Price Volatility of Revenue Managed Goods: Implications for Demand and Price Elasticity

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Abstract

Revenue management practices are widely employed in various sectors. These mechanisms dynamically adjust prices observed by consumers typically through the control of price classes and their availability. As such, these pricing environments tend to exhibit some predictable behaviors as the product approaches the expiration or consumption date but may also result in varying degrees of price volatility. Such price paths may ultimately alter consumer behavior, e.g., via delayed purchase timing (i.e., strategic behavior) or different willingness to pay (which could be measured by the degree of price elasticity). Accordingly, we assess consumers' responses to the realized price changes induced by revenue management mechanisms, using fare and sales data from aviation markets. Our empirical analyses reveal that price elasticity decreases (in absolute terms) in the degree of price volatility, whereas the realized demand is lower when price volatility is higher. This suggests that as prices become more volatile, consumers become more oblivious to these price fluctuations and may end up paying more for the products—thereby confirming and generalizing a behavior previously documented for consumer packaged goods (CPGs), which follow dramatically different pricing regimes. While this may suggest support for higher and more volatile prices, we find that given the higher prices, the overall demand decreases, highlighting a delicate trade-off firms face. To distill the insights from the empirical analyses, we formulate two hypotheses, which we then test in a laboratory setting by means of an ad hoc experiment.

Keywords: revenue management, dynamic pricing, price elasticity, price volatility, lab experiment

1. Introduction

Dynamic pricing and revenue management mechanisms have been successfully adopted by numerous industries (Klein et al., 2020; Talluri and Van Ryzin, 2004). The application of these mechanisms often gives rise to price fluctuations, which could result in two, rather orthogonal, consumer behaviors. On the one hand, consumers' uncertainties increase, thereby decreasing their price sensitivity (Janiszewski and Lichtenstein, 1999; Winer, 1986), suggesting consumers may end up buying at *higher* prices. On the other hand, consumers may respond by exhibiting strategic behavior as they patiently wait for price drops and take advantage of *lower* prices (Baucells et al., 2017; Li et al., 2014; Osadchiy and Bendoly, 2015), suggesting a downward pressure on prices.

The former insight is primarily derived from the context of consumer-packaged goods (CPGs), such as food and beverages (Kalyanaram and Little, 1994; Murthi et al., 2007; Winer, 1986). CPGs can be stored for later consumption, which can occur later than the actual purchasing moment. Differently, revenue-managed goods, such as airline seats, hotel rooms, or concert tickets, have a certain expiration and cannot be stockpiled for future use.

Revenue management has evolved as a broader tool offering a mechanism to dynamically match demand and supply. By identifying different segments of consumers and forecasting their arrival over time, revenue management aims to maximize expected revenues dynamically adjusting goods' prices as capacity varies (i.e., bookings are made) or expiration date approaches. Therefore, revenue management embodies variations in prices. Specifically, as demand is realized over the selling horizon of the good, fare classes are opened and closed and the fares associated with these classes are also adjusted dynamically as demand projections are regularly adjusted. Accordingly, varying degrees of price volatility emerge. [1]

To study the impact of price volatility in the context of dynamic pricing and revenue management, we resort to the proto-typical revenue management industry: air transport. This industry reflects the classical revenue management setting: a fixed number of items (e.g., seats) with a known expiration date (e.g., departure date) are at the disposal of the firm (e.g., air carriers) to be sold to a segmentable stream of consumers (e.g., air travelers) who arrive sequentially over time (Feng and Gallego, 2000; Gallego and van Ryzin, 1994; McAfee and Te Velde, 2008). Recognizing that consumers observe prices over time and may have access to past prices—which is particularly true in the context of the airline industry as

[1] Recent literature has proposed the implementation of revenue management practices with the integration of demand learning (Den Boer, 2015; Den Boer and Zwart, 2015; Kumar et al., 2018). This concept, which is often coupled with dynamic pricing, grounds on the opportunity of dynamically estimating an optimal price relying on customers' WTP, while accounting for the choice set, expiration date and the remaining capacity. Dynamic pricing, especially when price exploration is applied (e.g., Den Boer and Zwart, 2013), results in volatile prices that allow a better prediction of demand in a problem that otherwise would spiral-down (see Cooper et al., 2006 for further reference).

consumers have access to fare prediction tools which often provide access to past fare histories (e.g., *Kayak*, *AirHint* and *Hopper*)—our goal is to quantify the impact of price volatility on demand, with an emphasis on price elasticity. To pursue our aim, we first propose an innovative measure of price volatility, incorporating the relative price changes—in order to account for differences across markets—and comparing the offered prices with the predicted fare projections, serving as a proxy for the reference price.

With this price volatility construct, we contribute to the literature by empirically investigating how it affects demand, contemporaneously exploring the impact of product (i.e., flight) and market (i.e., route) features, as well as price, and an indicator of whether the fare has dropped since the previous day.

Importantly, we find that increased levels of price volatility are associated with reduced number of transactions, thus implying a potential decrease in revenues due to price volatile mechanisms. However, previous studies demonstrate that a higher consumers' uncertainty due to fare fluctuations induces them to be less sensitive to changes in price (e.g., Janiszewski & Lichtenstein, 1999). This implies that consumers may end up paying higher prices. As a consequence, higher paid prices have opposite effects on revenues: on the one hand, revenues potentially increase because of the higher prices, while, on the other hand, demand may decrease and strategic consumers take advantage of price volatility and wait for lower prices. This leads us to the next natural step of understanding how price volatility effectively influences consumers' price elasticity of demand. Accordingly, we estimate price elasticity at different levels of price volatility, and we find that price elasticity decreases (in absolute values) in the degree of price volatility.

The results derived by the empirical analysis suggest a significant impact of price volatility on demand and the related price sensitivity. However, in the real-life setting, we cannot appropriately isolate the effect of the exposure to price volatility on consumers' purchasing decisions and willingness to pay (WTP). To this extent, we conduct a lab experiment in which subjects were required to first solicit their WTP with respect to a set of revenue-managed goods and, after being exposed to volatile price patterns, they were required to make their purchasing decision at a certain spotted price (lower than, equal to, or higher than their willingness to pay). We have two treatments in the experiment: one where they are exposed to low price volatility and another where they are exposed to high price volatility. Subjects' responses indicate that, in line with the empirical outcomes formerly derived in this study, price volatility generally decreases demand and enlarges the range of acceptable prices.

The remainder of this paper is organized as follows. In Section 2, we revise the state of the art on the topics of price variations and consumers' price sensitivity and proceed with the definition of an appropriate measure of price volatility (§3). Section 4 focuses on the empirical research design and methodology and Section 5 reports the results of the empirical analyses. Given the insights, we validate the empirical results by developing an experimental design testing the impact of price volatility on purchasing decisions (§6). We summarize and offer directions for further research in Section 7.

2. Literature review

This section reviews the relevant literature on the impact of price fluctuations on consumers' purchasing behavior. For the scope of our paper, we first limit our attention to marketing research addressing the effect of price variations on consumers' price sensitivity and purchasing choices (§2.1). We then briefly review literature on the dynamics between price and demand in the context of revenue-managed goods, primarily discussing price elasticity estimates in air transportation that is the focus of our empirical study (§2.2).

2.1. Price changes and consumers' price sensitivity

Aiming to increase their revenues, firms tend to stimulate demand by relying on two main instruments, advertising and discounts (Jedidi et al., 1999). The latter, while an effective tool, can bear consequences relating to how consumers perceive the resulting price variations and how these affect their purchasing behavior—a research domain that has not attracted sufficient attention (Cheng and Monroe, 2013). A few studies show that price volatility has a significant impact on consumers' behavior (see, e.g., Murthi et al., 2007). For instance, consumers who are exposed to price fluctuations become less price sensitive (Han et al., 2001; Janiszewski and Lichtenstein, 1999). The reasons underpinning this decrease in price sensitivity rely on the uncertainty consumers face when exposed to price variations (Winer, 1986), which implies a lower perceived gain when discounts are applied (Pauwels et al., 2007). Higher levels of price volatility have also been found to increase the range of acceptable prices (Winer, 1986) as well as the value of the reference price, defined as the 'right price' perceived by consumers (Han et al., 2001; Kalyanaram and Little, 1994). Murthi et al., (2007) further corroborate former literature showing that price volatility increases the level and the range of reference prices, thus decreasing consumers' price sensitivity. This consequently distorts the difference between reference and actual price.

Additionally, previous studies demonstrated how discounts lead to strategic behavior of consumers, patiently waiting for price drops for making their purchases. This insight stems mainly from prevailing markdown pricing mechanisms used for certain revenue-managed goods. Markdown pricing commands the price of a good to decrease over time as its expiration approaches and is often practiced for goods with a short shelf life (Anderson and Blair, 2004; Dasu and Tong, 2010; Lazear, 1986; Yin et al., 2009). As such, most of the literature focusing on the impact of price fluctuations on consumers relies on empirical studies focusing on consumer-packaged goods (CPG). Certain features associated with CPGs (such as the storability, expiration, and availability of comparable products) raise concerns regarding the generalizability of the insights, overall, and to revenue managed goods, in particular. As mentioned above, revenue managed goods are broadly characterized (Talluri and Van Ryzin, 2004) as having a fixed limited capacity, with a fixed expiration (or consumption) date, which consumers cannot store for later consumption. Hence, they are a substantially different class of goods (usually services, such as travel or hospitality). Even more importantly is the fact that revenue managed goods exhibit quite characteristic price paths as time elapses towards their expiration/consumption time. Thus, as time approaches expiration (departure date in case of transport services), the expected price changes, indicating a dynamically changing reference price.

2.2. Revenue management and price elasticity

In the implementation of revenue management, pricing strategy plays a key role, as price is the most important determinant of consumers' purchasing behavior (Van Ryzin and McGill, 2000). However, current revenue management practices abstract away from the inherent role of price fluctuations. Revenue management generally relies on the creation of fare classes, which reflect different consumer segments with respect to their WTP and timing of arrival (Chen and Chen, 2015; Talluri and Van Ryzin, 2004). These fare classes are closed and (re)opened over time.[2] A closing of a fare class, e.g., following a sale or in expectation of future demand with higher WTP, increases the lowest fare available to consumers. When a fare class reopens, e.g., when demand does not materialize, lower fares become available to consumers. The dynamic opening and closing of fare classes imply changes in the spot prices, namely, price volatility.[3] As retailers' revenues greatly depend on a full understanding of how much a variation in prices would stimulate – or reduce – demand, accurate estimates of price elasticity are required (e.g., Fisher et al., 2018). For recent reviews of the expansive literature on revenue management, we refer the readers to Chen and Chen (2015) and Wei and Zhang (2018).

The lack of publicly available scanner level data generally prohibits the full exploration of price elasticity and the extent to which demand vary in response to fluctuating prices (e.g., Brons et al., 2002). In the context of air transport industry, studies of price elasticity are generally limited to the aggregate market level revealing, for example, variation across markets (Gillen et al., 2003), or the impact of competition as a positive driver of price elasticity (Smyth and Pearce, 2008). In their comprehensive review summarizing 254 estimates taken from 21 different studies, Gillen et al., (2003) conclude that price elasticity can vary from -3.2 to 0, with an average value of -1.22. Their review aggregates data according to three travel characteristics: the route length (short-haul vs long-haul, with the former being more price sensitive), the destination (domestic vs. international markets with the former being more price sensitive), and the type of travel (business vs. leisure with the latter being more price sensitive).

Price elasticity of demand and its variations are also investigated in more recent studies (e.g., Acuna-Agost et al., 2021; Granados et al., 2012; Morlotti et al., 2017; Mumbower et al., 2014; Perera and Tan, 2019). In line with the outcomes provided in Gillen et al., (2003), these papers demonstrate the presence of several features impacting on the estimates, ranging from booking and reservation days to the level

[2] Besides identifying different market segmentations associated with different fare classes, other strategies to manage capacity can be applied by sellers such as opaque products (see, e.g., Gönsch, 2020).

[3] Revenue management and dynamic pricing are oftentimes used interchangeably. Dynamic pricing is exercised by offering a single product while dynamically adjusting its fare based on capacity and demand (Gallego and van Ryzin, 1994; Marcus and Anderson, 2008; Talluri and Van Ryzin, 2004); this results in volatile prices.

of competition. Granados et al (2012) illustrate variations in price elasticity across different distribution channels, market segments, and level of service (associated with the degree of product bundling). Their estimates vary from -0.74 (for deeply discounted bundles offered via traditional channels to the business segment) to -0.26 (for deeply discounted bundles offered to leisure passengers via the à la carte channel), suggesting that demand is always inelastic. Mumbower et al. (2014) and Morlotti et al. (2017) show large ranges of price elasticity of demand at mean prices in the US and European market, respectively. Their results illustrate varying outcomes in relation to the departure time of the day (ranging between [-1.58,-2.81] in the US and between [-0.628,-0.911] in Europe), the departure day of the week (ranging between [1.67,-2.80] in the US and between [-0.642,-1.313] in Europe), the booking day (ranging between [-1.55,-3.11] in the US and between [-0.613,-1.303] in Europe), and the days of advance (ranging between [-0.73,-3.21] in the US and between [-0.638,-2.066] in Europe). Additionally, Mumbower et al. (2014) reveal that price elasticity of demand is higher during competitors' promotional sales, while Morlotti et al. (2017) indicate additional differences with reference to route and seasonal characteristics. Ultimately, Acuna-Agost et al., (2021) estimate a median price elasticity for leisure trips of -6.71, compared with -0.85 for business passengers. Consistently, they provide variations in relation to the departure days of the week and destination type (i.e., domestic or international).

