cases without substitution across departure dates. As a result, the observed demand with strategic consumers can be written as

$$\begin{aligned} d_{1t} &= (1-\theta)q_1(p_{1t}, p_{2t}, X_{1t}, t) + \theta(1-z_{1t})q_1(p_{1t}, p_{2t}, X_{1t}, t) \\ &\quad + \theta z_{1,t-1} q_1(p_{1t}, p_{2t}, X_{1,t-1}, t-1), \\ d_{2t} &= (1-\theta)q_2(p_{1t}, p_{2t}, X_{2t}, t) + \theta(1-z_{1t})q_2(p_{1t}, p_{2t}, X_{2t}, t) \\ &\quad + \theta z_{1,t-1} q_2(p_{1t}, p_{2t}, X_{2,t-1}, t-1), \end{aligned} \tag{C1}$$

where $z_{1t} = \mathbf{1}\{p_{1,t+1} < p_{1t}\}$ under perfect foresight, and $z_{1t} = \Pr(p_{1,t+1} < p_{1t})$ under rational expectation. Note that this definition is exactly the same as previous definition for z_t under no departure date substitution. Replace p_{2t} by $\alpha_0 + \alpha_1 p_{1t}$ in Equation (C1), and

$$\begin{aligned} d_{1t} &= (1-\theta z_{1t})(\tilde{\alpha} + \tilde{\beta} p_{1t} + X_{1t}\delta + \varepsilon_{1t}) + \theta z_{1,t-1} \\ &\quad \cdot (\tilde{\alpha} + \tilde{\beta} p_{1t} + X_{1,t-1}\delta + \varepsilon_{1t-1}), \\ &\quad \tilde{\alpha} = \alpha + \alpha_0, \quad \tilde{\beta} = \beta_1 - \alpha_1 \beta_{12}. \end{aligned} \tag{C2}$$

Note that Equation (C2) (i.e., demand with departure date substitution) has the exact same structure as the equation with no substitution across departure dates, except that the intercept and the (self-)price sensitivity are adjusted. Using the same estimation strategy laid out in this paper, we can obtain a consistent estimator for θ, though not for β_1. We only obtain an estimator of price sensitivity as a combination of both self-price and cross-price sensitivities.. □

To what degree can this condition of correlated prices across departure dates be satisfied? We found evidence of reasonably high price correlations for adjacent departure dates. In our data, the average daily price correlation is 0.70 (standard Deviation, 0.15) for pairs of departure dates within ±1 day difference. Considering the small fraction of consumers who are flexible in departure dates, and that this fraction decreases sharply in the number of days apart, we consider this effect to be secondary for the scope of this paper, although it may merit future research.

Appendix D. GMM Estimation of Nonlinear Panel Data Models

Estimation Strategy

We use nonlinear panel data GMM to obtain estimates of parameters. In this section, we provide details of our optimal nonlinear GMM estimator and derivation of its asymptotic variance for our context. For simplicity of illustration, in the following discussion we assume a constant fraction of strategic consumers and a constant price sensitivity. Similar logic can easily be applied to more complicated models with a time-variant fraction of strategic consumers or time-variant price sensitivities. For brevity, we drop subscript m hereafter because our estimation is done market by market. Consider the following demand model for a given market:

$$\begin{aligned} d_{dt} &= (1-\theta z_{dt})(\alpha + \beta p_{dt} + X_{dt}\delta + \varepsilon_{dt}) \\ &\quad + \theta z_{d,t-1}(\alpha + \beta p_{dt} + X_{d,t-1}\delta + \varepsilon_{d,t-1}), \\ &\qquad \varepsilon_{dt} = \rho \varepsilon_{d,t-1} + \nu_{dt}, \end{aligned} \tag{D1}$$

where $d = 1, 2, \ldots, N$ represents departure date, and $t = 1, 2, \ldots, T$ represents booking time. Recall that we denote $\Delta = (\alpha, \delta)$. The set of parameters $(\theta, \beta, \Delta, \rho)$ are estimated based on following moment conditions:

$$E[Y'\nu(\theta, \beta, \Delta, \rho)] = 0,$$

where Y denotes the matrix of instruments, and the demand shock ν is a nonlinear function of unknown parameters $(\theta, \beta, \Delta, \rho)$. The nonlinear GMM estimator solves the following minimization problem:

$$\begin{aligned} \min_{(\theta, \beta, \Delta, \rho)} Q_N(\theta, \beta, \Delta, \rho) &= \left[\frac{1}{N}\sum_{d=1}^{N} Y_d' \nu_d(\theta, \beta, \Delta, \rho)\right]' W_N \\ &\quad \cdot \left[\frac{1}{N}\sum_{d=1}^{N} Y_d' \nu_d(\theta, \beta, \Delta, \rho)\right], \end{aligned} \tag{D2}$$

In the following section, we first simplify the minimization problem by reducing its dimensionality. We then derive the asymptotic variance of the optimal nonlinear GMM estimator.

