Price Variation Aversion[1,2]

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Abstract: Survey evidence and theoretical research suggest that consumers may be averse to price changes intended to smooth demand fluctuations. We investigate this hypothesis using a dataset from a firm that has experimented with different pricing schemes. Each scheme is characterized by how much prices respond to demand shocks. We test for the existence of price variation aversion. We find evidence that demand depends negatively on unpredictable price variations and no evidence that it depends negatively on predictable price variations. We interpret this finding as consumers being antagonized by last minute price changes but taking advantage of the opportunities offered by price changes that can be anticipated. We discuss the policy implications of our findings.

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1 Introduction

Many economists have conjectured that consumers are averse to price changes triggered by changes in demand.[3] Using survey evidence on consumer fairness perception, Kahneman et al. (1986) show that consumers are most sensitive to changing prices in response to demand shocks and conclude that "charging the market-clearing price for the most popular goods would be judged unfair" (p.738). Frey and Pommerehne (1993) report similar findings: "The random survey reveals that pricing, at least in the context of an *excess demand* situation, is considered unfair by almost four of five respondents" (p. 296, italics ours). Consistent with this view, surveys of revenue managers reveal that firms are not willing to change prices because they are afraid to antagonize consumers (e.g. Blinder et al. 1998, and Zbaracki et al. 2004). Rotemberg (2004) assumes that consumers are antagonized by 'unfair' pricing, and proposes a theoretical model to investigate when firms may vary prices.

The conjecture that consumers are averse to price variation not related to changes in cost, could explain why many firms prefer to ration consumers than to increase prices. Similarly, many firms prefer to let unsold capacity go wasted or to carry large inventories rather than to lower prices. In fact, Kahneman et al. conjecture that "When a supplier provides a family of goods for which there is differential demand without corresponding variation in input costs, shortage of the most valued items will occur." (Proposition 2, p. 738.) Industries concerned include capacity constrained firms selling perishable products (e.g. sport and entertainment events, car rental, theme parks…) and more generally firms that manage inventories in the presence of demand uncertainty. In these industries, the argument goes, firms prefer to use inflexible allocation schemes, such as first-come first-served, rather than varying prices because consumers would find such practices unfair and would withhold future demand.[4]

[3] In an early contribution, Hall and Hitch (1939) claim that "price changes [are] disliked by buyers." Later, Okun (1981) argues that "suppliers must beware of rocking the boat with their price actions" because it could antagonize customers and destroy firm reputation.
[4] This conjecture also plays an important role in the debate on electricity pricing. The issue is whether consumers would accept more responsive pricing schemes. For example, the California Public

Despite its intuitive appeal, this argument runs into problems when one tries to draw a line between situations where prices should remain constant and situations where prices can be adjusted in response to demand shocks. Some industries do vary prices extensively. For example, some airlines, and particularly 'low-cost' airlines, have the deliberate policy of achieving as high load factors as possible and they do so by varying prices over time.[5] Some hotels have also started to vary prices to increase occupancy rates. This is known as dynamic pricing, real-time pricing, or responsive pricing among revenue managers (Borenstein et al. 2002). It seems that in these situations the 'consumer antagonism effect' must be small or at least be dominated by the potential efficiency gains from flexible pricing. It is therefore fundamental to understand when consumers are antagonized and to measure the such effect.

There is a gap between the survey evidence and the conclusion that firms do not use more flexible pricing policies because they fear antagonizing consumers. In fact, there is no evidence that consumers withhold consumption when firms vary prices in response to demand fluctuations. To fill this gap, one needs to measure the impact on demand of introducing more flexible pricing schemes.

We state the question in terms of a simple trade-off. When prices vary more, is it necessary to lower the overall level of prices to hold the quantity demanded constant? If so, what is the trade-off between the level of price variations consumers face and the price they are willing to pay? Establishing the existence of such a trade-off would support the general hypothesis that consumer antagonism may explain some industry pricing practices.

These questions are difficult to address empirically because one rarely observes consumer responses to pricing schemes that vary prices to different degrees in response to demand shocks. Firms that use different pricing schemes usually differ on other important dimensions. Moreover, firms rarely modify their pricing policies, and when they do so, it is usually done in conjunction with broader changes (e.g. product offerings).

Utilities Commission (CPUC) stated that "demand response is a vital resource." (R. 02-06-001, Order Instituting Rulemaking, June 6, 2002, CPUC OIR, p. 1.)

Our contribution to the debate is to measure the trade-off between the level of price and the amount of price variation using a unique dataset from easyEverything, the largest chain of Internet Cafés in the world. While acknowledging that out-of-home Internet access is not of direct interest to economists, we believe that this case study nonetheless provides valuable insights for several reasons. In contrast to the evidence used to support the conjecture that consumers are price variation averse, that is typically drawn from survey studies, our case study provides the first evidence using actual consumer responses. Because the demand for Internet access vary over the day and is also unpredictable at a given hour, an Internet Café fits the description of situations where it has been argued that consumers may demonstrate price variation aversion.[6] In addition, easyEverything introduced an innovative pricing rule that makes price responsive to demand shocks. Specifically, the firm updates prices every 5 minutes as a function of the realized occupancy in the store. Because a large fraction of sales involves repeat purchase, it is possible to ask whether consumers are more likely to withhold demand when prices vary more. Finally, the firm has experimented with different pricing regimes that vary prices with different degrees. These unique pricing experiments provide the ideal conditions for measuring consumer response to price variations.

We ask whether consumers are more likely to reject schemes that introduce more price variability, holding the expected level of price constant. Following the behavioral literature (Frey and Pommerehne, 1993), we distinguish between demand responses to predictable and unpredictable price variations. A given pricing regime in our sample generates predictable and unpredictable price variations. Predictable price variations measure changes in the expected hourly price over the day cycle. Unpredictable price variations correspond to small last minute price adjustments that are made to the expected hourly price. We estimate a standard demand

[5] The largest two European low cost airlines, Ryanair and easyJet, commonly vary prices for a seat in the same flight by an order of 5 and sometimes more.

[6] Both Okun (1981) and Kahnerman et al (1986) use the hotel industry to illustrate the conjecture that consumers may be price variation averse. Internet access is a service industry facing similar capacity management problems as the hotel industry.

function with additional terms for the level price variability (both predictable and unpredictable).

We find that the unpredictable variance in price enters negatively the demand function. Consumers are less likely to join the store, or are more likely to consume less, as unpredictable price variability increases. This finding is consistent with the behavioral hypothesis that consumers are averse to unpredictable price variations. In contrast, we find that the predictable variance in price does not enter negatively the demand function. This is inconsistent with the behavioral hypothesis that consumers are averse to predictable price variations. We interpret this finding as consumer taking advantage of opportunities offered by variation in prices when they can plan.

