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MANAGEMENT SCIENCE
Vol. 66, No. 11, November 2020, pp. 5362–5388
ISSN 0025-1909 (print), ISSN 1526-5501 (online)

Temporal Distance and Price Responsiveness: Empirical Investigation of the Cruise Industry

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Received: March 9, 2016
Revised: October 21, 2016; September 11, 2017; April 7, 2019; July 29, 2019
Accepted: July 31, 2019
Published Online in Articles in Advance: July 13, 2020

https://doi.org/10.1287/mnsc.2019.3468

Abstract. Temporal distance refers to the time between purchase and consumption in advanced-sales industries. We explore how the response of aggregate demand to price changes with temporal distance in a large, proprietary data set of Florida cruise prices, bookings, and product attributes. We offer the first evidence that cruise demand becomes more sensitive to price during the advance sales period, unlike extant findings in other settings. The results also show that demand is greatest late in the advance sales period, providing the first finding that a late-season high-demand period coincides with a late-season increase in aggregate price sensitivity. The high-demand effect more than offsets the high-price-responsiveness pattern, leading the firm to increase prices throughout the advance sales period. Although the data do not disentangle multiple competing explanations for the main findings, they are large enough to appear in simple data visualizations and robust enough to replicate across many model specifications, parameterizations, and partitions of the data.

History: Accepted by Matthew Shum, marketing.
Supplemental Material: The online appendices are available at https://doi.org/10.1287/mnsc.2019.3468.

Keywords: advance sales • cruise • price responsiveness • temporal distance • market differentiation • instrumental variables

1. Introduction

Many service industries—including airlines, cruises, hotels, rental cars, sports, and entertainment events—sell in advance to price discriminate among consumers and to hedge against demand uncertainty for their perishable, capacity-constrained products. When consumers buy in advance, the time between purchase and consumption is called *temporal distance*. For example, some consumers buy vacation tickets three months in advance, whereas others buy the same tickets just three weeks in advance. Consumers' self-selected purchase timing is often used for intertemporal price discrimination, as it often correlates with product valuation and price sensitivity.

The relationship between price responsiveness and temporal distance in any particular industry is an empirical question that may influence intertemporal pricing incentives during the advance sales window. A common pricing practice is to charge low prices when demand is more price sensitive for capacity utilization, and to charge high prices when demand is less price sensitive to enhance unit margins.[1] The extant empirical evidence comes from a limited set of industries (e.g., Li et al. 2014) and has shown that demand generally becomes less responsive to price as the advance sales period proceeds, leading early bird discounts to predominate. Due to the limited coverage, the empirical generalizability of extant knowledge is still in question.

The purpose of the current article is to investigate how the price responsiveness to demand changes with temporal distance in the Florida cruise market. The cruise industry is understudied relative to its size at $21.2 billion in United States revenues and $39.6 billion worldwide.[2] Cruises offer an interesting setting to study how price responsiveness changes with temporal distance, because cruise products compete against large numbers of functional substitutes, such as alternative destinations and other vacation options.

We analyze a proprietary data set of nearly 400,000 bookings of 805 distinct cruise products offered by a market-leading cruise line. Each cruise's price changed weekly over a 40-week advance sales period. Within each product, price generally increases as temporal distance between purchase and consumption falls. Across products, higher priced cruises tend to be booked farther in advance, indicating that demand is heterogeneous over the advance sales window. The association between temporal distance and the correlation between demand and price is shown to be negative and large enough to appear in simple data visualizations.

To achieve point identification and estimate causal effects, we specify a flexible discrete choice model, controlling for main effects of temporal distance, cruise characteristics, seasonality, and unobserved heterogeneity. Price sensitivity is modeled as a function of temporal distance as well as product attributes and unobserved heterogeneity. We interpret the static model as estimating the response of aggregate demand to price, rather than as a full representation of the individual-level purchase process, as there are multiple ways to model a dynamic consumer search process but no search data available to distinguish between them.[3]

As is often the case, it is challenging to find ideal instrumental variables to distinguish the effect of price from unobserved demand shocks or unobserved consumer heterogeneity. In particular, this application features large numbers of closely related products. We would ideally have product-specific cost shifters, but no such data are available. Therefore, we use two sets of instruments to identify the effect of product-specific price on product-specific demand: a weekly oil cost shock interacted with product characteristics (i.e., itinerary, cabin, and temporal distance) and exogenous variation in the choice set using the market differentiation instrumental variables approach proposed by Gandhi and Houde (2017).

We provide the first field evidence that demand can become more responsive to price as the advance sales period proceeds. The finding replicates across many alternate parameterizations, model specifications, and partitions of the data. Supplemental data analyses show no evidence that sellouts or competitive pricing can explain the observed price responsiveness patterns.

At first glance, it may appear counterintuitive that prices were highest late in the advance sales period when demand was most price sensitive. However, our second main finding is that consumers' baseline demand for cruises increases as temporal distance falls, more than offsetting the fall in demand due to higher prices and increased price responsiveness. This explains the firm's observed policy of increasing prices as the advance sales period proceeds. A series of revenue sensitivity tests based on the empirical model predicts that the firm could profitably increase the rate at which prices rise as temporal distance falls.

2. Relationship to Prior Literature

Advance selling has attracted significant theoretical attention, especially in the context of travel and entertainment industries (Fay and Xie 2010). A large literature has documented that the profitability of advance selling often comes from price discrimination during the advance sales window. For example, Dana (1998) showed that advance purchase discounts allow firms to profit from greater sales to low-valuation customers, consistent with second-degree price discrimination. Gale and Holmes (1993) found that advance pricing can be designed to maximize capacity-constrained profits by diverting demand from peak to off-peak periods. Theoretical models typically start with the assumption that demand becomes less responsive to price as the advance sales window proceeds and recommend increasing price paths to balance demand discovery with capacity utilization.[4]

The empirical literature investigating time-varying price responsiveness is scarce, yet generally supports these assumptions.[5] For example, Garrow et al. (2006) reported that leisure travelers in airlines are about twice as price-sensitive as business travelers. Li et al. (2014) found that airline demand sensitivity to price decreases as temporal distance falls because of differing times of arrival among leisure and business travelers. The existing demand-side analysis mostly comes from airline data.[6]

There are several behavioral literatures that study how temporal distance affects consumer preferences; such effects may partially drive the main finding in the current paper. Experimental studies find that savoring and other forms of anticipation motivate deferral of hedonic goods consumption (e.g., Loewenstein 1987, Chan and Mukhopadhyay 2010). Research in construal level theory has shown that consumers planning an event in the distant future focus more on the core benefits of the event, whereas those considering an event in the near future focus more on costs and logistics (Liberman and Trope 1998, Trope and Liberman 2000, Bornemann and Homburg 2011, Lee and Zhao 2014). Work on perceived substitutability suggests that substitution is often driven by consumers' commitment to the category (Hamilton et al. 2014), with highly committed consumers tending to be less responsive to price and more likely to buy farther in advance. We mention these results in passing because the available data do not offer any means to distinguish between or among supply-side and demand-side drivers of the main result.

This study is conceptually related to literatures that study dynamic consumer choices under uncertainty about prices, current qualities, and future qualities. This includes models of consumers forming expectations about future price changes (e.g., Gönül and Srinivasan 1996, Soysal and Krishnamurthi 2012) and consumers learning about product quality with experience (e.g., Erdem and Keane 1996, Crawford and Shum 2005, Narayanan et al. 2005, Erdem et al. 2008, Ching and Ishihara 2010). Consumer uncertainty often predicts purchase timing, as costs of waiting may be offset by quality improvements, availability of complements or tied goods, or price reductions, as has been shown in such contexts as video game consoles (Derdenger and Kumar 2013, Derdenger 2014), microprocessors (Gordon 2009, Goettler and Gordon 2011), video cameras (Gowrisankaran and Rysman 2012), razors and blades (Hartmann and Nair 2010), and printers (Melnikov 2013).

To the best of our knowledge, the current paper is the first analysis of market data showing that aggregate demand responsiveness to price can increase as temporal distance between purchase and consumption falls.[7] We also believe it offers the first empirical evidence that a period of high price sensitivity can co-occur with a period of high baseline utility or demand. So this finding may offer an important consideration for managers when designing pricing policies, in addition to enriching our academic understanding of advance sales and pricing.

3. Intertemporal Patterns in Demand and Pricing

3.1. Data

Booking data were obtained from a leading cruise company for 2004. The data include all two-person cabin sales. Each sales record specifies the purchase date, price paid, departure date, itinerary, and cabin type. The empirical analysis focuses on 11 itineraries and three cabin types that collectively accounted for 397,498 bookings, more than 90% of all tickets sold by the firm.[8]

The product set consists of 27 unique combinations of itinerary and cabin type, as shown in Table 1. This set was stable with no product introductions or deletions observed during the sample period. Each itinerary provided a constant duration between four and eight days. On average, each of the 11 itineraries departed 30 times during 2004. In total, there are 805 different combinations of cabin types, itineraries, and departure dates.

Cruise prices and bookings varied widely across product attributes. The average price for a balcony cabin was $834, more than double that of an interior cabin ($404). Interior cabins were booked the most frequently, and balcony cabins least often, as some ships did not offer the highest class of cabin. The 11 different itineraries included various destinations, such as multiple ports in the Caribbean. The highest-priced itinerary ($696) was more than twice as expensive as the lowest priced ($256). Itinerary 23 was the most popular itinerary with about 67,000 tickets sold, whereas itinerary 28 was the least popular with about 16,000 tickets sold.

3.2. Demand Variation over Temporal Distance

Cruise tickets were offered for purchase up to one year prior to departure. Cruise prices changed weekly, so the temporal distance in each purchase occasion is defined as the number of weeks between the purchase date and the departure date.

Figure 1 shows that total bookings increased throughout the advance sales period until the final three weeks prior to departure. We can see that 99.4% of bookings occurred during the final 40 weeks, with the final 20 weeks accounting for 87% of all tickets sold. Consequently, we analyze an advance sales window covering the 40 reservation weeks prior to each cruise's departure.

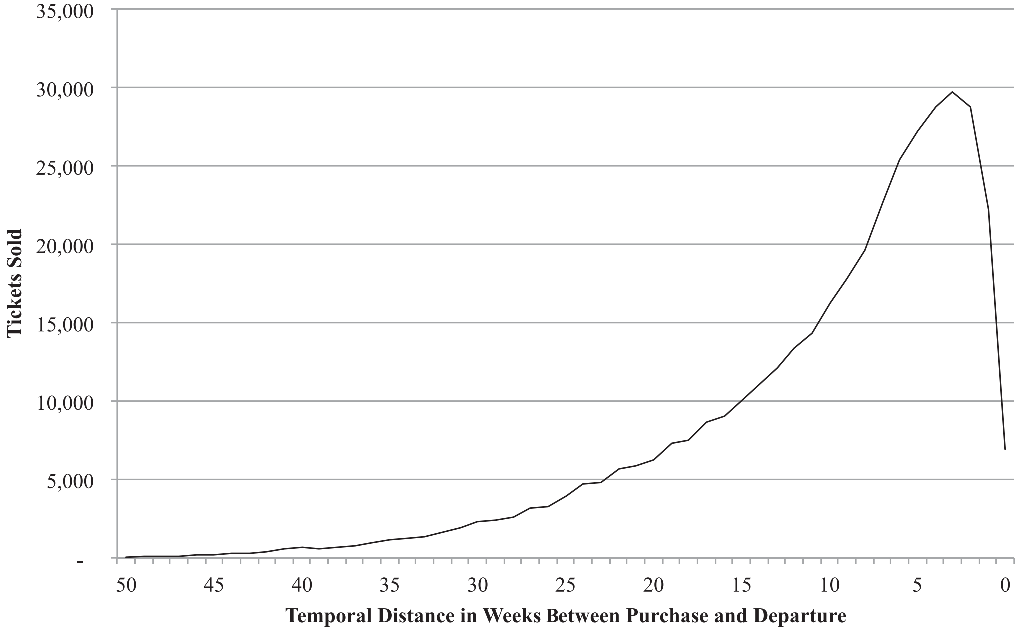
The aggregate ticket sales distribution in Figure 1 masks substantial product-specific heterogeneity. Figure 2 shows how the three highest-selling itineraries' (23, 43, and 55) shares of total bookings varied throughout the advance sales period. Each point in the graph is the sales of an itinerary in that week of temporal distance divided by all tickets sold in that week of temporal distance (e.g., itinerary 23 tickets sold 20 weeks prior to departure/all tickets sold 20 weeks prior to departure). The two higher priced itineraries (23 and 55) show larger purchase shares early in the advance purchase window, more than

Table 1. Mean Prices and Sales by Cruise Itineraries and Cabin Types

Itinerary	Interior	Ocean view	Balcony	All cabins	# tickets sold
Itinerary 19	$288.32	$339.05		$313.81	28,865
Itinerary 23	$524.91	$652.94	$812.70	$664.75	66,922
Itinerary 28	$494.39	$601.77	$1,018.58	$576.08	16,100
Itinerary 30	$553.57	$678.85	$860.31	$696.45	24,774
Itinerary 31	$557.76	$661.16	$1,057.31	$635.25	35,066
Itinerary 34	$321.72	$368.43		$345.08	29,260
Itinerary 37	$400.70	$472.90		$436.58	32,765
Itinerary 38	$439.80	$520.31		$479.55	21,980
Itinerary 39	$261.27	$308.49		$284.92	36,436
Itinerary 43	$234.57	$277.72		$256.19	65,603
Itinerary 55	$536.59	$638.88	$810.64	$663.31	39,727
All itineraries	$403.79	$479.51	$834.11	$494.96	397,498
# tickets sold	180,213	167,036	50,249		

Note. Itinerary numbers are internal codes used by the data provider.

Figure 1. Temporal Distance and Tickets Sold



20 weeks prior to departure. On the other hand, the lower-priced itinerary (43) sold fewer tickets early in the advance sales window, with increasing purchase shares in the final 20 weeks. These patterns show that consumers buying high-price itineraries often book tickets earlier, whereas those booking low-price itineraries tend to buy later. Similar trends hold for other itineraries.

A similar tendency is observed in sales of different cabin types. Figure 3 shows that the purchase share of balcony cabins ($834 average price) peaked at 30% of cabins sold 39 weeks before departure, but this share decreases over time until the week of departure. Meanwhile, purchase shares of the other two cabins (interior and ocean view) increase throughout the advance sales period, again showing that higher priced tickets are disproportionately likely to sell early in the advance sales period.

The descriptive summaries show that consumers who buy early are more likely to buy higher priced cruises, whereas late buyers tend to book cheaper cruises, suggesting possible heterogeneity in demand corresponding to consumers' time of arrival. Although there is no leisure/business distinction in the cruise context, the patterns suggest that segmentation based on temporal distance may be a feasible strategy.