While the mainstream literature has focused on fixed exogenous dimensions that affect price elasticity, in this study we focus on the degree of price volatility—the magnitude of which may heavily depend on airlines' strategic decisions in the various markets—which can play a role in influencing the consumers' price elasticity.

3. *Measuring price volatility*

When studying the impact of price fluctuations on consumers' purchasing decisions, two crucial concepts have to be clearly defined: reference price and price volatility. We start with reference price. Kalyanaram and Winer (1995) define reference price as an "internal standard" used by purchaser to compare the observed prices. Intuitively, when making purchasing decisions, consumers do not evaluate absolute prices, rather they take into account the difference of offered prices from their reference price (e.g., Rajendran and Tellis, 1994). If the reference price is lower than the offered price, the consumer perceives a transaction disutility (Han et al., 2001; Weaver and Frederick, 2012). Considering T (1) as the first (last) day of price observation, we rely on the adaptive formulation (e.g., Han et al., 2001) to define reference prices (RP) in period t as a function of the prior reference price (i.e., from period $t+1$) and offered price:

$$RP_t = \lambda RP_{t+1} + (1-\lambda)P_{t+1}, \qquad (1)$$

where λ is a smoothing constant between 0 and 1 (e.g., Fibich et al., 2005; Han et al., 2001; Kalyanaram and Little, 1994). Several refinements of this formulation exist, varying from replacement of offered prices with paid prices (e.g., Mayhew and Winer, 1992) to inclusion of additional contextual and temporal factors, such as historical and competitor prices and advertised or suggested retail prices (Rajendran and Tellis, 1994; Wang et al., 2021). Although there is a debate on the right formulation to account for reference prices, evidence suggests reference prices impact consumers' purchasing behavior, influencing their 'loss' and 'gain' perceptions and ultimately their brand choices (e.g., Kalyanaram and Winer, 1995; Murthi et al., 2007).[4]

We now proceed with price volatility. The traditional marketing approach states that price volatility "captures the price patterns by giving different weights to recent versus past changes in prices" (Han et al., 2001), in a fashion that is more consistent with human behavior. With respect to simpler formulations (like a variance measure or the most recent price variation), they propose a construct that captures price patterns by giving a different weight to recent and past price variations. Accordingly, it is formulated as follows:

$$PVOL_{i,t} = \theta PVOL_{i,t+1} + (1-\theta)\left(P_{i,t} - P_{i,t+1}\right)^2, \qquad \text{with } PVOL_{i.T} = 0, \tag{2}$$

where $PVOL_{i,t}$ and $P_{i,t}$ represent the price volatility and the price, respectively, of product i in period t, while θ is a smoothing constant indicating the weight assigned to past price changes with respect to the most recent price variation. Similarly, given the expiration date of a certain revenue-managed good, $PVOL_{i,t+1}$ and $P_{i,t+1}$ represent the price volatility and the price, respectively, of product i in one period of advance with respect to t.

Within the same product category (such as peanut butter or ground coffee), different products are expected to bear a comparable price. However, in airline markets price may differ dramatically from one market (defined as origin-destination airport pair) to another. This can be an outcome of the distance, the competition intensity in the market, or simply the market's leisure or business orientation (e.g., Salanti et al., 2012). To that end, Gillen and Mantin (2009) have considered a normalized measure of price volatility ($PVOLN_{it}$), capturing the daily percentage change in prices rather than the absolute price fluctuation. Their normalized price volatility is computed as follows:

$$PVOLN_{i,t} = \theta PVOLN_{i,t+1} + (1-\theta)\left(\frac{P_{i,t}-P_{i,t+1}}{P_{i,t+1}}\right)^2, \qquad \text{with } PVOLN_{i,T} = 0, \tag{3}$$

where $PVOLN_{i,t}$ is the normalized price volatility.

[4] Along with adaptive (e.g., Han et al., 2001) expectation models, other formulations have been proposed by the literature (De Maeyer and Estelami, 2013; Johnson et al., 1995; Muth, 1961; Nasiry and Popescu, 2011; Winer, 1986), including the extrapolative expectation model, which takes into account only the past and most recent prices (and accordingly ignoring past reference prices) so the updating equation becomes $RP_t = \lambda P_{t+1} + (1-\lambda)P_{t+2}$; the rational expectation model, where the reference price is a function of the most recent price plus a random error term so the updating rule is $RP_t = P_{t+1} + \epsilon_t$ with $\mathbb{E}[\epsilon_t] = 0$; and the peak-end model, arguing that the reference price depends on the peak (either highest or lowest) price and the most recent one in which case the updating rule is $RP_t = \lambda P_{t+1} + (1-\lambda)m_{t+1}$ where $m_{t+1} = \min(m_{t+2}, P_{t+1})$ for the low peak case and $m_{t+1} = \max(m_{t+2}, P_{t+1})$ for the high peak case. Note that the extrapolative expectation and rational expectation models only take into account most one or two recent prices, whereas the peak-end model assumes an infinite recall of peak historical prices. The adaptive model, which we employ in this paper, balances the most recent price observation and the history of observed prices.

In airlines markets, and by generalization to markets consisting of revenue-managed goods, the measurement of reference price is challenging and it has not been addressed thus far in the literature, to the best of our knowledge. While evidence shows that reference prices are greatly based on market prices (Weaver and Frederick, 2012), we also recognize that airfares vary dynamically according to factors such as the number of remaining seats, the remaining days to departure and other market, flight, and booking characteristics (e.g., Hofer et al., 2008; Malighetti et al., 2009; Salanti et al., 2012). While prices may be volatile on a day-to-day basis (Boyd and Bilegan, 2003), at the aggregate level, airfares still follow some predictable price trajectories (Mantin and Rubin, 2018). Accordingly, we substitute it with a close alternative: the expected price. Specifically, as the price paths of seats in different markets exhibit somewhat predictable price patterns, we assume that the reference price coincides with the projected price to be offered by the airline on given days as a function of time to departure and other features associated with the flight.

Following Malighetti et al. (2009), we include the following price formulation to enable fare predictions. Specifically, assuming a well-known increasing price pattern, the price path of flight i, $\tilde{P}_i(t)$, is expressed as follows:

$$\tilde{P}_i(t) = \mu_i + \frac{1}{\alpha_i(1 + \beta_i \cdot t + \gamma_i \cdot t^2)} \tag{4}$$

with μ_i being the minimum price level of a flight i, while α, β, and γ determine the influence of advance days (t) on airfares. In details, α reflects the level of prices towards the departure date, β represents the speed of increase in airfares, and γ adjusts the trend curvature. In our analysis, we fit this equation for identical flights in a given season, meaning we distinguish between different flights during the day while accounting for seasonality.[5] In Appendix A, we compare our choice of the predicted price with the traditional formulation of reference price.

Ultimately, following Mantin and Rubin (2018) and Mantin and Gillen (2011), we adapt Gillen and Mantin's (2009) $PVOLN$ definition to explicitly capture price fluctuations from predictable price paths. We refer to this measure as Price Volatility Normalized and Adjusted for Predictability, or $PVNAP$. The new measure of price volatility, therefore, becomes:

$$PVNAP_{i,t} = \theta \cdot PVNAP_{i,t+1} + (1-\theta) \cdot \left(\frac{\frac{P_{i,t}}{\tilde{P}_i(t)}}{\frac{P_{i,t+1}}{\tilde{P}_i(t+1)}} - 1 \right)^2, \text{with } PVNAP_{i,T} = 0. \tag{5}$$

[5] In our sample μ_{imr}, α_{imr}, β_{imr}, and γ_{imr} have a mean (median) value of 57 (53), 0.020 (0.014), 0.050 (0.049), 0.153 (0.032), respectively, demonstrating an increasing trend as departure date approaches.

4. *Data and estimation methodology*

In this section, we describe the data collection, the estimation strategy, the variables used and the instruments used for controlling the endogeneity existing between price and demand.

4.1. Data

In order to estimate how price volatility may influence passengers' price elasticity of demand, both air ticket prices and the number of daily purchases are needed. While such data is not publicly available, we have facilitated an innovative data collection approach to ensure both pricing and sales data. To gather pricing data, we downloaded on a daily basis fares offered by easyJet, a major European airline carrier. Although easyJet, like other low-cost carriers (LCC), appears to implement dynamic pricing strategies, according to Alderighi et al. (2018), the LCC relies on fare classes, replicating the traditional revenue management practices. Specifically, we collected data from its website spanning over the final 45 days prior to departure on 21 European destinations departing from Amsterdam Schiphol airport for all flights taking place between 8 March, 2015, and 23 September, 2015. Overall, we collected daily airfares for 7,211 flights, with a total of 319,029 records.

The resulting pricing sample is rather heterogenous as can be observed from Table 1. The fares in the various markets exhibit diverse trajectories with a generally increasing trend in particular during the final two weeks as departure day approaches (see top panels of Figure 1 for two sample markets). The middle panels of Figure 1, which exhibit the probability of a price drop prior to departure, clearly suggest that this probability generally decreases over time. This corroborates the notion that price trajectories in different markets are somewhat predictable, validating the need for using our price volatility measure, $PVNAP$, which accounts for this predictability and, hence, for the 'right price' at different points in time. To estimate $PVNAP$, we first compute $\tilde{P}_i(t)$ by fitting the nonlinear function from (4) for all flights, grouped according to the market served, the days in advance, as well as the month and other flight features (i.e., day of the week, and hour of departure), for a total of 2,101 combinations.[6] The bottom panels of Figure 1 show the progression of $PVNAP$ over days of advance for the two sample markets. By construction, since we set $PVNAP_{iT} = 0$, it tends to increase over time with sufficient variations across markets.

While daily sales are not directly available, we implement a procedure to compute the number of tickets sold, which was used in literature as a valid proxy of demand (Granados et al., 2012). Specifically, on a daily basis we query the maximum bookable seats for each flight, up to easyJet's website maximum

[6] The reasons underpinning the choice of estimating $\tilde{P}_i(t)$ for groups of flights are twofold. First, relying on the full sample would require linearization of all price trends, without taking into account specific market- or flight-attributes. Second, conducting the estimation on an individual flight basis would have led to a too specific estimation, hardly acknowledged by the consumer. To this extent, we group together all flights serving the same market, operating in the same month, the same day of the week and at the same hour.

threshold of 40 seats. The difference between this value and the previous day is our proxy for the daily ticket sales.[7]

Table 1. Descriptive statistics of the fares per each destination, sorted by mean fare (euros)

Destination	Airport code	Mean	Std. Dev.	Min	Max
Split, Croatia	SPU	130.999	64.594	42.99	430.99
Lisbon, Portugal	LIS	128.896	52.432	43.99	369.99
Prague, Czech Republic	PRG	119.725	31.736	44.99	308.99
Bristol, UK	BRS	114.751	36.580	36.99	288.99
Rome Fiumicino, Italy	FCO	104.592	34.721	37.99	308.99
Glasgow, UK	GLA	99.221	35.636	24.99	253.99
Milan Malpensa, Italy	MXP	96.922	42.537	27.99	492.99
Edinburgh, UK	EDI	96.810	37.656	34.99	369.99
Manchester, UK	MAN	93.343	36.942	29.99	337.99
Liverpool, UK	LPL	90.098	35.395	28.99	367.99
Belfast, UK	BFS	89.975	33.227	24.99	271.99
Berlin, Germany	SXF	87.068	31.018	30.99	492.99
New Castle, UK	NCL	86.643	30.480	34.99	205.99
Bordeaux, France	BOD	82.812	36.421	29.99	241.99
London Gatwick, UK	LGW	80.795	36.630	31.99	288.99
Basel, Switzerland	BSL	79.538	37.022	26.99	308.99
London Stansted, UK	STN	77.702	34.881	33.99	269.99
London Luton, UK	LTN	76.136	34.364	31.99	339.99
Genève, Switzerland	GVA	75.916	40.154	26.99	337.99
Southend, UK	SEN	67.903	30.768	28.99	234.99
Hamburg, Germany	HAM	43.527	20.070	24.99	202.99

[7] Overbooking mechanisms are not taken into account in our empirical analysis.