The rest of this paper is organized as follows. The next section presents our case study and a theoretical review. The next subsection introduces the dataset and outlines the empirical strategy. Section 4 presents the main evidence and discusses some implications of our results. Section 5 suggests directions for future research and concludes.

2 Case Study and Theoretical Framework

easyEverything is an Internet café that offers broadband out-of-home Internet access (Courty and Pagliero, 2001). easyEverything has experimented with responsive pricing, a scheme first proposed by Vickrey (1971). Each pricing regime is defined by a non-decreasing pricing function, which specifies a price for each level of store occupancy. Occupancy is measured every 5 minutes and the price is automatically updated. Prices are communicated to consumers who are charged in real time the minimum of the current price and their logon price. A typical pricing function in our sample is approximately linear

$$p(q)=\alpha+\beta q \qquad (1)$$

where $p(q)$ is the price per unit of time and q is the measured level of occupancy (fraction of terminals logged on). We say that a pricing scheme is more responsive if it has a higher slope β. Two pricing schemes are illustrated in Figure 1. Scheme p_1 is a flat pricing function. This implies that the price is constant independently of demand realizations. Scheme p_2 increases price as occupancy increases. This pricing scheme is responsive: Consumers are charged more when there are more consumers logged on. By changing the shape of the pricing function the firm changes the distribution of realized prices and store occupancy.

To motivate our theoretical framework, we briefly discuss how prices vary in our case study, although we postpone a more complete discussion of the topic until the next section. Figures 2 reports the average hourly prices and the hourly standard deviations for two regimes in our sample (regime 3 and regime 12). Each regime displays a price cycle over the day (Figure 2 reports the average price for each hour of the day). Moreover, the actual price at a given hour differs from day to day, which is illustrated by reporting the 2 standard deviation interval around hourly average prices. Regime 12 is more responsive than regime 3. As a consequence, prices vary more over the day (more pronounced day cycle) and also more for each hour across days (higher hourly standard deviation).[7] We expect different responses to these two sources of price variations. In the case of the price variations over the day cycle, consumers can base their consumption decision on the information on how the (expected) price varies. In contrast, consumers are likely find out about last minute price changes only when they arrive to the store and can at this point only decide to update the length of time they use the service.

Theoretical Framework

To motivate the hypothesis that the introduction of more responsive pricing schemes antagonize consumers to the point that they consume less, or that they stop consuming altogether, we review the survey evidence asking consumers how they feel toward price increases triggered by demand shocks. The typical finding is that about two thirds of the respondents find such price increases unfair. For example, a celebrated question from Kahneman et al. (1986) is: "A

[7] These two types of price variations correspond to two rationales for varying prices proposed in the literature. The former corresponds to peak-load pricing, a scheme that varies prices over the cycle to give incentives to consumers to consume off-peak. The latter is less commonly used and it corresponds to responsive pricing. Vickrey (1971) proposed to use responsive pricing to "promote

hardware store has been selling snow shovels for \$15. The morning after a large snowstorm, the store raises the price to \$20. Please rate this action as: (Completely Fair) (Acceptable) (Unfair) (Very Unfair)." In their sample, 82 percent responded 'unfair'.

Following the behavioral literature, we hypothesize that the demand should be lower, holding the cost of consumption constant, when prices respond more to demand changes. To express this hypothesis formally, we postulate that average consumption is given by

$$q=f(p,\sigma) \qquad (2)$$

where p is a price index measuring the expected cost of consumption and σ is the price variance. As with standard demand theory, we expect that the demand depends negatively on the price index $df/dp<0$. To motivate the presence of σ in f, consider the snow storm scenario. Interpret q as the number of snow shovels sold in a given period. Functional form (2) distinguishes between a situation in which the price of snow shovels is constant throughout the year $p=p_0$ and $\sigma=0$ with a situation in which the price is on average the same, $p=p_0$, but is higher during snow storms $\sigma>0$. Translating the behavioral hypothesis in this framework, we say that consumers are antagonized by price variations, or that they are *price variation averse*, if the demand responds negatively to an increase in the amount of price variations $df/d\sigma<0$ holding the price index constant.

Specification (2) is not without raising questions. To start, note that in contrast with the questions asked in consumer surveys, our study focuses on consumer responses to changes in the entire price distributions, holding a price index constant, rather than on a single price increase triggered to a positive demand shocks. To our knowledge, no survey has asked whether consumers would prefer constant prices over responsive prices, which is the fundamental question of interest to support, for example, Kahneman et al.'s Proposition 2. Second, and related to that previous point, the level of demand may depend on the entire distribution of prices. To keep matter simple, we follow a two dimensional mean-variance approach.

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efficiency through causing prices to fluctuate so as to clear the market [...] even in response to those fluctuations that can not be fully predicted in advance."

Another problem with functional form (2) is that it assumes that all price variations are the same. The behavioral literature, however, suggests that consumers express different fairness concerns to unpredictable price variation, as was the case in the example of an unexpected snow storm triggering a price increase, and predictable price variation. For example, Frey and Pommerehne (1993) consider the case of excess demand for cool drinking water and make the distinction between "How do you evaluate a price rise when a hot day was completely unforeseeable?" and "Do you consider a price rise to be more, equally, or less acceptable than when hot days normally occur in the season?" Their findings show that consumers are more likely to be antagonized by unpredictable price variations.

The main source of unpredictable price variations in our case study is the day price cycle. To decompose the effect of price variability into its two components, we propose to use a disaggregated demand model,

$$q_h=f_h((p_1,..., p_H),\sigma_P,\sigma_U), \quad h=1...H, \qquad (3)$$

where q_h is consumption in hour h, σ_U measures unpredictable price variation and σ_p measures predictable price variation. Functional form (3) recognizes the possibility of hour heterogeneity. In the context of our case study, predictable price variation would correspond to the variations in the day price cycle $(p_1,..., p_H)$ while unpredictable price variations correspond to price deviations from the expected price, caused, for example, by the random nature of the number of consumers who join the store at any point in time.

Another problem with functional forms (2) and (3) is that behavioral theory is not the only theory that makes prediction on the sign of $df/d\sigma$. To illustrate, consider the case of unpredictable price variations, as illustrated by the snow shovel example. If the only reason why consumers care about price variations is because they are price variation averse, then one would expect that $df/\sigma_U<0$. There are, however, additional explanations for why the demand may depend to unpredictable price variations. For example, consumers may be risk averse. Risk aversion would imply that demand should also depend negatively on σ_U. Alternatively, a risk neutral consumer may value price variability because s/he can adjust consumption according to realized prices.[8] If this would be the only channel through which one would expect consumer to respond to price variation, then one would expect $df/\sigma_U>0$. Unfortunately, our data will not allow to distinguish these different channels.