3.3. Descriptive Price Regression

The goal here is to describe how the cruise line changed prices within products over the advance sales window, controlling for product characteristics and seasonality in departure weeks. A cruise product j is uniquely defined by a cabin type and an itinerary (a unique combination of cruise ship, departure port, list of destination ports, and duration). We define time

Figure 2. Temporal Distance and Booking Shares of Top Three Itineraries

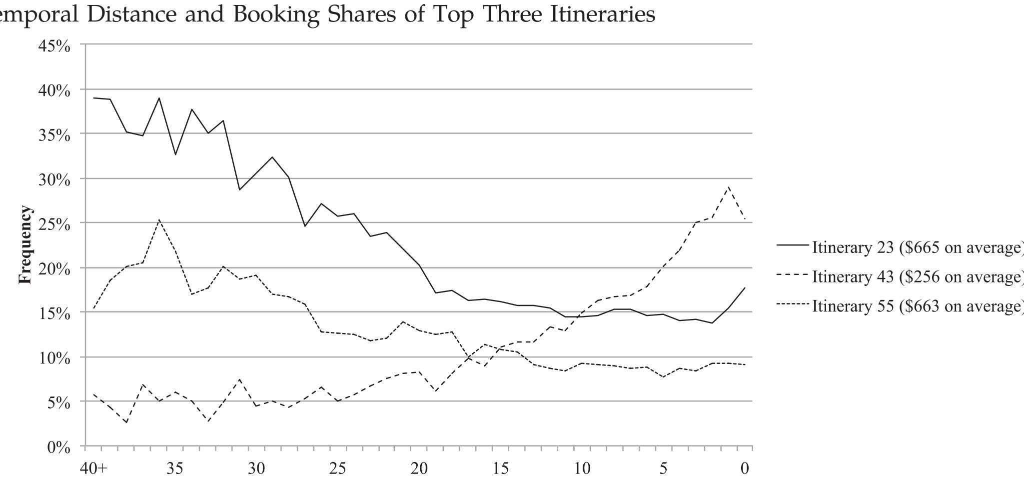
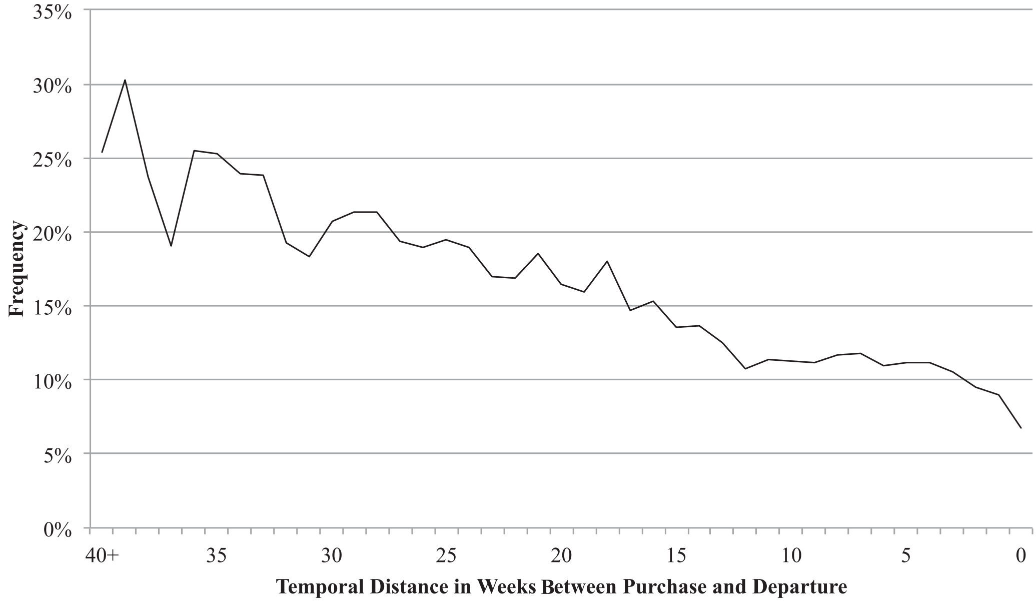


Figure 3. Temporal Distance and Booking Shares of Balcony Cabin ($834 on Average)



subscripts as follows: reservation weeks are indexed by t, the temporal distance in weeks between reservation week and departure week is indexed by r, and the week of cruise departure is therefore $t + r$. For example, suppose a consumer buys a ticket in week 5 for cruise product j departing in week 15. This purchase has reservation week $t = 5$, temporal distance $r = 10$, and departure week $t + r = 15$.

We regress log price p_{jtr}, observed for cruise product j in reservation week t with a departure date r weeks later, on unsold capacity and four sets of fixed effects:

$$p_{jtr} = W_{jtr}\zeta + C_j\phi_1 + I_j\phi_2 + K_{t+r}\eta_1 + K_r\eta_2 + \epsilon_{jtr}, \quad (1)$$

where W_{jtr} is the number of unsold cabins on cruise j departing in week $t + r$ in reservation week t; C_j and I_j are vectors of indicator variables describing cruise product j's cabin type and itinerary, respectively; K_{t+r} is a vector of indicator variables for departure weeks to control for seasonality in cruise departures; K_r is a vector of indicator variables for temporal distance, that is, the number of weeks between booking and departure, to estimate intertemporal price variation within products; and ϵ_{jtr} is an error term.

Figure 4 displays the point estimates in the vector of temporal distance fixed effects η_2 and the associated 95% confidence intervals. Average price changed little between 40 and 25 weeks prior to departure, but

Figure 4. Temporal Distance Fixed Effects in Log Price Regression

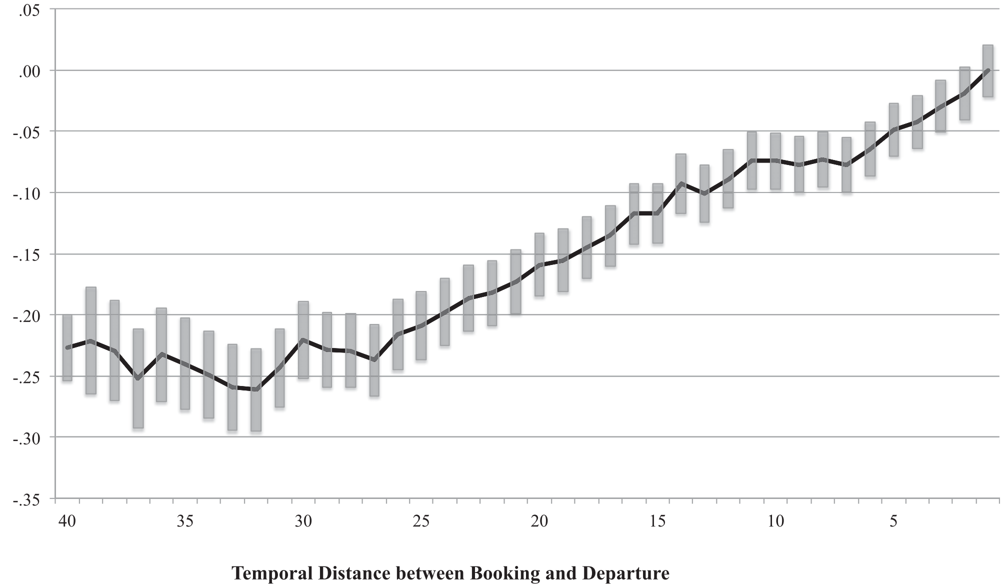
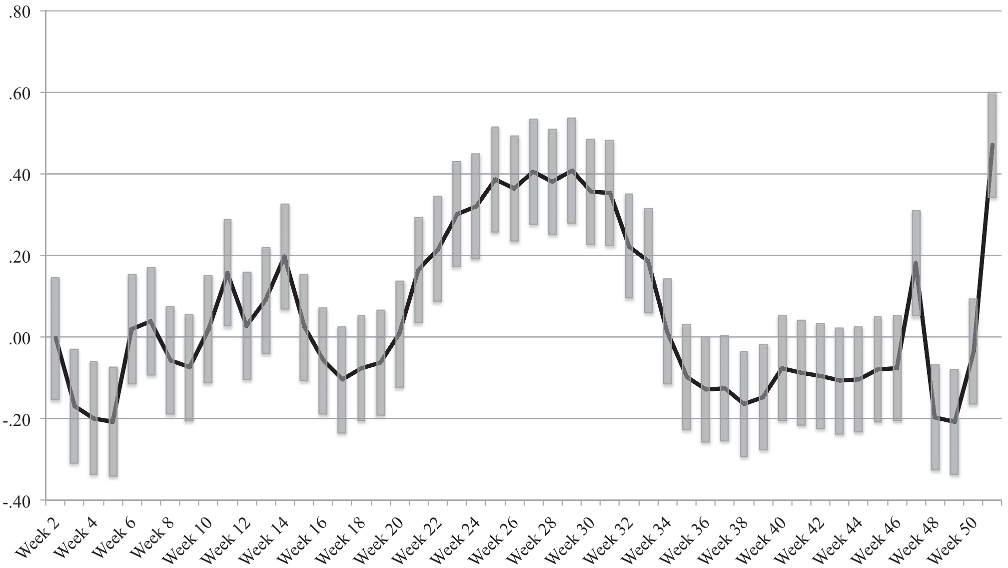


Figure 5. Departure Week Fixed Effects in Log Price Regression



cruise prices rose by about 20% in the final 25 reservation weeks. The increasing pattern is consistent with the early bird discount, where prices rise as temporal distance between purchase and consumption falls.

Figure 5 presents point estimates and the 95% confidence intervals of departure week fixed effects to control for the price variation across cruise departure seasons. The averages conform to intuition: average prices are greatest for cruises departing in summer (weeks 24–32 cover June to August), and major holiday weeks.

Table 2 presents correlational estimates between log price and unsold capacity, itinerary fixed effects, and cabin type fixed effects. Unsold capacity was not strongly associated with ticket prices when controlling for other factors.[9] The itinerary and cabin type fixed effect estimates are consistent with the descriptive statistics presented in Table 1. The variables in Equation (1) explain more than 85% of the variation in log price.

4. Temporal Distance and Price Responsiveness

The primary interest of this paper is to investigate how the price responsiveness of demand changes during the advance sales period. The causal modeling framework developed later is complicated in an effort to control for multiple competing explanations. Therefore, we begin with data visualizations to show that the main result is evident in the raw data, and to show the variation that identifies the main result.

We calculate approximate derivatives of demand with respect to price for every itinerary/departure week combination in every pair of consecutive reservation weeks. The approximate derivatives are given by $H_{jtr} = \frac{Tkt_{jtr} - Tkt_{j(t-1)(r+1)}}{P_{jtr} - P_{j(t-1)(r+1)}}$, where Tkt_{jtr} is the number of tickets sold and P_{jtr} is the price level. The denominator is the change in price of the cruise product between consecutive reservation weeks $t-1$ and t and the numerator is the corresponding change in bookings. We also consider approximate elasticities, $Elas_{jtr} = H_{jtr} * P_{jtr} / Tkt_{jtr}$.

Figure 6 shows that the mean of H_{jtr} and $Elas_{jtr}$ among all j and t within each week of temporal distance r.[10] Unlike the existing empirical findings, the approximate demand derivatives and elasticities increase (in absolute value) as the advance sales period proceeds.

Table 2. Log Price Variation Across Products and by Unsold Capacity

Product	Point estimate	Standard error
Intercept	6.066	0.065**
Unsold tickets	1.02e-5	8.83e-6
Itineraries—Base: Itinerary 19		
Itinerary 23	0.680	0.006**
Itinerary 28	0.464	0.009**
Itinerary 30	0.727	0.008**
Itinerary 31	0.619	0.007**
Itinerary 34	0.079	0.007**
Itinerary 37	0.335	0.008**
Itinerary 38	0.336	0.009**
Itinerary 39	−0.038	0.007**
Itinerary 43	−0.168	0.007**
Itinerary 55	0.631	0.008**
Cabin types—Base: Balcony		
Interior cabin	−0.457	0.005**
Ocean view cabin	−0.266	0.005**
Adjusted R^2	0.854	

**Significant at the 99% confidence level.

Figure 6. Approximate Derivatives and Elasticities by Temporal Distance

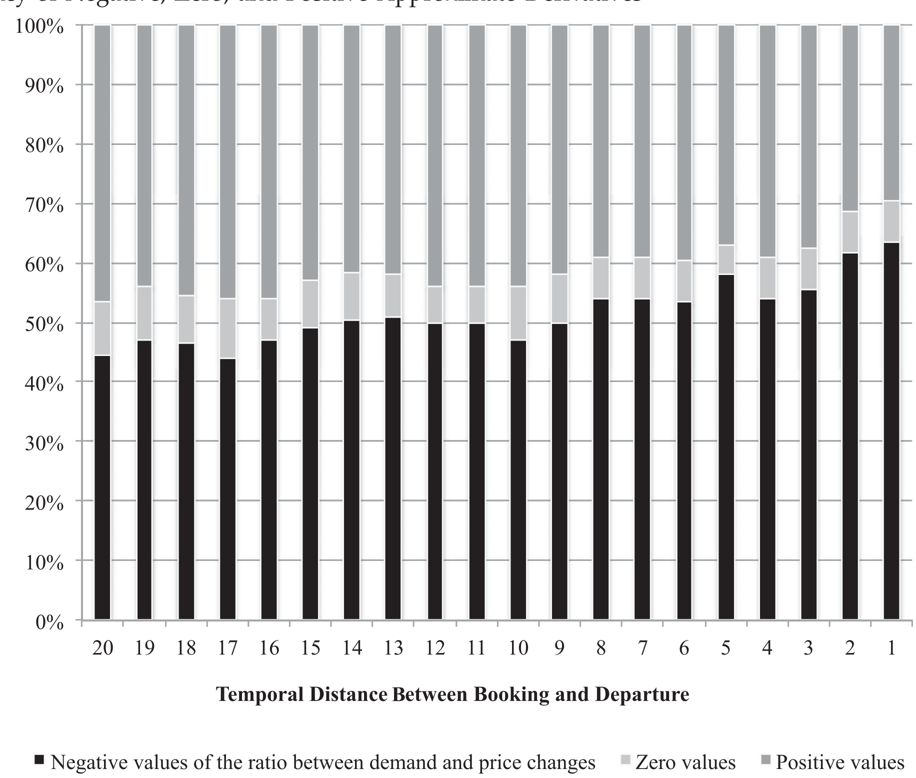
To provide more context, Figure 7 shows how the mass of positive, negative, and zero values of H_{jtr} change with temporal distance. As purchase dates approach consumption dates, increasing numbers of cruise products exhibit negative correlations between price changes and quantity changes.

Although the data illustrate the paper's main finding, we stress that these results are correlational and do not control for many important factors such as seasonality and price endogeneity. We proceed by developing an empirical model and identification strategy to isolate the causal effect of temporal distance on price responsiveness.

4.1. Empirical Model of Cruise Demand

A flexible random coefficient logit (RCL) model is specified to estimate the price responsiveness of cruise demand in our market-level data, controlling

Figure 7. Frequency of Negative, Zero, and Positive Approximate Derivatives



for other factors. We specify a utility function in which utility depends on price and product attributes (temporal distance, cabin type, and itinerary) as usual, but also on interactions between price and product attributes. The model nests the standard assumption of characteristics-invariant price sensitivity as a special case.

4.1.1. Random Coefficient Logit Model of Cruise Demand. Given a set R_t that includes all combinations of cruise products (j) and departure weeks ($t+r$ for $r = 0, 1, 2, \ldots, 40$) available for booking in week t, and standard logit model errors, the probability that a simulated consumer i chooses a cabin in reservation week t on cruise product j departing r weeks in the future is

$$\pi_{ijtr} = \frac{\exp\left(\beta_{ijr} p_{jtr} + C_j \delta_i + I_j \alpha + K_{t+r}\omega_1 + K_r \omega_2\right)}{1 + \sum_{(j',r') \in R_t} \exp\left(\beta_{ij'r'} p_{j'tr'} + C_{j'}\delta_i + I_{j'}\alpha + K_{t+r'}\omega_1 + K_{r'}\omega_2\right)}, \quad (2)$$

where p_{jtr} is log price for the focal cruise product and β_{ijr} represents the price sensitivity of simulated consumer i; C_j, I_j, K_{t+r}, and K_r are the vectors of indicator variables of cabin types, itineraries, departure week, and temporal distance; δ_i, α, ω_1, and ω_2 are parameter vectors to be estimated; and ω_2, in particular, represents the utility value of the degree of flexibility afforded by the week of temporal distance in which the consumer purchases.

