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ABSTRACT

Does Responsive Pricing Smooth Demand Shocks?*

Using data from a unique pricing experiment, we investigate Vickrey's conjecture that responsive pricing can be used to smooth both predictable and unpredictable demand shocks. Our evidence shows that increasing the responsiveness of price to demand conditions reduces the magnitude of deviations in capacity utilization rates from a pre-determined target level. A 10 percent increase in price variability leads to a decrease in the variability of capacity utilization rates between 2 and 6 percent. We discuss implications for the use of demand-side incentives to deal with congestible resources.

JEL Classification: D01, D12, L11 and L86
Keywords: capacity utilization, consumer demand, price variability and responsive pricing

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1 Introduction

In a seminal contribution, Vickrey (1971) introduced the concept of responsive pricing to advocate that prices of a congestible resource should be directly linked to congestion levels; economists have since investigated many schemes that adjust prices to reduce congestion and increase utilization rates (e.g. Harris and Raviv 1981, Wilson 1993, Vickrey 1994, MacKie-Mason and Varian 1995, Crew et al. 1995, Borenstein 2002, and Courty and Pagliero 2008). However, responsive pricing is different from the schemes that have been studied so far, and the current evidence does not necessarily imply that responsive pricing can achieve its stated goals.

This paper presents evidence from a unique pricing experiment by easyEverything, the world's largest chain of cafés offering public Internet access. easyEverything followed Vickrey's advice and directly linked instantaneous prices to congestion levels. We investigate whether consumers respond to responsive pricing and whether responsive pricing smoothes demand shocks.

Vickrey assumes that the resource's capacity, Q, is inflexible in the short run and that there exists a reference target level of utilization represented by $Q_0 \leq Q$ that 'maintains the quality of service at a "satisfactory" level' (p. 339). In the absence of responsive pricing, demand shocks generate fluctuation in utilization around Q_0. Under-capacity utilization takes place when occupancy is below Q_0 and congestion emerges when it is above Q_0. Vickrey started from the premise that such fluctuations were sub-optimal, and considered the possibility of using responsive pricing to maintain realized utilization close to the pre-set target Q_0. To achieve this objective, responsive pricing makes the current price p(q) a function of contemporaneous utilization q, offering discounts when utilization is below Q_0 and raising prices when it is above Q_0. To illustrate, assume that the relationship is linear as in our case study, $p(q)=P_0+\beta(q-Q_0)$, where P_0 is the base level of price corresponding to the level of utilization $q=Q_0$, and β measures how much price responds to deviations from Q_0. The parameter P_0 captures Vickrey's proposal to set the ‘base rate on average level of activity’ (p. 339), while the responsiveness parameter β captures the principle that ‘rates go up as capacity becomes inadequate’ (p. 340), that is as q increases above Q_0, and down when $q<Q_0$.

A given pricing function, characterized by (Q_0,P_0,β), generates a distribution of utilization rates, or occupancy rate in our case study. If responsive pricing works, as Vickrey conjectured, the percentiles of the distribution of occupancy rates should mass around Q_0 for more responsive schemes (higher β). In other words, occupancy should become more predictable and the distribution of occupancy should be more concentrated around Q_0. Vickrey acknowledged that the level of price, P_0, also influences the distribution of occupancy. Higher prices decrease overall demand by shifting the distribution of occupancy to the left, but he argued that this was a very inefficient way to handle the capacity constraint. Although congestion is less likely, unused capacity is more likely. Vickrey conjectured that using price responsiveness, β, would be a more efficient solution because it influences the variance (not the mean) of the distribution of occupancy, and therefore can keep occupancy close to the target level reducing both congestion and unused capacity.

There are two tenets to Vickrey’s proposal. First, the second moment of the distribution of occupancy should respond to the level of price responsiveness. Second, the designer has to set the parameters of the pricing function (Q_0,P_0,β) adequately to optimize capacity utilization. The pricing experiments in our dataset allow us to present evidence on the first tenet. After we describe our case study, it will become clear that we cannot meaningfully investigate the second one. Consequently, we investigate whether the distribution of demand becomes more compressed around Q_0 as β increases. We will argue shortly that this hypothesis is related to the hypothesis that demand is downward sloping, but the two are not equivalent.

We use data from one of the easyEverything Internet stores. While acknowledging that out-of-home Internet access is not of direct interest to economists, we believe that our case study nonetheless provides valuable insights for several reasons. (a) An internet café has a fixed capacity (number of terminals) and faces demand uncertainty—two features common to many applications where congestion pricing has been proposed. (b) easyEverything has adopted Vickrey's proposal to make prices responsive to congestion levels. (c) easyEverything has experimented with different pricing regimes to investigate the properties of local demand. These exogenous variations offer a unique environment for the study of demand responses.

The firm in our case study updates prices every 5 minutes as a function of the level of store occupancy using linear function as presented above. To illustrate, Figure 1 shows two pricing schemes in our sample. The curves specify a price for each level of occupancy q. Consider the flatter of the two curves in Figure 1. The price increases/decreases by 1.4FF/hour when occupancy is 10 percent above/below the target level of consumption. The more responsive curve implies a price change of 4.2FF/hour for the same deviation in occupancy.

Responsive pricing can, in fact, smooth demand shocks if consumers are allowed some discretion over consumption decisions. In our application, consumers may choose when to enter the store and how much to use the service once inside. Consumers have an incentive to enter the store during off-peak hours (since expected prices are lower). Likewise, they have an incentive to check only important email (or use the service less) when the instantaneous price is high, due to unusually high demand.

We measure how the distribution of occupancy rates changes with the level of responsiveness, β, holding the level of price P_0 and the reference occupancy level Q_0 constant. We implicitly assume that the stochastic demand environment remains stable (up to seasonal variations and time trends) while β changes, which is reasonable to assume in our case study. We present both non-parametric and parametric evidence consistent with Vickrey's hypothesis. Figure 2 provides a simple illustration of the impact of responsive pricing on the distribution of occupancy. Consider again the two pricing functions in Figure 1 and let Q_0 denote the point where they intersect. Figure 2 plots the cumulative distribution of occupancy rates generated by these two pricing functions. The curve corresponding to the less responsive regime dominates the more responsive curve for low occupancy levels, and the reverse holds true for high levels. We cannot reject the hypothesis that the two distributions are equal at Q_0, but we do reject it for occupancy levels that are further away from Q_0. The finding that the percentiles of the occupancy distribution generated by the more responsive curve are closer to Q_0 is consistent with the hypothesis that increasing the responsiveness parameter smoothes demand shocks. This paper generalizes this result by aggregating information from 12 pricing functions and controlling for a number of different factors.

Literature

Our evidence contributes to the empirical literature assessing the impact of pricing schemes that vary prices in real time. As stated earlier, we are aware of no other study that investigates whether responsive pricing smoothes demand shocks. Ample literature on electricity markets shows that users, both business and household, respond to schemes that announce future prices in advance—for example, the prices for each hour of the following day (e.g. Herriges et al., 1993, Aubin et al., 1995, Taylor and Schwarz, 2000, Patrick and Wolak, 2001, Schwarz et al., 2002, Taylor et al 2005).[3] However, our work differs from previous studies in important ways.

Firstly, previous empirical works have analyzed situations where prices are typically computed (on the basis of demand forecast, supply costs and other considerations) and set a day in advance.[4] Although responsive pricing and day-in-advance pricing are similar, there are some significant differences. Day-in-advance pricing does not introduce the immediate feedback loop between current congestion conditions and prices suggested by Vickrey. Consequently, day-in-

[3] For a review of experiments with real time pricing in electricity markets, see Barbose et al. (2004).

advance pricing cannot respond to within-day demand shocks, since they become known only after the price schedule has been announced. We will return to the issue of unpredictable demand shocks in our empirical analysis. In addition, in the day-in-advance schemes used in previous empirical works, prices may vary for reasons that are not related to congestion. This could happen, for example, if an imperfect model is used to estimate future demand. If this were the case, then the central hypothesis of this work, that demand should be more predictable when price vary more, may not hold.[5]

A second and related point is the novel empirical focus of our study. While previous studies focus on estimating price and substitution elasticities, we directly study whether it is possible to reduce occupancy variability by considering the impact of responsiveness on the overall *distribution* of occupancy. The reduced form approach taken in this work is justified for two reasons. First, Vickrey's conjecture is not couched in terms of unobservable parameters to be estimated, but in terms of observable outcomes (distribution of occupancy) that can be directly measured given the experimental nature of our data. Second, the structure of the consumer decision problem under responsive pricing is not standard because prices are endogenous, and consumer expectations play a central role, which is not the case when prices are announced a-day-in-advance and consumption decisions are made after price announcements.

Finally, our results are both qualitatively and quantitatively different from those of previous studies. For example, we find much larger responses than those reported in the literature. Taylor et al. found a net benefit to consumers of only 4% of the customer bill (p. 255). Barbose et al. (2004) also reported a limited response in their survey of 70 real-time pricing programs, concluding that 'most RTP programs have generated modest load reductions in terms of their

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[4] An exception is Brownstone et al. (2003) who study responsive pricing in traffic congestion but who estimate willingness to pay rather than the impact of responsive pricing on congestion.

[5] In addition, all consumers in our case study are charged according to responsive pricing, while in most electricity studies, consumers can choose between being billed according to responsive

magnitudes' (p. ES-6). Obviously, caution must be exercised in drawing such comparisons, since our application differs from others in many respects.

We compute the increase in price variability that must be introduced in order to decrease quantity variability by a given amount. This measure, which has never been calculated before, sheds some light on a central concern in congestion pricing debates (for example, see Lindsey and Verhoef (2000) for a review of the debate in road pricing and Barbose et al. (2004) for electricity pricing). The main drawback of congestion pricing is that it may significantly increase the risk faced by consumers. We contribute to this debate by measuring the trade-off between risk (price variability) and efficient use of capacity (reduction in congestion and increase in occupancy).[6] We find that, on average, a 10 percent increase in price variability leads to a reduction in occupancy variability between 2 and 6 percent.

The remainder of the paper is organized as follows. The next section provides some background information on our case study and a description of the data. Section 3 discusses the empirical framework and Section 4 presents the results. Section 5 summarizes the main findings and discusses policy implications.

2 The Internet Café and Dataset

Our dataset consists of the pricing policies and the average hourly occupancy for one of easyEverything's Paris stores (Paris Sebastopole) from February 22, 2001, to 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 experimented with 12 consecutive pricing regimes (displayed in Figure 3), each lasting an average of 13 days. In all cases, prices

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pricing or a default pre-existing pricing scheme. See Miravete (2003) for a study of choice between plans.

[6] In a different line of research, Borenstein and Rose (1994) documented the existence of price variation in the airline industry, but such price variations could stem from price discrimination or

are updated every 5 minutes as a function of the current occupancy level. Consumers are charged in real time the minimum of the current price and their logon price; shortly, we argue that in the absence of this feature, the impact of responsive pricing would be even higher.

After responsive pricing is introduced in a new store, the company typically experiments with different pricing functions to learn about local demand before attempting to optimise the pricing scheme (Courty and Pagliero, 2001). Figure 3 shows that the firm has changed both the slope and the intercept of the pricing functions. Changes to the pricing functions provide the exogenous variability in the degree of responsiveness that is used in the estimation. In fact, Table 1 shows that there is no predictable pattern in the timing of change of regimes or in the length of the regimes. Given the strong cyclical patterns in demand in our sample (according to time of day and day of the week), one would have expected to find clear patterns (such as daily or weekly regime changes) if the introductions had indeed responded to demand fluctuations.[7] The responsiveness of the pricing functions tends to increase over time, but there are also many variations, and our results are robust after controlling for a time trend.

The occupancy data consists of hourly average occupancy rates for 152 days. Although the store was open 24 hours a day, we restricted our analysis to the period between 8 a.m. and 12 midnight because the store never used responsive pricing during night hours. Overall, our dataset consists of 2,312 hourly observations.[8] Table 1 reports summary statistics. The average

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capacity management issues. Moreover, the authors do not document the relation between price variation and capacity utilization.

[7] Two additional points are worth mentioning. First, shortly after the end of our sample period, the company decided to change its pricing strategy and store layout, because it could not maintain high levels of occupancy while also holding prices above a level that would cover average costs. According to the managers, this decision was deliberately taken after the end of the experimentation period and was based on the information collected during this first phase. Second, our exogeneity assumption would hold even if the company designed new regimes using information learned from past ones, at least so long as the demand environment did not change throughout the period.

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

occupancy rate in the sample is 0.53, with a standard deviation of 0.16. The average price is 14FF/hour, with a standard deviation of 3.8 FF/hour. Prices vary from 2 FF per hour in the early morning to over 10 FF per hour in the afternoon, when the store is typically more crowded.

Table 1 also reports the responsiveness parameter (the slope) for each pricing curve. 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 have been excluded from the regression. The average slope, corresponding to β, is 17.1—meaning that the price decreases by 1.71 FF each time the occupancy rate decreases by 0.1 (or 37 computers). In all but three regimes, a linear approximation of the pricing curve explains more than 95 percent of the variation (the R^2 in Table 1 is higher than 0.95). In regimes 7, 8 and 9 the R^2 is between 0.75 and 0.87. These regimes are piecewise linear, with a kink at 60 percent. However, these non-linearities do not affect our results.