Keeping in mind these caveats, specification (2) and (3) are enough to test whether consumer aversion to price variation plays a 'first order role' as suggested by the behavioral literature. At the minimum, we can measure the sign of $df/d\sigma$ for both predictable and unpredictable price variations and establish the existence of a trade off between the level of price and price variability. We will interpret the finding that $df/\sigma<0$ as consistent with the behavioral hypothesis of consumer antagonism. Alternatively, the finding that $df/\sigma>0$ imply that the consumer antagonism hypothesis cannot be first order. More to the point, these specifications should be interpreted as a reduced form descriptive approach. Arguably, the question of whether price variations enter the demand function is of interest in itself.

3 Data

Our data set consists of the pricing policies and the average hourly occupancy for one of the Paris stores (Paris Sebastopole) from February 21, 2001, until July 23, 2001. During this period, store capacity remained fixed at 373 terminals, and the store's competitive environment did not change. In our sample, the store has used 12 different responsive pricing schemes. Each regime is characterized by its intercept α and slope β as in equation (1). The pricing function is the same for all hours of the day. Discussions with easyEverything management suggest that after opening a new store, the company typically experiments with several schemes to explore different features of local demand. The pricing schemes used in our sample are unlikely to be

[8] Consider the simplest case where the consumer utility is $U(m,\phi(x))=m+\phi(x)$ where m is a composite good, x is the good under consideration, and ϕ is increasing and concave. The consumer maximizes U subject to budget constraint $m+px=I$. Let $V(p)=I-px(p)+\phi(x(p))$ represent the indirect utility function where $x(p)$ is defined by $\phi'(x(p))=p$. Since the indirect utility is convex in price ($V''(p)=-x'(p)=-1/\phi''(x(p))>0$) we have $V(p_h)<E(V(p))$. Therefore, expected utility increases with the degree of price variations.

optimal (profit maximizing), or to be selected in response to changes in the local environment. We treat these experiments as exogenous.[9]

The occupancy data consists of hourly average occupancy rates for 152 days. Although the store was open 24 hours a day, we restrict our analysis to the period 8 a.m. to 12 p.m. because the store never used responsive pricing during night hours. Overall, our dataset consists of 2,312 hourly observations.[10]

Table 1 reports summary statistics. The average occupancy rate in the sample is 53 percent of store capacity, with a standard deviation of 17 percent. A feature that will play a role in interpreting the results is that the capacity never binds in our sample. This implies that quantity demanded equals quantity consumed. The average price per hour is 14.2FF. The standard deviation of price is 3.8FF or 27% of average price.

Price Variability

There are several ways to decompose overall price variations between a predictable and an unpredictable components. Figure 1 controls only for hour effects. Even when we introduce additional control variables to predict prices, we still find that the day cycle captures most of the predictable price variations. To show this, consider the following regression:

$$p_{i,j} = b_0 + W_{i,j} b_1 + e_{i,j} \quad j = 1..12,\ i = 1..i_j \tag{4}$$

where j=1..12 is a regime index, i_j is the number of observations in regime j, $p_{i,j}$ is the realized price in regime j observation i, $W_{i,j}$ is a vector of exogenous regressors including hour fixed effects (from 8am to 11pm) specific for each regime, day of the week fixed effects (Tuesday to

[9] Because of implementation constraints, the store had to use step functions instead of continuous functions. On average there are 30 steps per curve, with a minimum of 15. We compute linear approximations of the pricing curves by regressing the price at each step on the occupancy rate at the midpoint. Steps that are never reached during the regime are excluded from the regression. The average slope, corresponding to β, is 17.1—meaning that the price decreases by 1.71FF each time occupancy decreases by 10 percent (or 37 computers). In all but three regimes, a linear approximation of the pricing curve explains more than 95 percent of the variation. In regimes 12, 13, and 14, the R^2 is between 0.75 and 0.87. These regimes are piecewise linear, with a kink at 60 percent. These non-linearities do not affect our results.

Sunday), hour fixed effects for weekend days (from 8am to 11pm) and holiday fixed effects, and $\varepsilon_{i,j}$ is an error term. Model (4) is estimated by OLS using hourly observations on prices in all regimes. The R-square is 0.9. The day cycle, explains 89 percent of total variance while additional control variables account for the remaining 1 percent.

Denote by $\hat{p}_{i,j}$ the predicted price for observation i in regime j, $\overline{p}_j$ the average price in regime j, and $\hat{e}_{i,j}$ is the estimated residual of model (4). Table 2, Column 2 and 3, decompose the variance of prices in regime j, $s_j = \sum_i (p_{i,j} - \overline{p}_j)^2$ into its predictable component s_j^P and unpredictable component $s_{j,U}$:

$$s_{j,P} = \sum_i (\hat{p}_{i,j} - \overline{p}_j)^2 \ \ and \quad s_{j,U} = s_j - s_{j,P}\,.$$

The correlation coefficient between s_j^P and s_j^U in Table 2 is 0.64. The standard deviation of the predicted price $\hat{p}_{i,j}$ across all regimes ($\sqrt{s_{j,P}}$) is 3.6FF while the standard deviation of the estimated residual $\hat{e}_{i,j}$ across all regimes ($\sqrt{s_{j,U}}$) is 1.1FF. The standard deviation of $\hat{p}_{i,j}$ and $\hat{e}_{i,j}$ are respectively 26 and 8 percent of the mean price (computed across all regimes, as reported in Table 1).

4 Demand Responses to Price Variations

Our primary specification, corresponding to model (2), is a standard linear demand function with an additional term for the variability in price,

$$q_{j,i} = a_0 + a_1 p_j + a_2 s_j + X_{j,i} a_3 + u_{j,i} \quad j = 1..12,\ i = 1..i_j \qquad (5)$$

where $q_{j,i}$ is the ith occupancy observation in regime j. Hourly occupancy may vary for exogenous reasons: $X_{j,i}$ are control variables including indicator variables for national holidays, day of the week (Tuesday to Sunday), weekend day cycle (9am-11pm) and weekly advertising

[10] The raw occupancy data include breakdown periods during which the system crashed. In such events, all computers have to be restarted, and the hourly occupancy average shows a sudden drop. Using an additional data set on downtime periods, we removed all corresponding observations.

expenditures. Finally, p_j is a price index for regime j, s_j is a measure of price variability in regime j, and $u_{j,i}$ is an error term.