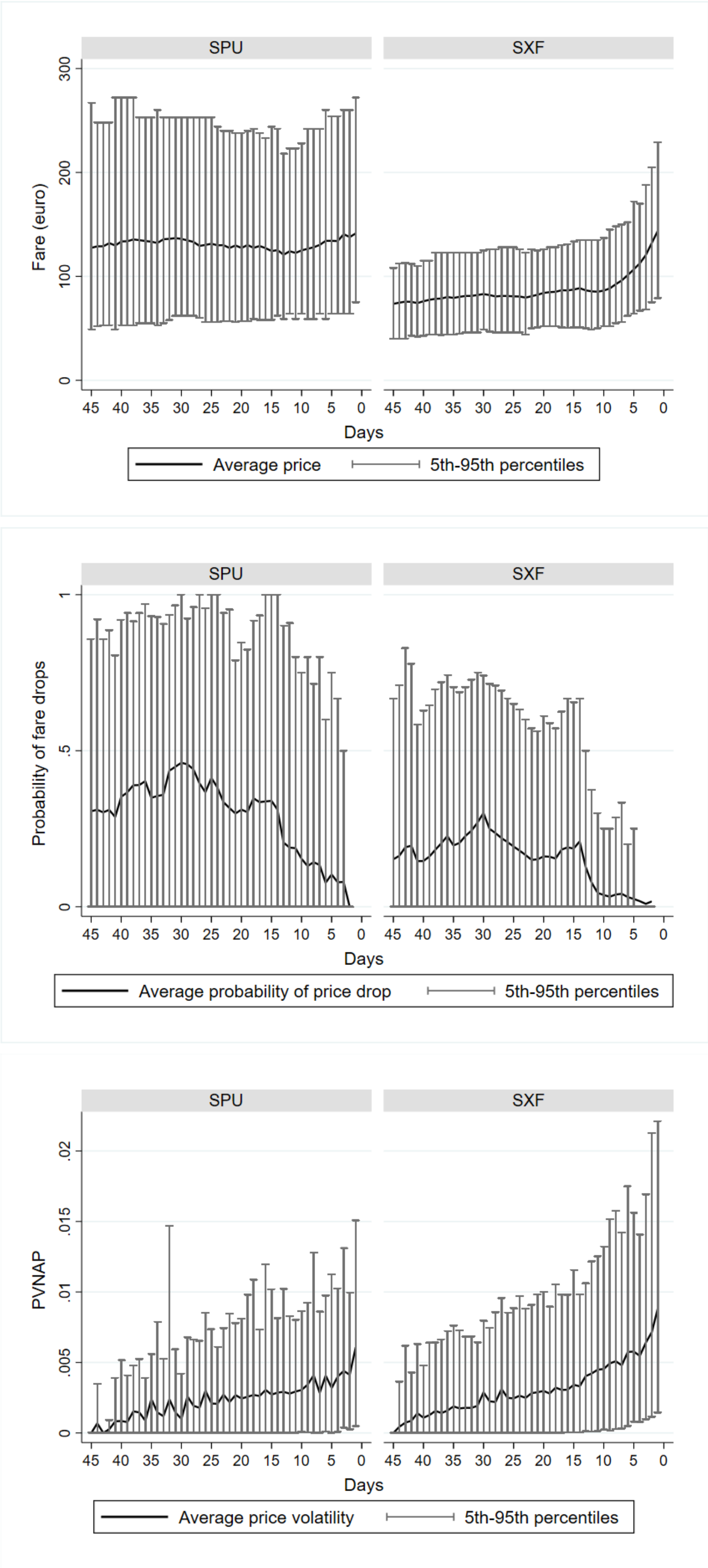

Figure 1. Average daily fares (top panels), probability of price drops (middle panels), and price volatility (bottom panels) over 45 days to departure with the respective 5th-95th percentiles from Amsterdam to Split (SPU) and Berlin (SXF)

4.2. *Determinants of demand*

To measure consumers' price sensitivity with respect to price volatility, we run a regression model. When investigating the relationship between price and demand, a reverse causality concern may arise, as the level of demand is affected by prices and, at the same time, demand may determine the levels of airfares (e.g., Gerardi and Shapiro, 2009). To address this potential endogeneity, we implement a two-stage least square (2SLS) instrumental variable (IV) method.[8] Several scholars have attempted to find a proper instrument for price in the context of air transport (see, e.g., review in Mumbower et al., 2014). In our study, we employ the airline's average prices in similar markets (Morlotti et al., 2017; Mumbower et al., 2014). Assuming the orientation of a market (i.e., leisure vs. business) does not vary over time (hence, treated as a fixed effect), we define similar markets according to their leisure or business orientation. Specifically, we rely on Salanti et al.'s (2012) Leisure Index.[9] This index is based on the degree of price discrimination in a market, with more negative values indicating the route is classified with a higher degree of business orientation. In our sample, the Leisure Index ranges from -0.067 (MXP) to -0.024 (SPU), suggesting the former has a higher business orientation than the latter. An alternative instrument is studied in Appendix C.

In order to identify similar markets, we generate 4 categories of routes corresponding to the 4 quartiles of the Leisure Index. Thus, Category 1 (resp., 4) includes routes with the lowest (resp., highest) values of the Leisure Index (namely, the first (resp., fourth) quartile of the sample) reflecting the most business (respectively, leisure) oriented markets. Then, for each route, we compute the average price on all other routes belonging to the same Leisure Index quartile. This average price, which is computed for each route at t days in advance, serves as the instrumental variable for the price on route r for flights departing on date d at t days before departure (IV_{rdt}).

Demand estimation is as follows:

$$D_{irdt} = \delta + \varphi \hat{P}_{irdt} + \rho \boldsymbol{Y}_{irdt} + \vartheta \boldsymbol{X}_{irdt} + \omega \boldsymbol{Z}_r + u_{irdt} + v_r \tag{6}$$

where D_{irdt} is the number of tickets sold t days in advance for flight i on route r departing on date d. The independent variables are summarized by $\boldsymbol{Y}_{irdt}$, which is a vector of our price related variables, $\boldsymbol{X}_{irdt}$, a vector of flight characteristics, and $\boldsymbol{Z}_r$, a vector of route characteristics. We elaborate on these

[8] 2SLS is an estimation method that accounts for the presence of endogenous explanatory variables. Different from ordinary least squares (OLS) regressions, 2SLS regressions are based on two stages: In the first stage, the variable considered as endogenous is estimated over a series of exogenous regressors and one, or more, instrumental variables (IVs). In the second stage, the estimated endogenous variable derived from the first stage is included as a regressor of the dependent variable. The presence and the correct identification of the IVs in the first stage is crucial. IVs have to meet two conditions in order to provide consistent estimations: (i) they should be correlated with the endogenous variable, and (ii) they should not be correlated with the error term of the second stage regression. We refer the reader to Wooldridge (2016) for further discussion on the topic. This method is widely used for demand estimations in the context of airline pricing, see, for example, Mumbower et al., (2014) and Perera and Tan (2019). In our study, the two stages of the 2SLS estimations are provided in Eq. (6) and Eq. (7), while the rationale underpinning the choice of our IV is available in the first paragraph of Section 4.2.

[9] See Appendix B for further details on the Leisure index.

variables below. u_{irdt} and v_r are the flight- and route-related error terms, and $\hat{P}_{irdt}$ is the predicted price estimated from:

$$P_{irdt} = \alpha + \beta IV_{rdt} + \gamma \boldsymbol{X}_{irdt} + \partial \boldsymbol{Z}_r + \varepsilon_{irdt} + \xi_r \quad (7)$$

where P_{irdt} is the posted fare (when booking a single seat), IV_{rdt} is the selected instrumental variable, and ε_{irdt} and ξ_r are flight- and route-related error terms, respectively.[10]

$\boldsymbol{X}_{irdt}$ is a vector of the flight-characteristic variables. Specifically, *Advance*, representing the number of days prior to departure; *Booking Weekdays* and *Departure Weekdays* are dummy variables equal to 1 when the booking and departure date is during weekdays (from Mondays to Thursdays), and 0 otherwise (from Fridays to Sundays); *Peak Hours* is a dummy variable equal to 1 when the departure hour is between 6 a.m. to 9 a.m. or from 5 p.m. to 9 p.m., and 0 otherwise; and *Summer* is a dummy variable equal to 1 for departures taking place between 21 June and 23 September, and equal to 0 for departures taking place during springtime.

$\boldsymbol{Z}_r$ is the vector of route characteristic variables, made up by a set of dummies identifying each of the considered route, where AMS-SXF represents the reference case, and two variables considering the route-level of competition. Specifically, *Relative MS* and *Eligible Alternatives* account for direct and inter-modal competition, respectively, and thus help to avoid under-estimated results (Oum et al., 1992). The former variable (*Relative MS*) represents easyJet's market share out of the market share of other low-cost carriers operating on the same route r, computed based on weekly operated flights operated on the route. In the markets in our sample, these include Vueling, Germanwings, Transavia, and Flybe. *Eligible Alternative* captures all eligible transportation alternatives, gathered from Rome2rio.com, a platform that provides information about all transport options between origin-destination pairs. An alternative is considered as eligible if (i) the product of its travel time and average price is no more than 20% higher than that of easyJet, and (ii) it has either a lower travel time or a lower price than easyJet. (see Appendix D for further details).

The vector $\boldsymbol{Y}_{irdt}$ consists of two variables which have an effect on demand and are not determinants of prices. The first is $PVNAP$, computed as in (5). Recall that $PVNAP$ captures price changes from one day to the next, however only as a squared term; hence, in order to distinguish between price increases and price decreases we introduce a dummy variable, *Price Drop*, which is equal to 1 when $P_{irdt} < P_{ird,t+1}$ and 0 otherwise (Soysal and Krishnamurthi, 2012). This variable is reminiscent of strategic consumer behavior as it captures, to some degree, consumer waiting from one day to the next in order to take advantage of lower fares. At a later stage, we elaborate on such behavior.[11]

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[10] Note that the estimation of price in (7) is different from that in (4). The former is the first stage of the 2SLS estimation, aiming at correcting the endogeneity of price-demand relationship, whereas the latter is an input for estimating consumers' perception of price volatility as price deviates from the expected path.

[11] Due to the lack of relevant instruments, we do not instrument for the price volatility and price drop variables. This is similar to Gerardi and Shapiro (2009), who do not instrument HHI in their analysis.

Descriptive statistics are provided in Table 2. Since we track demand only if the number of available seats is lower than 40, after data cleaning, our sample consists of 58,354 observations. We note that on average, 2.4 seats are sold daily, with a maximum of 39 tickets (recorded on the AMS-FCO market). Overall, zero sales were recorded in 28.7% of the cases. *Price Drop* indicates that in the 6.7% of cases, passengers experience a price drop. This is consistent with previous studies (e.g., Koenigsberg et al., 2008) to possibly discourage strategic waiting by consumers. Price volatility ($PVNAP$) ranges between 0 and 0.550, with an average of 0.005. The correlation matrix is available in Appendix E.

Table 2. Descriptive statistics of the variables taken into account

Variable	Mean	Std. Dev.	Min	Max
Demand	2.396	2.614	0	39
Price	117.219	42.964	29.990	461.990
Price Drop	0.067	0.250	0	1
PVNAP	0.005	0.009	0	0.550
Advance	8.952	6.057	2	45
Booking Weekdays	0.566	0.496	0	1
Departure Weekdays	0.494	0.499	0	1
Peak Hours	0.576	0.494	0	1
Summer	0.418	0.493	0	1
Relative MS	0.923	0.189	0.333	1
Eligible Alternatives	1.230	1.920	0	6

5. Results

This section presents the results of our analyses. We first provide the 2SLS IV regression outcomes and then the estimates of price elasticity with respect to price volatility.[12]

5.1. Regression Analysis

Table 3 reports the outcomes of the ordinary least squares (Columns 1 and 2) and the 2SLS (Columns 3 and 4) instrumental variable regressions. Table 3 shows regressions with $\theta = 0.8$, which is the standard value commonly used in the literature (e.g., Han et al., 2001; Kalyanaram and Little, 1994) and qualitatively, the insights persists for other θ values (Table 4). The results reveal quantitative differences in estimates; yet, they are qualitatively similar. That is all models are consistent. Introducing price volatility in the model (Columns 2 and 4 for the OLS and 2SLS models, respectively), does not affect the significance of other independent variables, suggesting that overall demand is significantly influenced by both flight and route characteristics. Indeed, consumers tend to book more seats as departure day approaches and during weekdays booking. Demand is stronger on routes where easyJet's market share is lower and there are fewer transport alternatives. This is consistent with Brons et al.

[12] As robustness check, we have repeated the analysis by employing three-stage least squares method, which estimates the coefficients of each equation simultaneously. Results are consistent with the outcomes of 2SLS provided in Table 3.

(2002), who find that the number of alternative modes plays a significant role in determining travelers' price sensitivity.

As expected, price is negatively associated with demand. This result is corroborated by the positive value of the *Price Drop* variable, which suggests that generally as the carrier lowers the price, it experiences a higher number of bookings. Such a price drop in a generally non-decreasing price pattern used by the carrier (see Koenigsberg et al., 2008), leads to an increase in demand, which can be due to different factors, such as demand stimulation (lower prices enlarge the pool of consumers who are willing to purchase) and strategic waiting among consumers. This result corroborates the theory on the presence of strategic consumers in the airline transport industry (Li et al., 2014). Namely, there are consumers who wait and book when airfares drop.