A final feature of our data that will play an important role in the empirical analysis is that the occupancy rate never reaches capacity in our sample. Therefore, quantity demanded equals quantity consumed, and we do not have to take into account demand rationing in estimating the impact on responsive pricing of the distribution of occupancy rates.[9] Finally, there is no evidence, for the level of occupancy reached in our sample period, that service quality degrades as occupancy increases.

How do consumers respond to responsive pricing?

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[9] Discussion with the company indicates that the initial capacity was set too high relative to demand. (See also, fn 7.)

Table 1 shows that prices vary within and across regimes. The standard deviation presented in the last column corresponds to the variability in average hourly price that a consumer would face when entering the store at a random time (where each hour of the day is weighted by average total consumption) every day to use the service for one hour. These standard deviations capture the fact that prices vary systematically over the day cycle and also that they are to some extent unpredictable at a given hour. These two sources of price variation should give consumers an incentive to adjust their consumption decisions through different channels:

(1) Consumers can plan in advance, that is, they can choose when to enter the store and how much to consume, on the basis of the expected daily price cycle and other predictable demand shifters.[10] For example, consumers have an incentive to switch to cheaper hours and consume more during those hours if there is a price differential between peak and off-peak hours.

(2) Consumers have an incentive to adjust their length of stay once they arrive in the store and learn the actual price. First, realized prices will typically be different from expected ones. About 7 percent of the price variance in our sample (corresponding to approximately 25 percent in terms of standard deviation) cannot be explained by a regime-specific daily price cycle.[11] Second, prices may change in unexpected ways, and consumers have an incentive to increase their length of stay in the event of a decrease in price.

This distinction is also important because announcing hourly prices a day in advance could smooth predictable variations in demand. As we reported earlier, the literature has shown that alternative mechanisms to responsive pricing can achieve this objective. However, only

[10] The demand for Internet access shows strong cycles. Occupancy changes systematically across time of day and, to a lesser extent, day of the week.

[11] The assumption that consumers use additional variables (such as day of the week and National Holiday fixed effects) to predict prices only very marginally reduces the amount of unpredictable price variability.

responsive pricing can smooth demand shocks that take place after the daily prices have been set. It has to be acknowledged that the price cap mitigates the incentive for incumbent consumers to reduce their length of stay when the price increases.[12] In our case study consumers stay 65 minutes on average (evidence from a smaller dataset on length of stay). Responsive pricing should smooth shocks that last several hours, since the fraction of consumers who face the updated prices increases as new consumers replace existing ones (to whom the price cap applies). Without price cap, the impact of responsive pricing on occupancy variability should be larger than in our sample.

The changes in the pricing curves generated significant differences in the level of price variability. We formally test and reject the hypothesis of equal price variability across regimes for most pair wise comparisons.[13] We expect consumers to respond to these changes through the two different response channels.

The magnitude of price variability in our sample is in line with other studies. The expected absolute difference for two hours selected at random in our sample is 30 percent of the average price. Studying price dispersion in the US airline industry, Borenstein and Rose (1994) found that the expected absolute difference in fares between two passengers for a given carrier and route is 36 percent of the mean fare. The mean absolute deviation from the average price in the sample is 0.27 of the average price. For comparison, in their survey of consumer attitude toward pricing, Kahneman et al. (1986) used a 33 percent increase in price due to a positive demand shock.[14]

[12] Due to the price cap, only new consumers have an incentive to consume less when the price increases. When the price falls, however, all consumers have an incentive to consume more.
[13] The tests of the equality of variance across regimes are reported in an Additional Materials section available at http://www.iue.it/Personal/Courty/.

What can we learn from easyEverything experiments?

Our primary interest is in the impact of the responsiveness parameter on the distribution of occupancy. A secondary interest is to decompose the overall impact according to the different channels of consumer response. We cannot directly investigate the existence of responses through channel two because we lack individual data and data on length of stay. We will provide evidence of the existence of these responses, however, by focusing on the distributions of occupancy conditional on time of day and other predictable demand shifters. The conditional distributions of occupancy eliminate the first channel of response, and isolate the second channel.

Note that easyEverything pricing experiments do not allow us to investigate the impact of Vickrey's proposal on overall welfare because we cannot characterize the adequate level of capacity utilization rate (Q_0/Q) in our case study; further, we have no information on the costs of congestion that would occur if occupancy rates reached such levels. Therefore, we leave aside welfare issues. We test whether the demand mechanism assumed in Vickrey's proposal actually operates in practice.

3 Empirical Framework

A given pricing function, characterized by (Q_0,P_0,β), generates the empirical distribution of occupancy rates $F(q|Q_0,P_0,\beta)$. Let

$$q_j(Q_0,P_0,\beta) = \text{Inf}\,(q \text{ s.t. } F(q|Q_0,P_0,\beta)\geq j) \quad (1)$$

represent the j^{th} percentile of the distribution of occupancy under pricing scheme (Q_0,P_0,β). Vickrey's conjecture can be expressed as follows. Holding (Q_0,P_0) constant, the percentile k

[14] The mean absolute difference is $\sum_{j=1}^{2,312}\sum_{i=1}^{2,312}|p_i - p_j|/n^2$, while the mean absolute deviation is $\sum_{i=1}^{2,312}|p_i - \overline{p}|/n$, where p_i denotes hourly price observations ($p_i=p(q_i)$) and $\overline{p}$ the average price.

such that $q_k = Q_0$ should not depend on β. In fact, the price is independent of β when capacity utilization is equal to the reference level Q_0, ($p(Q_0)=P_0$). The other percentiles are expected to depend on β. As β increases, while (Q_0,P_0) are held constant, all percentiles q_j should move toward the reference level Q_0. Stated formally, Vickrey's hypothesis becomes

$$\frac{d}{d\beta}\left|q_j(Q_0, P_0, \beta) - Q_0\right|_{Q_0, P_0} < 0 \quad \text{for any } (Q_0, P_0, \beta) \qquad (H_0)$$

To understand H_0, it is useful to consider two benchmark demand systems that can be interpreted as simplified versions of the channel one and two responses introduced earlier. Assume that consumers either consume one hour or nothing and that they have heterogeneous valuation for consumption. To illustrate channel one response, assume that there are n_h potential users in hour h=1..H. For the sake of simplicity, we abstract from substitution across time of day, but the example could easily be extended. Under this simple demand specification, the demand for Internet access depends only on the hour of day and on the price per hour: for hour h, the subset of n_h consumers who value consumption more than the posted price decide to consume. Equilibrium occupancy at hour h takes place at the point where the downward sloping hour h demand meets the upward sloping pricing curve. As β increases, the intersection point moves closer to Q_0 and H_0 holds. Hourly prices are perfectly predictable and only those consumers who value consumption more than the equilibrium price in hour h join the store at that time.

To illustrate channel two response, assume that a random number of consumers join the store every hour and each consumer decides whether to consume based on the realized price. The resulting demand depends only on the price per hour and on some random state of nature ω. Equilibrium occupancy in state ω takes place at the point where the (downward sloping) state ω demand meets the (upward sloping) pricing curve. As β increases, the intersection point moves closer to Q_0 and H_0 follows (Courty and Pagliero, 2008). Again, only those consumers who value consumption more than the price decide to consume. In this simple illustration, the price makes discrete jumps every hour, as new generations of consumers replace current ones. More generally, consumers could arrive continuously, and responsive pricing would still smooth demand shocks; the only caveat is that the price cap mitigates the effect, as mentioned earlier.

Despite these two benchmark cases, H_0 does not generalize to any demand system. In fact, one can easily construct counterexamples with substitution across times of day where H_0 is violated. In addition, there are more fundamental reasons to doubt that H_0 should hold in practice. Under responsive pricing, prices are set endogenously as a function of realized occupancy. Realized occupancy is itself a function of consumer decisions. Therefore, consumers have to form expectations about how average prices vary over the day cycle and for how the actual prices vary from hour to hour. Expectations about future prices could play an important role to the extent that there is much demand uncertainty. One can easily construct counterexamples, where there are multiple equilibrium or where consumers have heterogeneous beliefs, which violate H_0.

It is now clear that H_0 is not a test of downward sloping demand. Rejecting H_0 could happen either because demand is not downward sloping, or because substitution patterns, equilibrium selection, or consumer expectations are peculiar (Courty and Pagliero, 2008). Ultimately, whether H_0 holds or not in the real world is an empirical issue.

Conditional Responses

If a large component of demand variation is due to day cycle demand fluctuations and other predictable demand shifters, which is the case in our case study, then hypothesis H_0 captures to a large extent reduction in occupancy variations caused by channel one response. This evidence alone does not give a sense of whether channel two response plays a role. One may question whether the distribution of occupancy conditional on observable demand shifters, such as hour of day, day of the week and so on, also becomes more compressed for more responsive regimes. Denoting $q'_j(Q_0,P_0,\beta|h,X)$ the j^{th} percentile of the distribution of occupancy conditional on hour h and other demand shifters summarized by X, hypothesis H_0 generalizes to

$$\frac{d}{d\beta}\left|q'_j\,(P_0,Q_0,\beta\,|\,h,X)-Q_0\right|_{Q_0,P_0}<0\,. \qquad (H_{0,h})$$

Focusing on conditional distributions eliminates the reduction in day cycle variation (channel one response) and focuses on reduction in occupancy variations that are driven by channel two response.

4 Estimation and Results

We provide both non-parametric and parametric evidence supporting hypothesis H_0 and, due to data constraints, only parametric evidence for hypothesis $H_{0,h}$. Depending on the test under consideration, we only report evidence for a subset of 5 or 6 percentiles to balance conciseness and completeness. The results generalize when we consider more quantiles or alternative specifications (Section 4.3). We also sometimes refer to further robustness checks, which do not add extra insight; these can be consulted in the separate Additional Materials section.

4.1 Non-Parametric Test of H_0 for Pairs of Pricing Rules

In the introduction, we compared the cumulative distribution functions of regimes 8 and 12 (Figure 2). In this section, we develop this analysis in three directions: (a) we generalize this result to a larger set of pairs of pricing functions; (b) we present a formal test of H_0; and (c) we discuss the economic significance of the results.

The non-parametric approach proceeds in three steps. First, select a pair of regimes, x and y, where regime x is more responsive than regime y ($\beta_x > \beta_y$) and set Q_0 and P_0 equal to the coordinates of the intersection point of the two pricing functions. Second, compute the percentiles of the occupancy distribution under the two regimes $q'_j(P_0, Q_0, \beta_x)$ and $q'_j(P_0, Q_0, \beta_y)$. Finally, using the definition of percentile k ($q_k = Q_0$), test whether the differences in estimated percentiles have the predicted sign under H_0,

$$\begin{cases} q'_j(P_0, Q_0, \beta_y) < q'_j(P_0, Q_0, \beta_x) \text{ if } j < k \\ q'_j(P_0, Q_0, \beta_y) > q'_j(P_0, Q_0, \beta_x) \text{ if } j > k \end{cases} \qquad (H^{np}_0)$$

and whether they are statistically significant.

There are many pairs of curves in our sample, and for some pairs the difference in responsiveness is small. To address this problem, in this section we only compare pairs of pricing functions for which the difference in slope is higher than 22. This singles out 11 pairs: regimes 1 to 9 crossed with regime 12, and regimes 10 and 11 crossed with regime 1. Each pricing function in our sample occurs at least once. These pairs of pricing functions cross between 8 percent and 33 percent of capacity. The average crossing point is 20 percent.

The 10 panels in Figure 4 complement the evidence in Figure 2 and plot the 10 remaining pairs of empirical cumulative distributions functions (cdf). For example, Panel 1 reports the cdfs of regime 1 and 12. In each panel, the vertical red line corresponds to the point where the two pricing functions cross (Q_0). Each panel also reports the two-sample (Kolmogorov-Smirnov) tests of the equality of distributions. The null hypothesis is that the two samples come from the same population. The statistic is computed as $D=\sup|F(q|Q_0,P_0,\beta) - F(q|Q_0,P_0,\beta')|$, for $\beta \neq \beta'$ and any $0 \leq q \leq 1$.[15]

[15] The P-values for the D statistic are computed using the first five terms of the asymptotic distribution $\lim_{m,n\to\infty} \Pr[((mn/(m+n))^{1/2} D \leq a] = 1 - 2\sum_{i=1}^{\infty}(-1)^{i-1}\exp(-2i^2a^2)$, where n and m denote the size of the two samples.

The P-values reported in Figures 2 and 4 show that the maximum distance between the two empirical cumulative distributions is significantly different from zero. This is consistent with the effect of responsive pricing. However, Vickrey's conjecture makes stronger predictions on the relative ordering of the quantiles of the occupancy distributions. Under H^{np}_0, the cdf corresponding to the more responsive pricing function should lie above the less responsive cdf for $q>Q_0$, and the opposite should hold for $q<Q_0$. In the event Q_0 lies outside the support of the two cdfs, as in Panel 1, we do not expect the two cdf to cross, but only that the more responsive cdf dominates (be dominated by) the less responsive one if Q_0 lies on the left (right) of the support. This should hold over the entire support of the cdfs.