We note that including all available products in the choice set may be viewed as expansive. This decision is guided by the use of the Gandhi and Houde (2017) instrumental variable strategy described in Section 4.2, which approximates the optimal instruments as a function of product characteristic differentiation of all choices in the data. Gandhi and Houde (2017) argue that the attribute-level differentiation directly measures substitutability among differentiated products in a choice set, in a similar manner to identify a nested logit model. Therefore, instead of imposing a researcher's assumption, we include all potential choices in the data, and the exogenous attribute-level differentiation controls for the relative substitutability. We show the robustness of the qualitative results to various alternate assumptions, including smaller choice sets, in Section 5.

4.1.2. Time-Varying Price Responsiveness. The price coefficient β_{ijr} varies with product attributes and r, the temporal distance in weeks between ticket purchase and cruise departure:

$$\beta_{ijr} = \beta_{0i} + f(r|\beta_i) + C_j\beta^C + I_j\beta^I, \quad (3)$$

where β_{0i} is the baseline price responsiveness parameter and $f(r|\beta_i)$ is the time-varying component of price responsiveness of simulated consumer i; and C_j and I_j are the vectors of cabin and itinerary indicator variables, respectively. Parameter vectors β^C and β^I capture differences in purchasers' price sensitivity across cabin types and itineraries to allow price sensitivity to vary across products in different price tiers; a price change for a high-priced good may affect demand differently from that of a lower-priced good. Including the product attribute indicator variables helps to ensure that the temporal distance interactions with price are not confounded with other observable characteristics that correlate with temporal distance. For robustness, we also estimate and present a specification without β^C and β^I in Equation (3) in Section 4.4.3.

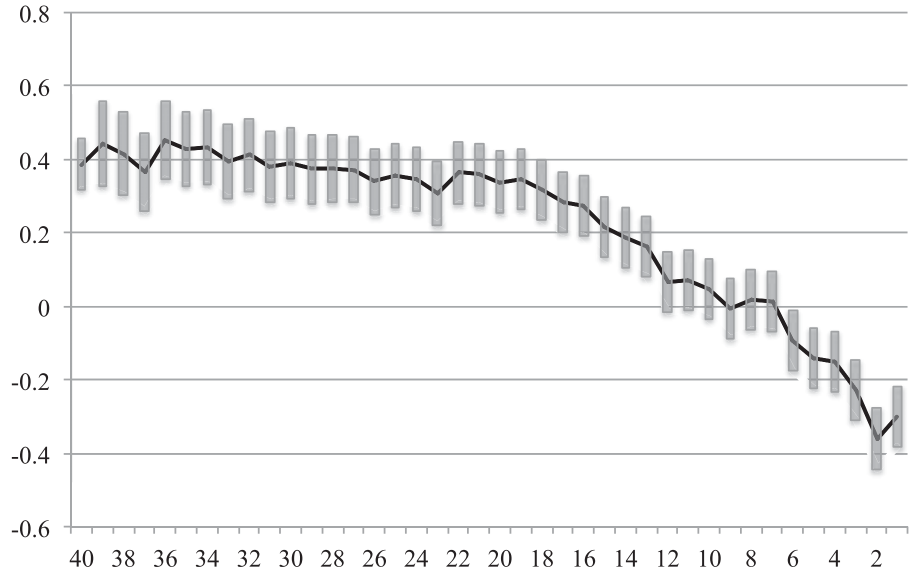
The time-varying component of the price coefficient, $f(r|\beta_i)$, represents the part of simulated consumer i's price sensitivity that may vary with temporal distance between ticket purchase and cruise departure. As a preliminary investigation of the data, we estimated a multinomial logit (MNL) model specifying $f(r|\beta_i)$ as a maximally flexible function of fixed effects for each individual value of temporal distance r. Figure 8 shows the estimated price sensitivity over weeks in the advance sales window. Fixed effect estimates were mostly flat between 40 and 20 weeks of temporal distance, then increasing (in absolute value) at an increasing rate thereafter. The baseline price coefficient β^0 is -0.66, so price responsiveness is negative in all ranges of temporal distance.

Other things equal, we prefer to specify a parsimonious and continuous function $f(r|\cdot)$. Therefore, we report a piecewise linear function $f(r|\beta_i)$ with three possible slopes over the advance sales window that can reflect the pattern observed in Figure 8:

$$f(r|\beta_i) = \begin{cases} \beta_{1i}\cdot(30-r), & \text{if } 20 \le r < 30 \\ \beta_{1i}\cdot 10 + \beta_{2i}\cdot(20-r), & \text{if } 10 \le r < 20 \\ \beta_{1i}\cdot 10 + \beta_{2i}\cdot 10 + \beta_{3i}\cdot(10-r), & \text{if } r < 10, \end{cases} \quad (4)$$

The baseline price coefficient β_{0i} captures price sensitivity of baseline product when r is greater than or equal to 30 weeks, and the three slope parameters, β_{1i}, β_{2i}, and β_{3i}, estimate marginal effects of temporal distance r on price sensitivity within each range of 10 weeks of temporal distance. The first 10 weeks of the reservation window (i.e., $r \ge 30$) are considered to be baseline due to the time-invariant price sensitivity shown in Figure 8 and small number of observations. The coefficient β_{1i} is the marginal impact of temporal distance on price responsiveness for $20 \le r \le 29$, β_{2i} is the marginal impact for $10 \le r \le 19$, and β_{3i} is the marginal impact for r less than 10 weeks. The additive terms in the second and third ranges of temporal

Figure 8. Price Coefficients with Temporal Distance Fixed Effects in the MNL Model



distance ensure continuity of $f(r|\beta_i)$ at the break points between ranges of weeks. A negative slope parameter indicates that demand becomes more responsive to price as time goes by, and a positive slope parameter indicates that demand becomes less responsive to price as time goes by.

4.1.3. Taste Heterogeneity. The price coefficients and cabin type preference vector $\theta_i = \{\beta_{0i}, \beta_{1i}, \beta_{2i}, \beta_{3i}, \delta_i\}$ are specified as the sum of mean responses $\bar{\theta} = \{\beta_0, \beta_1, \beta_2, \beta_3, \delta\}$ and an unobserved heterogeneity vector D_i, where $\theta_i = \bar{\theta} + D_i$ and D_i follows a mean-zero multivariate normal distribution denoted $F(D)$ with a diagonal covariance matrix Σ to be estimated. The aggregate-level choice probability or market share s_{jtr} of cruise product j in reservation week t departing in week $t + r$ is obtained by integrating the simulated individual choice probabilities π_{ijtr} over the distribution of unobserved heterogeneity $F(D)$:

$$s_{jtr} = \int \pi_{ijtr} dF(D). \tag{5}$$

4.2. Identification Strategy

It has become increasingly clear in recent years that there are two standard endogeneity concerns in identifying random utility demand models. Gandhi and Houde (2017, p. 4) explained it well: "Price endogeneity is a familiar problem in the literature with a long history . . . however, a key point in Berry and Haile (2014) is that the identification of substitution patterns poses a distinct empirical problem from price endogeneity. This is because there are in fact two different sets of endogenous variables in the model—prices and market shares—which require different sources of exogenous variation for the model to be identified."

Exogenous cost shifters are classic instrumental variables used to resolve price endogeneity (Berry and Haile 2014). We use the log price of West Texas Intermediate crude oil as a direct cost shifter, as West Texas Intermediate is the standard benchmark price for the light, sweet crude oil used to operate most cruise ships. Crude oil price is exogenously determined by an international commodity market, so it could only be influenced by unobserved drivers of cruise demand if the cruise line exercised market power (i.e., was not a price taker) in that global commodity market. We form additional instruments by interacting crude oil price with cruise product attributes. As shown in Section 4.2.1, crude oil price and its interactions with product attributes are both strong predictors for endogenous cruise prices.[11]

Three remarks are in order regarding the use of crude oil prices as a demand-side instrumental variable. First, at the time the data were produced, the focal cruise line and its competitors did not use oil futures to insure against unexpected changes in future oil prices, suggesting that the spot price at the time of ticket purchase is the right measure of the firm's expected input cost. Second, the focal firm did not pass along crude oil surcharges to consumers during the sample period. Third, an untestable weakness of the instrument is that crude oil price may correlate with cruise complements, such as airline ticket prices. In such a case, a rise in crude oil price would increase cruise price and airline ticket price, indirectly depressing cruise demand beyond the main depressive effect of crude oil price on cruise ticket sales.

To resolve the second identification concern, we follow the majority of the discrete choice literature in first assuming that nonprice product attributes are fixed in the short run. This assumption is credible in our context as cruise departures followed a regular schedule, with different ships leaving at different intervals, but with no alterations of the overall departure schedule observed during the sample period. Conditional on this assumption, we follow the approach of Gandhi and Houde (2017) to approximate the optimal instruments by constructing market differentiation instrumental variables. The basic intuition is that exogenous variation in the choice set leads to exogenous variation in each product's relative isolation or closeness to competing alternatives in attribute space, and therefore substitutability. Such attribute-level variation in the choice set across reservation weeks therefore exogenously identifies substitution patterns. The Gandhi and Houde (2017) approach is elegant in that it offers a set of low-order basis functions that provably approximate the optimal instruments, independent of the number of products in the choice set and without incurring a curse of dimensionality.

4.2.1. Cost Shifter Instrumental Variables. We construct the following sets of instruments with crude oil price and observed product characteristics:

$$\text{Product characteristics: } \mathbf{Z_1} = \begin{bmatrix}\mathbf{1} & C_j & I_j & K_r & K_{t+r}\end{bmatrix}, \quad (6)$$

$$\text{Cost shifter: } \mathbf{Z_2} = \begin{bmatrix}z_t & (C_j \cdot z_t) & (I_j \cdot z_t) & (h(r) \cdot z_t)\end{bmatrix}. \quad (7)$$

The product characteristics instrument vector $\mathbf{Z_1}$ contains intercept, and product attributes including cabin type, itinerary, departure week, and temporal distance dummies.

The cost shifter instrument vector $\mathbf{Z_2}$ contains crude oil price z_t and its interactions with cabin type and itinerary dummies and a vector of temporal distances by three segments of 10 weeks, $h(r)$, corresponding to the piecewise linear function $f(r|\cdot)$:

$$\begin{aligned} h(r) = [&\mathbf{1}\{20 \le r < 30\} \cdot (30 - r) \\ &\mathbf{1}\{10 \le r < 20\} \cdot (20 - r) \\ &\mathbf{1}\{r < 10\} \cdot (10 - r)], \end{aligned} \quad (8)$$

where $\mathbf{1}\{\cdot\}$ is an indicator variable that is one if the temporal distance r falls in to one of three ranges, and zero otherwise. The components of $h(r)$ generate an interaction between temporal distance changes and cost shifter value in three ranges of temporal distance, each of which corresponds to the price component that interacts with temporal distance by $f(r|\cdot)$. The dimension of the vector in Equation (7) matches the number of regressors affected by price endogeneity in Equation (3).

The correlation between instrumental variables and endogenous regressors can be empirically evaluated by a first-stage regression, and a sufficiently high F-statistic implies that the selected instrumental variables are relevant (Staiger and Stock 1997, Stock et al. 2002). To test the strength of the instruments, we regress log price p_{jtr} on the following three sets of explanatory variables:

$$p_{jtr} = \phi_0 + C_j\phi_1 + I_j\phi_2 + K_{t+r}\eta_1 + K_r\eta_2 + \epsilon_{jtr}, \quad (9)$$

$$p_{jtr} = \phi_0 + C_j\phi_1 + I_j\phi_2 + K_{t+r}\eta_1 + K_r\eta_2 + z_t\psi_1 + \epsilon_{jtr}, \quad (10)$$

$$\begin{aligned} p_{jtr} = &\phi_0 + C_j\phi_1 + I_j\phi_2 + K_{t+r}\eta_1 + K_r\eta_2 + z_t\psi_1 \\ &+ (C_j \cdot z_t)\psi_2 + (I_j \cdot z_t)\psi_3 + z_t \cdot f(r|\psi_4) + \epsilon_{jtr}, \end{aligned} \quad (11)$$

where Equation (9) captures log price variation by observed product characteristics, Equation (10) captures the additional variation by common cost shifter over reservation period t, and Equation (11) further captures the marginal log price variation by cost shifter across different product characteristics, that is, cabin type, itinerary, and temporal distance.

Table 3 reports model fits of three specifications and F-statistics between each pair. The adjusted R-squared values are monotonically increasing from 0.8515 in Equation (9) to 0.8596 in Equation (11), indicating that adding a cost shifter and its interactions with product characteristics enhances the explanatory power. The F-statistic between Equations (9) and (10) is 90.2 with p-value much smaller than 0.01 and that between Equations (10) and (11) is 69.6 with p-value much smaller than 0.01, rejecting the null hypotheses that the instruments are poor predictors of cruise price. This confirms that crude oil price in a reservation period t alone is already a strong predictor of cruise ticket price in week t in addition to observed product

Table 3. First-Stage Regression Comparison

Specification	Equation (9) *Char.Only*	Equation (10) *Char.&CrudeOil*	Equation (11) *Char.&CrudeOil* *Char. × CrudeOil*
Adjusted R^2	0.8515	0.8520	0.8596
F-Statistic w/Equation (9)	—	90.2	71.1
F-Statistic w/Equation (10)	—	—	69.6
# of observations	19,552	19,552	19,552

characteristics, and interactions between crude oil price and product characteristics further add predictive power of cruise ticket prices. Both F-statistics surpass the empirical threshold of 10 to gauge first-stage instrument strength suggested by Stock et al. (2002).

The first-stage parameter estimates for crude oil price and its interactions with product characteristics in Equations (10) and (11) are reported in Table 4. The crude oil price parameter estimate of Equation (10) is positive and statistically significant, which confirms that a cruise ticket price in a given reservation period t is positively correlated with an exogenous crude oil price index observed in the same time period t. Interaction parameter estimates in Equation (11) further describe how crude oil price is correlated with different cruise products' prices. The positive and statistically significant parameter estimates of interactions between crude oil and temporal distance for $r < 20$ indicates that crude oil prices observed in period t are more positively correlated with cruise ticket prices as departure dates are closer to the reservation period t as one would expect. This tendency is even stronger when $r < 10$ than when $10 \leq r < 20$. In addition, crude oil prices are more positively correlated with prices of cruises with seven-day duration (itineraries 23, 28, 30, 31, and 55) than the prices of shorter-duration cruises, as longer cruises travel farther and burn more crude oil. Ticket prices of interior cabins are more positively correlated with crude oil prices than those of balcony and ocean view cabins, indicating greater pass-through on lower price cabins. Parameter estimates for product attribute fixed effects of all three regressions are reported in Online Appendix A.

The estimated values from the first-stage regression with the entire set of instruments in Equation (11) predict the exogenous portion of price variation as below:

$$\hat{p}_{jtr} = \hat{\phi}_0 + C_j\hat{\phi}_1 + I_j\hat{\phi}_2 + K_{t+r}\hat{\eta}_1 + K_r\hat{\eta}_2 + z_t\hat{\psi}_1 + \left(C_j \cdot z_t\right)\hat{\psi}_2 + \left(I_j \cdot z_t\right)\hat{\psi}_3 + z_t \cdot f\left(r|\hat{\psi}_4\right). \tag{12}$$

The predicted price, $\hat{p}_{jtr}$, is considered to be the exogenous price index (Gandhi and Houde 2017), as strategic variables, such as the number of unsold cabins of a cruise j departing in week $t + r$ in reservation week t, are not included as predictor variables. This exogenous price index is used as a part of product characteristics to construct market differentiation instrumental variables in the next subsection.