We will modify specification (5) to distinguish predictable and unpredictable price variations. We will also consider more disaggregated specifications introducing hour heterogeneity effects and substitution effects. This secondary set of specifications correspond to model (3). To estimate specification (5), we have several options to construct the right hand side variables. Some of the choices we make are arguable debatable. We present the main results (Table 3 and 4) using a first set of right hand side variables described next. We later show that these results are robust (Table 5 and 6).

Specification (5) asks for controlling for price index p_j which is computed as follows. Define $p_{h,j}$ as the average price in hour h in regime j and w_h as the fraction of total consumption in the sample that takes place in hour h. The price index in regime j is $p_j=\Sigma_h w_h p_{h,j}$. The results are robust to the formula used to construct p_j. Using different hourly weights (i.e. weights computed using a given reference regime, rather than the average regime, or assuming equal weights) does not change the results.

The price index, p_j, may be endogenous. In fact, there might be unobservable demand shocks that cover entire regimes and that move both the average regime prices and the observed occupancy levels. Our estimates, described in the next section, are obtained using instrumental variables. The exogenous changes in the pricing functions, provide ideal instruments to identify a_1 in demand specification (5). The (excluded) instruments are the intercept and the slope of the pricing function (α_j, β_j) and their square (α_j^2, β_j^2).

In the analysis we use the measures of variance in price presented in Table 2 as our measure of price variability but our results do not change when we use standard deviation or other measures of variation. We assume that the price variation variables computed in Table 2 are exogenous. This assumption is reasonable if there are no unobserved shocks that change both the level of demand and the variability of demand. Our results are robust if we assume σ_j is endogenous.

4-1 Results

Overall Response (TABLE 3, COLUMN 1)

Table 3, column 1 presents the results of specification (5) where we use the aggregate measure of price variability presented in Table 2, column 1. According to standard economic theory, we expect that a_1 should be negative. As expected, the coefficient estimating the response to the price index is negative and significant. The implied price elasticity is 0.8.

However, the focus of this work is on a_2. The coefficient estimating the response to price variations is positive and significantly different from zero. Holding the price index constant, higher variability of prices is associated with higher consumption. The effect is large. Moving from the least responsive to the most responsive regime, for example, would increase capacity utilization by 14.5% of store capacity. Stated differently, it would increase consumption by 27%.

We rule out an obvious explanations for this effect. The increase in consumption could be due to a binding capacity effect. If the capacity binds, then increasing price variations holding average price constant, increases consumption in low demand states, but does not decrease consumption in high demand states. We rule out this interpretation because the capacity never binds in our sample.

A first conclusion is that the large positive demand response to increase in price variation rules out a *general statement* of the antagonism hypothesis saying that consumers always reject pricing schemes that adjust prices to demand shocks.

Responses to Predictable and Unpredictable Variations (TABLE 3, COLUMN 2)

We decompose the price variation variable into predictable and unpredictable components

$$q_{j,i} = a_0 + a_1 p_j + a_{2,P} s_{j,P} + a_{2,U} s_{j,U} + X_{j,i} a_3 + u_{j,i} \quad j = 1..12,\ i = 1..i_j \qquad (6)$$

where $s_{j,P}$ and $s_{j,U}$ are the measures of predictable and unpredictable price variations presented in Table 2, Column 2 and 3. The main point of this specification is to investigate the distinction that has been made in the behavioral literature between those adjustments to demand fluctuations that can be anticipated and those that cannot (Frey and Pommerehne, 1993).

Table 3, column 2, reports the results of model (6). As predicted, the coefficient a_1 is again negative and significantly different from zero. The coefficients on the price variability variables provides some evidence in line with the consumer antagonism hypothesis. First, higher unpredictable price uncertainty, holding constant the price index and the variability of prices over the day is associated with a lower overall consumption. (The coefficient $a_{2,U}$ is negative and significant.) This is consistent with the hypothesis that consumers are averse to unpredictable price variation. Second, we cannot reject the hypothesis that $a_{2,U}<a_{2,P}$, a finding consistent with Frey and Pommerehne (1993).

On the other hand, higher predictable price variations do not decrease consumption, a finding inconsistent with the hypothesis that consumer antagonism to predictable price variation plays a first order role. (The coefficient $a_{2,P}$ is positive and significant.) Putting the results of column 1 and 2 together, we cannot reject the consumer antagonism hypothesis only for unpredictable price variations. We also find that the effects of changes in predictable and unpredictable price variability are very different. This suggests that the result of column 1 could be explained by the disproportional role played by predictable price variations in our sample.

Disaggregated Specifications (TABLE 4)

Table 4, column 1 controls for heterogeneity across hours by including in model (6) hour specific fixed effects $a_{0,h}$ and hour specific price coefficients $a_{1,h}$,

$$q_{j,h,i} = a_0 + a_{0,h} + a_{1,h} p_{j,h} + a_{2,P} s_{j,P} + a_{2,U} s_{j,U} + X_{j,h,i} a_{3,h} + u_{j,h,i} \qquad j = 1..12,\ h = 8..23,\ i = 1..i_{h,j} \tag{7}$$

where the index h corresponds to the 16 hours included in our sample (from 8am to 11pm), and $p_{j,h}$ is the average price in regime j and hour h. Specification (7) also includes hour specific advertising effects in $X_{j,h,i}a_{3,h}$. As before, the coefficient on unpredictable price variations, $a_{2,U}$, is negative and significant.

The coefficient on predictable price variation, $a_{2,P}$ is still positive (significant only at 10 percent confidence level) but it decreases. Controlling for hour heterogeneity reduces the impact of predictable price variation on consumption. This suggests that the estimate of $a_{2,P}$ in Table 3 was, at least in part, capturing a demand composition effect. To illustrate, assume that different consumers come at the peak and at the trough (demand heterogeneity) and that peak consumers are less price sensitive than off peak consumers. More predictable price variability increases the difference between peak and off-peak prices. Peak consumers consume less and off-peak consumers more, but holding the price index constant, the later effect dominates the former one. The marginal effect of a price increase is larger during off-peak hours than peak hours. Consistent with this interpretation, we find that demand is more elastic off-peak than at the peak. This implies that varying price stimulates consumption more during off-peak hours than it chokes demand during peak hours.

