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Price Volatility in the Airline Markets: Wait or buy?

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Abstract

The dynamic patterns of prices in different markets may motivate strategic consumers to game against the vendors. Intentionally or unintentionally, vendors may induce volatility into their menu of prices. This price volatility could reflect demand volatility, but could also be employed as a tool to confuse consumers and change their price perceptions.

Conducting empirical work in the airline industry on close to 1000 US domestic routes, we find that measured price volatility carries information about future price drops: it is significant and consistent predictor of the probability of a price drop in the immediate future and the relative magnitude of this price movement. The result of this study supports the idea that airlines deliberately induce volatility into different markets.

Keywords: marketing/operations interface, price volatility, dynamic pricing, revenue management, consumer behavior, airline industry.

1. Introduction

The dramatic rise of the Chicago Board Options Exchange (CBOE) volatility index, VIX, which measures the implied volatility of S&P 500 index options, has been widely covered in the media on October 27, 2008. On that day, the VIX has reached its highest level ever - 80.06 points.¹ This is substantially above its long time average, which stands at about 19.² This index, as well as other volatility indices, reveal or measure the amount of uncertainty in different markets; the VIX is known as the ‘fear index’ because its value is an indication of how much we know, or do not know, based on stock trades in the marketplace. The extensive, prime time reportage of a volatility index clearly emphasizes the importance and relevance of volatility measures in different markets.

Uncertainty in markets could be quantified through frequent price changes—the more frequent the changes are and the larger the magnitude of these fluctuations is, the larger the volatility embedded in these markets is. Stock markets and other trading environments are characterized by hosts of buyers and sellers who interact with each other. Often these buyers and sellers alternate in their roles. In the presence of uncertainty, the trading price could swing substantially from one transaction to another.

In airline markets, whereby airlines are always sellers and consumers are always buyers, uncertainty about demand could unfold in the prices offered by the airlines to their pool of potential customers. In that respect, uncertainty could reflect the demand volatility that is present in the markets served.

Airlines update their airfares frequently utilizing advanced dynamic pricing and revenue management (DP/RM) systems. These systems generate forecasts about future demand,

¹ In fact, the turmoil in the markets has resulted with a new record on November 20, 2008, of 80.86 points.

² The VIX formula has been updated in 2003. Using stock values dating back to 1990, the mean VIX is estimated at a little bit over 19.

consider the corresponding arrival rates of different customers' types and remaining capacity, and offer a plethora of ticket classes to price-discriminate between the different customers in their ongoing effort to maximize the revenue generated from their network of flights.

The dynamic pricing schemes employed by the revenue management systems command fluctuating prices over time, as time to departure approaches. In essence, to facilitate consumer discrimination, these systems post lower prices far from the departure date as to capture demand from leisure passengers, and as time progresses, they post higher prices aimed at price insensitive business passengers. Due to fluctuations in demand, airlines generate booking curves for each flight, which outline the predicted progression of prices and bookings for each flight. When demand falls short of the booking curve, airlines usually drop prices, while excess demand, naturally, triggers a spike in prices. The sensitivity level of a DP/RM system determines how quickly prices are adjusted to reflect changes in the forecasted demand. Hence, the sensitivity of the DP/RM systems could very well describe the level of uncertainty about demand in these markets. Alternatively, price volatility could be determined by the sensitivity of these DP/RM systems.

However, as Gillen and Mantin (2008) have argued, price volatility could be the outcome of other mechanisms employed by vendors, in general, and airlines, in particular. Airlines could be using price volatility intentionally as a mechanism to induce demand. Namely, understanding consumer behaviour, airlines may be constantly changing prices as a tool to manipulate consumer behaviour, as price volatility affects the range of prices that consumers consider to be acceptable for a given product (Rao and Sieben, 1992, and Kalyanaram and Little, 1994). In other words, faced with uncertainty about prices, consumers find it harder to judge which prices are fair or reasonable. This argument about airline pricing is best summarized by Andrew Boyd

(2007): “... airlines are presenting us with constantly changing prices. What is our reference price point for calculating a just price? Is it today’s \$300 or tomorrow’s \$400? Should we feel happy that we’re saving \$100? Adding to our sense of discomfort is uncertainty about what tomorrow will bring.”

Boyd touches upon another behavioural aspect of consumers’ perceptions of prices: reference price point. Consumers, in general, possess an internal price reference for different products based on current and historical observations of the same product or similar ones. The reference prices are assumed to be updated continuously as new information is gathered and as time elapses. The rationale for this process stems from Helson's Adaptation-Level Theory (1964), according to which an individual’s judgment is based on a prevailing adaptation level, and this adaptation level is a function of current and previous related stimuli (their magnitude, range, and dispersion). During purchasing incidences consumers compare the encountered prices with their internal reference prices. Clearly, vendors may have the incentive to manipulate prices in order to influence consumers’ reference prices, a process that could induce demand—the larger the reference price is with respect to the observed price, the higher the probability is that the consumer will end up purchasing the good.

While airlines may be posting volatile prices, intentionally or unintentionally, it would be naïve to assume that consumers are myopic and react passively to airlines’ efforts to maximize their revenue streams over time by adjusting their price control continuously. It is possible that some passengers are completely price insensitive and choose their travel arrangements based on characteristics other than price. Yet, it is reasonable to assume that a number of customer segments have varying degrees of price awareness.

In their work, Anderson and Wilson (2003) have illustrated how strategic consumers, who understand airlines' pricing mechanisms, namely, the expected marginal seat revenue (EMSR)³, could utilize access to historical fare information to optimize their purchase timing. Specifically, such consumers are able to compute the probability that a currently closed fare class will reopen in the future. According to Anderson and Wilson's demonstration, such behaviour could significantly harm airlines' financial performance.

This work is in line with Anderson and Wilson's demonstration. However, here we take a different approach to theirs. Rather than working out the different probabilities associated with the reopening of the different fare classes, we empirically investigate the implications of the dynamic pricing mechanism as observed through the realized prices. Specifically, we seek to investigate the relationship between the volatility of prices and the probability of encountering lower or higher prices in the immediate future. We further look into the savings or the additional expenses that could be materialized due to a consumer's decision of postponing his/her purchasing decision.

By contrast with Anderson and Wilson, our analysis does not require the consumers to understand the DP/RM mechanism and does not require any extensive access to information (i.e., demand distribution and remaining capacity), which is often limited or restricted. Rather, it is assumed that consumers observe prices over a period of time and have a reasonably good assessment of the volatility of prices for the market and trip they are considering. We raise the question whether this assessment of price volatility could be used in any way to predict future swings of prices.

³ This also implies that consumers know which fare classes are generally available for the particular flight.

In other words, we bring to the test one of the travel planning tips provided by FareCompare.com. FareCompare is a trip planning website and a major airfare blog site. FareCompare's advice goes as follows: "Check the price volatility of your city pair. If the prices are bouncing around by \$100 or more a few times a month or more, make sure you buy on a down swing."⁴ Such a recommendation is somewhat vague—it is not clear why some particular value is the golden value for measure of volatility; the information gathering rate is vague as well. It also is unclear how far down a downswing is. In that respect, this work brings about greater insight into when price swings are likely to materialize into savings (or additional cost) for consumers and further quantify the magnitude of those savings (or costs).

The present paper establishes the importance of price volatility as an essential tool that could aid consumers in reaching inferences about future price swings and their magnitude. The potential impact of price volatility varies along the selling horizon. As volatility measures do not record the directions of the price swings, we further define a variable that accounts for the relative magnitude of a price with respect to its weekly average. Combined, these two price variables bear greater relevance and importance to the behaviour of future price fluctuations than any other market structure or route characteristics variable.

The paper is organized as follows. In Section 2 we review the literature on dynamic pricing, consumer behaviour, the interaction of retailers and strategic consumers, and empirical studies in the context of airlines' airfares. Section 3 develops the main research questions about the volatile prices, while Section 4 elaborates on the collection of data and definitions of the variables used in the empirical study. In Section 5 we outline the different models we test and their empirical results, and Section 6 concludes.

⁴ Source: www.farecompare.com/downloads/WhenIsTheBestTimeToBuyAirTravel/WhenIsTheBestTimeToBuyAirTravel.pdf retrieved on October 7, 2007.