4.2.2. Product Characteristic Differentiation. Following Gandhi and Houde (2017), we first define the distance between two different cruise products in a given reservation week, that is, a combination of j and r versus another combination of j' and r' in reservation week t, for each of the observed product characteristics—cabin type, itinerary, temporal distance, departure season, and price:

$$d^C_{jtr,j'tr'} = \mathbf{1}\{C_j \neq C_{j'}\}, \tag{13}$$

$$d^I_{jtr,j'tr'} = \mathbf{1}\{I_j \neq I_{j'}\}, \tag{14}$$

$$d^K_{jtr,j'tr'} = r - r', \tag{15}$$

$$d^{\hat{p}}_{jtr,j'tr'} = \hat{p}_{jtr} - \hat{p}_{j'tr'}. \tag{16}$$

The differences of cabin type and itinerary between two products in a choice set, $d^C_{jtr,j'tr'}$ and $d^I_{jtr,j'tr'}$, are one

Table 4. Crude Oil Parameter Estimates

Parameter	Equation (10) *Char.&CrudeOil*	Equation (11) *Char.&CrudeOil* *Char.×CrudeOil*
Crude oil	0.325**	–0.352**
(Baseline: $30 \leq r$, itinerary 19, balcony cabin)		
Crude oil × temporal distance ($r < 10$)		0.091**
Crude oil × temporal distance ($10 \leq r < 20$)		0.081**
Crude oil × temporal distance ($20 \leq r < 30$)		-0.079**
Crude oil × itinerary 23		0.321**
Crude oil × itinerary 28		0.378**
Crude oil × itinerary 30		0.337**
Crude oil × itinerary 31		0.622**
Crude oil × itinerary 34		0.243**
Crude oil × itinerary 37		0.132
Crude oil × itinerary 38		–0.198*
Crude oil × itinerary 39		0.310**
Crude oil × itinerary 43		–0.050
Crude oil × itinerary 55		0.437**
Crude oil × interior cabin		0.192**
Crude oil × ocean view cabin		0.082

*Significant at the 95% confidence level; **significant at the 99% confidence level.

if two products are different, and zero otherwise, as both attributes are discrete. The differences of temporal distance are defined as $d^K_{jtr,j'tr'}$, which is the difference between two temporal distances in a given reservation period t. The price difference $d^{\hat{p}}_{jtr,j'tr'}$ is measured by the difference of two predicted prices by exogenous regressors, $\hat{p}_{jtr}$ and $\hat{p}_{j'tr'}$, as observed prices are endogenous.

Using the characteristic differences of each product attribute, we now summarize the relative isolation of a cruise jtr against all other cruises $j'tr'$ in a given reservation week t for all observed attributes. The relative isolation of each product in a choice set constructs market differentiation instrumental variables (Gandhi and Houde 2017). Larger values of the attribute differences indicate that two products (jtr and $j'tr'$) are less likely to directly compete against each other, and smaller values indicate that two products are more likely to directly compete. Therefore, if the attribute difference between jtr and $j'tr'$ is shorter than one standard deviation of the particular attribute distribution, we consider $j'tr'$ as a neighbor of jtr. For discrete attributes, two options with zero attribute difference are considered neighbors. The number of neighboring products (i.e., close substitutes or direct rivals) represents the relative (non) isolation of a cruise product jtr in a choice set available in reservation week t:

$$\mathbf{Z}_{\mathbf{Diff}} = \Bigg[\sum_{j'r'} \mathbf{1}\Big\{d^C_{jtr,j'tr'} = 0\Big\} \quad \sum_{j'r'} \mathbf{1}\Big\{d^I_{jtr,j'tr'} = 0\Big\} \quad \sum_{j'r'} \mathbf{1}\Big\{d^K_{jtr,j'tr'} < \sigma^K\Big\} \quad h(r)\cdot \sum_{j'r'} \mathbf{1}\Big\{d^{\hat{p}}_{jtr,j'tr'} < \sigma^{\hat{p}}\Big\}\Bigg]. \tag{17}$$

The first and second terms ($\sum_{j'r'} \mathbf{1}\{d^C_{jtr,j'tr'} = 0\}$ and $\sum_{j'r'} \mathbf{1}\{d^I_{jtr,j'tr'} = 0\}$) count the numbers of all cruise products offering identical cabin types and itineraries as cruise product jtr in a given reservation week t, respectively. The third term ($\sum_{j'r'} \mathbf{1}\{d^K_{jtr,j'tr'} < \sigma^K\}$) counts the number of products departing in similar seasons, hence similar temporal distances, within one standard deviation of temporal distance distribution σ^K. The last term ($\sum_{j'r'} \mathbf{1}\{d^{\hat{p}}_{jtr,j'tr'} < \sigma^{\hat{p}}\}$) counts the number of products in a similar price range as direct competitors. This interacts with the three segments of temporal distances, $h(r)$, as random price coefficients interact with piecewise linear function of temporal distance $f(r|\cdot)$. A cruise product with fewer direct rivals (i.e., smaller values of each component of $\mathbf{Z}_{\mathbf{Diff}}$) is relatively more isolated in a choice set, thus more likely to be chosen by consumers with different tastes than the mean tendency.

The market differentiation instrumental variables (IV) in Equation (17) can be viewed as a histogram-based basis function to approximate optimal instruments, and the specification is empirically shown to outperform alternative specifications (Gandhi and Houde 2017). However, for the purpose of robustness check, we estimated the model with two alternate empirical specifications of IV's:

$$\mathbf{Z}^{\mathbf{Q}}_{\mathbf{Diff}} = \Bigg[\sum_{j'r'} \Big(d^C_{jtr,j'tr'}\Big)^2 \quad \sum_{j'r'} \Big(d^I_{jtr,j'tr'}\Big)^2 \quad \sum_{j'r'} \Big(d^K_{jtr,j'tr'}\Big)^2 \quad h(r)\cdot \sum_{j'r'} \Big(d^{\hat{p}}_{jtr,j'tr'}\Big)^2\Bigg], \tag{18}$$

$$\mathbf{Z}^{\mathbf{P}}_{\mathbf{Diff}} = \Bigg[\sum_{j'r'} \mathbf{1}\Big\{d^C_{jtr,j'tr'} = 0\Big\} d^{\hat{p}}_{jtr,j'tr'} \quad \sum_{j'r'} \mathbf{1}\Big\{d^I_{jtr,j'tr'} = 0\Big\} d^{\hat{p}}_{jtr,j'tr'} \quad \sum_{j'r'} \mathbf{1}\Big\{d^K_{jtr,j'tr'} < \sigma^K\Big\} d^{\hat{p}}_{jtr,j'tr'} \quad h(r)\cdot \sum_{j'r'} \Big(d^{\hat{p}}_{jtr,j'tr'}\Big)^2\Bigg]. \tag{19}$$

The first alternative specification ($\mathbf{Z}^{\mathbf{Q}}_{\mathbf{Diff}}$) is the quadratic sum of pairwise differences of attribute levels, where larger values of each component indicate more isolation of a cruise product jtr in a given choice set. The second alternative specification ($\mathbf{Z}^{\mathbf{P}}_{\mathbf{Diff}}$) is the sum of local price shocks, where the price differences among direct competitors inform the relative isolation of a product. The sum of local price shocks ($\mathbf{Z}^{\mathbf{P}}_{\mathbf{Diff}}$) can be a useful specification, especially when the choice set is constant and only prices vary over time (Gandhi and Houde 2017).[12] The three empirical specifications of the differentiation IV's yield nearly identical estimation results, so we report the main results using Equation (17).

4.3. Estimation

Demand is estimated by applying the generalized method of moments (GMM) using the standard procedure described by Greene (2008, p. 333). Moments are constructed by interacting market share residuals with a vector of instruments:[13]

$$\Big(\hat{\Theta}, \hat{\Sigma}\Big) = \underset{\Theta,\Sigma}{\operatorname{argmin}} \frac{1}{2}\big\{[\mathbf{S} - \mathbf{s}(\Theta, \Sigma, \mathbf{p})]'\mathbf{Z}\big\}(\mathbf{Z}'\mathbf{Z})^{-1} \big\{\mathbf{Z}'[\mathbf{S} - \mathbf{s}(\Theta, \Sigma, \mathbf{p})]\big\}, \tag{20}$$

where $\mathbf{S} = \{S_{jtr}\}$ is a vector of the observed market shares of all cruise products j,[14] reservation weeks t, and departure weeks $t + r$; $\mathbf{s}(\Theta, \Sigma, \mathbf{p}) = \{s_{jtr}(\Theta, \Sigma, \mathbf{p})\}$ is a vector of predicted market shares based on a set of all demand parameters Θ, variance parameters of random coefficients Σ, and observed price vector $\mathbf{p} = \{p_{jtr}\}$ for all j, t, and $t + r$; and $\mathbf{Z}$ is a vector of instruments.

The instrument vector contains exogenous product characteristics, cost shifter, interactions between cost shifter and product characteristics, and product characteristic differentiations, where $\mathbf{Z} = [\mathbf{Z_1} \;\; \mathbf{Z_2} \;\; \mathbf{Z_{Diff}}]$. The RCL model in Equation (2) has 125 model parameters to identify (six random coefficients, six corresponding variance parameters, and 113 fixed coefficients), and the instrument vector $\mathbf{Z}$ has 125 exogenous components, so the model is just identified by the instrumental variables.

4.4. Empirical Results

The discussion focuses on the relationship between price responsiveness and temporal distance from the RCL model. We also briefly discuss price responsiveness by product characteristics, and present a series of comparisons of time-varying parameter estimates across different price coefficient specifications and between inclusion/exclusion of expected future prices. Remaining results are covered in Online Appendix B.

4.4.1. Temporal Distance and Price Responsiveness. Table 5 presents the slope and variance parameter estimates in the price responsiveness specification. For example, β_{3i} is the mean effect of one less week of temporal distance on price responsiveness within the last range of temporal distance (0–9 weeks). So, $\beta_{3i} < 0$ indicates that price response becomes stronger (more negative) as temporal distance between purchase and consumption decreases.

As expected, the mean baseline price coefficient β_{0i} is negative and large enough that price responsiveness is negative for all ranges of temporal distance. Price responsiveness to tickets purchased more than 30 weeks prior to consumption is captured by β_{0i}. The estimation results show that β_{1i} is small but positive, indicating that price response diminishes slightly with temporal distance for tickets purchased between 20 and 29 weeks prior to consumption. Price responsiveness then amplifies (in absolute value) over time in the final 20 reservation weeks, when the remaining 87% of cruise bookings take place, and the slope becomes sharper in the final 10 weeks than in the prior 10 weeks (i.e., $|\beta_{3i}| > |\beta_{2i}|$). The heterogeneity parameter for baseline price coefficient β_{0i} is marginally significant with t-statistic of 1.74, but other heterogeneity parameters are not statistically significant.[15]

The size of this effect is most easily interpreted in terms of price elasticity. We calculate price elasticities of product-level market shares for all j, t, and r, (i.e., $\frac{\partial s_{jtr}/s_{jtr}}{\partial P_{jtr}/P_{jtr}}$), and summarize how price elasticity medians and 95% confidence intervals change with temporal distance r. Figure 9 shows that price elasticity monotonically increases (in absolute value) in the final 20 weeks prior to departure. Confidence intervals exclude zero throughout the entire reservation window. The 95% confidence intervals of the price elasticity estimates start to include the threshold of unitary elasticity from 12 weeks prior to departure until the end of the reservation window. Therefore, in the final 12 weeks, the null hypothesis that the demand is elastic cannot be rejected. This pattern shows that aggregate cruise demand is more responsive to prices shortly before departure than early in the reservation window.

At first glance, one might think that the observed price elasticity pattern implies that a decreasing price path would be optimal. However, to understand how demand changes with temporal distance, the main effect of temporal distance on demand must also be considered. Figure 10 shows that the main effect of temporal distance on demand increases strongly between the start and end of the advance sales period, reflecting an aggregate tendency toward later purchases. This tendency is nearly flat in the first 20 weeks of the reservation window, and monotonically increases until two weeks prior to departure with slight decrease in the final two weeks.

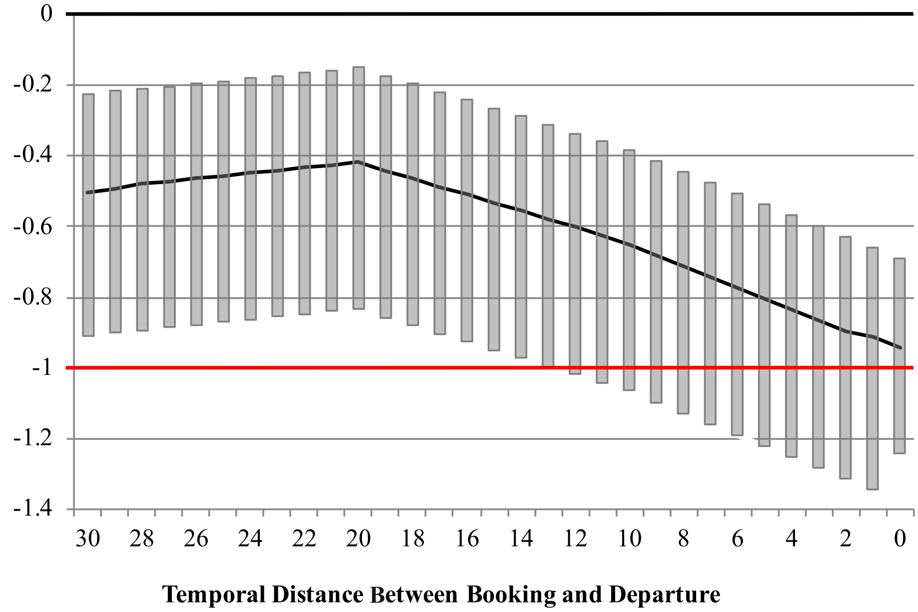
The time-varying patterns in Figures 9 and 10 indicate an important divergence between price responsiveness and baseline utility, which may have a pricing implication. Aggregate demand is more responsive to price during the period of high demand or utility, and it is less responsive to price during the period of low demand or utility. The pricing literature often assumes that high price sensitivity co-occurs

Table 5. Price Coefficients by Temporal Distance from Consumption

	Mean		Heterogeneity	
Coefficient	Point estimate	Standard error	Point estimate	Standard error
Baseline β_{0i}	−0.760	0.019**	0.042	0.024
Time-varying slope β_{1i} $(20 \le r < 30)$	0.007	0.002**	0.002	0.008
Time-varying slope β_{2i} $(10 \le r < 20)$	−0.023	0.001**	0.002	0.003
Time-varying slope β_{3i} $(r < 10)$	−0.031	0.001**	0.002	0.003
Pseudo R^2	0.547			

**Significant at the 99% confidence level.

Figure 9. (Color online) Time-Varying Price Elasticities



with low utility (i.e., low valuation or low willingness to pay) and low price sensitivity co-occurs with high utility (i.e., high valuation or high willingness to pay). On the other hand, our results show it is possible that demand during the period of high utility can be more sensitive to price. That said, a demand curve may shift up at the intercept during the high demand or utility period, yet its curvature with respect to price can be steeper. This suggests that it is a nontrivial problem whether to raise prices during the period of high utility or demand, if the time-varying price sensitivity amplifies during that period. Therefore, depending on the sensitivity, there exists a trade-off between price responsiveness and baseline utility.