The next two regressions investigate whether the demand responses to unpredictable and predictable price vary over the day. Table 4, column 2 reports the results where the effect of unpredictable price variability is hour specific.[11] The effect of predictable price variability is now not significantly different from zero. The response to unpredictable price variations is negative over the day, and the response is significant throughout most of the day. Table 4, column 3, reports the hour specific coefficients for both predictable and unpredictable price variability.[12] The response to unpredictable price variations is again negative over the day, and the response is significant throughout most of the day. The response to predictable price variation varies across hours and it is mostly not significant. Consumers demonstrate uniform price variation aversion for unpredictable price variations but not for predictable price

[11] The term $a_{2,U}\sigma_{j,U}$ in model (7) is replaced by $a_{2,U,h}\sigma_{j,U}d_h$, where d_h is a dummy variable equal to 1 in hour h and zero otherwise, and $a_{2,U,h}$ is the hour h specific coefficient for the unpredictable variance (h=8, …, h=23).
[12] The terms $a_{2,U}\sigma_{j,U}$ and $a_{2,P}\sigma_{j,P}$ in model (7) are replaced by $a_{2,U,h}\sigma_{j,U}d_h$ and $a_{2,P,h}\sigma_{j,P}d_h$ respectively, where d_h is a dummy variable equal to 1 in hour h and zero otherwise; $a_{2,U,h}$ and $a_{2,P,h}$ are hour h specific coefficients (h=8, …, h=23).

variations. This reinforces the conclusion that the responses to predictable and unpredictable price variations are of different nature.

Table 4, column 4 accounts for substitution between hours. In principle, one may want to include in the empirical specification, for each hour, the average price in each other hour, as substitution may occur between any hour. However, due to data limitation, we have to aggregate different hours to limit the number of coefficients to be estimated. We group hours into three main periods (from 8am to 3pm, from 4pm to 11pm and from midnight to 7am) and we assume that substitution response in each hour is a function of the average price in the two adjacent periods.[13] The effect of predictable price variation is again not significantly different from zero while the effect of unpredictable price variation is still negative and significant.

Summary

Wrapping up, Table 3 and 4 suggest several conclusions. To start, we find very different responses to predictable and unpredictable price variations. Responses to predictable price variations are never negative. This rejects the hypothesis that consumer antagonism to predictable price variations is first order. Second, responses to predictable price variations are positive at the aggregate level (Table 3, column 2) but disappear at the disaggregate level (Table 4, column 2-4). This suggests that such responses are driven by demand heterogeneity and substitution. Third, responses to unpredictable price variation are negative in all specifications. Therefore, we cannot reject the hypothesis that consumer antagonism to unpredictable price variations is first order.

Results in Table 4, column 2, can be used to compute the aggregate effects of introducing more flexible pricing schemes. These calculations are illustrative. Consider a switch from a regime that generates the smallest price variability observed in our sample to a regime that generates the largest price variability observed in our sample. Predictable price variance

[13] Hours are grouped into three periods, A={h=8, …, h=15}, B={h=16, …, h=23}, C={h=0, …, h=7}. For each hour h in group A, we include in model (7) the substitution effects $a_{4,h}p_{j,B}$ and $a_{4,h}p_{j,C}$, where $p_{j,B}$ and $p_{j,C}$ are the average prices for hours in group B and C respectively. Similarly for the hours in groups B and C. Since for night hours (group C) the store used fixed pricing, the average price $p_{j,C}$ is treated as exogenous.

increases by 24.9FF/hour^2 while unpredictable price variance increase by 2.1 FF/hour^2. In terms of standard deviations, this corresponds to an increase of 5FF/hour and 1.4FF/hour respectively. Increasing unpredictable price variations implies a decrease in occupancy of 11% of the average observed occupancy. For comparison, increasing predictable price variations implies an increase in occupancy of 14%. This latter figure captures consumption responses due to demand heterogeneity and substitution. Naturally, one should keep in mind that the relative size of these two responses is specific to the way price variability was generated in our case study.

4-2 Robustness

Tables 5 and 6 report several robustness specifications. For parsimony concerns, we report only robustness results to two baseline models: the model reported in Table 3, column 2, where the total price variability is decomposed in predictable and unpredictable variability, and the disaggregated model used in Table 4, column 2. Table 5 reports variations around the former model while Table 6 presents variations around the latter. Column 1 to 5 in these two tables report identical changes to these two baseline models.

(1) In column 1,Tables 5 and 6, price variability is measured by its standard deviation instead of its variance. The sign of the coefficients is not affected. Coefficients remain significantly different from zero.

(2) In column 2, Tables 5 and 6, the price index squared is included to control for non-linear effects of the price level. This specification allows for more general demand heterogeneity. In Table 6, the specification includes the mean squared price for each hour. The magnitude of the coefficients is not significantly different from the results in Table 3 and 4.

(3) In column 3, hourly observations within 24 hours after each regime change are excluded from the sample. Such deletion is motivated by the possibility that it may take time for consumers to adjust to a regime change. In fact, our empirical analysis assumes that

consumers know the average level of price and price variability. This is a realistic assumption in our case study, as consumers tend to habitually visit the store. Still, we test the robustness of the results by excluding those observations for which the adjustment effects could most relevant. Using a larger window does not change the results. Both aggregate and disaggregate results are not significantly affected.

(4) In column 4, Tables 5 and 6, the predictable and the unpredictable price variances are treated as endogenous. The effect of predictable variability is not significantly different from zero both using the aggregate and the disaggregate specification. In Table 5, column 4, the effect of an increase in unpredictable variance is larger than in Table 3, column 2, but with a large standard error. In Table 6, the effect of an increase in unpredictable variance is significant for most hours.

(5) In column 5, Tables 5 and 6, the square of the slope and the intercept of the pricing functions are excluded from the set of instruments. Aggregate results, in Table 5, are unchanged, while the effect of predictable variance is positive and significant using the disaggregate specification in Table 6.

Finally, Table 5, column 6, reports the results when the price index p_j is replaced by the (un-weighted) average price within each regime. The sign and the magnitude of the coefficients is not significantly affected by the way in which the price index is constructed.

5 Summary and Conclusions

This work investigates whether consumers are price variation averse. We find that aggregate demand depends positively on price variations that can be anticipated while disaggregated demand does not depend on predictable price variations. We interpret this finding as consumers taking advantage of price fluctuations when they can plan in advance. We also find that the unpredictable component of the standard deviation in price enters negatively the demand function. This finding is consistent with the behavioral hypothesis that consumers perceive last minute price adjustments as unfair and respond by withholding consumption.