2. Review of applicable literature

Airlines update the set of airfares they offer very frequently in their ongoing efforts to maximize revenues from their network of flights. These efforts are automated through the implementation of dynamic pricing and revenue management systems. A rich literature investigates different aspects in the instrumentations of these systems. Airlines operate in a difficult environment, as they have to deal not only with the inherent complexity of the interaction with the consumers, but also with difficulties stemming from, e.g., scheduling, capacity, routing, regulation, and changing weather conditions. For these reasons, most of the academic literature focuses on limited aspects of the revenue management challenge. Recent books, such as Talluri and van Ryzin (2004), Phillips (2005), Boyd (2007), excellently elaborate on the theory and practice of DP/RM.⁵

Faced with dynamic pricing mechanisms, consumers may adapt to the changing behaviour of prices. The economic literature has long considered the dynamic pricing mechanisms in the presence of strategic consumer. Strategic consumers are those consumers who develop expectations about future prices and time their purchase accordingly. Modeling the interaction between strategic consumers and retailers can be traced back to Coase (1972) who has conjectured that “with complete durability, the price becomes independent of the number of suppliers and is thus always equal to the competitive price.” This conjecture has been formalized by Stokey (1979) who showed that with pre-announced prices, dynamic pricing is not beneficial when consumers behave strategically. According to Stokey (1981), contingent pricing may end up with market saturation whereby the price equals to zero (assuming zero

⁵ Further reviews include McAfee and te Velde (2007), Bitran and Caldentey (2003), Elmaghraby and Keskinocak (2003), Chan et al. (2004), and Shen and Su (2007), which provide updated focused analysis and critique of the literature. An introductory review is provided by Kimes (1989).

marginal cost). Refinements of these models are studied in, e.g., Gul et al. (1986), Besanko and Winston (1990), and Güth and Ritzberger (1998).

An emerging stream in the operations literature further investigates these interactions while accounting for capacity limitations. For example Aviv and Pazgal (2008) consider Poisson arrival of consumers to a single store, which discounts the good only once along the selling horizon; Levin et al. (2005, 2006) study monopoly and duopoly settings with a fixed market of consumers whose valuations are random along the horizon; Su (2007) assumes a continuous deterministic arrival of consumers who have either low or high valuations and are either patient or impatient; and Elmaghraby et al. (2008) consider consumers with multi-unit demands.

Most related to ours is the work by Anderson and Wilson (2003) who demonstrate the impact strategic consumer behaviour could pose on airlines. Namely, they show how consumers, who are familiar with the construction of the protection levels as suggested by the expected marginal seat revenue (EMSR), may form expectations about possible future discounts (or more precisely, the probability of reopening a low fare class). According to Anderson and Wilson *“if the consumer has awareness of the price–time curve for an airline seat, [...] and has the ability to determine where current fare options are located along this curve then the consumer might engage in strategic purchasing behaviour.”* However, according to their calculations, the consumer also needs to know the demand distribution for the different fare classes and know the current seat availability on the plane. Sophisticated consumers with such knowledge and access to information might be able to reverse engineer some of the airlines’ decisions. Yet, it is questionable how likely consumers to exhibit such characteristics are.

In this paper, rather than adopting strong assumptions about consumers’ knowledge and information, we argue that consumers may be able to reach some inferences about future price

movements after they have been observing prices for some time. We demonstrate our claims in ways of empirical analysis.

Empirical analysis is common within the area of airline pricing, primarily due to readily available databases and access to online posted prices. Major databases in this respect are the US Department of Transportation's T-100, which contains monthly statistics of airlines' activities, and the Origin and Destination Survey Data Bank 1 (aka DB1B), which records on a quarterly basis 10% of all itineraries sold within the USA. The different works in this area that use the Department of Transportation's databases often study the impact of competition intensity (as quantified via the Herfindahl-Hirschman index) and other market structure and route characteristics on price levels and dispersion. Notably in this area are the works by Borenstein and Rose (1994), Stavins (1996), Hayes and Ross (1998). Tretheway and Kincaid (2005) review related empirical studies. In our analysis we make use of the standard explanatory variables common in this literature to control for the differences across the routes.

To explore the changing prices as commanded by the DP/RM systems, one needs to deviate from the above mentioned databases and actively collect prices from the Internet. The various works in this emerging area that examine the progression of prices about the departure date include MaAfee and te Velde (2007) who test several propositions about the rise/fall of prices, their variance, and price of substitutes; Pels and Rietveld (2004) who study prices on the London–Paris route; Gillen and Hazeldine (2006) who investigate the differences in inter-temporal price discrimination between legacy and low cost carriers; Piga and Bachis (2007) and Mantin and Koo (2008) who study the price dispersion across fare histories; Bilotkach et al. (2007) who look at the pricing dynamics on the non-stop New-York – London market; and Gillen and Mantin (2008) who assess the volatility of prices offered by airlines.

According to Gillen and Mantin volatile pricing could be prompted as a means to counter consumer behaviour. Essentially, as argued by the literature on consumer behaviour, consumers possess some internal mechanism that guides them about prices they encounter. This mechanism could follow the formation of reference prices (as justified by Helson's Adaptation-Level Theory, 1964) or acceptable price ranges (as suggested by Range Theory (Volkman, 1951)). Both theories posit that past and current exposures to the same good or similar ones affect the formation of this internal price indicator. Consistent with Range Theory, Janiszewski and Lichtenstein (1999) have shown, in a series of experiments, that price perceptions could be manipulated to form attractive prices. Further empirical work established the link between volatile prices and consumer behaviour: Rao and Sieben (1992) and Kalyanaram and Little (1994) have found that the range of price acceptance is affected by the volatility of prices, and Han et al. (2001) have stated that “higher own-price volatility makes consumers more sensitive to gains and less sensitive to losses”. In that respect, price variability could mitigate price sensitivity of price-sensitive consumers (Murthi et al., 2007). To conclude, consistent with the consumer behaviour and marketing literature, airlines may have the incentive to introduce volatility to stimulate demand by affecting consumers’ perceptions and by mitigating consumers’ price sensitivity.

Price volatility is closely related to price uncertainty. As prices change and fluctuate frequently, consumers are not able to judge what the “right” reference price is. Uncertainty about prices could be stimulated by volatile prices (Winer, 1989), as human beings are not good in deducing patterns in noisy or random environments. Such uncertainty could play to the hands of airlines, as it could increase the range of prices consumers consider as acceptable (Dickson and Sawyer, 1990, and Winer, 1986). Pushing the prices upwards could be conducted strategically by

airlines, as the upper threshold of acceptable prices is the best predictor of actual price consumers pay (Sorce and Widrick, 1991).

This view is supported by Mantin and Koo (2008) who argue that, in general, full service carriers (FSCs) initiate upward price spikes to induce volatile prices and to eventually mitigate consumers' price sensitivity behaviour. Clearly, as it follows from the discussion on reference prices, such price changes could also be in place to counter or influence consumers' reference points. However, in the presence of low cost carriers (LCCs), as Mantin and Koo continue, the market price is more likely to exhibit downward spikes. LCCs' prices are consistent and lower, on average, than FSCs' prices (Gillen and Hazeldine, 2006; Sin et al. 2007). When LCCs' presence in the market is substantial, FSCs price more aggressively as to capture some of the price-sensitive and leisure demand that migrate to the LCCs. These findings are in general agreement with Gillen and Mantin (2008) who find that FSCs contribute more to the price volatility than LCCs.

Volatility is not restricted to prices in the airline industry. In fact, it arises in many industries. As the preceding discussion suggests, it is a quite common marketing phenomena and it was studied by, e.g., Kalyanaram and Little (1994), Han et al. (2001), and Murthi et al. (2007). Volatility is also a widespread measure in the financial markets, and several approaches have been devised to measure the presence of fluctuations of the different financial instruments (Engle, 1982, and Bollerslev, 1986). The operations literature is often concerned about the Bullwhip effect (Metters, 1997), which refers to the increasing fluctuations in order magnitude upstream the supply chain, that may be directly linked to volatile prices in markets (Lee et al., 1997). The different measures of volatility are further discussed in Subsection 4.1.2.