The empirical results of time-varying price responsiveness provide the first evidence of potential divergence with baseline utility variation over time. This suggests an important trade-off in pricing decisions, as the baseline utility increase leads revenue improvement with higher prices, yet it may be offset by demand decrease due to consumers' responses to price.

4.4.2. Price Responsiveness Across Products. Table 6 presents the effects of itineraries and cabin types on price responsiveness. Aggregate demand for shorter itineraries is less responsive to price than demand for longer cruises, with a correlation of −0.5 between price-itinerary interaction coefficients and itinerary

Figure 10. Temporal Distance Main Effects

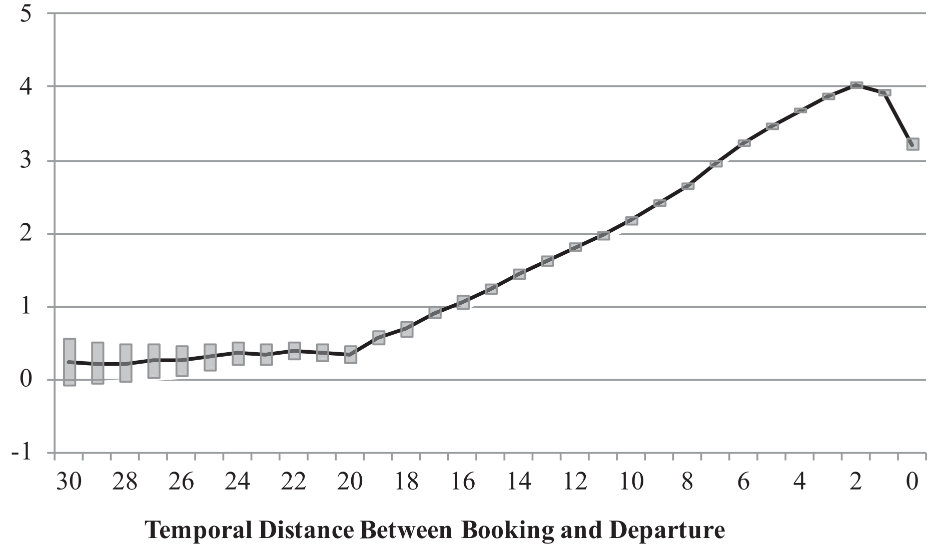


Table 6. Price Coefficients by Itineraries and Cabin Types

Itineraries—Base: Itinerary 19	Point estimate	Standard error
Itinerary 23	0.016	0.016
Itinerary 28	0.069	0.007**
Itinerary 30	−0.159	0.010**
Itinerary 31	0.168	0.011**
Itinerary 34	0.026	0.010**
Itinerary 37	0.235	0.005**
Itinerary 38	0.154	0.005**
Itinerary 39	−0.011	0.012
Itinerary 43	0.268	0.020**
Itinerary 55	0.016	0.011
Cabin types—Base: Balcony		
Interior cabin	0.259	0.047**
Ocean view cabin	0.137	0.030**

**Significant at the 99% confidence level.

durations. Demand for interior and ocean view cabins is less responsive to price than demand for balcony cabins. We view these attribute-specific effects as control variables and include them to prevent confounds from contaminating the effects of temporal distance on price sensitivity. The time-varying price sensitivity parameters in Table 5 remain nearly identical without the product-specific controls in the price coefficients, as shown in the next subsection.

4.4.3. Model Parameter Comparison. The core goal of estimating RCL model in Equation (2) is to recover the time-varying pattern of price responsiveness during the reservation window. The sharply increasing pattern of prices in Figure 4 implies that consumers' optimal purchase timing is to purchase as soon as they arrive on the market. However, price paths of individual cruises may deviate from the mean tendency, and such deviation may influence our estimates of time-varying price responsiveness pattern.[16]

To assess whether consumers' anticipation of price drops influences the aggregate time-varying price response pattern or not, we define a control variable of expected price change (EPC) as the expectation in week t of the change in price level between reservation weeks t and $t+1$ for a given cruise product j and departure week $t+r$:

$$EPC_{jtr} \equiv E_t\left[P_{j(t+1)(r-1)}\right] - P_{jtr}, \tag{21}$$

where P_{jtr} is the price level observed in reservation week t of cruise j departing r weeks later, and $E_t[P_{j(t+1)(r-1)}]$ is the expectation (in reservation week t) of the same cruise's price in the following reservation week $t+1$.[17]

We assume that consumers formulate a rational expectation of the next week's price by observing the prior week's price and other characteristics for the same cruise product. Therefore, we first run the following log price regression:

$$p_{jtr} = g\left(p_{j(t-1)(r+1)}, C_j, I_j, K_{t+r}, K_r|\Omega\right), \tag{22}$$

where $g(\cdot|\Omega)$ is a linear function with a set of parameters to be estimated Ω; $p_{j(t-1)(r+1)}$ is a lagged log price of the same cruise jtr in the previous reservation week; and C_j, I_j, K_{t+r}, and K_r are product attribute fixed effects previously defined. The number of unsold tickets may be an additional valid predictor of future prices from consumers' perspective, but it did not improve the predictive fit and its coefficient was not statistically significantly different from zero. Using parameter estimates $\hat{\Omega}$, the future price is predicted using the observed price and characteristics in the current reservation week t:

$$\begin{aligned} E_t\left[P_{j(t+1)(r-1)}\right] &= exp\left\{\hat{p}_{j(t+1)(r-1)}\right\} \\ &= exp\left\{g\left(p_{jtr}, C_j, I_j, K_{t+r}, K_{(r-1)}|\hat{\Omega}\right)\right\}, \end{aligned} \tag{23}$$

where this rational expectation is plugged into Equation (21) to construct the EPC variable.

For sensitivity testing, we include EPC_{jtr} in the RCL model as an explanatory variable:

$$\pi_{ijtr} = \frac{\begin{aligned}\exp\big(&\beta_{ijr}p_{jtr} + \kappa EPC_{jtr} + C_j\delta_i + I_j\alpha + K_{t+r}\omega_1 \\ &+ K_r\omega_2\big)\end{aligned}}{\begin{aligned}1 + \Sigma_{(j',r')\in R_t} &\exp\big(\beta_{ij'r'}p_{j'tr'} + \kappa EPC_{j'tr'} \\ &+ C_{j'}\delta_i + I_{j'}\alpha + K_{t+r'}\omega_1 + K_{r'}\omega_2\big)\end{aligned}}, \tag{24}$$

where κ captures potential increases/decreases in purchase probabilities due to consumers' expectation of future price changes. Although this model specification is not an individual-level forward-looking model, the inclusion of EPC_{jtr} may partially control potential biases in price coefficients potentially coming from a portion of consumers who may defer their purchases at the market level. In place of EPC_{jtr}, we also test a binary variable $\mathbf{1}\{EPC_{jtr} > 0\}$ to capture the influence of expected price increase and mitigate potential collinearity with current price.

We estimate the RCL model in Equation (24) using the same nonlinear GMM with instrumental variables in Equation (20). Because EPC_{jtr} is an endogenous variable that depends on observed price P_{jtr}, an additional set of instrumental variables are required for identification. We use the observed future change in cost shifter (i.e., crude oil price) and its interaction with product characteristics as an exogenous variation that influences ticket price changes:

$$\mathbf{Z_3} = \left[dz_t \;\; (C_j \cdot dz_t) \;\; (I_j \cdot dz_t) \;\; (h(r) \cdot dz_t)\right], \tag{25}$$

where $dz_t = z_{t+1} - z_t$, future changes of crude oil price between period t and $t+1$. To estimate models with the EPC variable, the instrument vector used is $\mathbf{Z} = [\mathbf{Z_1}\ \mathbf{Z_2}\ \mathbf{Z_3}\ \mathbf{Z_{Diff}}]$. In this case, the number of model parameters to identify is 126 and the number of instruments is 141, so the model is over-identified.

In addition to potential purchase deferral, one may also suspect that the inclusion of product characteristics in the price coefficient specification (i.e., β^C and β^I) influences the time-varying pattern of price responses and over-parametrizes the model. To further ensure that the time-varying pattern is not an artifact of the price coefficient specification, we test the RCL model with the following simple price coefficients:

$$\beta_{ijr} = \beta_{0i} + f(r|\beta_i), \tag{26}$$

where product characteristics are no longer included in the price coefficients.

Table 7 presents the mean estimates of time-varying price coefficients and the EPC parameter across six different specifications. For comparison, the first column in Table 7 duplicates the main model results from Table 5. First of all, the time-varying slopes (β_{1i}, β_{2i}, and β_{3i}) are remarkably stable with and without EPC variable and product characteristics coefficients, and consistent with the main model results. This confirms that our main finding of amplifying price responsiveness in the final 20 weeks of the reservation window is robust considering consumers' anticipation of future price drops/increases and potential confounds with product characteristics. The estimates of EPC parameter κ are positive and statistically significant across all specifications, indicating that a higher portion of consumers immediately purchase in reservation week t, if they expect the price to increase in the following reservation week $t+1$. However, one should use caution in interpreting this parameter as acceleration or deferral of consumer purchase, because observed prices present a monotonically increasing pattern on average and a period of $\mathbf{1}\{EPC_{jtr} > 0\}$ is highly likely to co-occur with a period with low absolute level of price.

Ultimately the current paper's intended contribution is to document a pattern that exists in the data we analyze, as opposed to focusing on a particular model to point-identify that pattern. Section 5 will show that the paper's main result is robust to a wide variety of models, parameterizations, and partitions of the data.

4.5. Revenue Sensitivity Tests with Alternate Pricing Slopes

Interesting questions to consider include: How does the firm's revenue change with alternative price slopes across weeks of temporal distance? How much would this revenue sensitivity with respect to price slopes vary across cruise itineraries?

We undertake these questions with substantial caution, as important caveats apply to the results. The data do not provide variation in the firm's observed pricing policy, so there are no data to identify consumer or competitor reactions to changes in firm pricing policy. Everything that follows must be interpreted as the model's prediction of an immediate market response to a change in pricing policy, prior to considering any response in competitor or consumer behavior. In other words, we undertake a partial-equilibrium analysis with the knowledge that the Lucas critique applies to the results.

With these caveats firmly in mind, we are interested in using the empirical model to predict how cruise itinerary revenues would respond to local changes in the slope with which cruise itinerary price changes with temporal distance. We do three things to try to limit concerns about external validity. First, we constrain policy experiments to vary the pricing policy for only one cruise itinerary at a time. Second, we impose a constraint on all policy experiments that the average cruise price must remain constant; the only thing that

Table 7. Comparison of Time-Varying Price Coefficients

	Main model	Alternate 1	Alternate 2	Alternate 3	Alternate 4	Alternate 5
Coefficient	estimate	estimate	estimate	estimate	estimate	estimate
β_{0i}	−0.760**	−0.465**	−0.588**	−0.465**	−0.188**	−0.313**
β_{1i} $(20 \le r < 30)$	0.007**	0.006**	0.009**	0.006**	0.005*	0.007**
β_{2i} $(10 \le r < 20)$	−0.023**	−0.024**	−0.025**	−0.024**	−0.022**	−0.025**
β_{3i} $(r < 10)$	−0.031**	−0.035**	−0.034**	−0.032**	−0.030**	−0.036**
EPC parameter κ		0.003**	0.439**		0.002**	0.505**
Specifications						
EPC_{jtr}	×	O	×	×	O	×
$\mathbf{1}\{EPC_{jtr} > 0\}$	×	×	O	×	×	O
β^C and β^I	O	O	O	×	×	×

*Significant at the 95% confidence level; **significant at the 99% confidence level.

varies is the slope, that is, the rate at which prices change with temporal distance. Third, we only consider relatively small changes in price slope. Overall, cruise prices rose at a weekly rate of 0.6% in the final 25 reservation weeks. We investigated cruise-specific revenue changes accruing to increments of 0.1% in price slope, for all increments between −1% and 2%. We focused on the data periods of $3 \le r \le 20$, where both price elasticity and total demand steadily increased, to investigate the tradeoffs in revenues. In applying these constraints, we hope to consider fairly subtle policy experiments, rather than stretching the model far beyond the bounds of the data used to estimate it.

The results indicate that, for 10 of 11 cruise itineraries, a further increasing slope of prices would increase revenue. However, for one itinerary, the model predicts that a decreasing slope of prices would increase revenues.

Figure 11 illustrates the predicted changes in revenues for three of the 11 itineraries. The three itineraries depicted were selected simply to facilitate understanding of the general results. Itinerary 23 shows that the price slope of 2% weekly increase would increase the revenue by about 2%, and itinerary 43 shows that the weekly price increase of 2% would further increase the revenue by about 7%. On the other hand, itinerary 30 presents that the price slope of 1% decrease would increase the revenue by about 1%.

Figure 12 illustrates why the revenue sensitivities with respect to price slopes varied across itineraries. For all cruise itineraries, a larger price slope means lower projected bookings, as it implies higher prices in the periods when demand is greatest. However, the degree to which sales are predicted to fall varies across itineraries. The itineraries where faster increasing price slopes are predicted to increase revenues are those for which sales are predicted to fall the least, whereas the itinerary decreasing price slopes are predicted to increase revenues are those for which sales are predicted to fall the most. Although only three itineraries are pictured, this explanation applies to all 11 itineraries studied.

These results are driven primarily by the offsetting effects of temporal distance on the baseline utility. Consumers value flexibility, on average, and therefore most consumers prefer to purchase late in the reservation window. At the same time, conditional on the firm's observed policy of increasing prices, demand is most responsive to price late in the advance sales period. The demand intercept effect dominates the price elasticity effect for most cruises, and the price elasticity effect outweighs for one itinerary in the sample.

5. Robustness Checks

This section presents evidence that the results of primary interest are robust to alternate modeling assumptions, parameterizations, partitions of the data, and alternate explanations. These robustness checks are descriptive, as this simplifies the exposition, but the same results hold when the cost shifter instrumental variables are used to produce causal estimates.