Overall, our evidence rejects a general statement of the conjecture, formulated by Kahneman et al., that consumers would be antagonized by any price fluctuations that are meant to respond to demand shocks. On the other hand, our findings suggest that the distinction between predictable and unpredictable price variations made by Frey and Pommerehne (1993) is important. The conjecture that consumers are price variation averse does apply to unpredictable price variations.

To conclude, the question of whether consumers respond aversely to price variations depends on the nature of these variations. Although consumers may accept pricing schemes that introduce predictable price variations such as peak load pricing, our calculations show that the potential gains from more flexible pricing, introducing unpredictable price variations, must be substantial to overcome the negative effects of unpredictable price variations.

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Figure 1. Examples of pricing functions

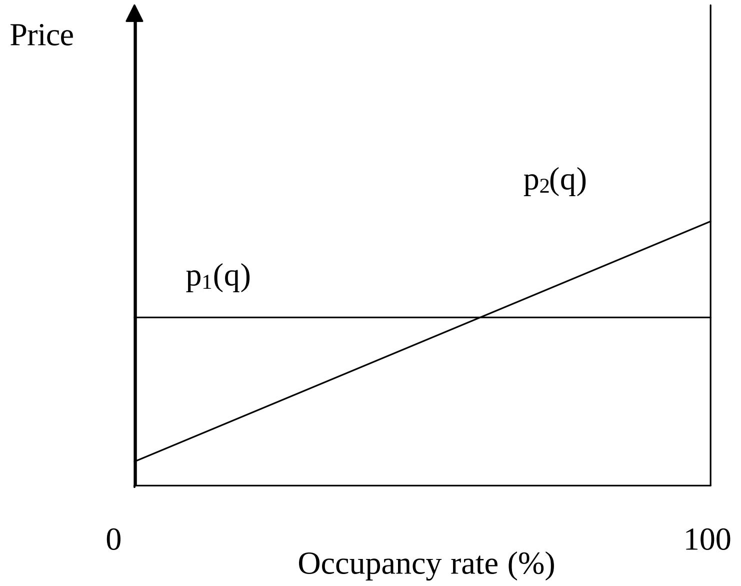
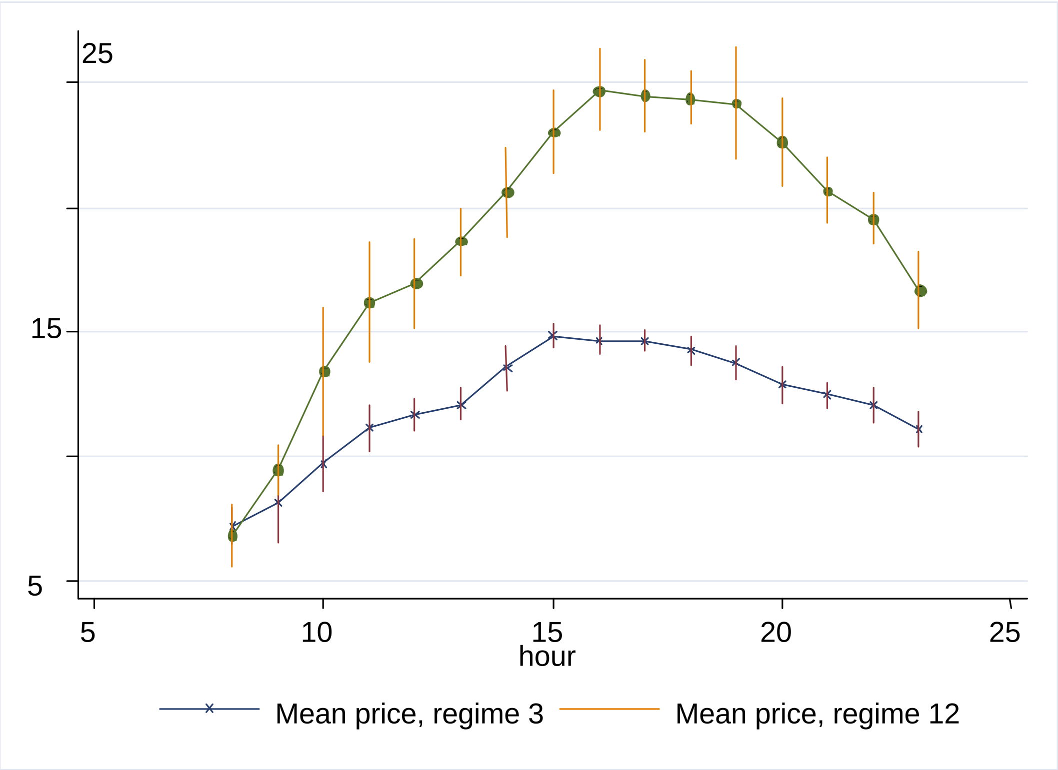


Figure 2. Mean price and variability of price in regime 3 and 12.



Note: vertical segments show the 2 standard deviation intervals around mean prices for each hour.

TABLE 1

Summary Statistics

Regime	Number of observations	Length of the regime (days)	Mean occupancy rate	S.d. occupancy rate	Mean Price	S.d. Price
1	85	6	0.618	0.160	9.616	1.757
2	110	7	0.596	0.149	10.773	1.794
3	221	15	0.600	0.150	12.085	2.320
4	208	15	0.578	0.159	12.344	2.518
5	183	11	0.550	0.171	12.906	2.747
6	224	16	0.539	0.159	13.642	2.463
7	444	28	0.492	0.161	14.477	2.887
8	342	22	0.501	0.165	15.419	3.010
9	196	13	0.516	0.148	15.176	3.168
10	94	6	0.513	0.152	17.519	5.151
11	112	7	0.509	0.154	18.306	5.189
12	93	6	0.461	0.131	18.714	5.492
All regimes	2,312	12.66667	0.533	0.163	14.174	3.808

Note: The table reports the value of each variable computed by regime (from 1 to 12) and for the entire sample. “S.d. occupancy rate” and “s.d. price” are the standard deviation of the observed occupancy rate and price. The table includes observations for hours between 8 am and 12 pm.

TABLE 2

Decomposition of the Variance in Price

Regime	Total Variance	Predictable Variance	Unpredictable Variance
1	3.09	2.98	0.10
2	3.22	3.09	0.13
3	5.38	4.94	0.44
4	6.34	5.89	0.45
5	7.55	6.35	1.19
6	6.07	4.92	1.14
7	8.34	6.41	1.92
8	9.06	7.75	1.31
9	10.04	7.93	2.10
10	26.53	24.51	2.02
11	26.93	25.49	1.43
12	30.16	27.95	2.21
All regimes	14.50	13.23	1.28

Note: The table reports the value of each variable computed by regime (from 1 to 12) and for the entire sample.