3. The research questions

It is well recognized that airlines change and update their menus of fares quite frequently in order to address different consumers segments that arrive at different points in time and to react to deviations of demand realizations from the predicted values. As stated earlier, these price movements could reflect demand volatility, especially when the revenue management systems deployed by the airlines are sufficiently sensitive and they quickly react to these deviations of demand from expectation.

In that sense, consumers may be aware that these price fluctuations could mimic demand fluctuations and may respond accordingly. For example, low prices that attract demand may trigger a price increase. Faced with a higher price, strategic consumers could decide to wait until the price dips back. With sufficiently many such consumers in the market, the demand at the higher price level dwindles, and eventually a price drop is set off by the DP/RM system. This illustrates the importance of consumers' expectations about future prices, as expectations for a price drop (or a price hike) when the price increases (or decreases), may cause the consumers to choose to wait (or not to), as suggested by the literature on strategic consumer behaviour.⁶

Such consumers' reactions could also be inherent to the dynamic pricing process, as explained in the previous section. If, for example, the posted price is low for a considerable amount of time, consumers may form a price reference or a price range anchored at this low price. As demand is materialized and/or as time progresses towards departure airlines may increase the price. However, a price increase could trigger an ebb in demand, as the new higher price may

⁶ Intuitively, such inter-temporal decisions by consumers affect the demand elasticity.

exceed consumers' reference points or price ranges. If consumers are firmly fixated at this low price, airlines may eventually drop the price to stimulate demand again.

To counter these consumers' reactions and further manipulate demand and consumers' expectations, airlines may induce volatility into the prices. The impact of price volatility on consumers' behaviour was elaborated on in the previous section. If indeed, this volatility is intentionally induced, then it may be following some underlying pattern.

Whether these price changes are intentional, as a means to affect consumers' perceptions about prices or to capture demand from competitors, or "unintentional" (as to refer to the automated) by the dynamic pricing and revenue management systems, there seems to be mounting arguments that volatile prices contain some information regarding future price movements. Our interest is in using ex ante information regarding ex post price movements. Specifically, we have two questions: could price volatility signal future price drop and, second, could price volatility signal the magnitude of these future price movements?

These two questions lead to another potential inference about price movements. It may hold true that some markets consist of a larger proportion of strategic consumers. In the presence of these consumers airlines are more inclined to induce price volatility to counter this behaviour. Hence, it may be that markets that exhibit volatile prices will continue to exhibit price swings in the near future, as airlines continuously change prices due to the strategic consumer behaviour.

4. Data and variables definitions

We have collected daily airfares from an online travel website and additional market and route characteristics from databases available through the U.S. Departments of Transportation and Commerce.

4.1. Daily airfare and volatility measure

4.1.1. Daily airfare

Since price volatility is more likely to affect price sensitive consumers, it is reasonable to assume that this segment of consumers considers the lower priced airfares in the market for their airborne trips. Following Baye and Morgan's (2001) clearinghouse model, the lowest available airfare in markets can be perceived as the competitive pricing equilibrium. That is, informed consumers (who have access to the clearinghouse—the Internet), purchase only from the vendor offering the lowest airfare. Uninformed consumers may purchase the good at a higher price.

We have collected daily lowest available airfares from the travel website Farecast.com.⁷ Farecast tracks airfare histories for a variety of US domestic and international roundtrip routes. Fare histories are recorded from 90 days prior to the scheduled departure date until the final day. As of February 2008, Farecast provided airfare histories for about 2,500 US domestic routes. 1,000 routes were arbitrarily chosen for this study. Our selection covers a wide span of different routes. For example, there are 87 different airports in our sample, out of which 29 are considered to be large airports (serving more than 8 million passengers annually), 33 are considered to be medium (with 2–8 million passengers) and the rest, 25 airports, are small.

We have collected airfare histories for round trips departing on Wednesday, February 27, 2008, and returning 7 days later. Our data was gathered on the night of the day prior to the departure date (i.e., on Tuesday night, February 26, 2008) as to obtain the entire 90 days of fare history for each of the routes on our sample. Due to some connection problems, three routes were not

⁷ Recently, Farecast.com became Farecast.live.com as it was acquired by Microsoft.

completely retrieved, and we ended up with data on 997 routes. Thus, we have accumulated close to 90,000 lowest daily airfare observations.

4.1.2. Volatility Measures

Volatility, in general, measures the instability in the value of an instrument over time. Often, volatility is represented via the standard deviation of the N most recent observations. Naturally, one is tempted to resort to adopt volatility measures commonly used in the financial sector, such as the ARCH, GARCH, or the CBOE volatility index (VIX). However, such measures are unlikely to reflect any consumer behaviour, due their inherent complexity. Moreover, these complex formulae often rely on access to a sheer amount of data and an array of tools that are available in the financial sector. Volatility is a good proxy for the amount of risk associated with a certain asset, and investors are often interested in risk minimization and risk distribution. Consumer behaviour is also a complex mechanism. Yet, it would be naïve to assume that consumers have access to historical fares on each route over the years and are able to conduct the complex analysis required to reach similar inferences as in the financial markets. It is more plausible to assume that consumers have limited access to prices posted by airlines, and often, they are not exposed to older fare histories.

In that context, it is reasonable to exploit mechanisms similar to those that have been utilized in the marketing literature and were constructed in order to reflect appropriate consumer behaviour. Specifically, we employ an own-price volatility measure that is based on exponential smoothing approach (Kalyanaram and Little, 1994, Han et al., 2001, and Murthi et al., 2007). The marketing studies are usually concerned with price volatility of products of the same category, which usually have a comparable price. The price volatility in that respect, to which we refer as PVOL, is given by

$$PVOL_{i,t} = \lambda PVOL_{i,t+1} + (1-\lambda)(P_{i,t} - P_{i,t+1})^2, \quad \text{with } PVOL_{i,90} = 0,$$

where $PVOL_{i,t}$ is the price volatility on route i at t days out, $P_{i,t}$ is the airfare on that route, and λ is the smoothing factor. Consistent with the marketing literature (Kalyanaram and Little, 1994, and Han et al., 2001), we set $\lambda = 0.8$. It should be noted that this measure “*is better than a simple variance measure since it captures the price patterns by giving different weights to recent relative to more distant changes in prices*” (Han et al. 2001).

PVOL performs well when products bear, more or less, that same magnitude of prices as is the case in the corresponding marketing studies. However, given the spread of the routes considered in our sample, the airfares on the different routes could differ substantially, depending on, e.g., the distance between the origin and destination airports. For that end, we adopt the approach used by Gillen and Mantin (2008) and we normalize the volatility measure.

In that case, we have

$$PVOLN_{i,t} = \lambda PVOLN_{i,t+1} + (1-\lambda) \left(\frac{P_{i,t}}{P_{i,t+1}} - 1 \right)^2, \quad \text{with } \sigma_{i,90}^2 = 0.$$

Note that PVOLN captures sensitivity of consumers to relative price changes. The behaviour of this volatility measure with respect to the realized prices is illustrated in Figure 1 for two, arbitrarily chosen, airport pairs. This figure illustrates that (i) the implicit volatility could be substantially different across routes—the volatility in the left panel is, on average, 10 times smaller than that on the route depicted in the right panel; (ii) price volatility is not necessarily the greatest in the final dates prior to departure. That is, even though prices rise upward during the last two weeks prior to the departure date, volatility may not follow the same pattern. In fact, early price shocks seem to have more impact on volatility than later price moves; and (iii)

there is no clear pattern that could describe the behaviour of the price volatility about the time to departure.