Figure 2 and 4 show that the differences in occupancy percentiles across regimes are broadly consistent with Vickrey's conjecture. In Figure 4, Panel 1, for example, Q_0 lies to the left of the support of the two cdfs, and the cdf of regime 12 (the more responsive regime) dominates the cdf of regime 1. For some pairs, Q_0 lies within the support of the cdfs. This is the case in Figure 2 and Figure 4, Panel 7, displaying pairs (8, 12) and (7, 12) respectively. In both cases, the two cdfs cross around Q_0 and the cdf corresponding to the more responsive regime is dominated by (dominates) the cdf corresponding to the less responsive regime on the left (right) of Q_0.

Test of H^{np}_0

We proceed to test whether the patterns displayed in Figure 4 are statistically different. We jointly estimate the percentiles of the occupancy distribution for each regime. Define the j^{th} percentile of the occupancy distribution in regime r as

$$q'_j(r) = b_{0,j} + d(r)\, b_{r,j}\,, \qquad (r = 1,\ldots,11) \tag{2}$$

where d(r) is a dummy variable for regime r (regime 1 is excluded) and $b_{0,j}$ and $b_{r,j}$ are coefficients to be estimated. We jointly estimate (2) for the 5^{th} percentile and the nine deciles using the standard Least Absolute Deviations (LAD) method (Koenker and Basset 1978 and Koenker 2005).[16] We test hypothesis H^{np}_0 by testing linear restrictions on the estimated coefficients $b_{r,j}$. For a pair of regimes x and y define $Q_0(x,y)$ as the point where the two cumulative distributions intersect and k(x,y) such that $q_{k(x,y)} = Q_0(x,y)$.[17] If regime x is more responsive than y, H^{np}_0 implies that

$$b_{y,j} < b_{x,j} \text{ if } j<k(x,y) \text{ and } b_{x,j} < b_{y,j} \text{ if } j>k(x,y).$$ [18]

Table 2 reports the estimated coefficients $b_{0,j}$ and $b_{r,j}$ in (2). The F-tests for the equality of the deciles across regimes are reported in Table 3.

Tables 2 and 3 should be read together with Figure 4. As an illustration, consider Panel 2 in Figure 4, which plots regimes 2 and 12. Then select a level on the vertical axis at which the two empirical cdfs will be compared, for example 0.3. In other words, we want to compare the 3rd deciles of the two occupancy distributions. Table 2 indicates that the estimated 3rd decile of the occupancy distribution in regime 2 is 55.89 percent (61.58-5.69), while the same decile for regime 12 is 40.14 percent (61.58-21.44). This is consistent with Figure 4, since 55.89>40.14. Are these two deciles significantly different from each other? Table 3 (third row and first column) reports the F-test using the estimates of the quantile regression. They are indeed different at a 1 percent confidence level.

16 The estimated coefficients minimize the absolute weighted difference between the observed occupancy rates in regime r, $q_{i,r}$, and the occupancy percentile $q'_j(r)$:

$$\min_{\{b_{0,j},b_{r,j}\}} \sum_{r=1\ldots11} \sum_{i=1\ldots i_r} (q_{i,r} - q'_j(r))[j - I(q_{i,r} - q'_j(r) \le 0)]$$

where I(.) is the indicator function and $q'_j(r)$ is defined in (2). Each deviation $q_{i,r}$-$q'_j(r)$ is weighted differently according to its sign and the quantile being estimated. We use the linear programming algorithm of Armstrong et al. (1979) to solve the minimization problem and we obtain the variance-covariance matrix of the estimators following the bootstrap resampling procedure described in Rogers (1992).

17 The two cumulative distributions should intersect only once and at the same point where the two corresponding pricing curves cross. We test and cannot reject these hypotheses in our sample.

18 If x=1, then the relevant hypothesis to test is $b_{y,j}<0$ if j<k and $b_{y,j}>0$ if j>k.

In general, for deciles sufficiently far away from Q_0, the differences displayed in Figures 2 and 4 are statistically significant. Since Q_0 is relatively small in our sample, we also provide the results for the 5th percentile. This allows testing of the effect of changes in slope on the left tail of the occupancy distribution. For the pairs of regimes (7, 12) and (8,12), where Q_0 is highest, the difference between the 5th percentiles of the two regimes has the predicted sign (Figure 4, Panels 7 and 8) and is significantly different from zero (Table 3).

Aggregate measure of the impact of responsive pricing

Various metrics demonstrate that responsive pricing reduces inefficiencies. Define the average level of congestion as

$$D^{q,+}(\beta)=\int_0^{100} (q_i(Q_0,P_0,\beta)-Q_0)^+ di$$

where $x^+=Max(x,0)$. [19] Note that this concept of congestion is purely hypothetical since excess demand never takes place in our case study. What we mean to capture is the average excess demand that would take place under the assumption that Q_0 was the target occupancy level. Similarly, define the average level of wasted capacity as

$$D^{q,-}(\beta)=\int_0^{100} (q_i(Q_0,P_0,\beta)-Q_0)^- di$$

where $x^- =Min(x,0)$. $D^{q,+}$ measures the importance of inefficiencies due to excess demand, while $D^{q,-}$ focuses on inefficiencies due to unused capacity. $D^q(\beta)=D^{q,+}(\beta)+ D^{q,-}(\beta)$ corresponds to the average deviation from the preset target Q_0 that would be observed by someone who randomly entered the store, and is interpreted as an overall measure of inefficiency. Empirically, we use the estimates reported in Table 2 to compute $D^q(\beta) = (1/10)\Sigma_j|q_j(Q_0,P_0,\beta)-Q_0|$.

To construct a measure of the impact of responsiveness, consider a change in the responsiveness from β to β'

$$\Delta D^q = \frac{D^q(\beta') - D^q(\beta)}{\left(\frac{D^q(\beta') + D^q(\beta)}{2}\right)}.$$

ΔD^q measures the percentage change in inefficiencies and captures the compression effect hypothesized by Vickrey.[20] Consider again the pairs of pricing functions compared in Figure 4. The compression effect (ΔD^q) implied by these pair-wise comparisons ranges between 24 and 38 percent. The magnitude of the overall reduction in inefficiencies is large.

$\Delta D^{q,-}$ and $\Delta D^{q,+}$ are defined similarly as ΔD^q. Referring to Figure 4, it is clear that the effect of changes in responsiveness comes from a reduction in congestion ($\Delta D^{q,+}$) for most pair-wise comparisons. However, for the pairs (8, 12) and (7, 12), (Figures 2 and 4, panel 7), there is also a significant decrease in unused capacity ($\Delta D^{q,-}$). For these pairs of regimes, we can compute $\Delta D^{q,-}$ and $\Delta D^{q,+}$ separately. The magnitude of the impact of the increase in responsiveness on unused capacity $\Delta D^{q,-}$ is 51 and 44 percent for these two pair-wise comparisons. The reduction in average congestion is 23 and 30 percent respectively.

4.2 Parametric Test of H_0 and $H_{0,h}$ Based on Quantile Regressions

A pricing function can be written as $p(q)=(P_0-\beta Q_0)+\beta q$ and therefore varies in only two dimensions: its level ($P_0-\beta Q_0$) and its responsiveness (β). For estimation purposes, we can arbitrarily fix Q_0 in (1) and rewrite q_j as

$$q''_j(P_0,\beta|Q_0). \quad (3)$$

Relation (3) describes how percentile j depends on the reference price P_0 (corresponding to the price level at Q_0) and on the responsiveness parameter β. Therefore, H_0 simplifies to

[19] $D^{q,+}(\beta)=\int_0^{100}(q_i(Q_0,P_0,\beta)-Q_0)^+di=\int_0^Q(q-Q_0)^+dF(q|Q_0,P_0,\beta)$.

[20] Since the responsiveness parameter β is measured in a unit that is difficult to interpret economically (FF/%occupancy), we do not report elasticities.

$$\frac{d}{d\beta}\left|q''_j(P_0,\beta \mid Q_0)-Q_0\right|_{P_0} < 0 .$$

Taking a linear approximation, we obtain

$$q''_j(P_0,\beta|Q_0)=a_{0,j}+a_{1,j}P_0+a_{2,j}\beta. \tag{4}$$

We estimate the parameters $a_{0,j}$, $a_{1,j}$ and $a_{2,j}$ for the 10th, 30th, 50th, 70th and 90th percentiles.[21] The choice of Q_0 is arbitrary. In the core of the analysis, we set the reference occupancy point at Q_0=0.28 and show in the next section that our results are robust to this choice.

Having obtained the estimated coefficients $a_{2,j}$, we can proceed with testing our main hypothesis. Using the percentile k previously defined, ($q_k(P_0,\beta \mid Q_0)=Q_0$), H_0 further simplifies to

$$a_{2,j}>0 \text{ if } j<k \text{ and } a_{2,j}<0 \text{ if } j>k \tag{H^p_0}$$

for any percentile j. We can test H^p_0 directly by inspecting the sign of the coefficients $a_{2,j}$. Using the conditional distribution of occupancy, $q'_j(P_0,Q_0,\beta|h,X)$, we derive the analogue $H^p_{0,h}$ to H^p_0.

Unconditional distribution

The estimated coefficients $a_{0,j}$, $a_{1,j}$ and $a_{2,j}$ of (4) are reported in Table 4. To provide a visual display of the impact of β on occupancy distribution, Figure 5 plots the simulated 10th, 30th, 50th, 70th and 90th percentiles, using the estimated parameters from Table 4. The horizontal axis measures the level of price responsiveness β and the vertical axis the level of store occupancy. The four curves trace the four different percentiles simulated. A vertical slice measured at β gives the location of the percentiles of the distribution of occupancy that corresponds to a responsiveness parameter equal to β. As the level of responsiveness increases, the distribution of occupancy becomes more compressed around the target level of occupancy (the four curves are closer to one another and closer to Q_0). As anticipated, an increase in the responsiveness of the pricing function reduces the variability of occupancy.

To test H^p_0 one first has to compute k. If we could estimate relation (3) without error we would compute k as the solution to $q_k(P_0, \beta \mid Q_0) = Q_0$. In practice, the quantiles are estimated with error. Therefore a range of quantiles $[k^-, k^+]$ may satisfy the above equation. In our application (see Figure 5), only the first decile meets this condition. We set k=0.1, keeping in mind that our conclusions would hold for any quantiles within $[k^-, k^+]$.[22]

Consistently with Vickrey's conjecture, the impact of responsiveness ($a_{2,0.1}$) is not significantly different from zero (Table 4, column 1). To the contrary, the coefficient $a_{2,0.9}$, in column 5, is negative and significant. To illustrate, increasing the responsiveness parameter from 16 to 34, corresponding to a change from regime 6 to regime 10, implies a decrease of 3 percentage points for the 9th decile. The difference in the estimated parameters is significantly different from zero.[23]

As before, $\Delta D^q(\beta)$ provides a measure of the overall effect of changes in responsiveness. Given the estimated coefficients in Table 4, the difference in slope between

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[21] We solve the analogous minimization problem as before $\min_{\{a_{0,j}, a_{1,j}, a_{2,j}\}} \sum_{i=1...2312} (q_i - q'_j(P_0, \beta \mid Q_0)[j - I(q_i - q'_j(P_0, \beta \mid Q_0) \le 0)]$ where and q_i denotes hourly observations of the occupancy rate in the store.

[22] An additional complication arises with the determination of k. In theory, k should be independent of β. Given our linear approximation, k solves $Q_0 = a_{0,k} + a_{1,k}P_0 + a_{2,k}\beta$, and it obviously depends on β (because the non-linear terms in P_0 and β are missing). This is not a problem because k=0.1 falls within the range of k that solves $q_k(P_0, \beta \mid Q_0) = Q_0$ for any slope within the range observed in our sample.

[23] We estimate the full variance covariance matrix of the estimators; it is therefore possible to test restrictions on coefficients across different quantiles. In this case, $\beta_{0.9} - \beta_{0.1} = -0.229$, $F(1,2309)=7.90$ with a P-value equal to 0.005.

regime 6 and 10, for example, implies a 13% change in the average distance from the target occupancy (ΔD^q=0.13).[24]

Conditional distribution

To isolate the effect of channel one and two, we now consider the impact of changing β on the conditional occupancy distribution. We estimate a modified version of (4),

$$q'_j(P_0,\beta|Q_0,h)=a_{0,j}+a_{1,j,h}P_0+a_{2,j,h}\beta+Xa_{3,j} \quad (5)$$

where the matrix of regressors X includes time-of-day fixed effects, day-of-week fixed effects, holiday effects, and weekend-cycle effects (time dummies for Saturday and Sunday) which are proxies for predictable demand changes. We also allow for hour-specific responsiveness and price level effects.

The results are illustrated in Figure 6, which reproduces Figure 5 for a subset of hours. Table 5 reports the coefficients $a_{2,j,h}$ capturing the effect of increasing the responsiveness parameter on a given percentile (columns) at a given hour of day (lines). We investigate $H^p_{0,h}$ separately for h=8 a.m.,…11 p.m.

Figure 6, Panel 1 displays the results for 8 a.m., while the corresponding coefficients are reported in line one of Table 5. Q_0 is located around the 9th decile of the occupancy distribution. Therefore, an increase in β gives discounts in most deciles. As expected, in Figure 6, the 9th decile does not respond to a change in β, while all others increase. Inspection of Table 5 confirms that all deciles lower than the 9th increase and that this increase is significant for the 3rd and 5th deciles. Increasing the responsiveness parameter from 16 to 34, corresponding to a change from regime 6 to 10, implies a significant 1-percentage point reduction in the distance between the 1st and the 9th decile.