TABLE 3

The impact of price variability on consumption - Aggregate evidence

	(1)	(2)
Total variance	0.536***	
	(0.153)	
Predictable variance		0.308**
		(0.125)
Unpredictable variance		-2.858**
		(1.225)
Price index (p_j)	-2.860***	-1.548*
	(0.512)	(0.721)
Advertising expenditures	0.062	0.064
	(0.126)	(0.134)
R-squared	0.36	0.37

Note: The data is comprised of 2312 hourly observations. The dependent variable is the mean occupancy rate x100. The price index p_j is treated as endogenous. Coefficients are estimated using instrumental variables. Instruments are the slope and the intercept of the pricing functions and their squares. Day fixed effects, weekend cycle fixed effects, National Holiday fixed effects and a constant are included in all specifications. The omitted day indicator variable corresponds to Monday. Robust standard errors (clustered by regime) are reported in parentheses

TABLE 4

The impact of price variability on consumption - Disaggregate evidence

	(1)	(2)	(3)	(4)
Price predictable variance	0.125*	0.115		0.057
	(0.063)	(0.074)		(0.191)
Price unpredictable variance	-3.870***			-1.237**
	(0.827)			(0.499)
Price unpredictable variance 8am		-3.156**	-2.767	
		(1.114)	(2.325)	
Price unpredictable variance 9am		-3.227***	-2.634**	
		(1.020)	(1.189)	
Price unpredictable variance 10am		-3.595***	-3.677***	
		(0.838)	(0.788)	
Price unpredictable variance 11am		-5.079***	-4.923***	
		(0.980)	(0.926)	
Price unpredictable variance 12am		-5.194***	-4.985***	
		(1.194)	(1.086)	
Price unpredictable variance 1pm		-5.158***	-4.677***	
		(1.090)	(1.138)	
Price unpredictable variance 2pm		-4.477***	-4.361***	
		(0.795)	(0.694)	
Price unpredictable variance 3pm		-2.657**	-5.597***	
		(0.989)	(1.339)	
Price unpredictable variance 4pm		-3.074***	-3.997***	
		(0.634)	(0.749)	
Price unpredictable variance 5pm		-4.406***	-4.842***	
		(0.861)	(0.981)	
Price unpredictable variance 6pm		-4.765***	-4.629***	
		(1.340)	(1.368)	
Price unpredictable variance 7pm		-4.784***	-4.866***	
		(1.189)	(1.132)	
Price unpredictable variance 8pm		-4.207**	-4.188**	
		(1.489)	(1.602)	
Price unpredictable variance 9pm		-3.539**	-3.093	
		(1.552)	(1.937)	
Price unpredictable variance 10pm		-3.000*	-2.225	
		(1.624)	(2.034)	
Price unpredictable variance 11pm		-1.293	-0.346	
		(1.554)	(1.882)	
Price predictable variance 8am			0.028	
			(0.363)	
Price predictable variance 9am			0.009	
			(0.139)	
Price predictable variance 10am			0.167***	
			(0.054)	
Price predictable variance 11am			0.474***	
			(0.138)	
Price predictable variance 12am			0.640*	
			(0.306)	
Price predictable variance 1pm			0.605**	
			(0.220)	
Price predictable variance 2pm			0.226	
			(0.236)	

Continued on next page

TABLE 4 - *Continued*
The impact of price variability on consumption - Disaggregate evidence

	(1)	(2)	(3)	(4)
Price predictable variance 3pm			-0.493***	
			(0.146)	
Price predictable variance 4pm			-0.094	
			(0.144)	
Price predictable variance 5pm			-0.309	
			(0.221)	
Price predictable variance 6pm			0.194	
			(0.169)	
Price predictable variance 7pm			-0.018	
			(0.235)	
Price predictable variance 8pm			0.280	
			(0.281)	
Price predictable variance 9pm			0.440	
			(0.497)	
Price predictable variance 10pm			0.520	
			(0.339)	
Price predictable variance 11pm			0.513	
			(0.375)	
Price 8am	-0.513	-0.560	-0.683	0.359
	(0.430)	(0.492)	(1.198)	(0.664)
Price 9am	-1.084	-1.214	-1.540*	-0.762
	(0.653)	(0.714)	(0.853)	(1.058)
Price 10am	-1.585*	-1.433**	-1.611**	-0.860
	(0.835)	(0.523)	(0.560)	(1.182)
Price 11am	-1.629**	-1.301**	-3.152***	-2.474
	(0.642)	(0.590)	(0.823)	(2.664)
Price 12am	-1.294**	-1.118**	-3.380**	4.549**
	(0.558)	(0.455)	(1.223)	(2.007)
Price 1pm	-1.261**	-1.093**	-2.972***	0.632
	(0.447)	(0.385)	(0.882)	(3.222)
Price 2pm	-1.287***	-1.177***	-1.559	6.497*
	(0.388)	(0.338)	(0.896)	(3.505)
Price 3pm	-0.658	-0.812	1.561**	6.790**
	(0.487)	(0.462)	(0.599)	(2.814)
Price 4pm	-0.415	-0.489	0.252	-0.962
	(0.381)	(0.370)	(0.227)	(1.721)
Price 5pm	-0.139	-0.003	1.184	-2.030
	(0.372)	(0.322)	(0.689)	(3.003)
Price 6pm	-0.355	-0.221	-0.475	-2.059
	(0.285)	(0.312)	(0.673)	(1.811)
Price 7pm	-0.219	-0.123	0.259	-0.452
	(0.248)	(0.259)	(0.676)	(1.126)
Price 8pm	-0.195	-0.156	-0.599	-0.125
	(0.266)	(0.299)	(0.871)	(1.146)
Price 9pm	-0.505	-0.511	-1.534	-0.238
	(0.330)	(0.372)	(1.673)	(1.110)
Price 10pm	-0.773*	-0.835*	-2.290	0.106
	(0.370)	(0.402)	(1.309)	(1.313)
Price 11pm	-1.582**	-2.006**	-3.951*	-0.212
	(0.589)	(0.749)	(2.178)	(3.151)
Substitution Effects?	No	No	No	Yes
R-squared	0.92	0.92	0.92	0.92

Note: The data is comprised of 2312 hourly observations. The dependent variable is the mean occupancy rate x100. Price denotes the average price (computed by hour and regime) and it is treated as endogenous. Coefficients are estimated using instrumental variables. Instruments are the slope and the intercept of the pricing functions and their squares (interacted with hour indicator variables). Day and hour fixed effects, weekend cycle fixed effects, National Holiday fixed effects, hour specific advertising effects and a constant are included in all specifications. The omitted day and hour indicator variables correspond to Monday and 8am. Robust standard errors (clustered by regime) are reported in parentheses.