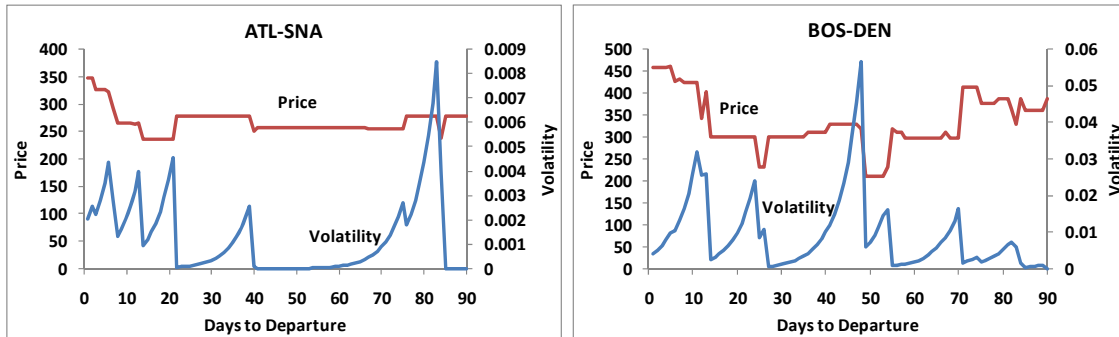


Figure 1: Prices and volatilities on two airport pairs

Indeed, each route may exhibit a unique pricing and corresponding price volatility pattern. Yet, examining the behaviour across the 997 routes in our sample could reveal some generalities about the behaviour of prices and price volatility. Figure 2 shows how the average price and average price volatility behave with respect to the time to departure. The average fare is slightly decreasing almost throughout the entire fare history up to about two weeks prior to the departure date—on the 15th day prior to departure the lowest average fare is recorded. At that point the average price changes direction—it trends upward and it completes roughly a 75% increase in the average fare.

On the other hand, the average price volatility exhibits a dramatically different pattern. The volatility fluctuates quite a bit throughout the 90 days of fare history. Up to about one month out, there seems to be mostly an increasing pattern. The next two weeks exhibit a significant drop in the volatility. This decline terminates at 15 days out, which records one of the lowest levels of average volatility throughout. The final two weeks are characterized by huge swings in the volatility, and a clear significant upward trend.

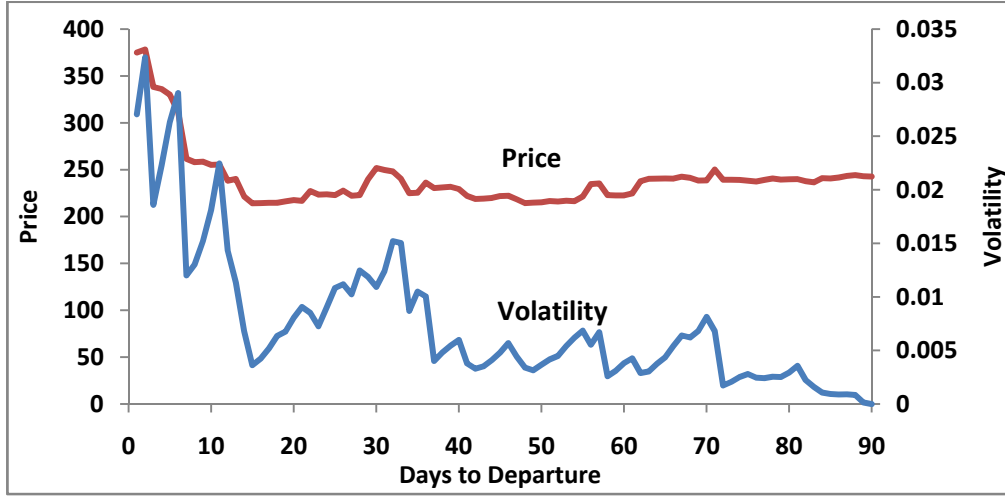


Figure 2: Average Price and Average Normalized Price Volatility

Recall that our volatility measure is initiated at 90 days prior to the date of departure. Therefore, it equals zero at that point for all routes. Obviously, the volatility at 90 days out could be higher than zero. Therefore, to avoid inconsistencies raised by the initiation algorithm, in the analysis that follows we handle with care volatilities measured at the beginning of our recorded fare history.

4.1.3. Relative Price

Our price volatility measure, like any other volatility measure, cannot distinguish between a swing upward and a swing downward. To capture this characteristic of prices we consider the possibility of the current price being higher or lower than recent previous prices. Specifically, we define

$$\text{Relative Price}_{i,t} = \frac{P_{i,t}}{\sum_{s=t}^{t+6} P_{i,s} / 7}$$

to measure the relationship between the current price and the overall weekly average of the price on that route. Similarly, we define another relative price measure of the current price with

respect to the price on the preceding day: Relative Price $D_{i,t} = \frac{P_{i,t}}{P_{i,t+1}}$, which captures a price move between the current price and yesterday's.

4.2. Additional explanatory variables

We have gathered additional variables from other sources that could potentially affect the behaviour of prices on the different routes considered in our sample.

Enplanements. For each route we have collected the total enplanements by all airlines on the route. This passenger data was gathered from the U.S. Department of Transportation's DB1B market database. Enplanements data serves as a measure of the market size.

Airlines' market shares. Gillen and Mantin (2008) show that in the context of price volatility, accounting for the different airlines' market shares could contribute substantially to the predictive power of the model. Similarly, we also account for these enplanements-based market shares in our study to investigate behaviour of prices with respect to past volatility.

Low Cost Carriers' (LCCs) market share. LCCs operate differently than legacy or full service carriers (FSCs). LCCs usually operate on a point-to-point basis, operate a single type of plane, offer limited service, and their pricing mechanism is much simpler than the FSCs'. The presence of such airlines exposes FSCs to a very fierce competition (Goolsbee and Syverson 2005; Sin et al. 2007). According to Mantin and Koo (2008) the price dynamics in the presence of LCCs could be very different than all FSCs competition, as FSCs tend to price more aggressively as to capture price sensitive consumers from the LCCs. This variable accounts for the combined enplanement-based market share captured by LCCs on the route.⁸

Herfindahl-Hirschman index (HHI). This variable measures the competitive environment, or alternatively, the level concentration, on each route. This measure is defined as the sum of the

⁸ Specifically, we include AirTran, ATA, Frontier, JetBlue, Southwest, and Spirit.

squared markets shares of each of the airlines in the market. HHI has been shown to affect market outcomes in the airline industry. For example, in Borenstein and Rose (1994) HHI is negatively correlated with price levels but positively correlated with price dispersion. We take forward this argument to see whether it could reveal any correlation with the inter-temporal behaviour of prices.

Distance. The distance between the origin and destination airports is calculated with a great circle route code. The distance is a proxy for the operating cost of a flight (Swan and Adler 2006). Distance could potentially serve as a proxy for the type of passengers on the flights and their ticket purchasing behaviour. Specifically, long distance flights usually require additional planning from the passengers, and therefore they are likely to purchase tickets earlier than on short haul flight. In the latter case substitution with other transportation modes may exist, e.g., passengers could commute back and forth between the origin and destination.

Population. We have collected population data of the metropolitan area (MA) of each origin airport from the U.S. Department of Commerce's Bureau of Economic Analysis (BEA). This variable is a proxy for the potential market.

Income per capita. Similar to the population variable, we have collected income data from the BEA, and generated the income per person for each of the origin airports' MA. This further characterizes the potential market at the origin MA.

Airport Size. We account for the size of the airport, by considering a continuous variable that measures the number of boarded passengers at the origin airport. These values are obtained from the BEA.

Business Index. This index aims at capturing the type of passengers that fly on the route. Several different measures have been proposed in the literature to capture this kind of variable

based, for example, on the temperature difference (Brueckner et al., 1992) or on the ratio of accommodation earnings to total non-farm earnings of the metropolitan area. Following Mantin and Koo (2008), the index is defined, based on actual enplanements.⁹ The business index on route j is

$$\text{Business index}_j = \frac{\text{Total number of passengers (class C + class F + class Y)}_j}{\text{Total number of passengers (all classes)}_j},$$

where C, F, and Y are the *unrestricted* business, first class, and coach respectively.¹⁰ These different class types are retrieved from the DB1B database. Hence, this business index categorizes passengers into those who fly on full fare unrestricted tickets, and those who fly on restricted fares. In this business index class Y is a full fare economy and would more likely be paid by last minute flyers and business people, especially in days when flying business class is forbidden.

Table 1 summarizes the descriptive statistics of the variables. Routes with zero enplanements during the relevant quarter or incomplete price data are eliminated, resulting in a total of 978 routes in the analysis. The time-independent variables (which do not vary along the fare history) present no multicollinearity issues (Table 2). Similarly, the correlation analysis for PVOLN and RelativePrice (lower panel of Table 2) for most of the observation points exhibit very low correlation, except at 56 and 28 days out. We will be careful interpreting result obtained for these two specific dates.