[24] This figure is consistent with previous results. The difference in responsiveness between regimes 6 and 10 is smaller than the corresponding difference for any of the pairs considered in Section 4.1. Therefore, the impact on our measure of inefficiency is smaller.

The distribution of occupancy at 9 a.m. gives a slightly different story (Figure 6, Panel 2), because demand at 9 a.m. is on average higher (occupancy typically increases in our store throughout the morning and consumption reaches its peak in the afternoon). Q_0 now lies within the support of the distribution of occupancy, not far from the median. An increase in the responsiveness parameter offers discounts in the 1st and 3rd deciles and increases prices in the 7th and 9th deciles. As expected, the 1st and 3rd deciles increase while the 7th and 9th deciles decrease, and the change is significant in the last case. Coefficients in Table 5 can be used to compute the magnitude of a change in responsiveness. Increasing the responsiveness parameter from 16 to 34 decreases the distance between the 1st and the 9th decile by 3 percentage points.

From 10 a.m. onwards, demand increases even further, and Q_0 lies to the left of the support of the distribution of occupancy. An increase in the responsiveness parameter increases prices in all states of the world and the quantiles of the occupancy distribution decrease as predicted. The decrease is significant for most deciles and hours.

Hypothesis $H^p_{0,h}$ implies that any two deciles located on different sides of Q_0 should move closer to one another as the responsiveness parameter increases, and the evidence is consistent with this prediction. However, $H^p_{0,h}$ does not say anything about the case of two deciles that lie on the same side of Q_0. Interestingly, Figure 6 shows that they often move closer to one another. An increase in the responsiveness parameter narrows the distance between deciles as well as moving all deciles closer to Q_0. Both effects imply that the distribution of occupancy tends to become more compressed.

The magnitude of the response to changes in responsiveness, for hour h, can be measured by $\Delta D^q_h(\beta)$. Given the estimated coefficients in Table 5 for 8 a.m., 9 a.m. and 10 a.m., the difference in slope between regimes 6 and 10 implies a decrease in average distance from the target occupancy of 13%, 40% and 20% respectively ($\Delta D^q_{8am}(\beta)$=0.13, $\Delta D^q_{9am}(\beta)$=0.4,

$\Delta D^q_{10am}(\beta)$=0.2). For the remaining hours, the compression effect $\Delta D^q_h(\beta)$ ranges between 4% and 28%.

To summarize, conditioning on time and other variables eliminates the impact of type one responses. Nonetheless, we find that the conditional distribution of demand becomes more compressed as responsiveness increases and the magnitude of the response is large. This implies that consumers respond to price changes that cannot be predicted by the econometrician, and that are likely to be discovered by consumers only at the last minute.

4.3 Robustness

We show that the results presented in Section 4.2 do not depend on the choice of the reference point Q_0. We select reference occupancy rates Q_0 that fall within the range in which the pricing functions in our sample intersect. Figure 3 shows that most pricing functions coincide at relatively low levels of occupancy rates. As discussed earlier, the 11 pairs of pricing functions with the highest difference in slope cross between 8 and 33 percent of capacity, with only two points of intersection below 12 and above 28 percent.

The analysis presented in section 4.2 assumed Q_0=0.28. In this section, we estimate (4) using Q_0=0.20, which corresponds to the mean crossing point, and Q_0=0.12. As before, we illustrate our results by simulating the quantiles of the distribution as the responsiveness of the pricing function changes. Figures 7 and 8 reproduce Figure 5 using our new estimates with Q_0=0.20 and Q_0=0.12. We set P_0=7.6, so that the pair (Q_0, P_0) corresponds to the intersection of the pricing functions in regimes 5 and 12. When using Q_0=0.12, we set P_0=4.2, so that (Q_0, P_0) corresponds to the intersection of the pricing functions in regimes 1 and 12. Again, these choices are somewhat arbitrary, but the conclusions would not change so long as (Q_0, P_0) falls within the range of crossing points in our sample.

Using these new reference occupancy levels, all deciles of the occupancy distribution are above Q_0. According to Vickrey's conjecture, increasing the responsiveness of the pricing function should have a negative impact on all deciles. Figure 7 and 8 are perfectly consistent with this hypothesis.

We also replicate the analysis for the conditional occupancy distribution and find that the results are robust to the choice of Q_0 and P_0. In addition, we repeat our analysis including in (4) and (5) a linear and quadratic time trend. The overall results are not affected. The impact of changes in responsiveness is significant for quantiles sufficiently far away from Q_0 and a significant compression effect occurs. All the estimated coefficients and the corresponding figures for these robustness tests are reported in the Additional Materials section.

4.4 Discussion

While the benefits from responsive pricing derive from a reduction in the variability of capacity utilization, an important drawback of responsive pricing is that it increases price variability. This drawback has received much attention both in the theoretical and applied literature. For example, a large literature has argued that fairness norms influence consumer decisions and has conjectured that prices should not respond to demand shocks because this would alienate or antagonize consumers (e.g. Okun 1981, Kahneman et al 1986). Similarly, studies in transportation, electricity and other applications have pointed out that the introduction of price variations, and the magnitude of such variations, is a central reason for the resistance to congestion pricing (e.g. Lindsey and Verhoef (2000), Barbose et al. (2004)).[25]

[25] According to Vickrey (1971, p. 346), "the main difficulty with responsive pricing is likely to be not mechanical or economic, but political. The medieval notion of the just price as an ethical norm, with its implication that the price of a commodity or service that is nominally in some sense the same should not vary according to circumstances of the moment, has a strong appeal even today."

Our case study contributes to this debate by quantifying the trade-off between efficiency gain (reduced congestion and idle capacity) and increases in price variability. Define the arc elasticity of reduction in occupancy deviation to increases in price variability as

$$\varepsilon^{q,p} = \frac{D^q(\beta') - D^q(\beta)}{D^p(\beta') - D^p(\beta)} \frac{\frac{D^p(\beta') + D^p(\beta)}{2}}{\frac{D^q(\beta') + D^p(\beta)}{2}} , \qquad (7)$$

where $D^p(\beta)$ is a measure of absolute price deviation: $D^p(\beta)=\int_0^{100} |p(q_i(Q_0,P_0,\beta),\beta) - p(Q_0,\beta)|di$, with $p(q,\beta)= (P_0-\beta Q_0)+\beta q$. The larger $\varepsilon^{q,p}$ the more likely that there will be resistance to the introduction of congestion pricing.

Given that we have estimates for 10 quantiles (Section 4.1, Table 2), we compute $D^p(\beta)=(1/10)\Sigma_\iota|p(q_i(Q_0,P_0,\beta),\beta) - p(Q_0, \beta)|$. We then obtain $\varepsilon^{q,p}$ for the 11 pair-wise comparisons between regimes discussed above. The resulting elasticities range between 0.2 and 0.6. This implies that, on average, a 10 percent increase in price variability leads to a reduction of between 2 and 6 percent in occupancy variability. Similar results are obtained with $D^p(\beta)$ and with $D^q(\beta)$ obtained using the results of Section 4.2.

To illustrate the magnitude of the absolute variability in both occupancy and price, we compare regimes 1 and 12. The average absolute deviation of occupancy rate from Q_0 is 47% and 31% respectively for regimes 1 and 12 (see also Figure 4, panel 1), or 175 and 115 computer terminals respectively. The average absolute deviation of price from P_0 is 5 FF and 13 FF respectively. The resulting arc elasticity $\varepsilon^{q,p}$ is 0.4.

To put this figure into perspective, note that the magnitude of the amount of price variations is large but not extraordinary. In fact, recall that the amount of price variations in our case study is of the same order of magnitude as the amount of price variation observed in the airline industry (Borenstein and Rose 1994) or presented in the survey scenarios used to assess consumer fairness attitudes (Kahneman et al., 1986). To conclude, these figures indicate that, in our case study, large efficiency gains could be captured by price variation within a range of magnitude already applied in some industries.

5 Concluding Remarks

We find that the distribution of occupancy is more compressed for more responsive pricing regimes. We interpret this as the result of consumers reacting to responsive pricing and conclude that responsive pricing can indeed smooth demand, as conjectured by Vickrey.

This research is not without limitations. To start, our study of responsive pricing focuses on a specific environment. Our evidence suggests that it should be possible to design a scheme that maintains an occupancy level close to a given level in our case study, but it is not clear whether responsive pricing would also smooth demand in different contexts with different sets of consumers. A second concern with our results is that there could be other responses to responsive pricing that do not appear when one considers only compression of the distribution of occupancy as we do in this study. For example, the use of responsive pricing may deter some consumers from returning to a store and the overall distribution of occupancy may shift to the left. We investigate this issue in a separate line of research (Courty and Pagliero, 2007), where we do not find negative demand responses to an increase in the responsiveness parameter.

Finally, our study does not address welfare issues. In order to compute the welfare gains from responsive pricing, one needs to model consumer behavior in the presence of congestion externalities. In principle, the welfare gain from demand smoothing could be high, since unused capacity and rationing are likely to take place under fixed pricing. The contribution of this work is to show that demand smoothing, the mechanism behind Vickrey's proposal, does work in practice. The next step would be to incorporate welfare calculations in order to investigate, for example, how welfare depends on the responsiveness parameter.

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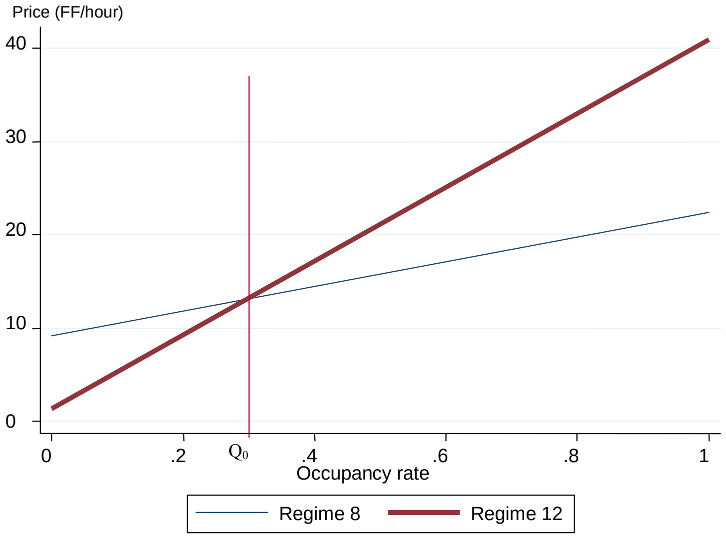
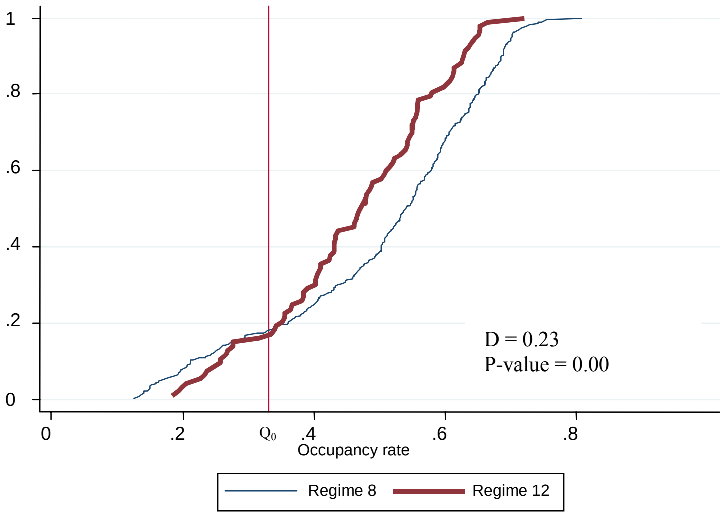
Figure 1: Examples of Pricing Functions (regime 8 and 12)



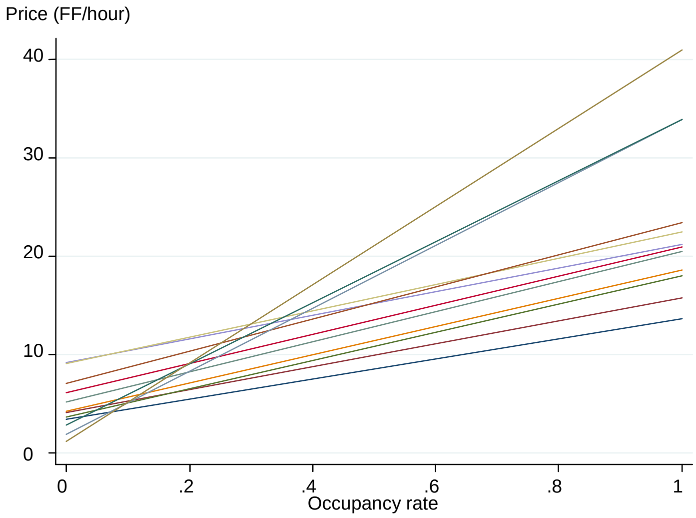
Note: The figure reports linear approximations of the pricing curves (see Table 1). The price is measured in French Francs / hour. The occupancy rate is the hourly average number of computers used divided by the total number of computers in the store.