The coefficient of price volatility is significant and negative. This is an important result. Existing literature on price volatility argues that volatile prices expose consumers to higher degree of uncertainty, thereby making them less sensitive to changes in prices (e.g., Janiszewski and Lichtenstein, 1999). This suggests consumers may end up paying higher prices, but absent is the effect on sales volume. Complementing this literature, our analysis suggests that an increase in price volatility is associated with lower sales volume. Although this result seems to go in the opposite direction with respect to previous literature, the typical relationship between prices and demand shall not to be overlooked. On the one hand, exposing consumers to price volatility (thus potentially increasing their uncertainty) decreases their price sensitivity and leads to a wider range of acceptable prices (Janiszewski and Lichtenstein, 1999; Kalyanaram and Little, 1994; Murthi et al., 2007; Winer, 1986). On the other hand, price volatility may lead consumers to act strategically (and hence may wait for prices to drop), choose an alternative good or airline, or abstain from purchasing altogether. Under these circumstances, sellers who take advantage of the decrease in price sensitivity could set higher prices in order to increase revenues. However, on top of strategic consumers and consumers who give up on purchasing, demand decreases following the basic relationship of price and demand. The intuition is as follows. The range of acceptable prices is not the same for all consumers in the market. While for some consumers the increased price would still be within their range, for others, this may not be the case. Consistently, with higher prices, a smaller proportion of consumers, who have a sufficiently high willingness to pay, actually purchase the good.

Table 3. OLS and 2SLS regression estimates of daily demand with $\theta = 0.8$

Variables	(1) OLS	(2) OLS	(3) 2SLS	(4) 2SLS
Price	-0.012***	-0.012***	-0.010***	-0.010***
	(0.000)	(0.000)	(0.001)	(0.001)
Price Drop	0.062	0.076*	0.107***	0.098**
	(0.040)	(0.040)	(0.040)	(0.042)
PVNAP		-5.033***		-5.737***
		(0.889)		(1.160)
Advance	-0.071***	-0.072***	-0.072***	-0.072***
	(0.001)	(0.001)	(0.002)	(0.002)
Booking Weekdays	0.807***	0.806***	0.825***	0.807***
	(0.021)	(0.021)	(0.019)	(0.020)
Departure Weekdays	0.267***	0.269***	0.265***	0.293***
	(0.022)	(0.022)	(0.022)	(0.023)
Peak Hours	0.261***	0.260***	0.238***	0.238***
	(0.023)	(0.023)	(0.023)	(0.025)
Summer	0.355***	0.353***	0.281***	0.330***
	(0.021)	(0.021)	(0.021)	(0.023)
Relative MS	0.754***	0.757***	0.665***	0.783***
	(0.153)	(0.153)	(0.131)	(0.145)
Eligible Alternatives	-0.076***	-0.077***	-0.060***	-0.076***
	(0.013)	(0.013)	(0.012)	(0.013)
Constant	3.547***	3.534***	3.359***	3.332***
	(0.104)	(0.114)	(0.128)	(0.135)
Observations	58,354	58,354	58,354	58,354
R-squared	0.135	0.136	-	-

*Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1; Hausman test value is 7.48.*[13]

The negative relationship between demand and price volatility is consistent across all values of θ. Table 4 shows the coefficient of $PVNAP$ for different values of θ, i.e., the importance given to past price changes with respect to most recent variations, in the case of OLS and 2SLS regressions. The more weight is given to past history, the greater the effect of price volatility on demand. This may suggest that when we assume consumers to have a greater recall of past price fluctuations, thus giving more importance to them, the deviation in prices beyond their predicted path is associated with greater impact on demand. Further, we notice high consistency between the OLS and 2SLS estimates. In our case, the F-statistic increases as the value of θ grows, suggesting that a high value of θ better estimates the impact of price volatility on demand (providing support for the use of $\theta = 0.8$). In Appendix F, we show estimation results by using traditional and alternative measures of price volatility. Although results are consistent through all used measures, $PVNAP$ better captures differences across markets and consumers' perceived reference price.

[13] Although the Hausman test suggests there is no endogeneity between prices and demand, we are aware that purchases are affected by airfares and vice versa. Therefore, we proceed our analysis with the 2SLS estimates, which are consistent with the OLS estimates.

Table 4. PVNAP coefficients from OLS and 2SLS regression estimates of daily demand

θ	0.2	0.4	0.6	0.8
OLS	-1.022***	-1.578***	-2.540***	-5.033***
	(0.285)	(0.373)	(0.517)	(0.889)
2SLS	-1.253***	-1.882***	-2.965***	-5.737***
	(0.386)	(0.494)	(0.683)	(1.160)
F-statistic	259.4***	259.8***	260.3***	260.7***

*Standard errors in parentheses. *** p<0.01*

5.2. Estimates of Price Elasticity

In the second step of our analysis, we estimate passengers' price elasticity according to the different levels (i.e., deciles) of price volatility. Following the 2SLS IV estimations, we compute the price elasticity of demand, starting with the common definition of price elasticity: $\eta_{D,\widehat{P}} = \frac{\partial D}{\partial \widehat{P}} \cdot \frac{\widehat{P}}{D} = \varphi \cdot \frac{\widehat{P}}{D}$, where $\widehat{P}$ and D represent the predicted price and the demand, respectively, and φ is the price coefficient of second stage in the 2SLS regression model (see Eq. (6)).

Price elasticity of demand at mean price is therefore equal to $\varphi \cdot \frac{\bar{\widehat{P}}}{\widetilde{D}}$, where $\bar{\widehat{P}}$ and $\widetilde{D}$ represent the overall average of the predicted prices and the predicted value of demand computed as in (6), respectively. To capture the variations of price elasticity in relation to price volatility, we compute the different deciles of price volatility characterizing a flight on a certain day of departure. For each decile k of $PVNAP$, we compute $\bar{\eta}_{D_k,\widehat{P_k}} = \varphi \cdot \frac{\overline{\widehat{P_k}}}{\widetilde{D_k}}$,with $k = 1, \ldots, 10$, where $\overline{\widehat{P_k}}$ and $\widetilde{D_k}$ are the average price and the predicted value of the demand, respectively, estimated for each decile.[14] Price elasticity of demand is found to be equal to -0.495. This value suggests that a 1% increase in mean prices induces a 0.5% decrease in air transport demand. This estimate of price elasticity is relatively low (possibly driven by the fact that our data is limited to last 40 seats available and the final 45 days of sale), but still within the range of values reported by Gillen et al., (2003).

As price elasticity estimates at the mean price hide the extent to which price volatility influences consumers' price elasticity, we measure price elasticity at different deciles of price volatility. Results reveal a more intricate relationship whereby price elasticity of demand actually exhibits a wider latitude of values ranging from -1.883 to -0.439 as can be observed from Figure 2. This figure depicts the change in estimates of price elasticity for the different price volatility deciles for various values of θ, the smoothing constant from the price volatility measure. Importantly, we observe how demand becomes less elastic in the decile level of price volatility. Specifically, when price volatility is at its lowest level (first decile), the price elasticity estimates range between -1.2 and -1.9, indicating a very price sensitive demand. Interestingly, it appears that the estimate of price elasticity increases as the weight associated

[14] To relax the assumption of a fixed φ, we also run an alternative model to Eq. (6), where we consider the interaction terms between price and deciles of price volatility. The results are qualitative and quantitatively consistent with those illustrated in Figure 2. We thank the anonymous reviewer for this suggestion.

with memory generally increases from $\theta = 0.2$ to $\theta = 0.8$. As price volatility increases (to the low-medium deciles), we witness how price elasticity drops to about -0.7 with minimal difference between the levels of θ values. With a further increase in price volatility, price elasticity maintains a quasi-constant behavior, hoovering at around -0.5. The rationale behind this relation is as follows. Our results complement previous literature in the context of consumer-packaged goods. Previous literature provides evidence to the notion that when prices fluctuate, consumers' uncertainty regarding the 'right price' for the product or service increases (Janiszewski and Lichtenstein, 1999; Kalyanaram and Little, 1994; Murthi et al., 2007; Winer, 1986). Our analysis corroborates results on the decreasing trend of price elasticity as price volatility increases (Janiszewski and Lichtenstein, 1999).

By considering the variation in price elasticity with respect to θ, the exponential smoothing factor associated with past price movements, we observe that, generally, as we assume that consumers associate a larger weight with past movement, the higher is their price sensitivity. This is particularly true for low deciles of price volatility.

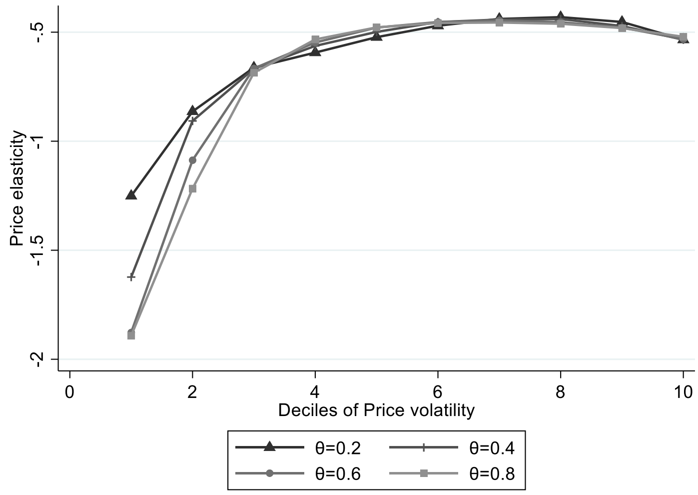

Figure 2. Price elasticity according to the different levels of price volatility

6. A lab experiment

Our empirical analysis is based on real-word data collected from an airline's website. Despite the advantages related to the investigation of this topic in such setting, with the empirical data described in previous sections, we are not able to observe consumers' actions prior to their purchase decisions. Namely, we are not aware if, and to which extent, consumers observe prices before making their purchasing decision. To remedy this caveat, we develop an ad hoc experiment to test the impact of price volatility on purchasing decisions. The use of lab experiments as a complementary method to empirical estimations allows us to simplify and isolate the effects of interest. In particular, such experiments take part in controlled settings which permit manipulation (referred to as treatments) so as to more clearly observe and analyze cause-effect relationships (Davis and Holt, 2021).

The previous sections provide evidence of the impact of price volatility on demand and its price elasticity in a real-life setting. Specifically, price volatility induces consumers to buy less (demand reduction) and, at the same time, those who purchase after having experienced price volatility may end up paying more. These can be translated into two testable predictions:

Hypothesis 1: A higher degree of price volatility suppresses demand;

Hypothesis 2: Conditional on making a purchase, a higher degree of price volatility induces consumers to pay more.

Subsection 6.1 describes the experimental design and 6.2 presents the results.

6.1. Experimental Design

To test the two hypotheses, we designed an experiment to first solicit the subjects' willingness to pay for a good and then expose them to varying prices over time to induce their purchasing decisions given different price volatility patterns. To enlarge the scope and validity of our insights, we expanded the range of revenue managed products from the context of air transportation to a larger set of six different goods: a flight to a continental destination, a hotel room for two people for two nights, a tour in a continental capital, a concert of a famous international star, a ticket for the Champions League final, and a one-star Michelin dinner for one person. We describe the goods to the subjects as having a clear expiration or usage date (set to take place three weeks after the experiment date), and a fixed limited capacity. Descriptions of the goods along with instructions of the experiment are provided in Appendix G.

The subjects' willingness to pay then serves as a benchmark against which we vary the prices. Specifically, we introduce price fluctuations as percentage variations from the willingness to pay reported by the subject. We expose each subject to six price history patterns, one per good. Instead of using a continuous measure of price volatility as in the previous sections, for the purpose of the experiment, we design each price pattern in two flavors which correspond to the two treatments carried out in this experiment: low-price volatility or high-price volatility. The only difference between the two treatments is the magnitude of price variations. Specifically, the two price histories trace the same directional movements over time with the magnitude of variations with respect to the WTP being double under the high-volatility treatment. For instance, a price movement of 5% (resp., 10%) in the low-volatility treatment corresponds to a price movement of 10% (resp., 20%) in the high-volatility treatment.