5. Empirical analysis

We separate our analysis into prediction of price decreases and prediction of price increases. To operationalize the analysis, we have segmented the fare history into weekly intervals. Thus, we

⁹ Mantin and Koo (2008) have found this index to be significant in their study of price dispersion across fare histories.

¹⁰ The other class types are D, G, and X, representing the *restricted* business, first class, and coach, respectively.

are considering the 7th, 14th, ..., 84th day prior to departure as the decision points. Accordingly, we record whether the ensuing seven days exhibit a price decrease, and the average saving materialized with respect to the fare at the decision point. That is, rather than assuming that the consumer will purchase right after the first price swing, we consider the average lower fare and measure the difference between this value and the current fare

5.1. Predicting lower prices

As we consider only the seven days ensuing the decision day, we introduce the following variable

$$\text{LoPrice}_{i,t} = \begin{cases} 1 & \text{if } \sum_{x=1}^7 1_{P_{i,t+x} < P_{i,t}} \geq 1, \\ 0 & \text{otherwise,} \end{cases}$$

where $1_{r < s}$ is the indication function which equals 1 if $r < s$ and zero otherwise. That is, LoPrice indicates whether the posted price drops in any of the days in the ensuing week following the decision point. Due to the nature of the response variable LoPrice, which could take only zero or one as values, we employ logistic regressions.

The first logistic regression to predict $\text{LoPrice}_{i,t}$ has only $\text{PVOLN}_{i,t}$, $t=7r$, $r=1,2,\dots,12$, as an explanatory variable. That is, we estimate

$$\text{MODEL 1: } \text{Logit}(\text{LoPrice}_{i,t}) = \alpha_{0,t} + \alpha_{1,t} \text{PVOLN}_{i,t}, \quad t = 7r, \quad r = 1, 2, \dots, 12.$$

This regression is conducted to estimate the potential benefit that price volatility may have as the *only* cue consumers use in their estimation process, while neglecting all other potential explanatory variables. In other words, this regression considers the situation wherein consumers do not understand the market structure or the special characteristics of the route they consider,

and they only use this price cue to reach inferences about future behaviour of prices. The results of these logistic regressions are provided in Table 3 and visually illustrated in Figure 3.

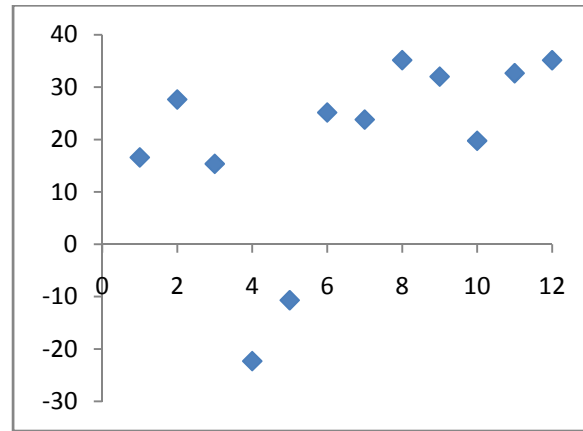


Figure 3. Coefficients of PVOLN in MODEL 1

Note: + significant at 10%; ♦ significant at 5% or at 1% (non-significant coefficients are not plotted)

As Figure 3 demonstrates, in the absence of any other variables, PVOLN is a highly significant explanatory variable. This clearly indicates that PVOLN bears some underlying relationship with future price movements. With the exception of the coefficients on weeks 4 and 5 prior to departure, this figure illustrates a decreasing pattern in the coefficients of PVOLN: as time to departure approaches, PVOLN is less likely to indicate a decrease in the price in the next seven days. We believe that the negative coefficients observed at Week 4 and 5 could be triggered by the surge in PVOLN roughly between 40 to 30 days out (refer to Figure 2).

In the second set of logistic regressions, we incorporate additional explanatory variables: enplanements, population, income, airport size, HHI, PVOLN, RelativePrice, Business Index, and each of the airlines' market shares.

$$\begin{aligned}
\text{MODEL 2: } \text{Logit}(\text{LoPrice}_{i,t}) = & \alpha_{0,t} + \alpha_{1,t} \text{PVOLN}_{i,t} + \alpha_{2,t} \text{enplanements}_i + \alpha_{3,t} \text{population}_i \\
& + \alpha_{4,t} \text{income}_i + \alpha_{5,t} \text{airport size}_i + \alpha_{6,t} \text{HHI} \\
& + \alpha_{7,t} \text{RelativePrice}_{i,t} + \alpha_{8,t} \text{Business Index}_i + \sum_j \beta_{j,t} \text{MS}_{i,j}, \\
& t = 7r, \quad r = 1, 2, \dots, 12,
\end{aligned}$$

where $\text{MS}_{i,j}$ is the market share (in terms of enplanements) of airline j on route i . We report on the results of this set of logistic regressions in Table 4. A surprising result stemming from Table 4 is that almost any control variable, other than the price variables—PVOLN and RelativePrice—do not seem to provide a consistent significant relationship with the probability of encountering a lower price.

The coefficients of PVOLN and RelativePrice are depicted in Figure 4. Excluding Week 8 prior to departure, PVOLN (Panel (a)) seems to provide a consistent relationship with the probability of encountering a lower price, while RelativePrice (Panel (b)) exhibits a decreasing trend up to 4 weeks prior to departure, in which point the direction reverses. This behaviour of RelativePrice is interesting as it tells us that a price that is currently relatively high with respect to the weekly average could indicate that the price may drop, but this tendency is decreasing from Week 9 to Week 4, at which point the trend reverses. In general, despite the additional control variables, PVOLN is still highly significant along the fare history and the pattern exhibited here echoes the pattern and magnitude from Figure 3, wherein PVOLN was the only explanatory variable.

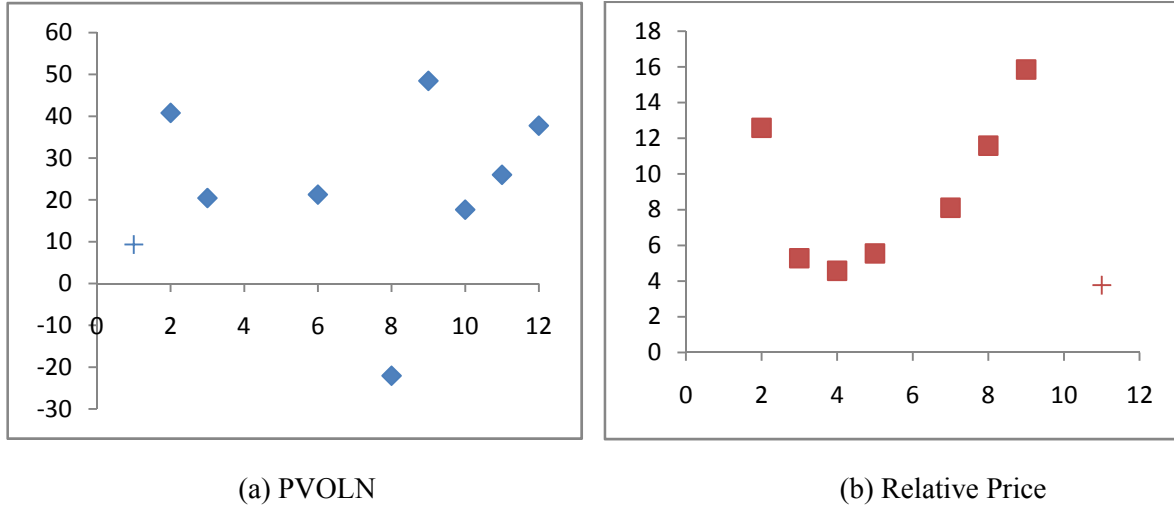


Figure 4. Coefficients of PVOLN and RelativePrice (MODEL 2)

Note: + significant at 10%; ♦ significant at 5% or at 1% (non-significant coefficients are not plotted)

To gain more insights into the meaning of the variables' coefficients, we look into the marginal effects (MEs) of PVOLN and RelativePrice. The marginal effect of variable x_i tells us by how much the probability (that the price will drop in the next seven days) will change in response to a change in x_i . The marginal effects are estimated at the mean value of the variables:

$$ME = \frac{\text{change in } \text{prob}(\text{LoPrice} = 1)}{\text{change in } x_i} = \hat{\gamma}_i \cdot \text{prob}(\text{LoPrice} = 1) \cdot [1 - \text{prob}(\text{LoPrice} = 1)],$$

where $\hat{\gamma}_i$ is the estimated coefficient of x_i .