Figure 2. Empirical Cumulative Distribution Functions (regimes 8 and 12)



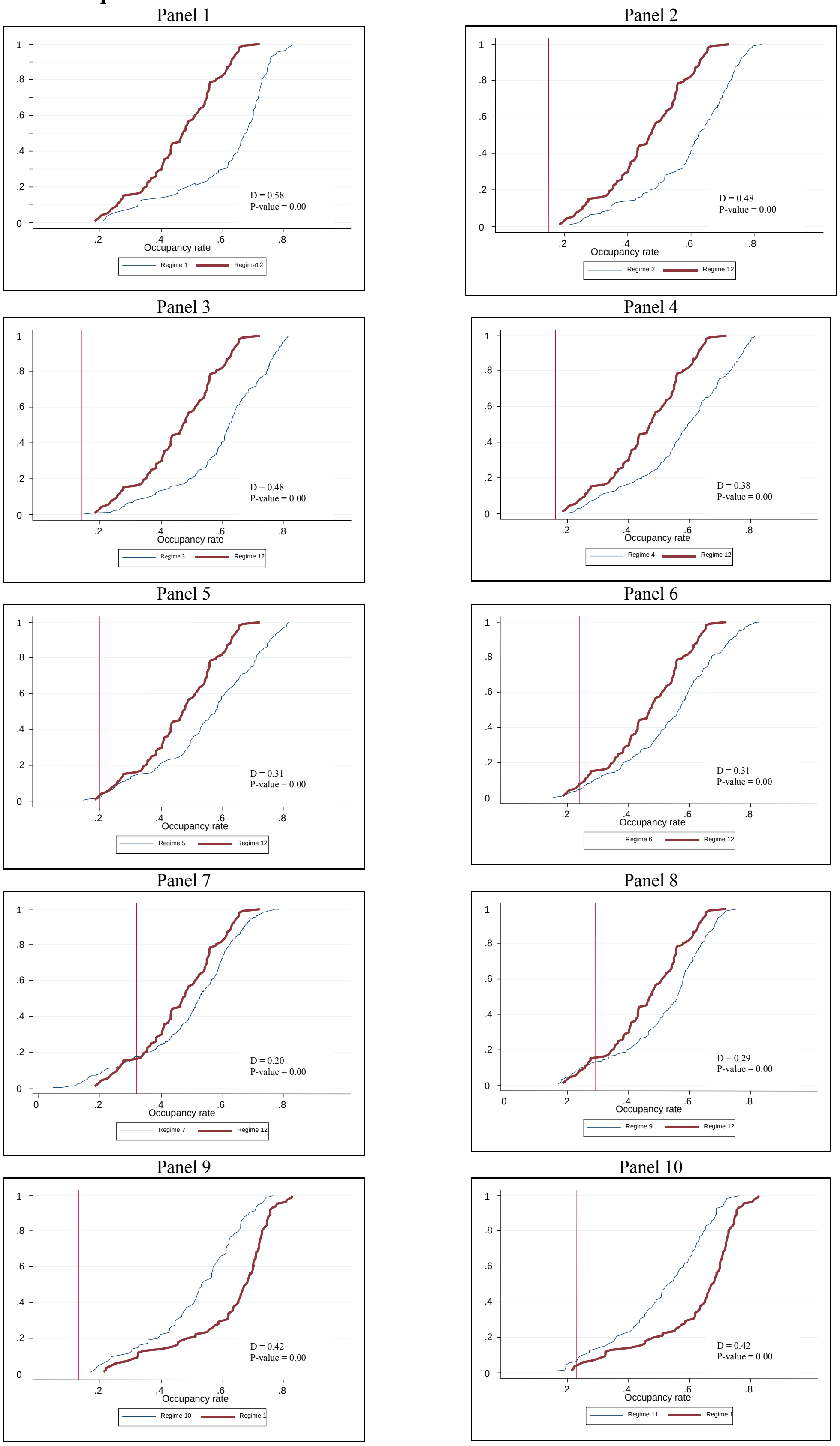
Note: The figure reports the empirical cumulative distribution function of the occupancy rate for regimes 8 and 12. The occupancy rate is the hourly average number of computers used divided by the total number of computers in the store. D is the maximum vertical distance between the two empirical distributions (Kolmogorov-Smirnov statistic).

Figure 3. Pricing Curves



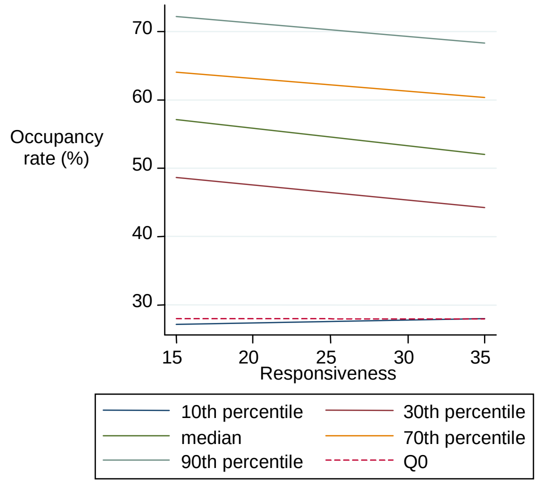
Note: The figure reports linear approximations of the pricing curves (see Table 1). The price is measured in French Francs / hour. The occupancy rate is the hourly average number of computers used divided by the total number of computers in the store.

Figure 4. Empirical Cumulative Distribution Functions



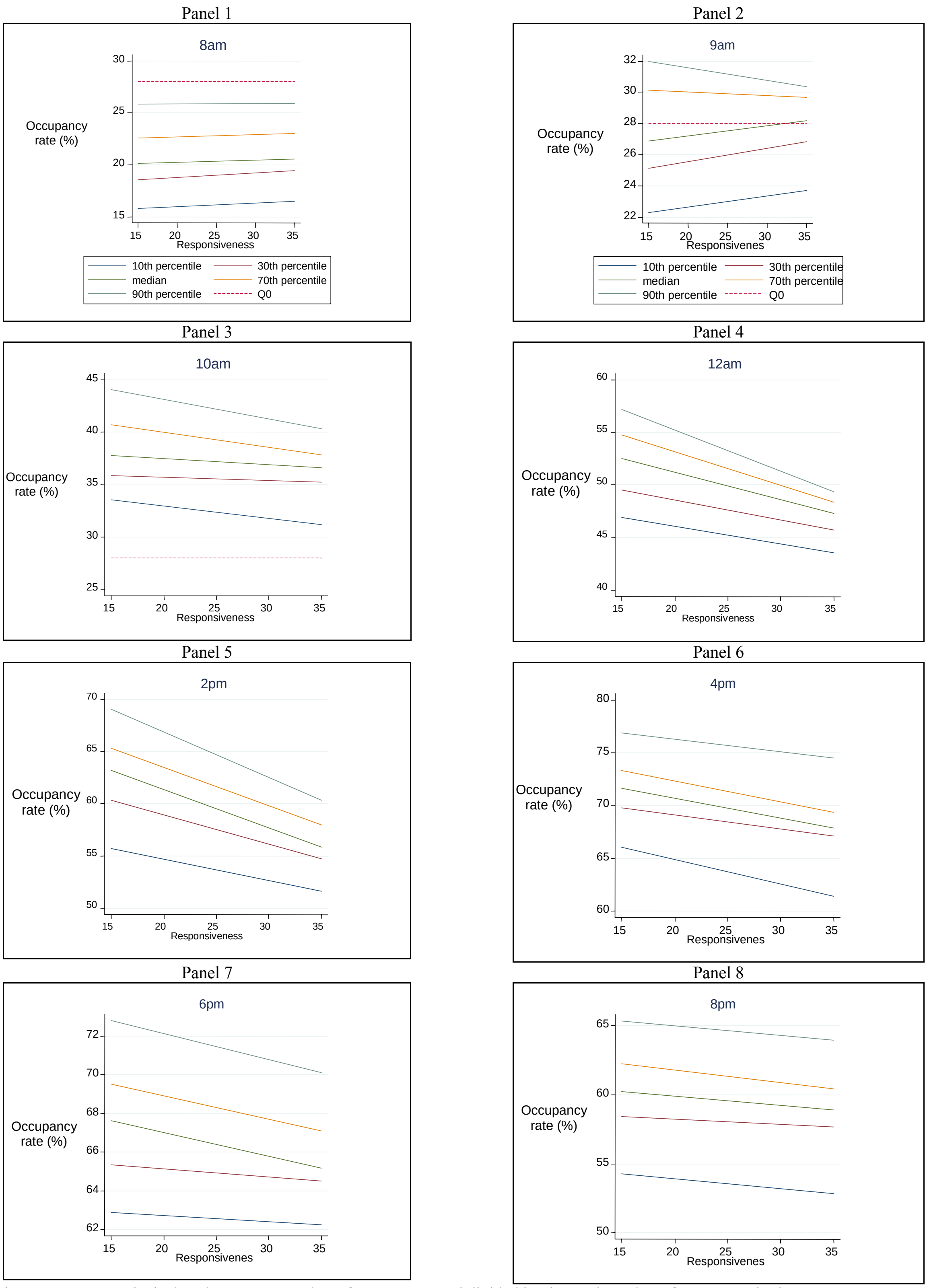
Note: The figure compares pairs of regimes for which the difference in responsiveness is larger than 22. This singles out 11 pairs: regimes 1 to 9 crossed with regime 12, and regimes 10 and 11 crossed with regime 1. The comparison of regimes 8 and 12 is reported in Figure 2. Each pricing function in our sample is represented at least once. The vertical axis denotes the fraction of hourly observations for which the occupancy rate is below the corresponding level reported on the horizontal axis. The occupancy rate is the hourly average number of computers used divided by the total number of computers in the store. D is the maximum vertical distance between the two empirical distributions (Kolmogorov-Smirnov statistic).

Figure 5. Simulated Quantiles (Q_0 = 0.28)



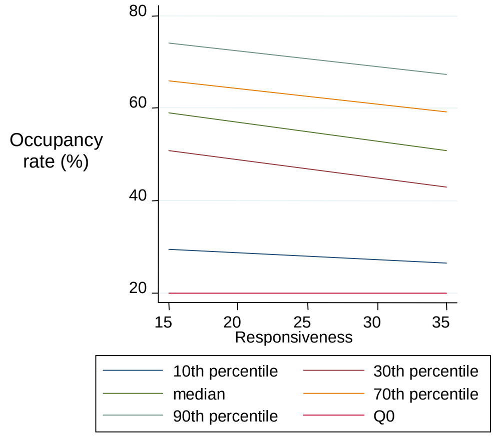
Note: The occupancy rate is the hourly average number of computers used divided by the total number of computers in the store. Responsiveness is the slope of the pricing function.

Figure 6. Simulated Quantiles (Hour of Day Interactions and Q_0 = 0.28)



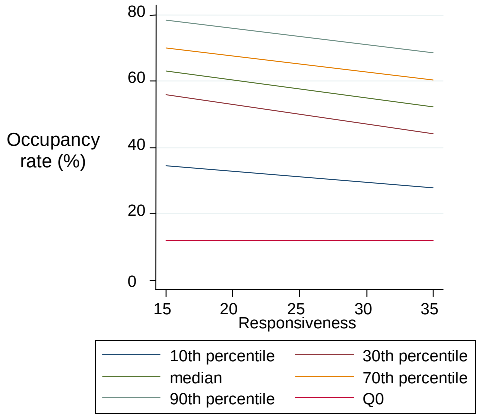
Note: The occupancy rate is the hourly average number of computers used divided by the total number of computers in the store. Responsiveness is the slope of the pricing function. The predicted quantile correspond to Thursday, with no national holiday.

Figure 7. Simulated Quantiles (Q_0 = 0.2, P_0=7.6)



Note: The occupancy rate is the hourly average number of computers used divided by the total number of computers in the store. Responsiveness is the slope of the pricing function.

Figure 8. Simulated Quantiles (Q_0 = 0.12, P_0=4.2)



Note: The occupancy rate is the hourly average number of computers used divided by the total number of computers in the store. Responsiveness is the slope of the pricing function.

Table 1. Summary Statistics

Regime	Number of observations	Length of the regime (days)	Responsiveness (R^2)	Mean occupancy rate	S.d. occupancy rate	Mean Price	S.d. Price
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1	85	6	10.733 (0.99)	0.618	0.160	9.616	1.757
2	110	7	12.235 (0.99)	0.596	0.149	10.773	1.794
3	221	15	15.098 (0.99)	0.600	0.150	12.085	2.320
4	208	15	15.141 (0.99)	0.578	0.159	12.344	2.518
5	183	11	16.090 (0.95)	0.550	0.171	12.906	2.747
6	224	16	15.536 (0.96)	0.539	0.159	13.642	2.463
7	444	28	12.670 (0.75)	0.492	0.161	14.477	2.887
8	342	22	14.082 (0.83)	0.501	0.165	15.419	3.010
9	196	13	17.272 (0.87)	0.516	0.148	15.176	3.168
10	94	6	33.722 (0.96)	0.513	0.152	17.519	5.151
11	112	7	32.782 (0.95)	0.509	0.154	18.306	5.189
12	93	6	41.879 (0.99)	0.461	0.131	18.714	5.492
All Regimes	2,312	12.667	17.112	0.533	0.163	14.174	3.808

Note: The responsiveness of each pricing regime is measured by the slope of the pricing curve; the slope is estimated by regressing (OLS) the price in each step on the occupancy rate at the midpoint of each step (the R^2 is reported in parentheses); in estimating the slope of the pricing curves we do not consider occupancy levels that are not reached in the sample. "S.d. occupancy rate" and "s.d. price" are the standard deviation of the occupancy rate observed and the price. The table includes observations for hours between 8 am and 12 midnight.