The subjects were shown a series of 10 prices—9 historical prices (denoted as day of advance ranging from -9 to -1, p_{-9} to p_{-1}) and one current price. The current price (that is, the price at time 0, p_0) was identical across the treatments. Table 5 show the price variations with respect to the WTP over time ($\Delta\%p_t$) in six different patterns across the two treatments. For each of the six goods, each subject was randomly assigned to either the low-volatility treatment or to the high volatility treatment, such that each subject experienced three low-volatility and three high-volatility history patterns. The six price patterns are designed not to deceive the subjects into phantom price trends and such that they provide a range of current prices to test the impact of price volatility on actual price paid. Namely, one price pattern (P1) ends with a current price lower than the subject's WTP, one with current price equal to the WTP (P2), four with current prices that are greater than the WTP with some variations (P3 to P6). The prices were visualized by the subjects on a graph and the scale across the treatments was fixed (in a range varying from $\pm$40%) so that price variations in the high-volatility treatment look larger than under the low-volatility treatment (see an example in Figure 3). Based on the prices provided, the subjects had to decide whether to buy or not the good. Additional monitoring or waiting after period 0 was excluded.[15]

Table 5 – Patterns of $\Delta\%p_t$ for high (H) and low (L) price volatility treatments

Day of advance (t)	P1		P2		P3		P4		P5		P6	
	H	L	H	L	H	L	H	L	H	L	H	L
-9	0%	0%	10%	5%	0%	0%	-10%	-5%	-10%	-5%	0%	0%
-8	-30%	-15%	-30%	-15%	-10%	-5%	20%	10%	-10%	-5%	-30%	-15%
-7	20%	10%	10%	5%	-10%	-5%	10%	5%	-30%	-15%	-30%	-15%
-6	-10%	-5%	-30%	-15%	30%	15%	-30%	-15%	0%	0%	10%	5%
-5	10%	5%	0%	0%	0%	0%	0%	0%	-10%	-5%	-30%	-15%
-4	20%	10%	30%	15%	20%	10%	-20%	-10%	0%	0%	10%	5%
-3	0%	0%	10%	5%	-10%	-5%	10%	5%	30%	15%	20%	10%
-2	-10%	-5%	30%	15%	0%	0%	25%	12.5%	-10%	-5%	15%	8%
-1	-30%	-15%	-10%	-5%	-20%	-10%	-10%	-5%	30%	15%	35%	18%
0	-5%	-5%	0%	0%	5%	5%	10%	10%	10%	10%	15%	15%

[15] Differently from previous studies on strategic consumers (e.g., Osadchiy and Bendoly, 2015), our experimental design does not allow waiting for future (lower) prices, thus not capturing the strategic behavior of consumers. Analyzing only the purchase-or-not decision allows us to better isolate the impact of price volatility on both purchasing behavior and the final paid prices. Future studies aimed at estimating the portion of strategic consumers in the market may evaluate the integration of the wait alternative as an option, consistently assessing the impact of price volatility on the wait decision.

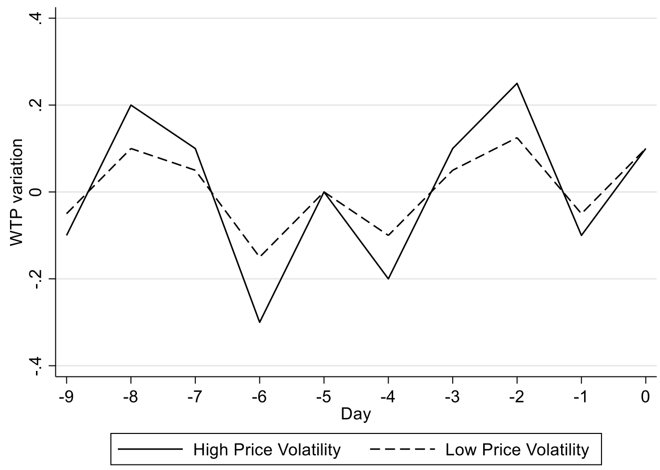

Figure 3. Low- and High- price volatility treatments of pattern 4 (P4)

The experiment was coded in OTree, an open-source platform for online and lab experiments (Chen et al., 2016). The participants were recruited from a pool of students enrolled in an English master course of a European university. Following a pilot with 10 participants that facilitated some tweaking of the experiment, we collected responses of 48 students. At the beginning of the experiment, we also collected socio-economic characteristics (e.g., 24% of the subjects were male), risk profiles as well as attachment (degree of interest) to each of the six goods.[16]

6.2. Analysis and results

The subjects' decisions in the experiment are summarized in Table 6. Overall, in 54% of the instances, subjects decided to buy the good. Quite naturally, the purchase incidence decreases in the current price variation with respect to subjects' WTP ($\Delta\% p_0$). Indeed, when the current price is lower than (or equal to) the WTP, the percentage of purchases is 78% (or 82%).

The portion of purchasing choices is higher in the low-price volatility treatment (58%) than in the high-price volatility treatment (51%). This is in line with our first hypothesis that demand decreases as price volatility increases. However, the average portions of purchasing decision in the two treatments are not statistically different. Interestingly, if we test the difference in the portion of purchasing instances when subjects were exposed to high-volatility and low-volatility treatments by pattern, we find that this result is consistent across almost all price patterns. Additionally, when the relative price variation is lower than zero (i.e., the offered price is lower than subjects' willingness to pay), there is a statistically significant difference in the portion of people buying when they are exposed to high- or low-volatility treatments.

[16] Responses from 3 of the subjects were removed as their responses to risk profiling questions were inconsistent.

68% (94%) of the subjects exposed to the high (low) price volatile version of P3 choose to buy if the final offered price is 5% lower than their willingness to pay. Similarly, 43% (only 17%) of students choose to buy when the final offered price is 15% higher than their willingness to pay in case of low (high) price volatility. This corroborates the findings that price volatility generally decrease demand (Hypothesis 1). The uncertainty generated by price volatility is especially evident when the final price is lower than subjects' WTP. Indeed, even if the offered price is lower than the amount of money that subjects are willing to pay for that specific good, a high portion of students exposed to a higher level of price volatility decides not to buy.

The significance (and the respective lack of significance) of difference in purchasing decisions among individuals and goods may be affected by the interest that each subject generally has in the good at issue. To this extent, we check for subjects' interest in the different kinds of goods, asking them to rate their general interest in buying each good on a scale from 1 (not interest at all) to 5 (very interested). By considering as interested those who answer to the abovementioned question with a score higher than or equal than the median value in the sample (i.e., 4), we test the impact of interest on purchasing decisions. Overall, 59% of the purchasing decisions are made when the interest is high (Pearson $X^2 = 2.991$, p-value = 0.087).

Table 6. Portion of purchasing choices by current price variations (with respect to subjects' WTP)

Purchasing Decisions [out of total instances]	Price pattern ($\Delta\%p_0$: current price variation with respect to WTP)						
	P1 (-5%)	P2 (0%)	P3 (+5%)	P4 (+10%)	P5 (+10%)	P6 (+15%)	Total
Overall	35 [45]	37 [45]	21 [45]	24 [45]	17 [45]	13 [45]	147 [270]
L	16 [17]	18 [22]	12 [23]	8 [24]	15 [28]	9 [21]	78 [135]
H	19 [28]	19 [23]	9 [22]	9 [21]	9 [17]	4 [24]	69 [135]
Overall (%)	78%	82%	47%	38%	53%	29%	54%
L (%)	94%	82%	52%	33%	54%	43%	58%
H (%)	68%	83%	41%	43%	53%	17%	51%
Pearson X^2	4.220**	0.005	0.573	0.002	0.432	3.740 *	1.210

*** p<0.01, ** p<0.05, * p<0.1

Preliminary analysis provides evidence of the importance of the current price, price volatility, and interest in inducing subjects to purchase. To jointly test the impact of these three factors, we perform a logistic regression, where the dependent variable is represented by the probability of purchase decisions ($\Pr(Y = 1)$):

$$\Pr(Y = 1) = F(\beta X) = \frac{\exp(\alpha_0+\beta X)}{1+\exp(\alpha_0+\beta X)}. \quad (8)$$

where X is a vector of independent variables comprising $HighPVOL$, $\Delta\%p_0$, and $Interest$. $HighPVOL$ is a dummy variable equal to 1 if the pattern is displayed in its high-volatility flavor, 0 otherwise. $\Delta\%p_0$ is the current price variation with respect to the subjects' willingness to pay (see Table 6 for its values in different patterns). Finally, consistently with the preliminary analysis, $Interest$ represents the interest in the good and it is equal to 1 if subject evaluate it higher than or equal to 4 on a scale from 1 to 5. Results are provided in Table 7. As observations are repeated for each subject, standard errors allow for intragroup correlation. Column 1 jointly tests the impact of price volatility and $\Delta\%p_0$ on purchasing decisions. Results confirm our first hypothesis. Specifically, when individuals are exposed to a high-level of price volatility, they are 36% less likely to purchase compared to people exposed to a low-price volatility treatment. Marginal effects of $HighPVOL$ on $\Pr(Y = 1)$ and the predicted probability values are illustrated in Figure 4. On average, exposing subjects to high price volatility reduces the probability of purchasing of around -9%. Similarly, as the variation with respect to the WTP increases, the purchasing probability drops. Ceteris paribus, with an increase of +15% in price we expect the odds of purchasing to reduce by about 84% on average.

(a) (b)

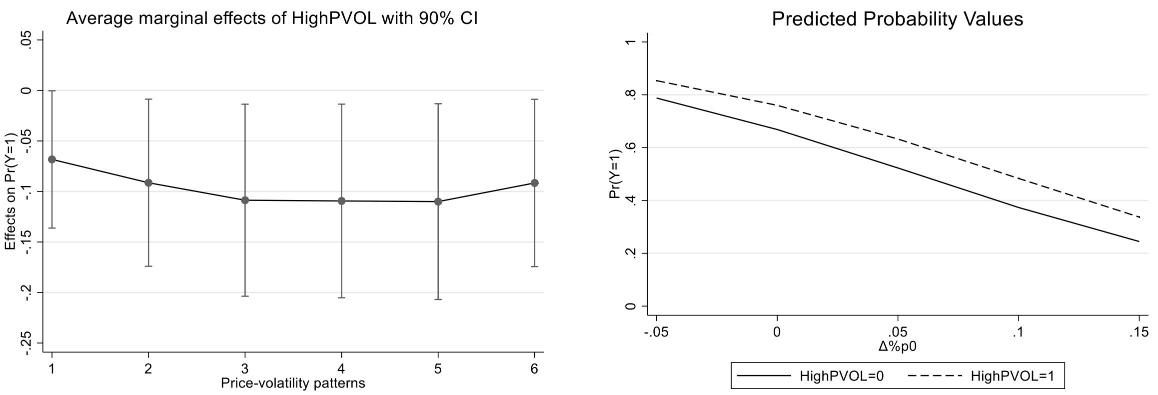

Figure 4. Marginal effects of $HighPVOL$ on $Pr(Y = 1)$ by price-volatility pattern (a) and predicted probability values with respect to $\Delta\%p_0$

When controlling for interest (Column 2) and for both interest and for good-fixed effects (Column 3), price volatility and $\Delta\%p_0$ still significantly impact purchasing decisions. Additionally, results suggest that the higher the interest in the good, the higher is the probability of purchasing—having a higher interest in the good leads subjects to be 79% more likely to purchase.

Table 7. Logistic regression results

	(1) Purchasing Choice	(2) Purchasing Choice	(3) Purchasing Choice
$HighPVOL$	-0.451*	-0.490**	-0.443*
	(0.245)	(0.244)	(0.243)
$\Delta\%p_0$	-12.193***	-12.631***	-12.532***
	(2.392)	(2.437)	(2.475)
$Interest$		0.585**	0.769**
		(0.254)	(0.329)
Constant	1.153***	0.885***	0.436
	(0.205)	(0.228)	(0.440)
Good-fixed effects			Yes
Subjects	45	45	45
Observations	270	270	270
Log pseudolikelihood	-166.535	-164.135	-163.057
Pseudo R2	0.105	0.118	0.124

Standard errors allowing for intragroup correlation in parentheses
*** p<0.01, ** p<0.05, * p<0.1

While HP1 finds its evidence in these outcomes, additional analysis is needed to demonstrate that higher price volatility leads consumers to buy at higher prices (Hypothesis 2). Accordingly, we study the subjects' paid prices conditional to the positive purchasing decision ($p_0 = WTP \cdot (1 + \Delta\%p_0)$). By focusing on the price patterns that offer a final price which is higher or equal than students' WTP, we analyze the difference between the price paid and their WTP denoted as ΔP (that is, $\Delta P = p_0 - WTP$) in case of low- and high- price volatile version of patterns. For patterns offering an increase in the current price which is lower or equal to 10%, there is no statistical difference in ΔP (see Figure 5). Interestingly, P6 (+15% in the final paid price with respect to WTP) suggests a statistically significant difference in ΔP, that has an average of +€21 (+€36) for the low-price (high-price) volatile version of P6 (T statistic: -2.526—p-value =0.028). On the contrary, the initial WTP of the subjects that choose to purchase in case of P6 is not statistically different between the two versions (T statistic: -1.058—p-value = 0.296). This result sheds light on the potential impact of price volatility on the final price paid, corroborating the belief that higher price volatility may induce consumers to pay more.[17]

[17] Although there is evidence of an increase in the price paid when subjects are exposed to high price volatile versions of P6, this is not true across all price patterns, thus suggesting that the result could strictly depend on the P6 sequence. This outcome provides avenues for future research: an in-depth analysis on the impact of price history sequence on purchasing decision could be conducted, shedding light on how specific volatility patterns (and not solely two different treatments—i.e., high and low price volatility) affect purchasing decisions.