The MEs of PVOLN and RelativePrice are provided in Table 5 and plotted graphically in Figure 5, which strongly resembles Figure 4. To understand this figure, consider, for example, the result obtained for Week 3. The value of the ME of PVOLN at this point is about 5. It implies that 1 percentage point increase in the measured volatility at 3 weeks prior to departure reflects a 5 percentage points increase in the probability that the price will drop in the ensuing seven days. Similarly, the value of the ME of RelativePrice at Week 3 is about one, which

implies that a 1 percentage point increase in the relative price at the point increases the probability of a price decrease by 1.3 percentage points. Indeed, the change in each of the probabilities is not very large, but when the probabilities are added up and are further combined with the potential savings that could be materialized, they could make a big difference for consumers who consider postponing their purchase for some time.

Panel (a) of Figure 5 illustrates that, with the exception of Week 8, the marginal effect of PVOLN is fairly consistent and ranges between 3% and 10%. The marginal effect of RelativePrice (Panel (b) of Figure 5), depicts a U-shaped pattern: From Week 12 to Week 4, the ME of RelativePrice is decreasing. The change of direction of the ME of RelativePrice at Week 4 indicates that even closer to the departure date, gains from waiting are possible. In fact, the likelihood of encountering a price drop is increasing as suggested by RelativePrice. These gains are quantified in the next subsection.

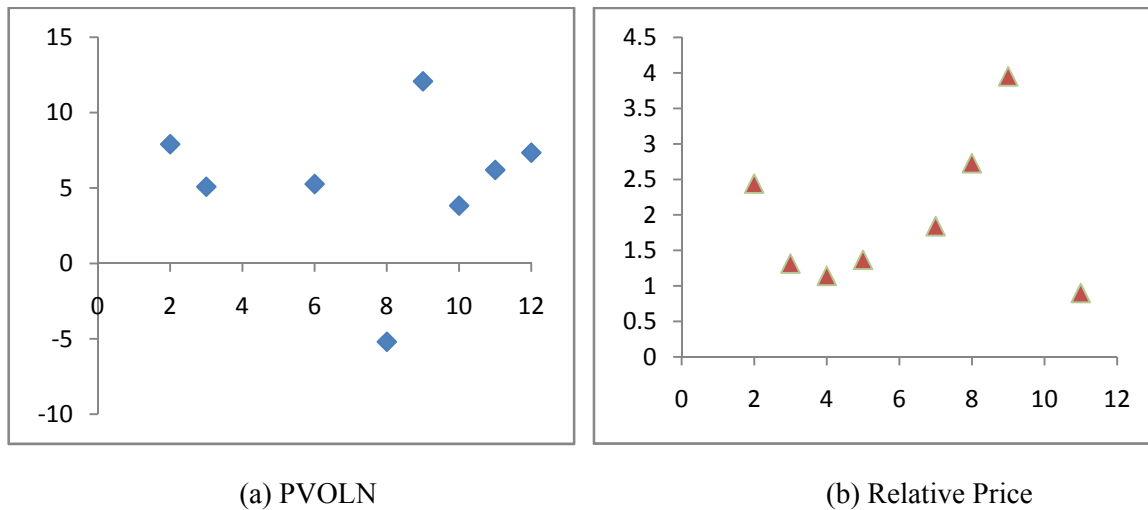


Figure 5. Marginal effects of PVOLN and RelativePrice (MODEL 2)

Note: + significant at 10%; ♦ significant at 5% or at 1% (non-significant coefficients are not plotted)

We have carried out additional logistic regressions to test for the robustness of the above results. In particular, we have estimated logistic regressions similar to MODEL 2 with LCC_MS instead of individual airlines' market shares, and with RelativePriceD_t (with and without RelativePrice_t). Essentially, these regressions do not differ in their qualitative results, and therefore are not reported here.

5.2. Quantifying lower prices

In this subsection we seek to quantify the benefit from waiting for a lower fare. For that purpose we define the following relative savings variable

$$\text{RelSave}_{i,t} = \frac{\sum_{x=1}^7 \left((P_{i,t} - P_{i,t+x}) \cdot 1_{P_{i,t+x} < P_{i,t}} \right)}{\sum_{x=1}^7 1_{P_{i,t+x} < P_{i,t}}} \bigg/ P_{i,t},$$

which accounts for the average relative savings to be realized, if the consumer happens to purchase the ticket on either of the days on which a lower price is posted. That is, RelSave is a conditional variable—given a lower price is realized, what is the average percentage drop in the price. We employ a relative measure of savings rather than an absolute measure, since, as discussed earlier, prices could be significantly different on the set of routes in our database (\$10 savings on a \$500 ticket is perceived differently than on a \$100 ticket). Hence, to streamline the savings a normalized measure is required, just like PVOLN, which is quantified by the relative measure.

Since RelSave is a truncated variable (it is always strictly positive), we use Tobit regressions to predict relative savings.

$$\begin{aligned}
\text{MODEL 3: Tobit}(\text{RelSave}_{i,t}) = & \alpha_{0,t} + \alpha_{1,t}PVOLN_{i,t} + \alpha_{2,t}\text{enplanements}_i + \alpha_{3,t}\text{population}_i \\
& + \alpha_{4,t}\text{income}_i + \alpha_{5,t}\text{airport size}_i + \alpha_{6,t}\text{HHI} \\
& + \alpha_{7,t}\text{RelativePrice}_{-i,t} + \alpha_{1,t}\text{Business Index}_i + \sum_j \beta_{j,t}MS_{i,j}, \\
& t = 7r, \quad r = 1, 2, \dots, 12,
\end{aligned}$$

The results of the corresponding Tobit regressions are provided in Table 6. Again, PVOLN and RelativePrice emerge as consistent significant predictors of the relative savings to be materialized. Similar to the previous subsection, we illustrate the coefficients of PVOLN and RelativePrice in Figure 6. Notice the resemblance of the two panels in this figure to those depicted earlier (in Figure 4 and Figure 5). To understand this figure, consider, for example, Week 9, and assume that the price at this time on a certain route is \$500. At this week, one percentage point increase in the volatility corresponds to one percentage point increase in RelSave (or \$5 on this certain route); and one percentage point increase in the relative price translates to about 0.8 percentage point increase in RelSave (or \$4 on this certain route). Recalling the example illustrated earlier in the right panel of Figure 1 (BOS-DEN), these number could add up quickly to significant numbers that could affect consumers' decision making.¹¹

¹¹ We have further carried out linear regressions which resulted with very similar results, which revealed that the adjusted R^2 for some of the weeks could be as high as 0.4.