Figure 11. Predicted Changes in Revenues by Price Slope

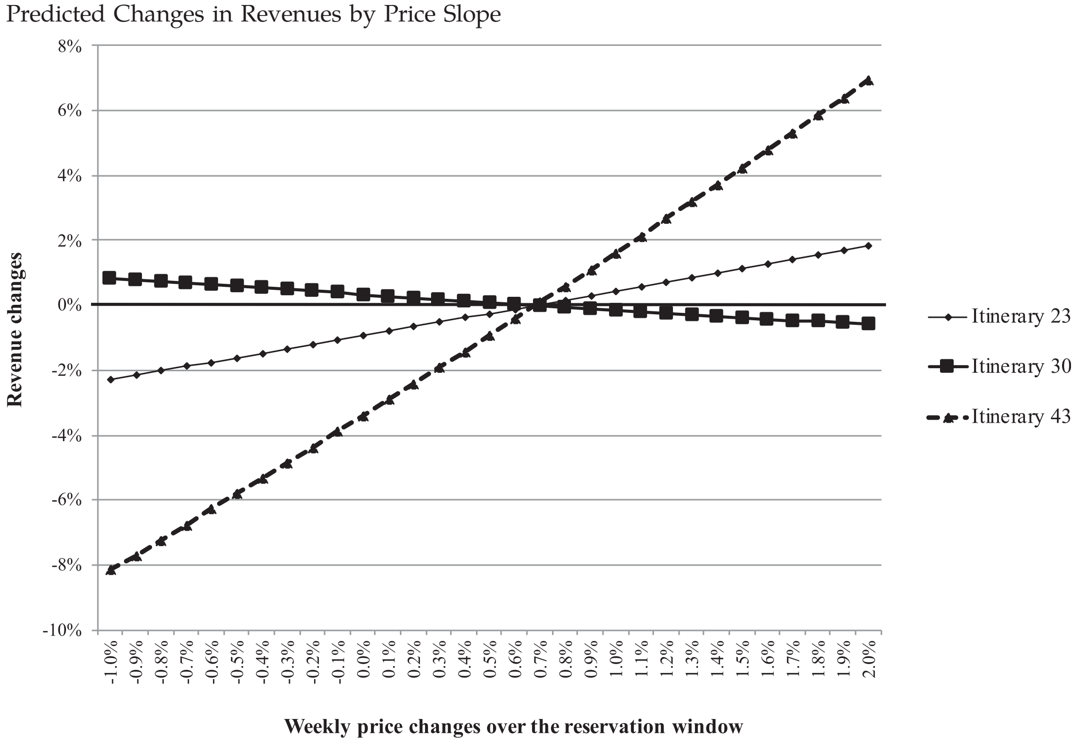
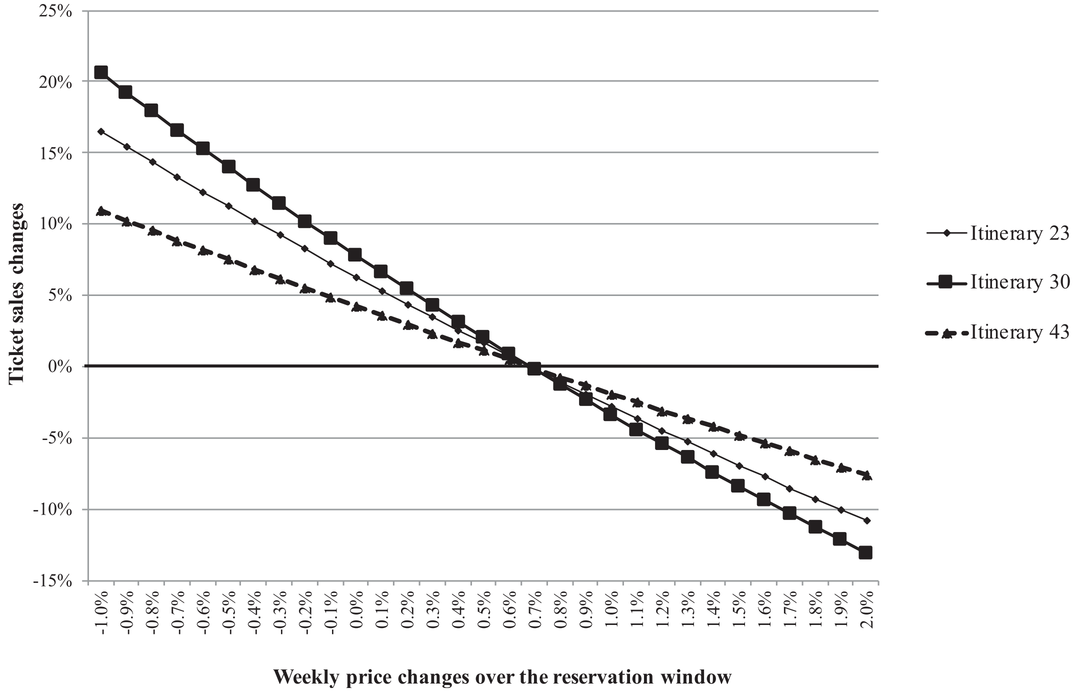


Figure 12. Predicted Changes in Bookings by Price Slope



5.1. Alternate Model Specifications and Parameterizations

An alternate model might reasonably posit that consumers do not substitute across ranges of temporal distance. For example, consumers may predetermine their travel schedules and focus on particular departure weeks in such a way that the RCL model overstates the true set of choices considered. Therefore, we estimate the following log-log demand model as a benchmark for comparison:

$$T_{jtr} = \beta_{jr} p_{jtr} + C_j \delta + I_j \alpha + K_{t+r}\omega_1 + K_r \omega_2 + \epsilon_{jtr}, \qquad (27)$$

where T_{jtr} is log of the number of tickets sold plus one, and the predictors include price, attributes, and timing variables, as before. The time-varying price coefficient is specified as $\beta_{jr} = \beta_0 + f(r|\beta) + C_j\beta^C + I_j\beta^I$, identical to Equation (3) expect for the unobserved heterogeneity specification. For comparison, we also estimate the following MNL model:

$$\log S_{jtr} - \log S_{0t} = \beta_{jr} p_{jtr} + C_j \delta + I_j \alpha + K_{t+r}\omega_1 + K_r \omega_2 + \epsilon_{jtr}, \qquad (28)$$

where S_{jtr} is the observed market share for a combination of j and r booked in week t, and S_{0t} is the outside share.

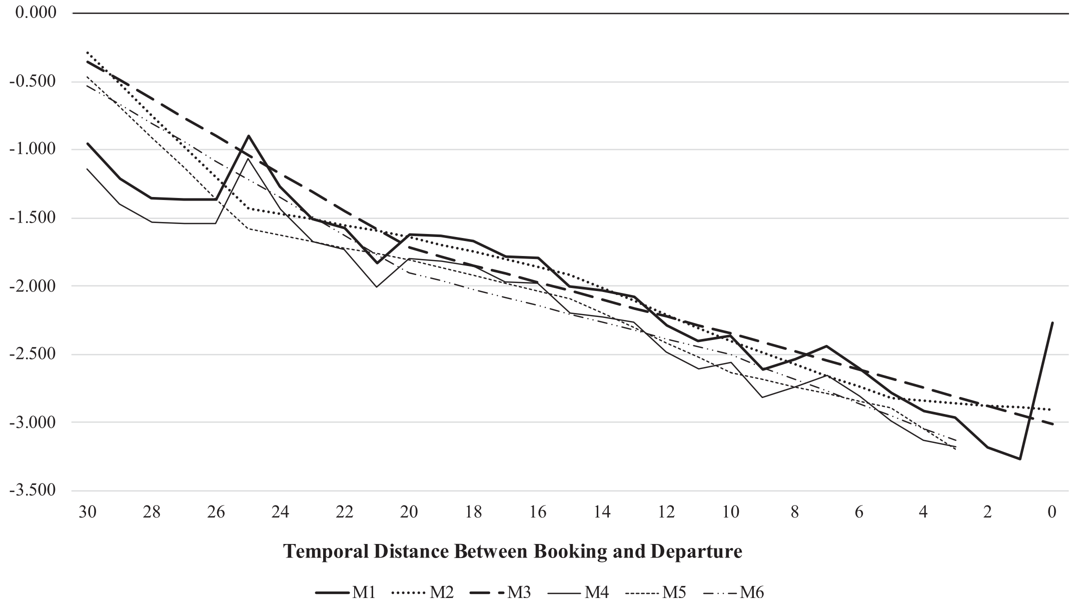
We further investigate the following questions: (i) whether the piecewise specification with 10-week brackets affects the main empirical results, and (ii) whether inclusion of the final three reservation weeks (which featured a sharp drop in sales) affects the results. Therefore, we estimate Equations (27) and (28) with the following specifications and data samples:

- M1: $f(r|\beta)$ including 30 week-specific temporal distance indicators, estimated using the full sample.
- M2: $f(r|\beta)$ including five-week ranges of temporal distance, estimated using the full sample.
- M3: $f(r|\beta)$ including 10-week ranges of temporal distance, estimated using the full sample.
- M4: $f(r|\beta)$ including 30 week-specific temporal distance indicators, dropping data from the final three weeks of temporal distance.
- M5: $f(r|\beta)$ including five-week ranges of temporal distance, dropping data from the final three weeks of temporal distance.
- M6: $f(r|\beta)$ including 10-week ranges of temporal distance, dropping data from the final three weeks of temporal distance.

In all specifications, the first 10 weeks of reservation window (i.e., $r \geq 30$) are considered to be baseline.

Figure 13 presents point estimates for $f(r|\beta)$ in all six models, showing that price elasticities are amplifying over time regardless of model specification, parameterization, and exclusion of anomalous reservation weeks. The log-log model results confirm that the main results are not driven by the choice set in the RCL model. Figure 14 presents point estimates for $f(r|\beta)$ of the final 20 weeks of reservation window in multinomial logit models, showing that price coefficients are increasing (in absolute value) with temporal distance across all six specifications in the second half of

Figure 13. Time-Varying Price Elasticities in Log-Log Models



the reservation window and do not change much with temporal distance when $20 \leq r < 30$.

The reason the multinomial logit models show a kink at about 20 weeks prior to cruise departure, whereas the log-log models do not, is because of the inflection point in weekly ticket sales observed at $r = 20$ in Figure 1. This sales acceleration causes the demand quantity (T_{jtr}) to increase more sharply over time than the log odds ratio ($\log S_{jtr} - \log S_{0t}$) before the 20-week mark. In the second half of the advance sales period, T_{jtr} and $\log S_{jtr} - \log S_{0t}$ change at nearly identical rates.

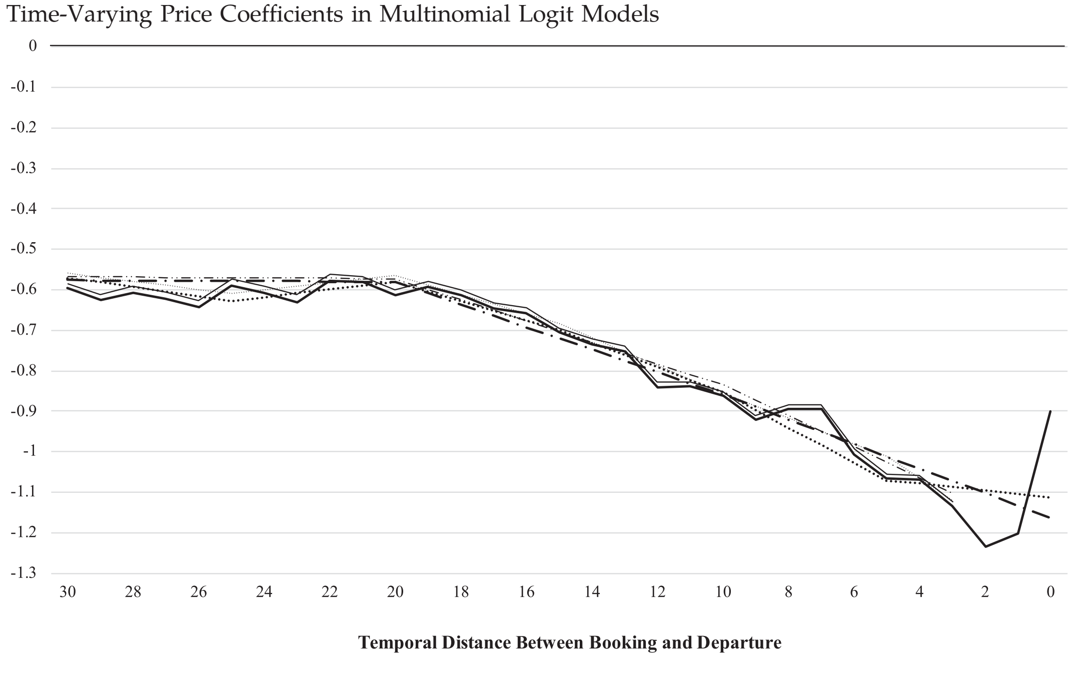
5.2. Partitioned Regressions, Seasonality, and Choice Set Assumptions

Another potential question is whether price responsiveness patterns might be explained by different types of consumers arriving to purchase in different times of the year. To investigate, we partition the data by reservation week and estimate log-log demand models within each partition:

$$T_{jtr} = \theta_{0t} + \theta_{1tr} p_{jtr} + K_r \theta_{2t} + C_j \theta_{3t} + I_j \theta_{4t} + \epsilon_{jtr}, \quad (29)$$

where θ_{0t} is a partition-specific intercept and ϵ_{jtr} is a mean-zero error term; θ_{1tr} is a partition-specific

Figure 14. Time-Varying Price Coefficients in Multinomial Logit Models



parameter that estimates price elasticity for each value of temporal distance r within each reservation week partition; and θ_{2t}, θ_{3t}, and θ_{4t} are fixed-effects parameter vectors estimated separately by partition.

Figure 15 presents point estimates of θ_{1tr}, limited to the first 10 partitions of reservation weeks for visual interpretability. Of course, the estimates are quite noisy, since each is based on a 1/52 subset of data. Still, amplifying price elasticities are estimated within each partition for the final 20 weeks of temporal distance. It appears that cohort differences are not likely to explain the results of primary interest.

Another reasonable alternate model is that some consumers fix a departure date prior to shopping for a cruise. This might be the case if some consumers are more schedule constrained than others, for example, if they would only cruise during summer or a major holiday week when schools are out of session. Or, some consumers' purchases might be driven by concerns that their desired cruise during a high-demand period may sell out or become significantly more expensive, suggesting differences in risk tolerance between consumers. If so, then the results of primary interest might be driven by some form of latent consumer heterogeneity.

To investigate, we first categorized departure weeks into three seasons, according to revenue: Christmas (the highest revenue at \$9 million), high-season weeks with revenue of \$5–8 million, and low-season weeks (below \$5 million). We estimated a multinomial logit model identical to M3 in the previous subsection, where $f(r|\beta)$ interacts with three seasonality dummies. As presented in Figure 16, the time-varying price coefficients increase over time in the final 20 weeks of temporal distance, suggesting that the main result does not change much between peak, high-season, and low-season periods.[18]

We further test the robustness of our findings to choice set assumptions. Our main model in Equation (2)