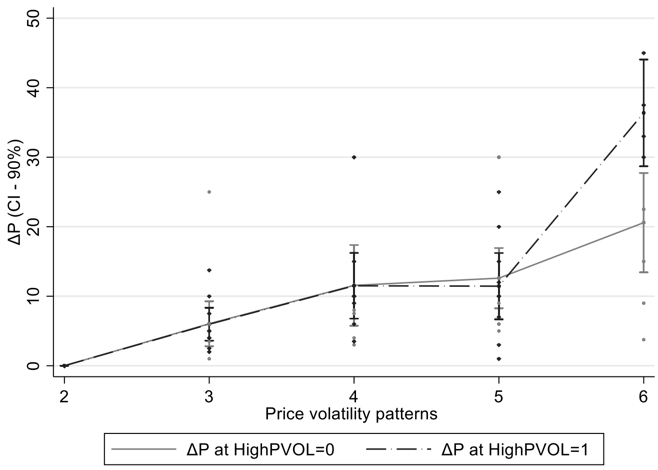

Figure 5. *Difference in the price paid with respect to WTP (ΔP) in case of low- and high- price volatility versions in different patterns*

7. Conclusions

Our study lies at the interface between revenue management and marketing, and crucially it highlights the importance of considering both aspects when dealing with revenue-managed goods. A key outcome that often emerges when firms embrace revenue management is price volatility. Despite the enhanced sophistication and the incorporation of consumer behavior into revenue management models, understanding and integrating responses to fluctuating prices has been rather mute. Marketing literature has previously explored how price changes impact consumers' perception of prices and ultimately their purchasing behavior. These changing behaviors clearly bear implications on sellers' profits, and hence deserve closer attention to the conditions affecting their purchase decisions. These marketing studies were conducted primarily with consumer packaged goods and the conclusions may not immediately gravitate to the context of revenue managed goods. Further, they were carried out more than a decade ago and consumers' interactions with firms have evolved dramatically in recent years. To that end, we revisit the exploration of price volatility in the context of revenue managed goods while expanding to understand its impact on consumers' price sensitivity.

As we carry out analysis in the context of the air transport industry, the implementation of revenue-managed practices generally exhibits somewhat predictable price trajectories. Consumers may very well expect those price movements, and this would certainly influence their reference price. Accordingly, we have modified the measure of price volatility to account for consumers' perception of the 'right price', represented by such predictability of airfares, while further normalizing for differences between routes. Our empirical estimations lead to several important insights. First, we find some implicit evidence for the presence of strategic consumers, whereby they wait for a decrease in airfares to make their purchase (e.g., Cachon and Swinney, 2009). Second, we find that increased levels of price volatility are associated with lower seat sales. While previous works have implied that consumers may end up paying more, the link to the volume of sales has been overlooked. Namely, would all consumers end up paying more given the higher volatility of prices they observe, or would some consumers abstain from buying given the higher prices? Our results reveal that higher price volatility may not necessarily translate into increased profit levels as, at least in the context of revenue-managed goods, we find that price fluctuations are associated with a decreased consumers' purchasing propensity. Therefore, there are two opposite effects stemming from price volatility, that need to be balanced. On the one hand, sellers are incentivized to increase prices, as price volatility increases the range of acceptable prices: airlines can leverage price volatility to set higher prices increasing their revenues. On the other hand, not all demand becomes inelastic, therefore leading to a lower load factor. Indeed, while for some consumers the increased price would still be in their (larger) range of acceptable prices, for others, this is not the case. We next estimated the price elasticity of demand and its magnitude at different levels of price volatility. We find that as price volatility increases, consumers exhibit a lower price sensitivity. This result corroborates the literature (Kalyanaram and Little, 1994; Murthi et al., 2007; Winer, 1986) and reveals that the existing insights—that price volatility may increase consumers' uncertainty about prices and, hence, range of acceptable prices—extend and prevail also when goods are revenue managed. Our analysis offers an important generalization. Price volatility induces demand to be less elastic, which could incentivize firms to increase prices, as consumers may end up paying more. At the same time, higher prices generally decrease demand: if the offered price is too high, the risk is to limit the pool of consumers who would make a purchase, as the offered price may exceed their range of (larger) acceptable prices. These insights carry important practical implications. The prices presented to consumers over time have a substantial impact on what consumers actually do upon observing these prices as (i) some consumers may wait for the price to drop, (ii) some may become less sensitive to prices, thus willing to pay more, and (iii) others may give-up purchasing altogether. To that end, when implementing revenue management practices, there is the need to carefully weigh the benefit of inducing price fluctuations—typically associated with the opening and closure of fare buckets, or even the choice of the number of fare buckets and the related fares—with the lost demand.

Ultimately, we developed an experimental design to test our results in a laboratory setting. Specifically, we tested two hypotheses, derived by our two main outcomes of the empirical analysis. The first hypothesis is that price volatility reduces demand. The second hypothesis investigates the extent to which consumers exposed to price volatility who decide to purchase end up paying more. The experiment corroborates the empirical insights, providing evidence of a decreasing demand and a higher paid price at high levels of price volatility.

This study opens avenues for ample future research. First, the empirical analysis could be expanded. A broader sample of goods and services employing revenue management practices (to generalize beyond air travel markets) could be taken into consideration. Additionally, enlarging the time frame of observed fares and relying on more precise data (if available) would allow to have a broader overview on the impact of price volatility on consumers' purchasing behavior. Ultimately, in relation to the pandemic outbreak and the changes in the European socioeconomical equilibria, more recent data could be collected to test whether pricing patterns and demand dynamics have changed and if so, to what degree. Second, further research could be developed to test the presence of strategic consumers in empirical and laboratory settings, to estimate how price fluctuations may alter the proportion of such consumers in the population and their propensity to buy.[18] Such experiments could explore, for instance, whether and to which extent consumers (i) are induced to wait for lower prices, (ii) become less sensitive to prices, and (iii) give up purchasing altogether (or switch to a competitor). Third, relying on our outcomes, a simulation model studying the impact of price volatility on revenue management mechanisms and estimated revenues can be developed. Lastly, encapsulating our insights in an analytical model could ultimately provide firms with additional concrete guidance on when and how to manage price volatility in the context of revenue management, estimating the optimal, revenue-maximizing, level of price volatility that balances the increase in revenues due to lower price sensitivity and the decrease in sales due to the drop in demand.

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[18] The idea that the proportion of strategic consumers in the population may change as a function of certain pricing behaviors is inspired by Aflaki et al., (2020) who endogenize consumers choice on whether to behave strategically or not.

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Appendix A: Predicted price and reference price

Our price volatility measure, $PVNAP$, encapsulates the predicted price, as a proxy for the reference price (Eq. (5)). Here, we demonstrate our choice of this measure, compared with the traditional formulation of reference price (Eq. (1)). Figure A.1 compares the average values of the predicted price and the reference price for two markets (SPU and SXF). While, for both estimates, the correlations between actual price and the measures are over 75%, it is rather evident that the predicted prices better follow the actual price trends over time. Accordingly, we strongly believe our measure is preferred of reference price.

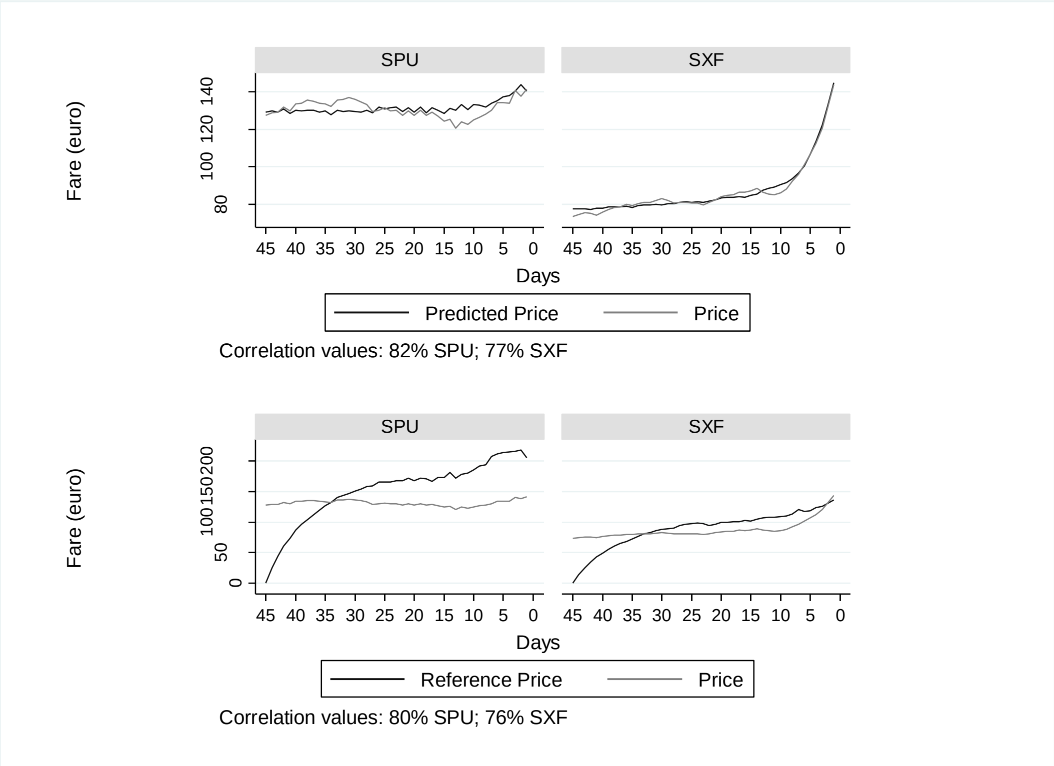


Figure A.1. Average values of price, reference price ($\theta = 0.8$), and predicted price over days of advance for AMS-SPU and AMS-SXF

Appendix B: Leisure index

Salanti et al. (2012) first introduced the leisure index to distinguish between leisure- and business-oriented route according to the pricing strategy the airlines apply. This index is based on the idea that carriers, especially LCCs, undertake intertemporal price discrimination to offer different prices to business passengers, who are known to have a higher willingness to pay and to buy flight tickets a few days before departure, and leisure ones, who are greatly price sensitive and tend to book in advance (Salanti et al., 2012). The greater the increase in fares in the last 15 days prior to departure (compared with an overall fare history of 90 days), the greater is the discrimination between leisure vs. business passengers and hence more likely to be a business-oriented route. The Leisure Index is defined as follows:

$$L_r = \frac{\sum_i (\beta_{1-90,i,r} - \beta_{1-15,i,r})}{n_i} \tag{9}$$

with $\beta_{1-90,i}$ and $\beta_{1-15,i}$ being the dynamic price indicators computed over 90 and 15 days of advance, respectively, per each flight i of route r, which are calculated based on the airfare formula in Malighetti et al. (2009):

$$P_{ir}(t) = \frac{1}{\alpha_{ir}\,(1+\beta_{ir} \cdot t)} \tag{10}$$

where $P_{ir}(t)$ is the price for a seat offered *t* days in advance for flight *i* on route r, and α_{ir} is a constant parameter related to the average price level over the considered period. A low value of β_{ir} indicates a steady price trend, whereas a high β_{ir} suggests that prices tend to increase more exponentially towards departure.

A highly negative leisure index $\mathrm{L_r}$ means that two weeks before departure, fares tend to be substantially higher than expected. By comparing the last two weeks behaviour with the overall trend, a highly negative leisure index suggests that during the last 15 days airlines aim to address consumers with a higher willingness to pay, i.e., business passengers (Salanti et al., 2012). As a consequence, the more negative the Leisure Index is, the more the route can be defined as a 'business-oriented route'.

Our sample presents a large heterogeneity of markets with respect to their Leisure Index. The Milan Malpensa destination (MXP) has the most negative Leisure Index in our sample, with $\mathrm{L_r}$ = -0.067. In this case we observe the airfare steadily increasing until two weeks to departure with a significant transition in the slope upwards during the final 15 days (Figure B.1). Hence, AMS-MXP exhibits the classical J-curve shape, typical of intertemporal price discrimination. By contrast, Split (SPU) has a Leisure Index of -0.024. While still suggesting an increase in price during the final 15 days prior to departure, the increase in fares is quite suppressed.