Table 2. The Impact of Regimes on Quantiles of the Occupancy Distribution

	Occupancy Rate (%)					
	Quantile 0.05	**Quantile 0.10**	**Quantile 0.30**	**Quantile 0.50**	**Quantile 0.70**	**Quantile 0.90**
Regime 2	2.610	2.340	-5.690	-5.530	-2.330	-0.220
	(6.652)	(10.023)	(4.710)	(2.559)**	(1.279)*	(1.801)
Regime 3	3.300	4.620	-6.250	-5.720	-3.280	1.670
	(5.424)	(9.318)	(3.449)*	(1.710)***	(1.697)*	(1.372)
Regime 4	1.610	-1.720	-9.830	-8.610	-3.190	1.920
	(4.980)	(9.145)	(2.707)***	(1.823)***	(1.458)**	(1.105)*
Regime 5	-3.060	-5.770	-13.020	-10.170	-5.500	0.140
	(4.855)	(8.002)	(2.524)***	(2.188)***	(1.439)***	(1.708)
Regime 6	-0.560	-3.750	-14.000	-11.390	-7.970	-1.390
	(5.257)	(9.072)	(3.185)***	(1.802)***	(1.384)***	(2.114)
Regime 7	-9.110	-10.860	-17.330	-15.470	-12.580	-8.360
	(5.100)*	(8.355)	(2.616)***	(1.573)***	(0.961)***	(1.333)***
Regime 8	-8.060	-11.160	-18.020	-13.970	-11.190	-6.890
	(5.570)	(8.313)	(3.181)***	(1.652)***	(1.365)***	(1.315)***
Regime 9	-3.890	-7.000	-14.910	-12.050	-10.640	-7.280
	(5.286)	(8.621)	(3.100)***	(2.328)***	(1.698)***	(1.418)***
Regime 10	-4.340	-5.770	-16.550	-14.830	-10.530	-6.750
	(5.950)	(8.032)	(3.079)***	(2.586)***	(1.984)***	(2.365)***
Regime 11	-4.480	-6.440	-17.770	-14.750	-9.910	-6.720
	(5.285)	(8.387)	(3.615)***	(3.373)***	(1.662)***	(1.731)***
Regime 12	-2.200	-6.660	-21.440	-20.640	-16.780	-12.610
	(5.733)	(8.708)	(3.700)***	(2.549)***	(1.238)***	(1.587)***
constant	24.920	32.440	61.580	67.860	71.720	75.470
	(5.090)***	(8.459)***	(2.447)***	(1.488)***	(0.750)***	(1.207)***

Note: The table reports the LAD quantile regression coefficients of model (2), for the 5th, 10th, 30th, 50th, 70th and 90th percentiles of the occupancy distribution. The independent variables are regime specific indicator variables (regime 1 omitted). Bootstrap standard errors (with 20 replications) are reported in parentheses. The number of observations is 2,312. The results for the other deciles of the distribution are reported in the Additional Materials section.

* Significant at the 10 percent level.

** Significant at the 5 percent level.

*** Significant at the 1 percent level.

Table 3. Test of Equality of Quantiles between Pairs of Regimes with the Highest Differences in Responsiveness

	Pairs of regimes to be compared							
	2 and 12	3 and 13	4 and 12	5 and 12	6 and 12	7 and 12	8 and 12	9 and 12
Quantile 0.05								
F(1, 2300) =	2.41	3.41	1.66	0.07	0.24	6.50	4.25	0.38
P-value	(0.12)	(0.06)	(0.20)	(0.80)	(0.63)	(0.01)	(0.04)	(0.54)
Quantile 0.10								
F(1, 2300) =	2.30	3.53	2.24	0.37	0.92	0.18	0.07	0.26
P-value	(0.13)	(0.06)	(0.13)	(0.54)	(0.34)	(0.67)	(0.80)	(0.61)
Quantile 0.30								
F(1, 2300) =	39.62	30.39	19.90	12.32	16.84	6.22	7.02	13.53
P-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
Quantile 0.50								
F(1, 2300) =	50.45	37.04	22.13	12.94	18.37	7.04	7.12	16.07
P-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
Quantile 0.70								
F(1, 2300) =	28.49	24.81	16.02	8.54	12.20	3.24	3.42	9.36
P-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.07)	(0.06)	(0.00)
Quantile 0.90								
F(1, 2300) =	17.79	17.01	10.65	4.55	7.15	0.74	0.98	4.48
P-value	(0.00)	(0.00)	(0.00)	(0.03)	(0.01)	(0.39)	(0.32)	(0.03)

Note: the table reports the F-test and P-value for the equality of the 5th, 10th, 30th, 50th, 70th and 90th percentiles of the occupancy distribution for pairs of regimes. The tests are based on the estimates in Table 2. The table does not report the F-tests for the pairs of regimes (1, 12) and (1, 11) because such a comparison can be made using the results in Table 2. The results for the other deciles of the distribution are reported in the Additional Materials section.

Table 4. The Impact of the Responsiveness of the Pricing Function on Occupancy Distribution

	Quantile 0.1	**Quantile 0.3**	**Quantile 0.5**	**Quantile 0.7**	**Quantile 0.9**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Responsiveness β	0.037	-0.223	-0.249	-0.185	-0.192
	(0.075)	(0.055)***	(0.050)***	(0.049)***	(0.048)***
P0	-2.317	-2.216	-1.903	-1.896	-1.902
	(0.519)***	(0.338)***	(0.204)***	(0.177)***	(0.167)***
Constant	49.379	73.729	79.426	85.319	93.711
	(5.135)***	(3.560)***	(2.529)***	(2.163)***	(1.656)***

NOTE: The dependent variable is the quantile q_y of the occupancy rate distribution (%), y=0.1, 0.3, 0.5, 0.7, 0.9. Responsiveness is the slope of the pricing curve in each regime; Q_0=0.28. The number of observations in the sample is 2,312. Bootstrap standard errors (with 20 replications) are reported in parentheses.
* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

Table 5. The Impact of Responsiveness of the Pricing Function on the Quantiles of the Conditional Occupancy Distribution

	Occupancy Distribution				
	Quantile 0.1	**Quantile 0.3**	**Quantile 0.5**	**Quantile 0.7**	**Quantile 0.9**
Responsiveness * h8	0.074	0.086	0.041	0.045	0.005
	(0.062)	(0.036)**	(0.021)**	(0.074)	(0.083)
Responsiveness * h9	0.073	0.084	0.064	-0.025	-0.082
	(0.065)	(0.085)	(0.048)	(0.029)	(0.030)***
Responsiveness * h10	-0.117	-0.034	-0.059	-0.143	-0.187
	(0.091)	(0.056)	(0.039)	(0.032)***	(0.035)***
Responsiveness * h11	-0.049	-0.138	-0.227	-0.260	-0.346
	(0.070)	(0.032)***	(0.045)***	(0.056)***	(0.068)***
Responsiveness * h12	-0.165	-0.187	-0.264	-0.320	-0.394
	(0.055)***	(0.042)***	(0.058)***	(0.053)***	(0.102)***
Responsiveness * h13	-0.200	-0.232	-0.265	-0.379	-0.393
	(0.085)**	(0.049)***	(0.042)***	(0.050)***	(0.139)***
Responsiveness * h14	-0.206	-0.278	-0.367	-0.366	-0.437
	(0.070)***	(0.063)***	(0.072)***	(0.049)***	(0.054)***
Responsiveness * h15	-0.218	-0.293	-0.335	-0.292	-0.359
	(0.083)***	(0.067)***	(0.062)***	(0.083)***	(0.054)***
Responsiveness * h16	-0.233	-0.134	-0.189	-0.201	-0.119
	(0.116)**	(0.071)*	(0.043)***	(0.056)***	(0.100)
Responsiveness * h17	0.006	-0.162	-0.172	-0.167	-0.197
	(0.073)	(0.047)***	(0.040)***	(0.070)**	(0.038)***
Responsiveness * h18	-0.032	-0.042	-0.123	-0.121	-0.135
	(0.085)	(0.020)**	(0.054)**	(0.083)	(0.051)***
Responsiveness * h19	-0.125	-0.159	-0.075	-0.084	-0.164
	(0.050)**	(0.087)*	(0.074)	(0.060)	(0.173)
Responsiveness * h20	-0.069	-0.038	-0.066	-0.090	-0.070
	(0.114)	(0.041)	(0.047)	(0.046)**	(0.080)
Responsiveness * h21	-0.130	-0.156	-0.161	-0.116	-0.080
	(0.057)**	(0.050)***	(0.083)*	(0.064)*	(0.085)
Responsiveness * h22	-0.097	-0.167	-0.225	-0.230	-0.221
	(0.064)	(0.044)***	(0.055)***	(0.073)***	(0.096)**
Responsiveness * h23	-0.164	-0.168	-0.237	-0.318	-0.482
	(0.104)	(0.057)***	(0.033)***	(0.035)***	(0.053)***
P_0 * hour interactions?	Yes	Yes	Yes	Yes	Yes
Hour fixed effects?	Yes	Yes	Yes	Yes	Yes
Day fixed effects?	Yes	Yes	Yes	Yes	Yes
Weekend cycle?	Yes	Yes	Yes	Yes	Yes
Holiday fixed effects?	Yes	Yes	Yes	Yes	Yes

Note: The dependent variable is the quantile q_y of the occupancy rate distribution (%), y=0.1, 0.3, 0.5, 0.7, 0.9. Responsiveness is the slope of the pricing curve in each regime. The coefficients for the level of the pricing function (with hour interactions), hour of day, day of the week, holiday periods, and weekend cycle are not reported in the table. The number of observations is 2,312. Bootstrap standard errors (with 20 replications) are reported in parentheses.
* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

ADDITIONAL MATERIALS

Table A1. Tests for Equality of Variance of Price (F-tests)

Regime	1	2	3	4	5	6	7	8	9	10	11
2	0.96 (0.85)										
3	0.57 (0.00)	0.60 (0.00)									
4	0.49 (0.00)	0.51 (0.00)	0.85 (0.23)								
5	0.41 (0.00)	0.43 (0.00)	0.71 (0.02)	0.84 (0.22)							
6	0.51 (0.00)	0.53 (0.00)	0.89 (0.37)	1.04 (0.75)	1.24 (0.12)						
7	0.37 (0.00)	0.39 (0.00)	0.65 (0.00)	0.76 (0.02)	0.91 (0.43)	0.73 (0.01)					
8	0.34 (0.00)	0.36 (0.00)	0.59 (0.00)	0.70 (0.00)	0.83 (0.16)	0.67 (0.00)	0.92 (0.41)				
9	0.31 (0.00)	0.32 (0.00)	0.54 (0.00)	0.63 (0.00)	0.75 (0.05)	0.60 (0.00)	0.83 (0.12)	0.90 (0.41)			
10	0.12 (0.00)	0.12 (0.00)	0.20 (0.00)	0.24 (0.00)	0.28 (0.00)	0.23 (0.00)	0.31 (0.00)	0.34 (0.00)	0.38 (0.00)		
11	0.11 (0.00)	0.12 (0.00)	0.20 (0.00)	0.24 (0.00)	0.28 (0.00)	0.23 (0.00)	0.31 (0.00)	0.34 (0.00)	0.37 (0.00)	0.99 (0.95)	
12	0.10 (0.00)	0.11 (0.00)	0.18 (0.00)	0.21 (0.00)	0.25 (0.00)	0.20 (0.00)	0.28 (0.00)	0.30 (0.00)	0.33 (0.00)	0.88 (0.54)	0.89 (0.56)

Note: The table reports the test for equality of variance across pairs of regimes. The test is the ratio of the variance of price for the column regime and the row regime. The degrees of freedom (N_1-1, N_2-1) can be computed for each test using the number of observations for each regime in Table 1. P-values are reported in parenthesis.