TABLE 5
Robustness results - Aggregate evidence

	(1)	(2)	(3)	(4)	(5)	(6)
Price predictable variance		1.052***	0.351**	-0.459	0.308**	0.268**
		(0.335)	(0.140)	(0.594)	(0.125)	(0.105)
Price unpredictable variance		-3.175**	-2.758*	-11.209	-2.858**	-2.741**
		(1.239)	(1.383)	(6.933)	(1.225)	(1.243)
Price predictable standard deviation	2.308*					
	(1.259)					
Price unpredictable standard deviation	-5.662*					
	(2.586)					
Price index (p_j)	-1.504	5.612*	-1.854**	2.502	-1.548*	
	(0.932)	(2.784)	(0.805)	(3.249)	(0.721)	
Price index squared (p_j^2)		-0.301**				
		(0.117)				
Mean price						-1.656**
						(0.750)
Advertising expenditures	0.100	-0.119	-0.015	0.228	0.064	0.052
	(0.139)	(0.161)	(0.149)	(0.393)	(0.134)	(0.136)
R-squared	0.37	0.36	0.39	0.33	0.37	0.37

Note: The dependent variable is the mean occupancy rate x100. Day, weekend cycle, National Holiday fixed effects and a constant are included in all specifications. The omitted day indicator variable corresponds to Monday. In all columns, the price index and the mean price (simple average by hour and regime) are considered endogenous. Coefficients are estimated using instrumental variables. Robust standard errors (clustered by regime) are reported in parentheses. In all but column 3, the data is comprised of 2312 hourly observations. In column 3, the data set does not include the observations within the 24 hours following each regime change, therefore the data set is comprised of only 2135 hourly observations. In column 4, the predictable and unpredictable variances are treated as endogenous. In all but column 5, instruments are the slope and the intercept of the pricing functions and their squares. In column 5, only the slope and the intercept of the pricing functions are used as instruments. In column 6, the price index (p_j) is replaced by the mean (un-weighted) price for each regime.

TABLE 6

Robustness results - Disaggregate evidence

	(1)	(2)	(3)	(4)	(5)
Price predictable variability	0.615	0.180	0.129	-0.129	0.215***
	(0.444)	(0.101)	(0.083)	(0.485)	(0.054)
Price unpredictable variability 8am	-5.263**	-3.815***	-3.532**	-1.290	-3.611***
	(2.200)	(0.952)	(1.227)	(4.865)	(1.079)
Price unpredictable variability 9am	-6.119**	-3.278**	-3.282***	-0.593	-3.869***
	(2.066)	(1.341)	(0.995)	(7.428)	(0.984)
Price unpredictable variability 10am	-8.579***	-3.088**	-3.813***	-35.547	-3.739***
	(1.807)	(1.218)	(0.939)	(149.824)	(0.885)
Price unpredictable variability 11am	-11.583***	-4.001***	-5.109***	-11.497**	-5.103***
	(1.634)	(1.019)	(1.078)	(3.754)	(0.970)
Price unpredictable variability 12am	-11.500***	-3.951**	-5.282***	-11.049***	-5.009***
	(1.987)	(1.330)	(1.382)	(3.137)	(1.172)
Price unpredictable variability 1pm	-11.320***	-4.516***	-5.337***	-9.966***	-5.008***
	(1.435)	(1.293)	(1.266)	(2.270)	(1.119)
Price unpredictable variability 2pm	-8.340***	-4.903***	-4.894***	-8.008**	-4.226***
	(2.349)	(0.764)	(0.888)	(2.898)	(0.904)
Price unpredictable variability 3pm	-2.596	-5.023***	-2.779**	-5.031	-0.913
	(3.411)	(1.577)	(0.984)	(6.539)	(1.643)
Price unpredictable variability 4pm	-4.894*	-4.603***	-3.478***	-6.908	-2.087*
	(2.240)	(0.584)	(0.591)	(5.181)	(1.004)
Price unpredictable variability 5pm	-6.496**	-5.956***	-4.520***	-6.273	-3.941***
	(2.862)	(0.669)	(0.890)	(3.991)	(0.961)
Price unpredictable variability 6pm	-8.728**	-5.291***	-4.610**	-8.424**	-4.506***
	(3.077)	(1.410)	(1.594)	(3.426)	(1.329)
Price unpredictable variability 7pm	-9.040***	-4.840***	-4.699***	-8.331***	-4.685***
	(2.603)	(1.211)	(1.405)	(2.085)	(1.246)
Price unpredictable variability 8pm	-8.879***	-4.220**	-4.183**	-8.358***	-4.147**
	(2.636)	(1.598)	(1.592)	(1.911)	(1.586)
Price unpredictable variability 9pm	-8.282***	-3.206	-3.511*	-8.691***	-3.364*
	(2.563)	(1.894)	(1.692)	(2.194)	(1.658)
Price unpredictable variability 10pm	-7.168**	-2.433	-3.109	-9.289***	-2.721
	(2.653)	(1.882)	(1.769)	(2.257)	(1.705)
Price unpredictable variability 11pm	-4.016	-0.256	-1.438	-7.428**	-0.975
	(3.061)	(2.175)	(1.453)	(3.346)	(1.620)
R-squared	0.92	0.92	0.92	0.86	0.91

Note: The dependent variable is the mean occupancy rate x100. Day fixed effects, weekend cycle fixed effects, National Holiday fixed effects, advertising expenditures (interacted with hour dummies) and a constant are included in all the regressions. The omitted day and hour indicator variables correspond to Monday and 8am. The average price $p_{j,h}$ (computed by hour and regime) is also included and it is treated as endogenous. Coefficients are estimated using instrumental variables. Robust standard errors (clustered by regime) are reported in parentheses.

In column 1, price variability (predictable and unpredictable) is measured by its standard deviation (measured by hour and regime). In all other columns the price variability is measured by its variance (measured by hour and regime). In column 2, the square of the average price (computed by hour and regime and interacted with hour dummies) is included. In all but column 3, the data is comprised of 2312 hourly observations. In column 3, the data set does not include the observations within the 24 hours following each regime change, therefore data set is comprised of only 2135 hourly observations. In column 4, the predictable and unpredictable price variances are treated as endogenous. In all but column 5, instruments are the slope and the intercept of the pricing functions and their squares (interacted with hour dummies). In column 5, only the slope and the intercept of the pricing functions are used as instruments.