Theorem 2. *Given strictly exogenous X, i.e., $E[v \mid X] = 0$, the minimization problem in Equation* (D2) *can be transformed to the following minimization problem*:

$$\begin{aligned} &\min_{(\theta, \beta)} Q_N(\theta, \beta, \Delta^*(\theta, \beta), \rho^*(\theta, \beta)) \\ &\quad = \left[\frac{1}{N}\sum_{1}^{N} Y'\nu(\theta, \beta, \Delta^*(\theta, \beta), \rho^*(\theta, \beta))\right]' W_N \\ &\quad\quad \cdot \left[\frac{1}{N}\sum_{1}^{N} Y'\nu(\theta, \beta, \Delta^*(\theta, \beta), \rho^*(\theta, \beta))\right], \end{aligned} \tag{D3}$$

where $\Delta^*(\theta, \beta)$, $\rho^*(\theta, \beta)$ can be estimated using an ordinary least squares (OLS) estimator with correction for autocorrelation.

Proof of Theorem 2. Demand model in Equation (D1) can be rearranged in the following way:

$$\begin{aligned} &d_{dt} - (1-\theta z_{dt})\beta p_{dt} - \theta z_{d,t-1}\beta p_{dt} \\ &\quad = (1-\theta z_{dt})(X_{dt}\Delta + \varepsilon_{dt}) + \theta z_{d,t-1}(X_{d,t-1}\Delta + \varepsilon_{d,t-1}), \\ &\qquad \varepsilon_{dt} = \rho \varepsilon_{d,t-1} + \nu_{dt}. \end{aligned}$$

Rewrite these equations in matrix format,

$$Z^{-1}(\theta)\tilde{d}(\theta,\beta) = X\Delta + \varepsilon \quad \nu = \Omega(\rho)\varepsilon, \tag{D4}$$

where $\tilde{d}(\theta,\beta)$ is a vector with elements $\tilde{d}_{dt} = d_{dt} - (1 - \theta z_{dt})\beta p_{dt} - \theta z_{d,t-1}\beta p_{dt}$, and $Z(\theta)$ is an $N*T$–by–$N*T$ transformation matrix,

$$Z(\theta) = \begin{pmatrix} 1-\theta z_{11} & 0 & 0 & \cdots & 0 & 0 & \cdots & 0 \\ \theta z_{11} & 1-\theta z_{12} & 0 & \cdots & 0 & 0 & \cdots & 0 \\ 0 & \theta z_{12} & 1-\theta z_{13} & \cdots & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & 0 & \cdots & 0 \\ 0 & 0 & 0 & \cdots & 1-\theta z_{1T} & 0 & \cdots & 0 \\ 0 & 0 & 0 & \cdots & 0 & 1-\theta z_{21} & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \ddots & 0 \\ 0 & 0 & 0 & \cdots & 0 & 0 & \cdots & 1-\theta z_{NT} \end{pmatrix},$$

where $\Omega(\rho)$ is an autocorrelation transformation matrix of the same size as Z,

$$\Omega(\rho) = \begin{pmatrix} 1 & 0 & 0 & \cdots & 0 & 0 & \cdots & 0 \\ -\rho & 1 & 0 & \cdots & 0 & 0 & \cdots & 0 \\ 0 & -\rho & 1 & \cdots & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & 0 & \cdots & 0 \\ 0 & 0 & 0 & \cdots & 1 & 0 & \cdots & 0 \\ 0 & 0 & 0 & \cdots & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \ddots & 0 \\ 0 & 0 & 0 & \cdots & 0 & 0 & \cdots & 1 \end{pmatrix}.$$

In model (D4), since $E[X \mid \varepsilon] = 0$, it follows that for any given parameter set (θ,β), we can estimate (Δ,ρ) consistently and efficiently using OLS with correction for autocorrelation. Specifically, we use the Cochrane–Orcutt recursive procedure to estimate ρ. Moreover, since transformation matrix Ω essentially takes partial differences, the degree of freedom decreases by one within each group. Simply omitting the first observation is likely to cause inefficiency when the number of groups is small, i.e., 45 departure dates in each market. We apply Prais–Winsten transformation to the first observation in each group, i.e., multiply by the first error term by $\sqrt{1-\rho^2}$. □

Now the dimension of the optimization problem has been significantly reduced to two parameters only, θ and β. We then use iterative GMM with randomized initial values to obtain the *optimal* GMM estimator. In most cases, the estimation converges after four to five iterations.