Figure 15. (Color online) Time-Varying Price Elasticities by Reservation Weeks

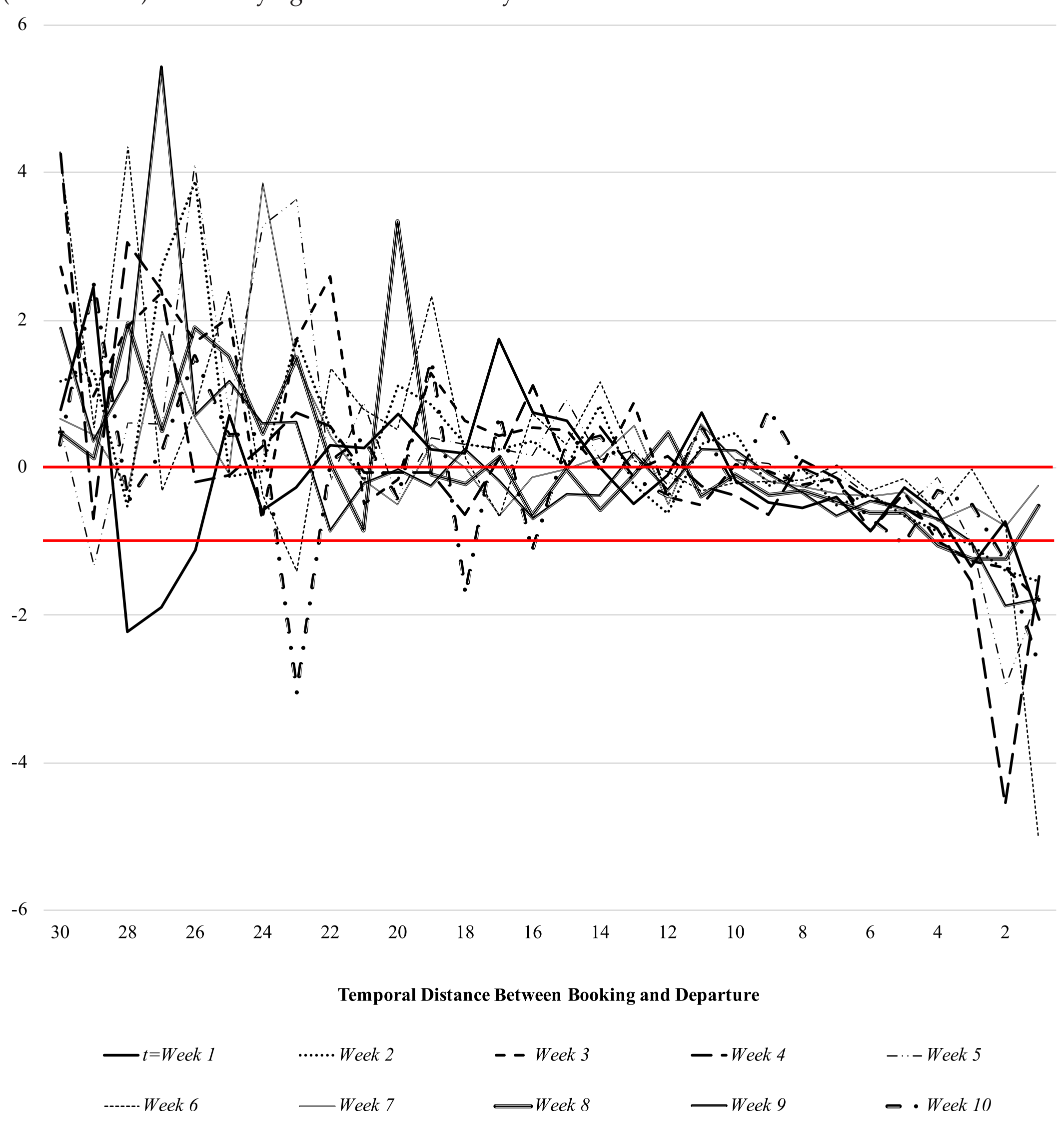
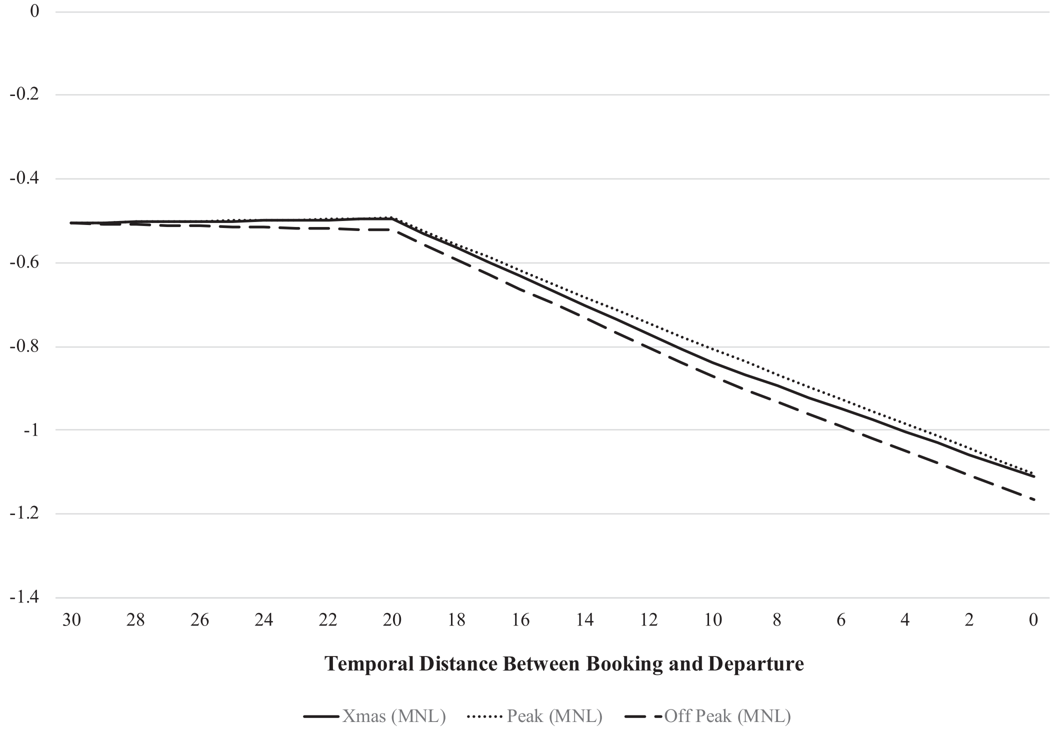


Figure 16. Time-Varying Price Coefficients Across Different Seasons



does not impose any assumption in the choice set, and the market differentiation IV's control for relative substitutability among different products. To explicitly test the potential influence of an alternative choice set assumption, we estimate the MNL model in Equation (28) assuming that consumers predetermine a certain range of dates as their travel schedule and may substitute among cruises departing in neighboring weeks. Therefore, we constrain each choice set to include the neighboring 10 departure weeks in each reservation week t.[19] We specify $f(r|\beta)$ as a piecewise linear function of 10-week ranges of temporal distance, identical to M3.

Table 8 reports time-varying price sensitivity parameter estimates in $f(r|\beta)$. All time-varying slopes are negative and statistically significant, indicating that price responsiveness amplifies as temporal distance falls. The result confirms that our main finding of amplifying price responsiveness is qualitatively robust to an assumption of smaller choice sets with a predetermined range of travel schedule. In addition, point estimates of β_1 and β_2 are larger in absolute magnitudes than the main model results in Table 5, suggesting that our main results may present conservative estimates.

5.3. Alternate Explanation: Sellout-Driven Substitutions

Figures 2 and 3 show that more expensive itineraries and cabins have higher purchase shares early in the advance sales window, whereas less expensive tickets have higher shares late in the reservation period. Could the estimated relationship between temporal distance and price responsiveness be driven by sellouts of expensive itineraries early in the advance sales period? If yes, then the main result may simply be an artifact of consumer switching to lower-priced alternatives later in the reservation period as more expensive alternatives gradually become less available.

To explore this scenario, Table 9 presents sellout frequencies of the three highest-selling itineraries. Nonpictured cruise itineraries show similar patterns. Cruises rarely sell out before the final two weeks of temporal distance, suggesting that sellout-driven substitution is unlikely to cause the observed price elasticity pattern (especially in the range of 10–19 weeks of temporal distance).

Figure 17 summarizes average capacity utilization (i.e., the cumulative number of tickets sold/the total number of tickets available) of these three itineraries over the advance sales window. Mean capacity

Table 8. Time-Varying Price Coefficients in MNL with Smaller Choice Sets

	Point estimate	Standard error
Baseline β_0	–0.177	0.028**
Time-varying slope β_1 ($20 \leq r < 30$)	–0.038	0.003**
Time-varying slope β_2 ($10 \leq r < 20$)	–0.045	0.004**
Time-varying slope β_3 ($r < 10$)	–0.030	0.005**
Adjusted R^2	0.324	

**Significant at the 99% confidence level.

Table 9. Frequency of Sellouts for of Top Three Itineraries

Itinerary	5 weeks ahead	4 weeks ahead	3 weeks ahead	2 weeks ahead	1 week ahead	Total # of cruise products
Itinerary 23 ($665 on average)	0.00%	0.00%	0.00%	3.47%	17.36%	144
Itinerary 43 ($256 on average)	0.00%	0.00%	0.00%	0.00%	10.20%	98
Itinerary 55 ($663 on average)	0.00%	1.35%	1.35%	1.35%	12.16%	74

utilization is actually higher in the week of departure for the cheaper cruise (itinerary 43) than the more expensive cruises. In addition, capacity utilization of the more expensive cruises (23 and 55) increases almost linearly over time, whereas that of the cheaper cruise (43) increases sharply at the last minute. This pattern suggests that consumers buying more expensive options are less constrained by capacity in the final few weeks of temporal distance.

A similar tendency is observed across cabin types. Figure 18 shows that mean final-week capacity utilization is higher for the lowest priced cabin (93% for interior) than for higher priced cabins (80% for ocean view and 86% for balcony). This again suggests that buyers of high-price cabins are less constrained by capacity than low-price cabin buyers.

We note that we lack data on cabin quality other than cabin type. It is plausible that cabins sold earlier in the advance sales period have different unobserved attributes from cabins sold later, such as proximity to the deck or engine room. Therefore, unobserved differences in cabin quality may contribute to explaining the paper's primary result.

To further check whether the main result is driven by substitution among cabin types, we partitioned the data by cabin type and estimated three separate multinomial logit models within each partition. The models incorporated interactions between price and each possible value of temporal distance. Figure 19 graphs the interactions, showing that the pattern of increasing price sensitivity is observed within each partition of the data.

5.4. Alternate Explanation: Competitor Prices (Evidence from 2015)

It is possible that competitive cruise prices covaried with the focal firm's cruise prices. If competitors' prices changed with temporal distance, the apparent relationship between temporal distance and price elasticity may be an artifact of changes in price competition corresponding to ranges of temporal distance. Unfortunately, despite our best efforts, we were not able to obtain competitive cruise prices corresponding to the 2004 booking data.[20]

To investigate correlations among competitors' prices, we purchased newer data from a cruise price tracking firm. The data report weekly Florida cruise ticket prices for the focal cruise line and its three most similar competitors from June to December 2015, by itinerary and cabin type.[21]

Figure 17. Mean Capacity Utilization over Time of Top Three Itineraries

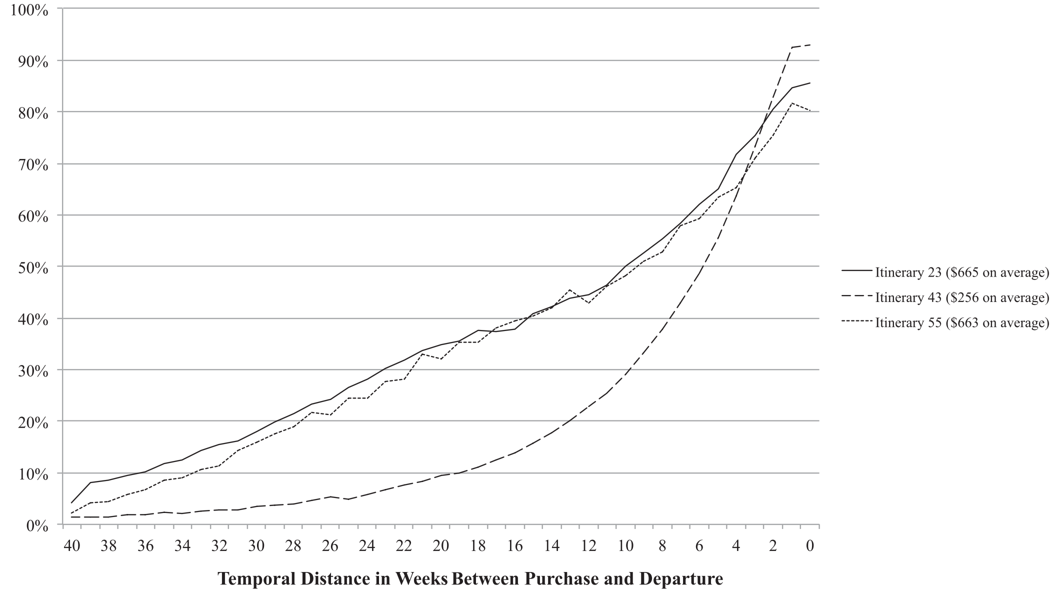
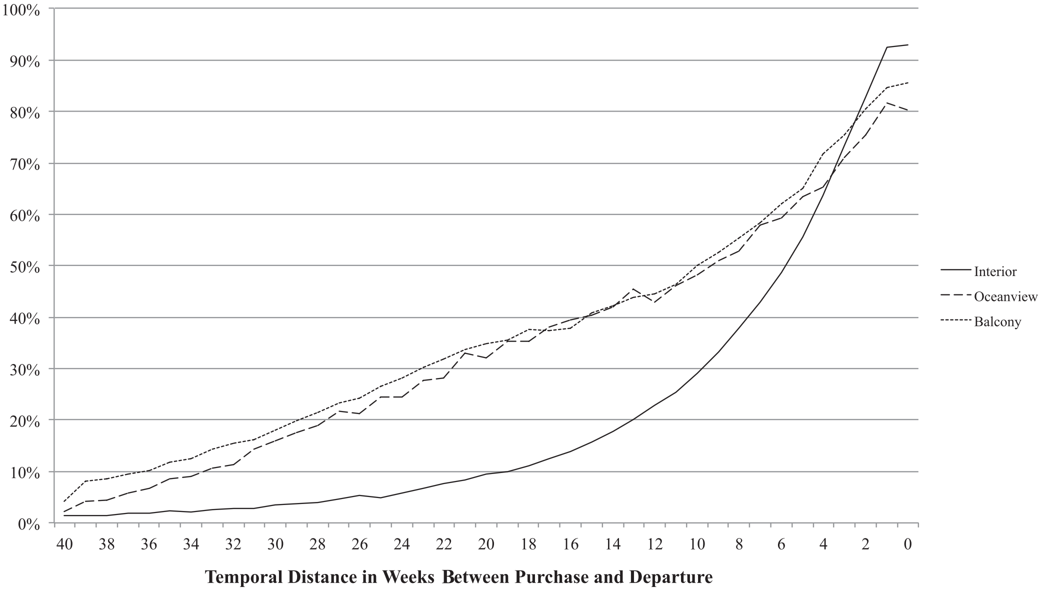


Figure 18. Temporal Distance and Mean Capacity Utilization by Cabin Type



One pattern that may lead to the observed price elasticity finding is convergence of competitive prices late in the advance purchase window. If cruise lines differentiate their prices early in the advance sales window then gradually converge to a more competitive price range late in the booking period, aggregate demand may show an increasing sensitivity to price due to increasing competition among competing cruises. Figure 20 presents average prices of the four main competitors over the advance sales window. It is clear that the four cruise lines showed no regular pattern in price competition across the final 40 weeks of temporal distance.