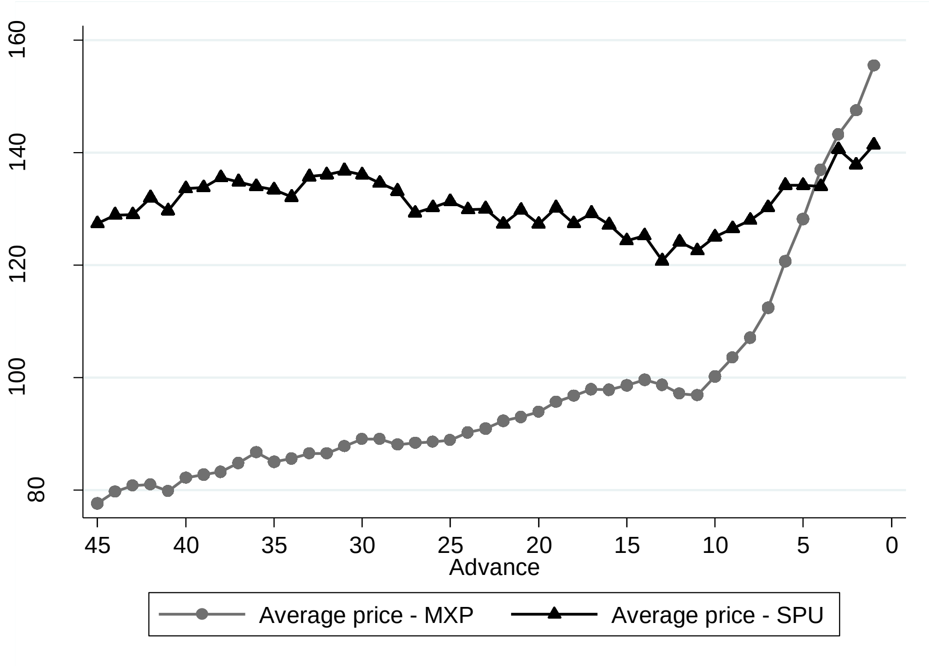


Figure B.1. Average price trends of a leisure- (SPU) and a business- (MXP) oriented route

Appendix C: OLS and 2SLS IV regressions with alternative instrumental variables

Table C.1 shows the result of 2SLS IV regressions where the instrumental variable is constructed based on the average price on similar routes based on distance. To identify similar routes, we aggregate them according to the distance, generating three categorical classes: between 300 km and 550 km, between 551 km and 800 km, and more than 800 km. Afterwards, for each route, we compute the average price on all other routes in the same distance category. The average price, which is computed for each route at t days in advance, represents the instrumental variable for the price on route r departing on date d at t days before departure. Results are consistent with respect to the estimations provided in Table 3.

Table C.1. 2SLS IV estimates on demand at different values of θ when the instrumental variable is the average price on similar routes with respect to distance

	θ=0.1	θ=0.2	θ=0.3	θ=0.4	θ=0.5	θ=0.6	θ=0.7	θ=0.8	θ=0.9
Price	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Price Drop	0.128***	0.129***	0.130***	0.131***	0.131***	0.131***	0.131***	0.130***	0.129***
	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)
PVNAP	-1.322***	-1.605***	-1.941***	-2.355***	-2.891***	-3.638***	-4.790***	-6.879***	-12.223***
	(0.343)	(0.382)	(0.429)	(0.488)	(0.566)	(0.674)	(0.842)	(1.146)	(1.953)
Advance	-0.073***	-0.073***	-0.073***	-0.073***	-0.073***	-0.073***	-0.073***	-0.073***	-0.073***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Booking Weekdays	0.811***	0.811***	0.811***	0.811***	0.811***	0.811***	0.811***	0.811***	0.811***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Departure Weekdays	0.333***	0.333***	0.333***	0.333***	0.333***	0.333***	0.332***	0.331***	0.330***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Peak Hours	0.204***	0.204***	0.205***	0.205***	0.205***	0.205***	0.205***	0.205***	0.204***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Summer	0.293***	0.294***	0.294***	0.294***	0.294***	0.294***	0.294***	0.293***	0.293***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Relative MS	0.850***	0.851***	0.852***	0.852***	0.852***	0.852***	0.850***	0.847***	0.841***
	(0.145)	(0.145)	(0.145)	(0.145)	(0.145)	(0.145)	(0.145)	(0.145)	(0.145)
Eligible alternatives	-0.076***	-0.076***	-0.076***	-0.076***	-0.076***	-0.076***	-0.076***	-0.076***	-0.076***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Constant	2.966***	2.968***	2.971***	2.974***	2.977***	2.982***	2.989***	2.999***	3.013***
	(0.123)	(0.123)	(0.123)	(0.123)	(0.123)	(0.123)	(0.122)	(0.122)	(0.122)
Observations	58,354	58,354	58,354	58,354	58,354	58,354	58,354	58,354	58,354

Similar conclusions can by drawn from Table C.2, which illustrates outcomes of the 2SLS IV regressions with different values of θ when the instrumental variable is the price lag, computed as the airfare for the same flight during the previous week, with the same booking days left.

Table C.2. 2SLS IV regression estimates on demand at different values of θ when the instrumental variable is the one-week lagged price

	θ=0.1	θ=0.2	θ=0.3	θ=0.4	θ=0.5	θ=0.6	θ=0.7	θ=0.8	θ=0.9
Price	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Price Drop	0.090*	0.091*	0.092*	0.092*	0.092**	0.092**	0.092**	0.092**	0.091*
	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)
PVNAP	-1.104***	-1.343***	-1.343***	-1.976***	-2.428***	-3.058***	-4.030***	-5.790***	-10.303***
	(0.371)	(0.413)	(0.413)	(0.528)	(0.612)	(0.730)	(0.911)	(1.245)	(2.148)
Advance	-0.072***	-0.072***	-0.072***	-0.072***	-0.072***	-0.072***	-0.072***	-0.073***	-0.073***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Booking Weekdays	0.794***	0.794***	0.794***	0.794***	0.794***	0.794***	0.794***	0.794***	0.794***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Departure Weekdays	0.306***	0.306***	0.306***	0.306***	0.306***	0.306***	0.305***	0.305***	0.304***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Peak Hours	0.224***	0.224***	0.224***	0.225***	0.225***	0.224***	0.224***	0.224***	0.224***
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Summer	0.336***	0.336***	0.336***	0.336***	0.336***	0.336***	0.336***	0.336***	0.336***
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Relative MS	0.949***	0.950***	0.950***	0.951***	0.951***	0.951***	0.951***	0.949***	0.945***
	(0.161)	(0.161)	(0.161)	(0.161)	(0.161)	(0.161)	(0.161)	(0.161)	(0.161)
Eligible alternatives	-0.081***	-0.081***	-0.081***	-0.081***	-0.081***	-0.081***	-0.081***	-0.081***	-0.081***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Constant	3.062***	3.064***	3.066***	3.068***	3.070***	3.074***	3.078***	3.085***	3.095***
	(0.147)	(0.147)	(0.147)	(0.147)	(0.147)	(0.147)	(0.147)	(0.147)	(0.147)
Observations	45,940	45,940	45,940	45,940	45,940	45,940	45,940	45,940	45,940

Appendix D: Example of Eligible Alternative as derived from rome2rio.com

Recall that *Eligible Alternative* accounts for all the eligible alternatives to reach the destination city from Amsterdam. The data was derived from the website Rome2rio.com. Figure D.1 demonstrates a representative search result for alternative transport modes for a trip from Amsterdam Schiphol airport to Berlin Schoenefeld. On the left, the website provides a list of transport alternatives including air travel, train, bus, car sharing and solo driving, along with the average travel time and the cost range. This information allows us to properly take into consideration those transport alternatives considered as eligible, according to Morlotti et al., (2017).

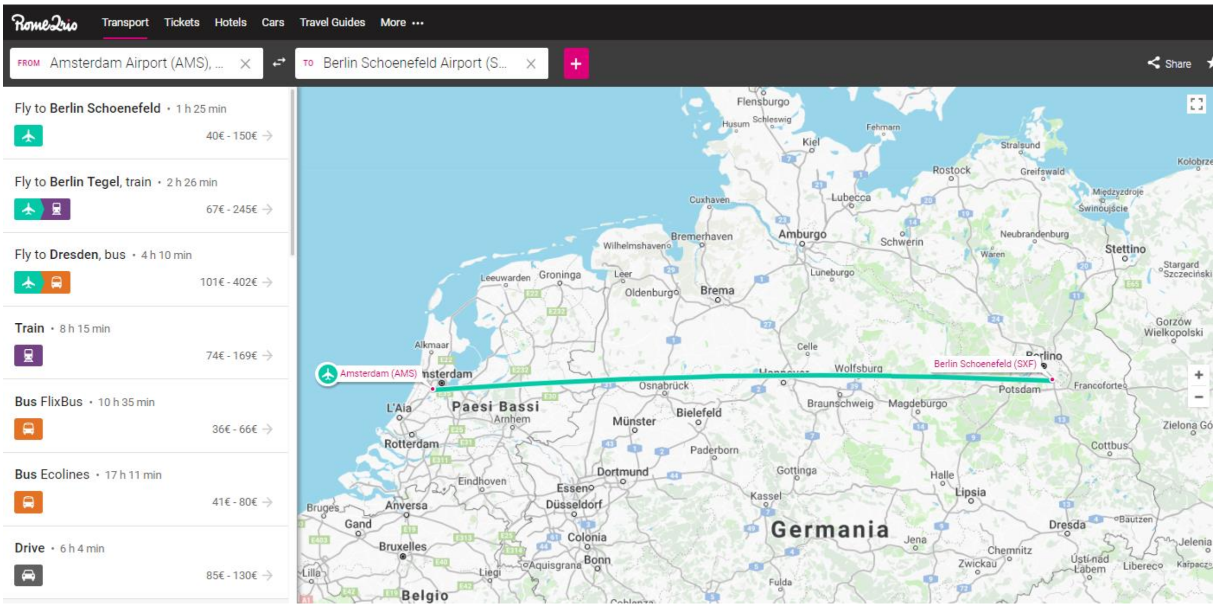


Figure D.1. Example of a rome2rio.com search to evaluate Eligible Alternative between Amsterdam and Berlin

Appendix E: Correlation matrix

Table E.1 shows the correlation values among the variables considered for our analysis.

Table E.1. Correlation matrix of variables used in the regression analysis

	Demand	Price	Price Drop	PVNAP ($\theta = 0.8$)	Eligible Alternatives	Relative MS	Advance	Booking Weekdays	Departure Weekdays	Peak Hours	Summer
Demand	1										
Price	-0.1699*	1									
Price Drop	-0.0056	-0.0545*	1								
PVNAP ($\theta = 0.8$)	-0.0152*	0.0847*	0.0656*	1							
Eligible Alternatives	0.1017*	-0.0461*	-0.0394*	-0.018*	1						
Relative MS	0.0104*	-0.0887*	-0.0183*	-0.0314*	0.2358*	1					
Advance	-0.2237*	0.0585*	0.0982*	-0.0648*	-0.1374*	0.0036	1				
Booking Weekdays	0.0791*	-0.1386*	-0.0302*	0.0106*	-0.0473*	-0.0102*	-0.0756*	1			
Departure Weekdays	0.1499*	-0.0027	0.0234*	-0.0068	-0.0036	-0.0069	-0.0144*	-0.0817*	1		
Peak Hours	0.0808*	0.0892*	-0.0332*	0.0194*	0.087*	0.074*	-0.1048*	0.0432*	-0.0158*	1	
Summer	0.0389*	0.1554*	-0.0057	-0.0104*	0.0241*	-0.0213*	0.0007	0.0336*	0.0249*	-0.0351*	1

* p<0.05

Appendix F: Regression results with different measures of price volatility

Throughout the manuscript, we have relied on $PVNAP$ as our key price volatility measure. In this appendix, we demonstrate its performance compared with $PVOL$ and $PVOLN$, while constructing an additional price volatility measurement, $PVNAP_{week}$. This latter measure assumes that consumers do not have access to the entire fare history and, instead, it is based on a rolling window of seven days only. These four measures are depicted in the four panels of Figure F.1 for two sample markets: Split (SPU) and Berlin (SXF). Interestingly, $PVOLN$ exhibits a similar behavior consistent with that of $PVNAP$: their pattern of increase and range of values are fairly aligned for the two markets. By contrast, $PVOL$ displays a radically different behavior with a more erratic range of values over time and a sharp increase during the final days of the selling horizon. $PVNAP_{week}$, mainly due to the truncation of the relevant history, exhibits a rather flat pattern.