Table A2. The impact of regimes on quantiles of the occupancy distribution (extended version of Table 2 in the paper)

	Occupancy Rate (%)				
	Quantile 0.05	**Quantile 0.10**	**Quantile 0.20**	**Quantile 0.30**	**Quantile 0.40**
Regime 2	2.610	2.340	-2.270	-5.690	-5.140
	(6.652)	(10.023)	(8.378)	(4.710)	(2.382)**
Regime 3	3.300	4.620	-1.000	-6.250	-5.390
	(5.424)	(9.318)	(6.651)	(3.449)*	(2.279)**
Regime 4	1.610	-1.720	-6.640	-9.830	-9.390
	(4.980)	(9.145)	(6.874)	(2.707)***	(1.565)***
Regime 5	-3.060	-5.770	-11.580	-13.020	-12.370
	(4.855)	(8.002)	(6.361)*	(2.524)***	(1.873)***
Regime 6	-0.560	-3.750	-12.610	-14.000	-12.840
	(5.257)	(9.072)	(7.100)*	(3.185)***	(2.129)***
Regime 7	-9.110	-10.860	-15.500	-17.330	-15.700
	(5.100)*	(8.355)	(6.674)**	(2.616)***	(1.706)***
Regime 8	-8.060	-11.160	-15.110	-18.020	-14.810
	(5.570)	(8.313)	(7.419)**	(3.181)***	(1.602)***
Regime 9	-3.890	-7.000	-11.160	-14.910	-13.670
	(5.286)	(8.621)	(7.280)	(3.100)***	(2.473)***
Regime 10	-4.340	-5.770	-12.190	-16.550	-14.200
	(5.950)	(8.032)	(6.629)*	(3.079)***	(3.201)***
Regime 11	-4.480	-6.440	-14.970	-17.770	-16.060
	(5.285)	(8.387)	(7.683)*	(3.615)***	(3.263)***
Regime 12	-2.200	-6.660	-16.000	-21.440	-22.090
	(5.733)	(8.708)	(8.468)*	(3.700)***	(2.431)***
Constant	24.920	32.440	51.080	61.580	65.060
	(5.090)***	(8.459)***	(6.528)***	(2.447)***	(1.503)***

(Continued on next page)

Table A2. (continued) The impact of regimes on quantiles of the occupancy distribution (extended version of Table 2 in the paper)

	Quantile **0.**50	Quantile **0.**60	Quantile **0.**70	Quantile **0.**80	Quantile **0.**90
Regime 2	-5.530	-3.500	-2.330	-0.280	-0.220
	(2.559)**	(1.981)*	(1.279)*	(1.283)	(1.801)
Regime 3	-5.720	-5.330	-3.280	1.410	1.670
	(1.710)***	(1.197)***	(1.697)*	(1.082)	(1.372)
Regime 4	-8.610	-6.470	-3.190	0.250	1.920
	(1.823)***	(1.192)***	(1.458)**	(1.463)	(1.105)*
Regime 5	-10.170	-9.250	-5.500	-1.980	0.140
	(2.188)***	(1.382)***	(1.439)***	(1.096)*	(1.708)
Regime 6	-11.390	-10.360	-7.970	-5.670	-1.390
	(1.802)***	(1.544)***	(1.384)***	(2.052)***	(2.114)
Regime 7	-15.470	-13.550	-12.580	-10.640	-8.360
	(1.573)***	(1.086)***	(0.961)***	(1.078)***	(1.333)***
Regime 8	-13.970	-12.000	-11.190	-7.920	-6.890
	(1.652)***	(1.085)***	(1.365)***	(1.297)***	(1.315)***
Regime 9	-12.050	-12.050	-10.640	-9.140	-7.280
	(2.328)***	(1.389)***	(1.698)***	(1.587)***	(1.418)***
Regime 10	-14.830	-12.750	-10.530	-7.530	-6.750
	(2.586)***	(2.577)***	(1.984)***	(1.443)***	(2.365)***
Regime 11	-14.750	-11.770	-9.910	-7.890	-6.720
	(3.373)***	(2.514)***	(1.662)***	(1.499)***	(1.731)***
Regime 12	-20.640	-19.020	-16.780	-14.950	-12.610
	(2.549)***	(2.335)***	(1.238)***	(2.579)***	(1.587)***
constant	67.860	69.940	71.720	72.920	75.470
	(1.488)***	(1.007)***	(0.750)***	(0.895)***	(1.207)***

Note: The table is an extended version of Table 2 in the paper. The table reports the LAD quantile regression coefficients of model (2), for the 5th percentile and the 9 deciles of the occupancy distribution. The independent variables are regime specific indicator variables (regime 1 omitted). Bootstrap standard errors (with 20 replications) are reported in parentheses. The number of observations is 2,312.

* Significant at the 10 percent level.

** Significant at the 5 percent level.

*** Significant at the 1 percent level.

Table A3. Test of equality of quantiles between pairs of regimes with the highest differences in responsiveness. (extended version of Table 3 in the paper)

	Pairs of regimes to be compared							
	2 and 12	3 and 13	4 and 12	5 and 12	6 and 12	7 and 12	8 and 12	9 and 12
Quantile 0.05								
F(1, 2300) =	2.41	3.41	1.66	0.07	0.24	6.50	4.25	0.38
P-value	0.12	0.06	0.20	0.80	0.63	0.01	0.04	0.54
Quantile 0.10								
F(1, 2300) =	2.30	3.53	2.24	0.37	0.92	0.18	0.07	0.26
P-value	0.13	0.06	0.13	0.54	0.34	0.67	0.80	0.61
Quantile 0.20								
F(1, 2300) =	8.82	8.22	5.09	2.63	3.80	0.85	0.98	2.85
P-value	0.00	0.00	0.02	0.11	0.05	0.36	0.32	0.09
Quantile 0.30								
F(1, 2300) =	39.62	30.39	19.90	12.32	16.84	6.22	7.02	13.53
P-value	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00
Quantile 0.40								
F(1, 2300) =	57.52	49.70	27.49	16.11	23.71	9.80	10.10	22.04
P-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Quantile 0.50								
F(1, 2300) =	50.45	37.04	22.13	12.94	18.37	7.04	7.12	16.07
P-value	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00
Quantile 0.60								
F(1, 2300) =	48.14	32.09	19.20	10.87	15.72	5.15	5.40	13.00
P-value	0.00	0.00	0.00	0.00	0.00	0.02	0.02	0.00
Quantile 0.70								
F(1, 2300) =	28.49	24.81	16.02	8.54	12.20	3.24	3.42	9.36
P-value	0.00	0.00	0.00	0.00	0.00	0.07	0.06	0.00
Quantile 0.80								
F(1, 2300) =	16.60	14.07	9.61	4.89	7.03	1.34	1.59	4.72
P-value	0.00	0.00	0.00	0.03	0.01	0.25	0.21	0.03
Quantile 0.90								
F(1, 2300) =	17.79	17.01	10.65	4.55	7.15	0.74	0.98	4.48
P-value	0.00	0.00	0.00	0.03	0.01	0.39	0.32	0.03

Note: the table reports the F-test and P-value for the equality of the 5th percentile and the 9 deciles of the occupancy distribution for pairs of regimes. The tests are based on the estimates in Table A2. The table does not report the F-tests for the pairs of regimes (1, 12) and (1, 11) because such a comparison can be made using the results in Table 2.

Table A4. The impact of the responsiveness of the pricing function on occupancy distribution (Q_0=0.2)

	Quantile 0.1	Quantile 0.3	Quantile 0.5	Quantile 0.7	Quantile 0.9
	(1)	(2)	(3)	(4)	(5)
Responsiveness b	-0.401	-0.337	-0.400	-0.344	-0.148
	(0.071)***	(0.043)***	(0.042)***	(0.070)**	(0.031)***
P0	-2.317	-1.896	-1.902	-2.216	-1.903
	(0.133)***	(0.269)***	(0.337)***	(0.155)***	(0.150)***
Constant	79.426	73.729	85.319	93.711	49.379
	(3.145)***	(1.653)***	(3.718)***	(1.528)***	(1.501)***

NOTE: The dependent variable is the quantile q_y of the occupancy rate distribution (%), y=0.1, 0.3, 0.5, 0.7, 0.9. Responsiveness is the slope of the pricing curve in each regime; Q_0=0.2. The number of observations in the sample is 2,312. Bootstrap standard errors are reported in parentheses.
* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

Table A5. The impact of the responsiveness of the pricing function on occupancy distribution (Q_0=0.12)

	Quantile 0.1	Quantile 0.3	Quantile 0.5	Quantile 0.7	Quantile 0.9
	(1)	(2)	(3)	(4)	(5)
Responsiveness b	-0.334	-0.578	-0.553	-0.489	-0.496
	(0.100)***	(0.070)***	(0.065)***	(0.052)***	(0.032)***
P0	-2.317	-2.216	-1.903	-1.896	-1.902
	(0.452)***	(0.281)***	(0.157)***	(0.104)***	(0.117)***
Constant	49.379	73.729	79.426	85.319	93.711
	(4.783)***	(2.898)***	(1.961)***	(1.394)***	(1.326)***

NOTE: The dependent variable is the quantile q_y of the occupancy rate distribution (%), y=0.1, 0.3, 0.5, 0.7, 0.9. Responsiveness is the slope of the pricing curve in each regime; Q_0=0.12. The number of observations in the sample is 2312. Bootstrap standard errors are reported in parentheses.
* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

Table A6. The impact of responsiveness of the pricing function on the quantiles of the conditional occupancy distribution (Q_0=0.2)

	Occupancy Distribution				
	Quantile 0.1	**Quantile 0.3**	**Quantile 0.5**	**Quantile 0.7**	**Quantile 0.9**
Responsiveness * h8	-0.055	-0.064	-0.134	-0.146	-0.166
	(0.080)	(0.056)	(0.048)***	(0.061)**	(0.063)***
Responsiveness * h9	-0.065	-0.089	-0.134	-0.224	-0.281
	(0.068)	(0.062)	(0.027)***	(0.046)***	(0.053)***
Responsiveness * h10	-0.320	-0.247	-0.265	-0.355	-0.409
	(0.093)***	(0.041)***	(0.056)***	(0.041)***	(0.054)***
Responsiveness * h11	-0.256	-0.383	-0.450	-0.478	-0.547
	(0.060)***	(0.039)***	(0.026)***	(0.046)***	(0.053)***
Responsiveness * h12	-0.383	-0.391	-0.454	-0.493	-0.530
	(0.045)***	(0.041)***	(0.044)***	(0.050)***	(0.093)***
Responsiveness * h13	-0.357	-0.410	-0.436	-0.549	-0.550
	(0.078)***	(0.066)***	(0.040)***	(0.044)***	(0.076)***
Responsiveness * h14	-0.374	-0.445	-0.570	-0.566	-0.595
	(0.083)***	(0.089)***	(0.060)***	(0.059)***	(0.076)***
Responsiveness * h15	-0.367	-0.472	-0.523	-0.458	-0.500
	(0.097)***	(0.085)***	(0.086)***	(0.089)***	(0.071)***
Responsiveness * h16	-0.366	-0.281	-0.333	-0.347	-0.225
	(0.104)***	(0.096)***	(0.043)***	(0.064)***	(0.112)**
Responsiveness * h17	-0.172	-0.300	-0.307	-0.312	-0.334
	(0.044)***	(0.054)***	(0.074)***	(0.099)***	(0.069)***
Responsiveness * h18	-0.168	-0.184	-0.274	-0.262	-0.279
	(0.085)**	(0.053)***	(0.061)***	(0.068)***	(0.060)***
Responsiveness * h19	-0.241	-0.301	-0.236	-0.267	-0.320
	(0.046)***	(0.073)***	(0.053)***	(0.037)***	(0.197)
Responsiveness * h20	-0.191	-0.178	-0.194	-0.239	-0.203
	(0.100)*	(0.070)**	(0.052)***	(0.057)***	(0.086)**
Responsiveness * h21	-0.225	-0.299	-0.290	-0.248	-0.234
	(0.071)***	(0.068)***	(0.090)***	(0.051)***	(0.097)**
Responsiveness * h22	-0.216	-0.303	-0.361	-0.367	-0.358
	(0.108)**	(0.056)***	(0.057)***	(0.095)***	(0.103)***
Responsiveness * h23	-0.283	-0.297	-0.373	-0.482	-0.698
	(0.075)***	(0.058)***	(0.034)***	(0.057)***	(0.027)***
P_0 * hour interactions?	Yes	Yes	Yes	Yes	Yes
Hour fixed effects?	Yes	Yes	Yes	Yes	Yes
Day fixed effects?	Yes	Yes	Yes	Yes	Yes
Weekend cycle?	Yes	Yes	Yes	Yes	Yes
Holiday fixed effects?	Yes	Yes	Yes	Yes	Yes

Note: The dependent variable is the quantile $q_y$of the occupancy rate distribution (%), y=0.1, 0.3, 0.5, 0.7, 0.9. Responsiveness is the slope of the pricing curve in each regime. The coefficients for the level of the pricing function (with hour interactions), hour of day, day of the week, holiday periods, and weekend cycle are not reported in the table. The number of observations in the sample is 2,312. Bootstrap standard errors are reported in parentheses.

* Significant at the 10 percent level.