Asymptotic Variance

Nonlinear *optimal* GMM estimator is asymptotically normal with variance matrix consistently estimated by (see Cameron and Trivedi 2005, Chapter 23),

$$\hat{V}([\theta,\beta]) = \frac{1}{N}\left[\left(N^{-1}\sum_{d=1}^{N}\hat{D}_d' Y_d\right)\hat{S}^{-1}\left(N^{-1}\sum_{d=1}^{N} Y_d'\hat{D}_d\right)\right]^{-1}, \tag{D5}$$

where $\hat{D}_d = [\partial\nu_{dt}(\theta,\beta)/\partial(\theta,\beta)|_{(\hat{\theta},\hat{\beta})}, t = 1,2,\ldots,T]$, and $\hat{S} = N^{-1}\sum_{d=1}^{N} Y_d'\nu_d(\theta,\beta)\nu_d'(\theta,\beta)Y_d|_{(\hat{\theta},\hat{\beta})}$. We now derive $\partial\nu(\theta,\beta)/\partial(\theta,\beta)$. According to Equations in (D4),

$$\nu(\theta,\beta) = \Omega\varepsilon = \Omega[I - X(X'X)^{-1}X']Z^{-1}(\theta)\tilde{d}(\theta,\beta).$$

Denote $M_X = I - X[X'X]^{-1}X'$. Rearranging the above equation, we have

$$Z(\theta)M_X^{-1}\Omega^{-1}\nu(\theta,\beta) = \tilde{d}(\theta,\beta).$$

Taking derivatives on both sides with respect to θ,

$$\frac{\partial Z(\theta)}{\partial\theta}M_X^{-1}\Omega^{-1}\nu(\theta,\beta) + Z(\theta)M_X^{-1}\Omega^{-1}\frac{\nu(\theta,\beta)}{\partial\theta} = \frac{\tilde{d}(\theta,\beta)}{\partial\theta},$$

$$\frac{\nu(\theta,\beta)}{\partial\theta} = \Omega M_X Z^{-1}(\theta)\left(\frac{\partial\tilde{d}(\theta,\beta)}{\partial\theta} - \frac{\partial Z(\theta)}{\partial\theta}M_X^{-1}\Omega^{-1}\nu(\theta,\beta)\right),$$

$$\frac{\nu(\theta,\beta)}{\partial\theta} = \Omega M_X Z^{-1}(\theta)\left(\frac{\partial\tilde{d}(\theta,\beta)}{\partial\theta} - \frac{\partial Z(\theta)}{\partial\theta}Z^{-1}(\theta)\tilde{d}(\theta,\beta)\right), \tag{D6}$$

$$\frac{\nu(\theta,\beta)}{\partial\beta} = \Omega M_X Z^{-1}(\theta)\frac{\partial\tilde{d}(\theta,\beta)}{\partial\beta}. \tag{D7}$$

Plugging derivatives (D6) and (D7) back into Equation (D5), we can calculate asymptotic variance of the estimated parameters. Note that Ω is replaced by its consistent estimator $\hat{\Omega}|_{(\hat{\theta},\hat{\beta})}$ using the Cochrane–Orcutt procedure.

In the rational expectation models, our estimator is a two-stage estimator. In the first stage, we predict the probability of price falling using either weak-form or strong-form rational expectation assumptions. In the second stage, we plug this estimated probability in the nonlinear GMM estimator derived above. Theoretically, the variance–covariance matrix from the second stage should be adjusted to take into account that the probability is *estimated* rather than observed. However, since the standard errors from the first stage are substantially smaller than those from the second stage, and since deriving the variance–covariance matrix is both analytically and computationally expensive, we treat the predicted probability as known, similarly to other complex sequential structural estimation papers such as Aguirregabiria and Mira (2007). Nevertheless, we evaluate the gap between uncorrected standard errors and corrected standard errors using a panel bootstrapping method in one market (market L) as an example. We found that the corrected standard errors are very close to the uncorrected standard errors, only 1.3% higher, and do not affect the statistical significance.

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