Another possibility is that competitive prices may be falling with temporal distance, whereas the focal firm's prices rise with temporal distance. Then it would appear that the outside option was becoming more attractive, increasing the apparent price sensitivity of aggregate demand late in the advance sales period. To isolate how competitors' prices vary with temporal distance from other drivers of price variation, we run a separate log price regression for each

Figure 19. MNL Price Coefficients Estimated Within Cabin Type Partitions

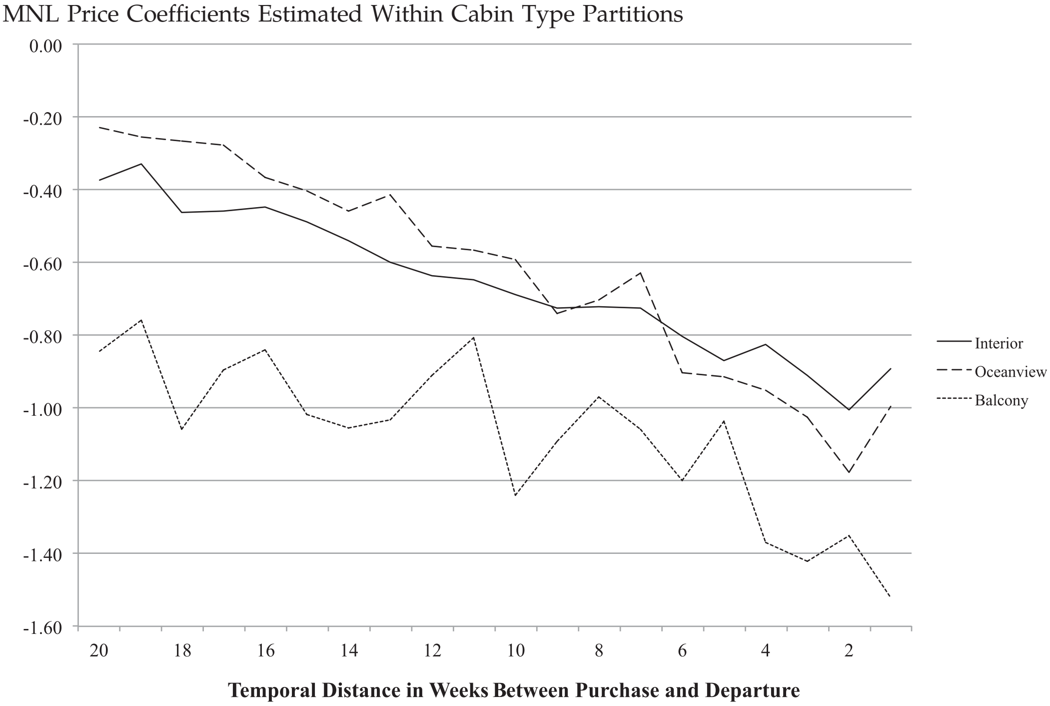
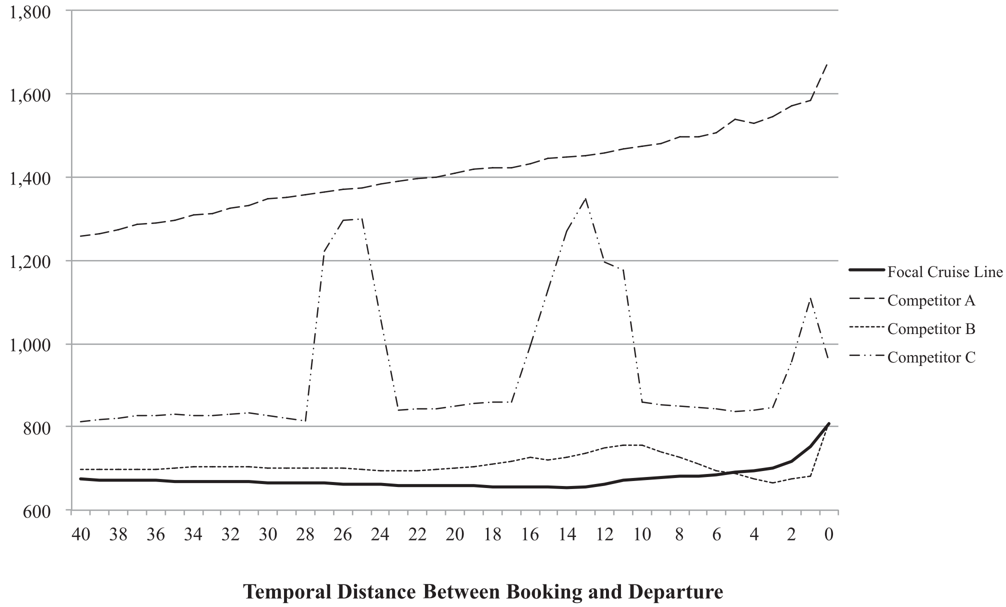


Figure 20. Temporal Distance and Average Prices in 2015



competitor $l_{2015} (\in L_{2015})$ observed in 2015 on the indicator variables in Equation (1):

$$p_{jtr}^{l_{2015}} = C_j^{l_{2015}} \chi_1^{l_{2015}} + I_j^{l_{2015}} \chi_2^{l_{2015}} + K_{t+r}^{l_{2015}} \psi_1^{l_{2015}} + K_r^{l_{2015}} \psi_2^{l_{2015}} + \xi_{jtr}^{l_{2015}}. \tag{30}$$

Figure 21 presents point estimates of temporal distance fixed effects, $\psi_2^{l_{2015}}$, to compare price trends across competitors. Competitors A and C show increasing tendencies overall, whereas competitor B shows no monotonic pattern. Therefore, competitors' pricing patterns do not suggest that increasing utility of the outside option can explain the observed relationship between temporal distance and price elasticity.

Although the competitive data did not come from the same data period as our demand observations in 2004, they showed that the focal cruise line instituted similarly sized price increases over the final 14 weeks of temporal distance in both 2004 and 2015.

5.5. Alternate Explanation: Strategic Purchase Delay

It also seems unlikely that the amplifying price elasticity pattern was driven by strategic purchase delay. In particular, mean prices rose 20% during the final 25 weeks of temporal distance, suggesting that the optimal dynamic strategy in most cases was to buy on the spot. Airfares also tend to rise as temporal distance falls, further disincentivizing purchase delay.[22] Various models with anticipated price drops in Section 4.4.3 preserve the amplifying price responsiveness pattern.

In fact, firm pricing managers explicitly discussed with us the dynamic game between the firm and its consumers as a strong disincentive to last-minute discounts, even on cruises with substantial capacity remaining. They said explicitly that they did not want to train their consumers to expect last-minute deals. Therefore, we view the estimated relationship as consistent with a model in which the most knowledgeable, experienced, and committed consumers arrive early and buy early. Less committed cruisers arrive late and pay more (if they purchase at all).

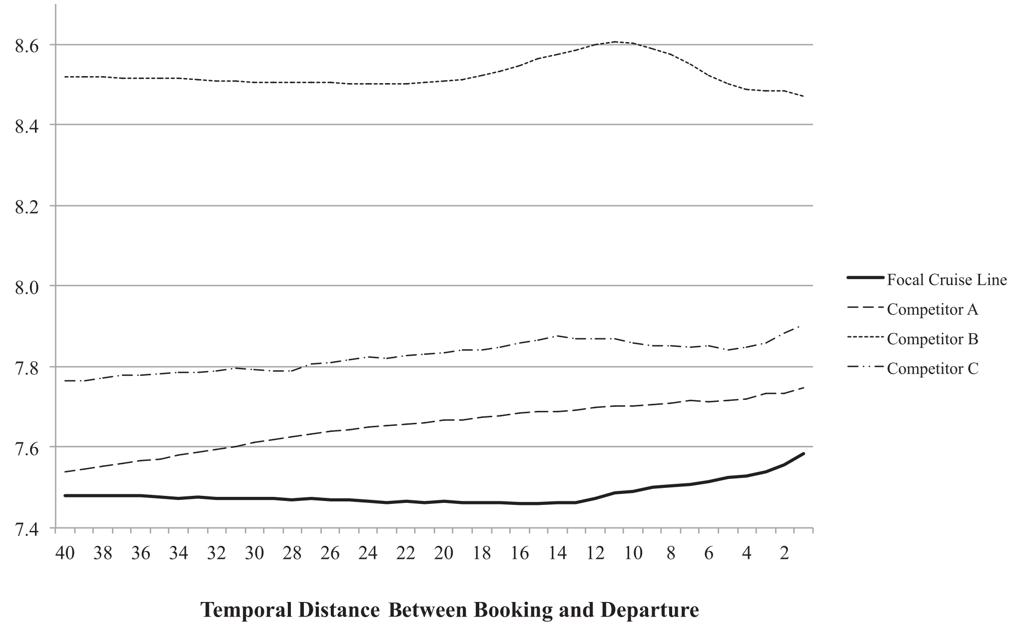
The series of robustness checks indicates that the estimated relationship between price responsiveness and temporal distance is remarkably robust to model specifications, parameterizations, data subsamples, and alternate explanations.

6. Discussion and Conclusion

The main result of this paper is twofold: (i) aggregate demand can become more responsive to price as the advance sales period proceeds, and (ii) aggregate demand can become more responsive to price during the period of peak demand. As far as we know, this is the first field evidence of a negative causal relationship between price responsiveness and temporal distance in any advance sales industry. However, this absolute increase in price responsiveness does not necessarily imply that the optimal price path declines with temporal distance, as the baseline utility or main effect of temporal distance on demand was estimated to more than offset the change in price sensitivity during most of the advance sales period.

It is important to be aware that the estimated relationship between price responsiveness and temporal distance—indeed the entire data set and the entire analysis—conditions on the firm's observed

Figure 21. Intertemporal Log Price Variation Across Temporal Distance



pricing policy and consumer response to the observed pricing policy. There is no evidence that either of those two factors varied during the sample, so we cannot say how the findings would differ under an alternate pricing policy.[23] Therefore, the available data cannot disentangle the underlying mechanism, that is, how much of the aggregate effect occurs naturally among cruise purchasers and how much of it was induced by the firm's pricing policy. We see this as a compelling topic for future research.

It would also be interesting to better understand consumer search for cruises at the micro level. For example, one could investigate consumer-level online search data for cruise attributes and prices. This might be possible using data from a cruise line that sells online and requires shoppers to log in prior to searching for fares and attributes, or data from a panel of Internet users' visits to websites.

A third interesting topic for related research would be examining dynamic interactions between firm pricing policy and consumer demand. If the firm moves to monetize its inelastic consumers early in the reservation window, or if the firm removes the disincentives to buy late by flattening the price path, how many consumers would change their shopping behavior, and how quickly? Such dynamic consumer reactions to meaningful changes in firms' dynamic pricing strategies have rarely been explored empirically, but in this context the strategic interactions between sellers and buyers could be fascinating.

We hope this paper will stimulate further empirical study of advance sales industries. Such work would complement the already substantial theoretical literature on the topic. The relationship between temporal distance and consumer preferences is critical to optimal pricing, so understanding how this relationship may vary across advance sales industries and dynamic pricing policies is needed to improve allocative efficiency. Further empirical studies in various industrial and competitive contexts are needed to better understand how much of the existing knowledge relies on general, as opposed to industry-specific, conduct and behavior. We are confident that further research will refine our understanding and test theories about how firms and consumers behave in dynamic pricing games.

Acknowledgments
The authors thank Greg Allenby, Hai Che, Javier Donna, Michaela Draganska, Rex Du, Jean-Francois Houde, Guofang Huang, Minha Hwang, Burak Kazaz, Dong Soo Kim, Gürhan Kök, Minjung Kwon, Hyojin Lee, Selin Malkoc, Kanishka Misra, Vincent Nijs, Sungho Park, Robbie Sanders, Hyoduk Shin, and Sha Yang. They also thank seminar participants at Boston College; University of Arizona; Ohio State University Economics; University of California, Riverside; University of California, San Diego; University of Southern California; University of Texas at Dallas Bass Conference; the Production and Operations Management Society Annual Conference; and the INFORMS Marketing Science Conference for helpful comments and discussions. Dinesh K. Gauri provided the data.

Endnotes
[1] Bitran and Caldentey (2003) and Kimes (2010) discuss industry practices to balance the tradeoffs between capacity utilization and unit margin.

[2] See, for example, http://www.cruisemarketwatch.com and https://www.statista.com.

[3] We present theoretical arguments about dynamic consumer behavior and robustness checks, including reduced-form controls for

expected future price changes and various restrictions on the choice set, in Section 5.

[4] A handful of papers have characterized optimal dynamic pricing policies without assuming that price sensitivity diminishes as the advance sales window proceeds. These papers show that, even without diminishing price sensitivity, advance selling can contribute to profitability by providing capacity assurance to risk-averse buyers (Png 1989, Xie and Shugan 2001), protecting the seller against low realizations of stochastic demand (Png 1991), and altering consumers' incentives to time purchases strategically (Cachon and Feldman 2010). Su (2007) characterizes an optimal pricing path based on the correlation between consumers' valuation and willingness to wait. McAfee and te Velde (2008) theoretically present an efficient monopoly pricing solution under stochastic demand with constant demand elasticity.

[5] For a more detailed review of theoretical models in airline pricing, see McAfee and te Velde (2006).

[6] Abrate et al. (2012) descriptively summarize intertemporal pricing patterns in European hotels but do not analyze demand patterns.

[7] Sweeting (2012) estimated time-varying price response parameters using data from baseball game ticket resale markets. This is a substantially different industry structure as baseball tickets were resold by numerous atomistic sellers and ticket prices fell throughout the advance sales window. Sweeting's time-varying price responsiveness parameter estimates are directionally consistent with the results reported in this paper, but the differences between those estimates were not statistically significant.

[8] All 11 itineraries departed from Florida, the firm's most active cruise departure market. The data do not report distribution channel, but all tickets were sold directly by the cruise line or by travel agents; no tickets were sold through consolidators. Price did not vary between distribution channels. Cancellations carried heavy financial penalties and were extremely rare.

[9] Puller et al. (2015, p. 1) found a similar result in airline data: Scarcity had "virtually no effect on fare dispersion."

[10] In Figures 6 and 7, we retain only the 88.5% of observations with $|P_{jtr} - P_{j(t-1)(r+1)}| \geq \$5$ to avoid giving too much importance to minimal price changes. The \$5 threshold is approximately 1% of the average sale price. The patterns are robust to large and small changes in the \$5 threshold.

[11] There are several theoretical reasons to believe that different cruise products would respond differentially to crude oil price. For greater temporal distance r, contemporaneous crude oil prices would be a riskier estimate of future crude oil prices. Cruise itineraries vary substantially in distance traveled and oil used. If consumer price responsiveness varies across cruise product attributes, then the cruise line would optimally respond to oil price shocks differentially across products.

[12] Although further empirical specifications are entirely possible (e.g., nominal distance or interactions between attributes), we followed Gandhi and Houde's (2017) selection criteria for characteristics with strong variation, which may help avoid too-many-IV problems.

[13] The objective function in Equation (20) allows for measurement error in observed market shares (Fox et al. 2011).

[14] The observed market share in reservation week t is defined as the number of tickets sold in week t for Florida cruises in the focal cruise line divided by weekly market size in that week.

[15] We note that the heterogeneity parameters for cabin type main effects (i.e., δ_i) are statistically significantly different from zero as reported in Online Appendix B, indicating that the demand estimates are distinguished from the typical results of multinomial logit models.

[16] Recent empirical work by Li et al. (2014) found that a small yet significant number of airline consumers strategically defer their purchases when prices are expected to fall.

[17] An alternative specification of $EPC_{jtr} \equiv E_t[P_{j(t+1)(r-1)} - P_{jtr}]$ was also considered yet dropped, because it is inconsistent with consumers' observation of true P_{jtr} in reservation week t.

[18] Similar results are observed in log-log demand models (not reported).

[19] The market share of outside option is adjusted for each choice set to conform the average purchase proportion of each departure week given reservation week.

[20] We were told by pricing managers at the focal cruise line that they did not systematically incorporate competitors' prices in their pricing algorithm in 2004. We were unable to find any source of historical price data.

[21] Despite our best efforts, we were not able to find any source of corresponding booking data for 2015 pricing data. Therefore, we must assume that correlations between competitors' prices and temporal distance were not too dissimilar between 2004 and 2015.

[22] In the airline context, McAfee and te Velde (2008, p. 432) stated that "If the initial supply is not too large, consumers have no incentive to delay their purchases to get a lower price at the average inventory prevailing at any time."

[23] We are not aware of any papers that estimate consumers reactions to changes in firms' advance sales policies. The nearest paper on the topic is Lazarev (2013), which uses data from monopoly airline markets to estimate a structural model of optimal advance pricing. The model is then used to evaluate a policy experiment in which consumers can mitigate the discriminatory effects of intertemporal pricing by offering tickets on a resale market. However, purchasers' optimal behavior is predicted based on theory-driven assumptions, as it is not identifiable in the available data.

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