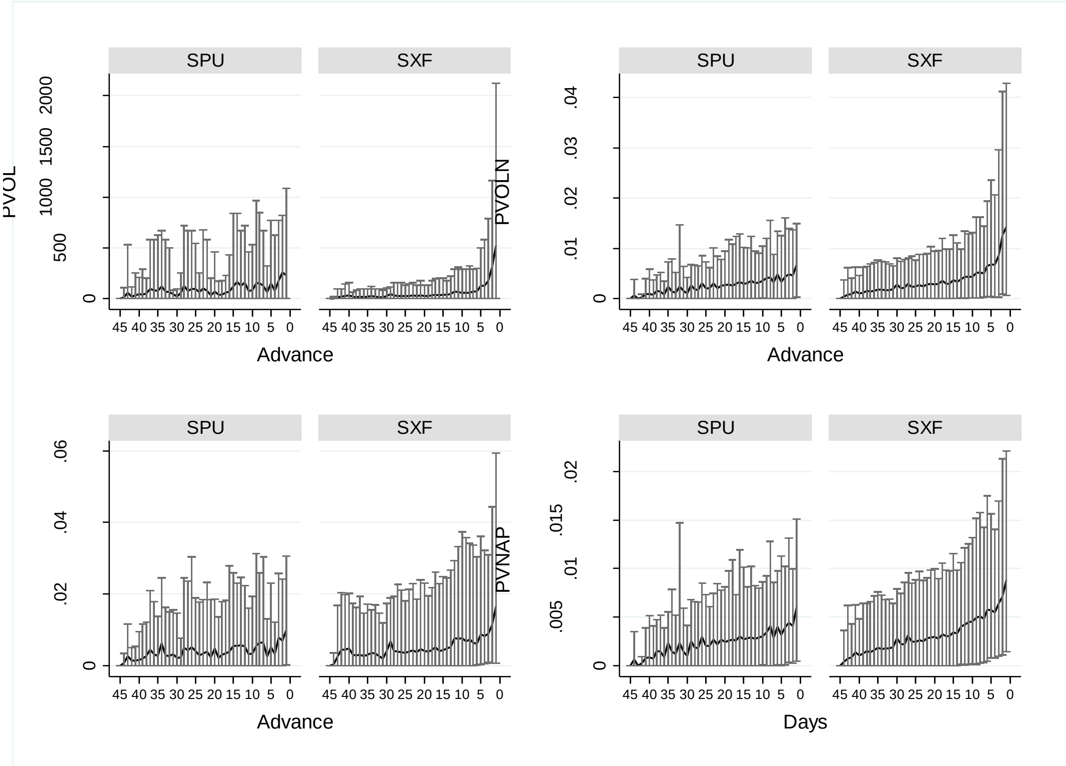


Figure F.1. Average values (and 5th-95th percentiles) of $PVOL$, $PVOLN$, $PVNAP_{week}$, and $PVNAP$ with $\theta = 0.8$ over days of advance for AMS-SPU and AMS-SXF

Next, we embed these four measures in our empirical analysis to contrast their impact on demand. Specifically, using 2SLS-IV method, we estimate our equations using the four alternative approaches to measure price volatility. Results are provided in Table F.1 and Table F.2. Table F.1 illustrates the complete regression estimations when $\theta = 0.8$ with the four alternative price volatility measures: $PVOL$, $PVOLN$, and $PVNAP_{week}$ and $PVNAP$ and, as in Table 4, Table F.2 only shows the coefficient of the price volatility measure as it is estimated at different θ

values. Results are similar and consistent across all the variables included and, consistently, price volatility negatively impacts demand and the coefficient's magnitude increases in θ. Note that the F-statistic values of $PVNAP$ exceed that of PVOLN and $\text{PVNAP}_{\text{week}}$, indicating that our price volatility measure is, indeed, the preferred choice in representing the way in which demand is affected by price variations. While $PVOL$ still features higher F-statistic values, the rationale to prefer $PVNAP$ to $PVOL$ is threefold. First, $PVOL$ does not take into consideration that airfares greatly differ from one market to another (see Table 1) (Gillen and Mantin, 2009). Second, this variable does not take into consideration the predictability of prices and, hence, consumers' reference price. Third, it is highly correlated with $Price\ Drop$, which is not significant anymore at low values of θ.

Table F.1. 2SLS IV regression estimates on demand with $\theta = 0.8$

Variables	(1) $PVOL$	(2) $PVOLN$	(3) $PVNAP_{week}$	(4) $PVNAP$
Price	-0.0099***	-0.0113***	-0.0100***	-0.0101***
	(0.0007)	(0.0009)	(0.0007)	(0.0007)
Price Drop	0.1047**	0.1410***	0.1165**	0.0983**
	(0.0416)	(0.0526)	(0.0480)	(0.0416)
Price volatility^{+}	-0.0001***	-4.2787***	-7.3677***	-5.7370***
	(0.0000)	(1.0538)	(1.1215)	(1.1596)
Advance	-0.0716***	-0.0707***	-0.0724***	-0.0723***
	(0.0018)	(0.0021)	(0.0021)	(0.0018)
Booking Weekdays	0.2976***	0.2367***	0.3171***	0.2931***
	(0.0232)	(0.0297)	(0.0265)	(0.0232)
Departure Weekdays	0.8043***	0.8142***	0.7913***	0.8070***
	(0.0203)	(0.0261)	(0.0238)	(0.0205)
Peak Hours	0.2359***	0.2871***	0.2274***	0.2383***
	(0.0241)	(0.0310)	(0.0281)	(0.0245)
Summer	0.3311***	0.5433***	0.3167***	0.3301***
	(0.0225)	(0.0334)	(0.0267)	(0.0226)
Relative MS	0.7176***	1.2203***	0.8740***	0.7834***
	(0.1389)	(0.2120)	(0.1647)	(0.1449)
Eligible Alternatives	-0.0690***	-0.0862***	-0.0723***	-0.0762***
	(0.0122)	(0.0190)	(0.0143)	(0.0127)
Constant	3.3137***	2.9969***	3.1963***	3.3318***
	(0.1345)	(0.1740)	(0.1525)	(0.1348)
Observations	58,354	58,354	58,354	58,354
F-stat	272.7***	165.5***	192.8***	260.7***

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

$^{+}$*Price volatility variable corresponds to the used measure of price volatility (i.e.,* $PVOL$. $PVOLN$, $PVNAP_{week}$, *and* $PVNAP$ *for columns 1,2,3 and 4, respectively.*

Table F.2. Price volatility coefficients from 2SLS regression estimates of daily demand

	$PVOL$		$PVOLN$		$PVNAP_{week}$		$PVNAP$	
θ	Coefficient	F_Stat	Coefficient	F_Stat	Coefficient	F_Stat	Coefficient	F_Stat
0.2	-0.0001*** (0.0000)	270.915 ***	-0.594* (0.330)	163.609 ***	-1.262*** (0.413)	189.462 ***	-1.253*** (0.386)	259.372 ***
0.4	-0.0001*** (0.0000)	273.523 ***	-1.027*** (0.428)	164.065 ***	-2.120*** (0.521)	190.270 ***	-1.882*** (0.494)	259.827 ***
0.6	-0.0002*** (0.0000)	274.553 ***	-1.880*** (0.604)	164.674***	-3.741*** (0.698)	191.493 ***	-2.965*** (0.683)	260.259 ***
0.8	-0.0001*** (0.0000)	272.650 ***	-4.279*** (1.054)	165.530***	-7.368*** (1.122)	192.801 ***	-5.737*** (1.160)	260.664 ***

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1;

Appendix G: Lab experiment

Instructions of the experiment are shown in Figure G.1, while Table G.1 reports the description of the goods provided and the related solicitation question. Finally, Figure G.2 illustrates pattern 4 (P4) in the case of low (top panel) and high (bottom panel) price volatility.

Instructions

Welcome and thank you for participating in the experiment. In this experiment, we will ask you some questions to analyse your purchasing behaviour in relation to different goods.

These goods include:

1. A two-night hotel room reservation for two people
2. A newly established flight to a European destination
3. An organized tour in a European capital
4. A concert of an international star
5. The final Champions League football match
6. A one-star Michelin dinner reservation for one person

Although the goods are quite different from each other, they share some common characteristics. Importantly, they have limited capacity, an expiration date, and consumers place their reservation at different points in time. In order to maximize profits, many sellers adjust their prices dynamically over time while taking into account the consumers' reservations and their remaining capacity.

The experiment is structured in three main parts. In the first part, we provide a description of the goods involved and we solicit your willingness to pay for these goods. In the second part, you are asked to answer some questions regarding your preferences and your profile. Finally, in the third part, we simulate purchasing behaviour. Assuming you have decided to monitor the prices for a duration of 10 days, we show you a series of observed prices for several products upon which you need to make a decision: either to purchase the good or not to buy it at all (and stop monitoring the price movements). Please note that each possible purchase is independent from the others.

The experiment's duration is around 12 minutes.

Next

Figure G.1. Instructions of the experiment provided to subjects

Table G.1. Description of the goods and WTP solicitation question per each good

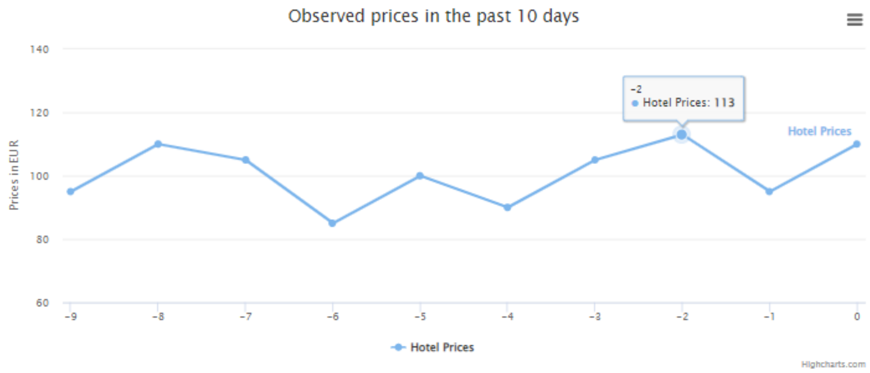
Good	Description	WTP solicitation question
Three-star hotel room for a weekend	You are planning to do a weekend out with one of your family or friends in a major European city. You have to book your twin or double room for that weekend (three weeks from now). The hotel reservation includes all city taxes and breakfast for two people for two nights. The hotel is a three-star hotel and it is short walking distance from the center.	What is the maximum € amount that you are willing to pay for the hotel room for two people?
Flight to a European destination	At your city airport, the flag carrier is going to open a new route to a European destination which was not served before from your airport. You are planning to visit that destination for a weekend in three weeks. You are looking for a round trip departing on Friday morning and returning on Sunday afternoon. The price includes allowance for both one carry on and one check-in luggage.	What is the maximum € amount that you are willing to pay for the flight for one person?
Tour in a European capital	You are planning to visit a European capital in three weeks and you would like to join an organized tour that includes access to the capital city attractions. The tour does not include accommodations and meals.	What is the maximum € amount that you are willing to pay for the tour for one person?
Concert	In your city, a famous international star/band that you are a fan of is coming for one night only concert in three weeks from now. Tickets are sold via an online platform.	What is the maximum € amount that you are willing to pay for the concert ticket for one person?
Champions League Football Match	You are planning to go to the stadium to watch the final Champions League football match. At the moment, you have no information with respect to the final teams. The match will be in three weeks from now.	What is the maximum € amount that you are willing to pay for the match for one person?
One-star Michelin dinner	With your friends, you are planning to go to a one-star Michelin restaurant for a dinner in three weeks from now. In this occasion, you will have the opportunity to taste delicious dishes prepared by a starred chef.	What is the maximum € amount that you are willing to pay for the dinner per person (excluding drinks)?

Observed Prices - Hotel

You are planning to do a weekend out with one of your family or friends in a major European city. You have to book your twin or double room for that weekend (three weeks from now). The hotel reservation includes all city taxes and breakfast for two people for two nights. The hotel is a three star hotel and it is short walking distance from the center.

You have monitored the prices in the past 10 days, and you can observe them in the following graph.

By hovering over the graph with the mouse, you will be able to see the spot price for each day of observation.



Given the price history you have observed in the last 10 days, would you book the hotel room at the current price (the price is for two people)?

- Yes
- No

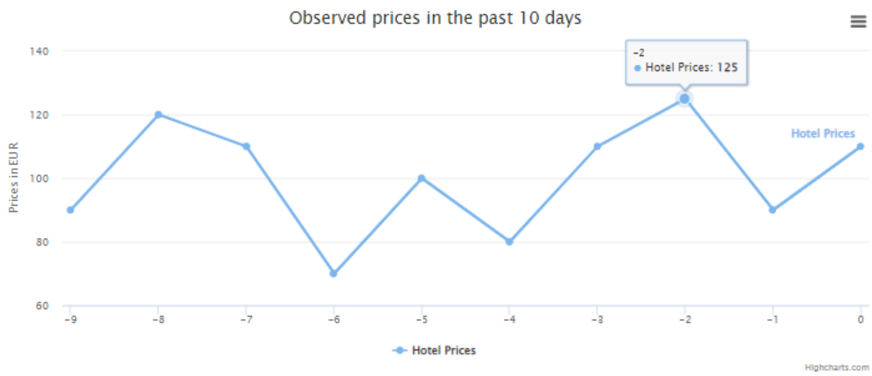
Next

Observed Prices - Hotel

You are planning to do a weekend out with one of your family or friends in a major European city. You have to book your twin or double room for that weekend (three weeks from now). The hotel reservation includes all city taxes and breakfast for two people for two nights. The hotel is a three star hotel and it is short walking distance from the center.

You have monitored the prices in the past 10 days, and you can observe them in the following graph.

By hovering over the graph with the mouse, you will be able to see the spot price for each day of observation.



Given the price history you have observed in the last 10 days, would you book the hotel room at the current price (the price is for two people)?

- Yes
- No

Next

Figure G.2. Example of price pattern displayed to subjects that declared a WTP equal to 100€—Low (top) and high (bottom) price volatility treatment of pattern 4 (P4)