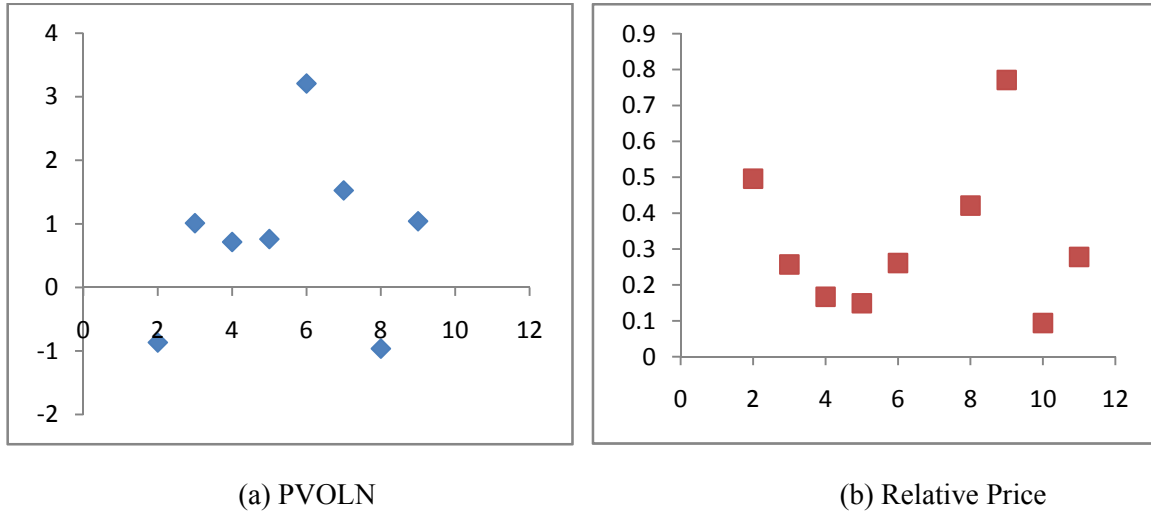


Figure 6. Coefficients of PVOLN and RelativePrice (MODEL 3)

Note: + significant at 10%; ♦ significant at 5% or at 1% (non-significant coefficients are not plotted)

In this set of regressions, Distance is also a significant and consistent predictor, which is mostly negative (roughly -0.02 on average). That is, long haul flights are far less likely to exhibit substantial savings for consumers. This echoes an earlier argument that long haul flights require passengers to plan ahead of time and in the absence of other travel alternatives, passengers would rather book their travel arrangements accordingly. For these reasons, one expects long distance trips to exhibit smaller fluctuations in prices.

6. Conclusions and discussion

In airline markets consumers often face the decision of whether to purchase the ticket right away or to wait in expectation of a lower price in the future. This work offers consumers an important decision aid as it uncovers a valuable hidden relationship between the behaviour of past prices and future prices in various US domestic routes.

We have gathered empirical data on prices on close to 1000 routes, and measured the volatility on these routes. Price volatility could reflect the accumulation of uncertainty about demand in

markets or the sensitivity level of the dynamic pricing and revenue management system employed by the airlines competing on the route. Price volatility could also be initiated by airlines as a means to stimulate demand by manipulating consumers' decision making. Whether these price swings are intentionally induced or are simply the outcome of other factors, they potentially contain information about future price movements. In that regard, we have raised two questions: could price volatility indicate a future price drop and, second, could price volatility indicate the magnitude of these future price movements?

The empirical analysis we have conducted affirms these two questions. Price variables, in general, and price volatility in particular, emerge as significant variables in our empirical study as drivers of future price fluctuations. As volatility measures cannot record directions of fluctuations, we have also accounted for the relative level of a price with respect to the overall weekly average, which could reveal something about the direction of the most recent price swings. These two price variables are not only significant, but they also appear to have consistent importance along the fare history. This is in sharp contrast to other market structure and route characteristics variables which seem to bear no consistent predictive value in predicting future price moves. This result is somewhat surprising given that the legacy airline business model leads to complex pricing and generally significant intertemporal price discrimination while the low cost carrier business model does not. Given this, one would expect routes dominated by one type of carrier to behave differently.

Price volatility, then, could indicate future price drops, and this behaviour changes as time progresses towards the departure date. In particular, we have seen that the marginal effects of price volatility are mostly positive. This analysis suggests that, in general, routes that are already infected by high volatility measures are likely to exhibit additional downward price

swings in the immediate future (ensuing seven days). This further supports Gillen and Mantin (2008) suspicion that price volatility may be intentionally induced, as it seems that price volatility could be a self sustaining process, in that price fluctuations trigger additional ones down the road. This is potentially in place in order to confuse consumers and distort their perception of prices on the route.

Strategic consumers, who already try to time their purchase in order to maximize their surplus, are likely to further abuse the results of this study. Carefully noticing the price swings and the relative price behaviour could be utilized to reach important inferences. Indeed, as was shown, price could fluctuate either way, depending on the number of weeks out and the magnitude of the price variables. Such an analysis is important in the context of consumers' varying degree of risk aversion. This study paves the way for a rich contextual work that incorporates consumers' risk aversion and is left for future research.

The benefit also unfolds for the airlines as well. As consumers may be paying more attention to prices and making inferences about future moves, airlines could plan ahead and predict how their own moves and moves by the competitors may affect consumers' expectations. Though inducing volatility may be beneficial in the short term, long term analysis of prices may prove to be detrimental, and airlines should be cautious with their volatility inducing mechanisms.

This work was limited to a single departure date, and, hence, a single fare history for each route. Future research may benefit from gathering data on other travel dates and other seasons of the year. Such analysis may reveal different pricing behaviour for different periods of the year, and therefore more refined rules on how to perceive price volatility over the year.

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Appendix

Table 1. Summary Statistics of Variables

Variable	mean	sd	Percentile		
			5%	50%	95%
Route's enplanements (k)	4.739474	4.672605	0.079	3.339	14.986
LCC market share	0.231335	0.259769	0	0.128414	0.757561
HHI	0.46641	0.196033	0.17	0.46	0.83
Distance (1,000 km)	1.933764	1.090821	0.538976	1.632972	3.937803
Origin's population (mil)	4.948337	4.916919	0.951809	3.14105	18.81372
Origin's average income per capital (\$1,000)	38.89965	5.529494	31.79173	37.2086	48.69727
Origin airport's boarding passengers (mil.)	13.59763	9.942732	1.862325	11.04522	36.8251
Business index (UR Index)	0.07749	0.081461	0.00564	0.053498	0.241839

Airlines' market shares are not reported.

Table 2. Correlation tables

Correlations between fixed explanatory variables	Distance	Enplanements	Origin Population	Origin Income/capita	Origin's Airport Boarding	LCC MS	HHI	UR Index
Distance	1.0000							
Enplanements	-0.2575	1.0000						
Origin Population	0.0478	0.1208	1.0000					
Origin Income/capita	0.1275	-0.0196	0.3793	1.0000				
Origin's Airport Boarding	0.0372	0.3711	0.3745	0.0818	1.0000			
LCC Market Share	-0.1019	0.0878	-0.0959	-0.1294	-0.1609	1.0000		
HHI	-0.4171	0.0625	0.1473	0.0940	0.0242	-0.0577	1.0000	
Business index (UR Index)	-0.0085	-0.0121	-0.1198	-0.1761	-0.1335	0.4302	-0.0730	1.0000

t	84	77	70	63	56	49	42	35	28	21	14	7
Correlation between PVOLN _t and RelativePrice _t	0.1544	0.2159	0.3467	-0.2405	0.6690	-0.0141	0.0592	-0.1914	-0.6303	0.0539	0.7140	-0.0049

Table 3. Logit regressions of the probability of a lower price with only PVOLN as an explanatory variable (MODEL 1)

	loprice84	loprice77	loprice70	loprice63	loprice56	loprice49	loprice42	loprice35	loprice28	loprice21	loprice14	loprice7
PVOLN _t	35.127	32.651	19.753	32.001	35.148	23.798	25.144	-10.692	-22.317	15.352	27.637	16.568
	(14.866)*	(11.835)**	(5.148)**	(14.656)*	(9.472)**	(9.605)*	(9.728)**	(4.107)**	(3.960)**	(4.983)**	(7.535)**	(5.932)**
Constant	-0.97	0.296	-0.782	0.042	0.115	-0.665	0.102	-0.007	0.354	-0.028	0.401	1.259
	(0.073)**	(0.067)**	(0.079)**	-0.074	-0.073	(0.073)**	-0.07	-0.076	(0.075)**	-0.074	(0.073)**	(0.093)**
LL	-592.67	-671.27	-638.54	-687.87	-671.9	-648.34	-685.22	-687.82	-668.68	-685.32	-645.45	-487.51
Chi2	6.18	11.91	17.81	6.45	24.49	6.67	7.75	7.29	46.23	13.15	23.79	11.76