** Significant at the 5 percent level.

*** Significant at the 1 percent level.

Table A7. The impact of responsiveness of the pricing function on the quantiles of the conditional occupancy distribution (Q_0=0.12)

	Occupancy Distribution				
	Quantile 0.1	**Quantile 0.3**	**Quantile 0.5**	**Quantile 0.7**	**Quantile 0.9**
Responsiveness * h8	-0.183	-0.213	-0.310	-0.336	-0.338
	(0.091)**	(0.056)***	(0.050)***	(0.071)***	(0.069)***
Responsiveness * h9	-0.202	-0.262	-0.333	-0.424	-0.480
	(0.107)*	(0.090)***	(0.055)***	(0.064)***	(0.046)***
Responsiveness * h10	-0.522	-0.461	-0.470	-0.568	-0.630
	(0.066)***	(0.044)***	(0.053)***	(0.039)***	(0.062)***
Responsiveness * h11	-0.463	-0.628	-0.673	-0.697	-0.748
	(0.125)***	(0.070)***	(0.049)***	(0.071)***	(0.070)***
Responsiveness * h12	-0.600	-0.596	-0.644	-0.667	-0.665
	(0.042)***	(0.049)***	(0.040)***	(0.043)***	(0.096)***
Responsiveness * h13	-0.513	-0.588	-0.607	-0.719	-0.706
	(0.068)***	(0.067)***	(0.047)***	(0.042)***	(0.162)***
Responsiveness * h14	-0.542	-0.612	-0.772	-0.766	-0.754
	(0.082)***	(0.071)***	(0.087)***	(0.080)***	(0.109)***
Responsiveness * h15	-0.515	-0.651	-0.711	-0.625	-0.641
	(0.122)***	(0.081)***	(0.089)***	(0.124)***	(0.088)***
Responsiveness * h16	-0.500	-0.428	-0.476	-0.493	-0.332
	(0.104)***	(0.109)***	(0.086)***	(0.069)***	(0.101)***
Responsiveness * h17	-0.349	-0.438	-0.441	-0.457	-0.472
	(0.147)**	(0.081)***	(0.061)***	(0.097)***	(0.068)***
Responsiveness * h18	-0.304	-0.326	-0.424	-0.403	-0.424
	(0.036)***	(0.039)***	(0.036)***	(0.073)***	(0.073)***
Responsiveness * h19	-0.357	-0.444	-0.397	-0.449	-0.476
	(0.085)***	(0.081)***	(0.071)***	(0.068)***	(0.183)***
Responsiveness * h20	-0.312	-0.318	-0.323	-0.388	-0.336
	(0.119)***	(0.094)***	(0.061)***	(0.079)***	(0.114)***
Responsiveness * h21	-0.321	-0.442	-0.419	-0.380	-0.388
	(0.108)***	(0.084)***	(0.099)***	(0.087)***	(0.133)***
Responsiveness * h22	-0.335	-0.438	-0.498	-0.505	-0.496
	(0.095)***	(0.060)***	(0.050)***	(0.067)***	(0.119)***
Responsiveness * h23	-0.401	-0.427	-0.510	-0.646	-0.914
	(0.118)***	(0.086)***	(0.106)***	(0.113)***	(0.046)***
P_0 * hour interactions?	Yes	Yes	Yes	Yes	Yes
Hour fixed effects?	Yes	Yes	Yes	Yes	Yes
Day fixed effects?	Yes	Yes	Yes	Yes	Yes
Weekend cycle?	Yes	Yes	Yes	Yes	Yes
Holiday fixed effects?	Yes	Yes	Yes	Yes	Yes

Note: The dependent variable is the quantile q_y of the occupancy rate distribution (%), y=0.1, 0.3, 0.5, 0.7, 0.9. Responsiveness is the slope of the pricing curve in each regime. The coefficients for the level of the pricing function (with hour interactions), hour of day, day of the week, holiday periods, and weekend cycle are not reported in the table. The number of observations in the sample is 2,312. Bootstrap standard errors are reported in parentheses.
* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

Table A8. The impact of the responsiveness of the pricing function on occupancy distribution (including time trend)

	Quantile 0.1	Quantile 0.3	Quantile 0.5	Quantile 0.7	Quantile 0.9
	(1)	(2)	(3)	(4)	(5)
Responsiveness b	0.106	-0.246	-0.396	-0.241	-0.131
	(0.178)	(0.091)***	(0.049)***	(0.083)***	(0.051)**
P0	-1.739	-2.359	-2.615	-2.104	-1.506
	(1.228)	(0.567)***	(0.296)***	(0.302)***	(0.282)***
Time trend (day)	-0.031	0.008	0.048	0.015	-0.023
	(0.057)	(0.032)	(0.017)***	(0.021)	(0.017)
Constant	44.956	74.967	85.480	87.130	90.454
	(6.771)***	(4.890)***	(2.993)***	(3.022)***	(2.672)***

NOTE: The dependent variable is the quantile q_y of the occupancy rate distribution (%), y=0.1, 0.3, 0.5, 0.7, 0.9. Responsiveness is the slope of the pricing curve in each regime; Q_0=0.28. Time trend is defined in days. The number of observations in the sample is 2,312. Bootstrap standard errors (with 20 replications) are reported in parentheses.
* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

Table A9. The impact of the responsiveness of the pricing function on occupancy distribution (including quadratic time trend)

	Quantile 0.1	Quantile 0.3	Quantile 0.5	Quantile 0.7	Quantile 0.9
	(1)	(2)	(3)	(4)	(5)
Responsiveness b	0.073	-0.323	-0.457	-0.239	-0.068
	(0.165)	(0.128)**	(0.090)***	(0.085)***	(0.047)
P0	-1.108	-0.931	-1.856	-2.020	-2.347
	(1.035)	(0.988)	(0.561)***	(0.502)***	(0.427)***
Time trend (day)	-0.159	-0.244	-0.113	0.002	0.159
	(0.166)	(0.126)*	(0.081)	(0.074)	(0.066)**
Time trend^2 (day^2)	0.001	0.001	0.001	0.000	-0.001
	(0.001)	(0.001)**	(0.000)**	(0.000)	(0.000)***
Constant	43.572	71.234	84.320	86.726	91.563
	(8.065)***	(6.454)***	(3.931)***	(3.109)***	(2.254)***

NOTE: The dependent variable is the quantile q_y of the occupancy rate distribution (%), y=0.1, 0.3, 0.5, 0.7, 0.9. Responsiveness is the slope of the pricing curve in each regime; Q_0=0.28. Time trend is defined in days. The number of observations in the sample is 2,312. Bootstrap standard errors (with 20 replications) are reported in parentheses.
* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

Table A10. The impact of responsiveness of the pricing function on the quantiles of the conditional occupancy distribution (Q_0=0.28; including time trend)

	Occupancy Distribution				
	Quantile 0.1	**Quantile 0.3**	**Quantile 0.5**	**Quantile 0.7**	**Quantile 0.9**
Responsiveness * h8	0.033	0.104	0.018	0.044	0.066
	(0.097)	(0.037)***	(0.064)	(0.071)	(0.066)
Responsiveness * h9	0.034	0.101	0.041	-0.026	-0.026
	(0.083)	(0.054)*	(0.032)	(0.041)	(0.054)
Responsiveness * h10	-0.151	-0.009	-0.080	-0.148	-0.121
	(0.107)	(0.058)	(0.050)	(0.046)***	(0.042)***
Responsiveness * h11	-0.076	-0.117	-0.249	-0.263	-0.278
	(0.094)	(0.061)*	(0.068)***	(0.049)***	(0.052)***
Responsiveness * h12	-0.194	-0.165	-0.285	-0.324	-0.332
	(0.074)***	(0.049)***	(0.045)***	(0.067)***	(0.079)***
Responsiveness * h13	-0.247	-0.210	-0.285	-0.383	-0.332
	(0.088)***	(0.047)***	(0.047)***	(0.054)***	(0.143)**
Responsiveness * h14	-0.235	-0.270	-0.386	-0.368	-0.367
	(0.106)**	(0.070)***	(0.068)***	(0.065)***	(0.059)***
Responsiveness * h15	-0.246	-0.273	-0.366	-0.294	-0.259
	(0.073)***	(0.074)***	(0.067)***	(0.103)***	(0.097)***
Responsiveness * h16	-0.274	-0.115	-0.199	-0.204	-0.010
	(0.119)**	(0.090)	(0.064)***	(0.059)***	(0.107)
Responsiveness * h17	-0.032	-0.150	-0.195	-0.171	-0.088
	(0.081)	(0.036)***	(0.064)***	(0.082)**	(0.068)
Responsiveness * h18	-0.075	-0.026	-0.135	-0.125	-0.084
	(0.097)	(0.047)	(0.038)***	(0.091)	(0.113)
Responsiveness * h19	-0.136	-0.145	-0.104	-0.088	-0.079
	(0.067)**	(0.090)	(0.074)	(0.055)	(0.176)
Responsiveness * h20	-0.101	-0.022	-0.068	-0.094	0.004
	(0.124)	(0.070)	(0.050)	(0.070)	(0.094)
Responsiveness * h21	-0.153	-0.131	-0.179	-0.121	0.010
	(0.095)	(0.060)**	(0.088)**	(0.098)	(0.110)
Responsiveness * h22	-0.118	-0.147	-0.243	-0.233	-0.141
	(0.109)	(0.050)***	(0.064)***	(0.087)***	(0.128)
Responsiveness * h23	-0.191	-0.152	-0.264	-0.322	-0.424
	(0.087)**	(0.063)**	(0.058)***	(0.077)***	(0.043)***
Time trend (days)	0.010	-0.007	0.007	0.001	-0.025
	(0.016)	(0.008)	(0.008)	(0.009)	(0.011)**
P_0 * hour interactions?	Yes	Yes	Yes	Yes	Yes
Hour fixed effects?	Yes	Yes	Yes	Yes	Yes
Day fixed effects?	Yes	Yes	Yes	Yes	Yes
Weekend cycle?	Yes	Yes	Yes	Yes	Yes
Holiday fixed effects?	Yes	Yes	Yes	Yes	Yes

Note: The dependent variable is the quantile q_y of the occupancy rate distribution (%), y=0.1, 0.3, 0.5, 0.7, 0.9. Responsiveness is the slope of the pricing curve in each regime. The coefficients for the level of the pricing function (with hour interactions), hour of day, day of the week, holiday periods, and weekend cycle are not reported in the table. The number of observations in the sample is 2,312. Bootstrap standard errors are reported in parentheses.

* Significant at the 10 percent level.

** Significant at the 5 percent level.

*** Significant at the 1 percent level.

Table A11. The impact of responsiveness of the pricing function on the quantiles of the conditional occupancy distribution (Q_0=0.28; quadratic time trend)

	Occupancy Distribution				
	Quantile 0.1	**Quantile 0.3**	**Quantile 0.5**	**Quantile 0.7**	**Quantile 0.9**
Responsiveness * h8	0.084	0.069	-0.003	0.015	0.037
	(0.066)	(0.041)*	(0.068)	(0.072)	(0.062)
Responsiveness * h9	0.002	0.057	0.049	-0.046	-0.051
	(0.080)	(0.062)	(0.040)	(0.036)	(0.052)
Responsiveness * h10	-0.114	-0.012	-0.114	-0.135	-0.145
	(0.106)	(0.048)	(0.043)***	(0.049)***	(0.046)***
Responsiveness * h11	-0.119	-0.162	-0.238	-0.283	-0.302
	(0.070)*	(0.055)***	(0.073)***	(0.086)***	(0.076)***
Responsiveness * h12	-0.230	-0.212	-0.279	-0.299	-0.298
	(0.047)***	(0.044)***	(0.056)***	(0.043)***	(0.103)***
Responsiveness * h13	-0.246	-0.248	-0.289	-0.391	-0.354
	(0.084)***	(0.045)***	(0.054)***	(0.050)***	(0.203)*
Responsiveness * h14	-0.280	-0.290	-0.403	-0.396	-0.390
	(0.091)***	(0.086)***	(0.072)***	(0.055)***	(0.081)***
Responsiveness * h15	-0.283	-0.313	-0.361	-0.322	-0.269
	(0.089)***	(0.130)**	(0.126)***	(0.099)***	(0.074)***
Responsiveness * h16	-0.221	-0.148	-0.204	-0.192	-0.012
	(0.099)**	(0.095)	(0.078)***	(0.070)***	(0.125)
Responsiveness * h17	-0.044	-0.189	-0.222	-0.160	-0.088
	(0.120)	(0.061)***	(0.064)***	(0.097)	(0.089)
Responsiveness * h18	-0.049	-0.066	-0.155	-0.133	-0.106
	(0.126)	(0.043)	(0.047)***	(0.076)*	(0.061)*
Responsiveness * h19	-0.191	-0.140	-0.127	-0.060	-0.093
	(0.050)***	(0.061)**	(0.072)*	(0.049)	(0.154)
Responsiveness * h20	-0.129	-0.044	-0.114	-0.097	0.010
	(0.129)	(0.082)	(0.073)	(0.055)*	(0.061)
Responsiveness * h21	-0.202	-0.144	-0.222	-0.131	0.014
	(0.098)**	(0.084)*	(0.111)**	(0.132)	(0.116)
Responsiveness * h22	-0.151	-0.184	-0.261	-0.246	-0.161
	(0.114)	(0.051)***	(0.054)***	(0.090)***	(0.108)
Responsiveness * h23	-0.225	-0.176	-0.282	-0.321	-0.416
	(0.100)**	(0.080)**	(0.057)***	(0.073)***	(0.065)***
Time trend (days)	-0.107	-0.079	-0.061	-0.073	-0.114
	(0.031)***	(0.025)***	(0.030)**	(0.033)**	(0.038)***
Time trend^2 (days^2)	0.001	0.000	0.000	0.000	0.000
	(0.000)***	(0.000)***	(0.000)***	(0.000)**	(0.000)**
P_0 * hour interactions?	Yes	Yes	Yes	Yes	Yes
Hour fixed effects?	Yes	Yes	Yes	Yes	Yes
Day fixed effects?	Yes	Yes	Yes	Yes	Yes
Weekend cycle?	Yes	Yes	Yes	Yes	Yes
Holiday fixed effects?	Yes	Yes	Yes	Yes	Yes

Note: The dependent variable is the quantile q_y of the occupancy rate distribution (%), y=0.1, 0.3, 0.5, 0.7, 0.9. Responsiveness is the slope of the pricing curve in each regime. The coefficients for the level of the pricing function (with hour interactions), hour of day, day of the week, holiday periods, and weekend cycle are not reported in the table. The number of observations in the sample is 2,312. Bootstrap standard errors are reported in parentheses.
* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.