Standard errors in parentheses

+ significant at 10%; * significant at 5%; ** significant at 1%

Table 4. Logit regressions of the probability of a lower price with all explanatory variables (MODEL 2)

	loprice84	loprice77	loprice70	loprice63	loprice56	loprice49	loprice42	loprice35	loprice28	loprice21	loprice14	loprice7
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km_k	0.282	0.304	0.406	0.611	0.234	0.124	-0.033	-0.167	0.488	-0.06	0.368	-0.299
	(0.092)**	(0.084)**	(0.090)**	(0.090)**	(0.091)*	-0.084	-0.082	(0.087)+	(0.087)**	-0.084	(0.093)**	(0.106)**
enplanements_k	0.013	-0.021	-0.033	-0.019	0.018	0.021	-0.031	-0.016	0.001	-0.002	-0.054	0.012
	-0.02	-0.019	-0.021	-0.019	-0.02	-0.018	(0.019)+	-0.019	-0.018	-0.018	(0.020)**	-0.024
opop_m	-0.038	0.04	-0.049	-0.062	0.01	-0.01	0.023	-0.048	-0.037	-0.054	0.042	-0.005
	(0.020)+	(0.019)*	(0.020)*	(0.019)**	-0.02	-0.018	-0.018	(0.019)*	(0.018)*	(0.018)**	(0.021)*	-0.023
oincpop	0	0.005	-0.005	-0.017	0.001	-0.007	0.01	0.008	0	0.009	0.01	0.036
	-0.016	-0.015	-0.016	-0.015	-0.016	-0.015	-0.014	-0.015	-0.015	-0.014	-0.016	(0.020)+
ohubboard_m	0.014	-0.015	0.007	0.002	0.011	0.01	-0.003	0.011	0.001	0.015	-0.005	-0.007
	-0.009	(0.009)+	-0.01	-0.009	-0.01	-0.009	-0.009	-0.01	-0.009	(0.008)+	-0.01	-0.011
HHI	0.42	0.304	0.375	0.742	0.749	-0.492	-2.353	-0.475	-0.338	0.166	0.718	2.502
	-0.516	-0.489	-0.505	-0.489	-0.52	-0.485	(0.489)**	-0.494	-0.482	-0.468	-0.535	(0.647)**
PVOLN_t	37.749	25.995	17.654	48.464	-22.078	16.464	21.262	0.37	-2.211	20.429	40.792	9.321
	(15.796)*	(12.180)*	(6.179)**	(19.442)*	(7.990)**	-10.929	(10.490)*	-5.913	-4.691	(6.667)**	(12.311)**	(5.253)+
Relprice_t	1.03	3.769	0.906	15.85	11.579	8.102	-1.834	5.543	4.57	5.275	12.581	-0.13
	-2.408	(1.967)+	-0.658	(3.553)**	(1.377)**	(2.376)**	-1.576	(0.709)**	(0.921)**	(1.029)**	(1.828)**	-1.214
UR_Index	-1.567	-1.275	-0.76	-0.526	-1.832	1.299	4.347	0.331	0.888	1.349	0.798	-0.136
	-1.691	-1.341	-1.387	-1.475	-1.484	-1.343	(1.688)*	-1.385	-1.668	-1.346	-1.495	-1.477
Constant	-5.009	-4.662	-3.519	-15.391	-13.289	-11.098	-3.01	-6.671	-6.051	-5.619	-12.354	0.184
	(2.799)+	(2.327)*	(1.519)*	(3.773)**	(1.839)**	(2.687)**	-2.187	(1.412)**	(1.560)**	(1.573)**	(2.266)**	-1.858
LL	-529.65	-575.5	-542.39	-556.84	-521.63	-583.1	-593.67	-561.15	-573.67	-609.3	-509.78	-403.92
Chi2	113.1	172.53	178.33	240.41	288.95	108.58	162.11	228.04	204.6	133.91	265.37	143.32

Standard errors in parentheses

+ significant at 10%; * significant at 5%; ** significant at 1%

Coefficients of airlines' market shares are not reported.

Table 5. Marginal effects of PVOLN and RelativePrice (MODEL 2)

t	PVOLN_t	RelativePrice_t
84	7.346818	0.20052
	(3.07739)*	(0.46855)
77	6.20006	0.898898
	(2.89489)*	(0.46819)+
70	3.835088	0.196744
	(1.34894)**	(0.14303)
63	12.08144	3.951117
	(4.83683)*	(0.88603)**
56	-5.19992	2.727124
	(1.89107)**	(0.31747)**
49	3.737402	1.839178
	(2.48362)	(0.53848)**
42	5.263799	-0.45395
	(2.59602)*	(0.39023)
35	0.091188	1.367187
	(1.45851)	(0.17433)**
28	-0.55165	1.140058
	(1.1703)	(0.22976)**
21	5.08687	1.313374
	(1.65597)**	(0.25585)**
14	7.90991	2.439482
	(2.19528)**	(0.29952)**
7	0.997334	-0.01389
	(0.66178)	(0.13)

Table 6. Tobit regressions of the relative savings

	RelSave84	RelSave77	RelSave70	RelSave63	RelSave56	RelSave49	RelSave42	RelSave35	RelSave28	RelSave21	RelSave14	RelSave7
km k	-0.024	-0.011	-0.019	0.018	-0.025	-0.027	-0.018	-0.018	0.014	-0.002	-0.016	-0.003
	(0.006)**	(0.004)**	(0.007)**	(0.005)**	(0.005)**	(0.005)**	(0.003)**	(0.005)**	(0.004)**	-0.004	(0.005)**	-0.01
enplanements k	0.004	-0.001	0.001	-0.002	0.001	0.001	-0.002	0.001	0	-0.001	0	0.002
	(0.001)**	-0.001	-0.001	-0.001	-0.001	-0.001	(0.001)*	-0.001	-0.001	-0.001	-0.001	-0.003
opop_m	0	0.001	0.001	0.001	0	0	0	0	-0.001	0	0	0.003
	-0.001	-0.001	-0.002	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.003
oincpop	-0.001	-0.002	0.003	-0.001	0	0.001	0	0.001	0	0.001	0	0
	-0.001	(0.001)**	(0.001)**	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	(0.001)+	-0.001	-0.002
ohubboard_m	0	0	-0.001	0	0.001	0	0	-0.001	0	0	0	0.001
	-0.001	0	-0.001	-0.001	(0.000)*	0	0	0	0	0	0	-0.001
hhi	-0.019	0.009	0.02	-0.057	0.011	0.033	-0.04	0.05	0.053	0.018	0.04	0.006
	-0.031	-0.022	-0.036	(0.028)*	-0.027	-0.027	(0.019)*	(0.025)*	(0.027)+	-0.019	(0.024)+	-0.056
PVOLN _t	0.692	-0.5	0.257	1.042	-0.963	1.526	3.209	0.761	0.715	1.012	-0.866	-0.073
	-0.907	-0.359	-0.238	(0.256)**	(0.279)**	(0.590)*	(0.588)**	(0.291)**	(0.297)*	(0.101)**	(0.293)**	-0.424
RelPrice _t	-0.047	0.278	0.094	0.771	0.421	0.166	0.261	0.149	0.167	0.257	0.496	0.021
	-0.157	(0.107)**	(0.041)*	(0.140)**	(0.061)**	-0.121	(0.089)**	(0.036)**	(0.052)**	(0.033)**	(0.055)**	-0.118
urindex	0.093	-0.082	-0.007	-0.094	0.067	0	0.089	-0.125	0.035	-0.025	0.149	-0.069
	-0.129	-0.09	-0.073	-0.065	-0.118	-0.055	(0.045)*	-0.08	-0.062	-0.045	-0.112	-0.192
Constant	0.175	-0.054	0.008	-0.659	-0.255	0.023	-0.214	-0.121	0	-0.117	-0.332	-0.189
	-0.169	-0.125	-0.112	(0.155)**	(0.098)**	-0.13	(0.113)+	-0.076	-0.083	(0.052)*	(0.080)**	-0.234
Observations	292	542	267	505	539	290	458	416	473	446	256	118
LL	319.11	564.59	231.08	485.67	507.49	363.98	643.25	499.01	495.65	626.47	374.18	119
Chi2	105.74	87.14	67.3	114.83	295.52	109.11	162.24	99.17	38.86	273.19	258.77	39.51

Standard errors in parentheses

+ significant at 10%; * significant at 5%; ** significant at 1%

Coefficients of airlines' market shares are not reported.