Does responsive pricing smooth demand shocks?

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Does responsive pricing smooth demand shocks? [1,2]

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Abstract: 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: D01, D12, L11, L86.
Keywords: Consumer demand, responsive pricing, capacity utilization, congestion pricing, price variability.

1 Introduction

In a seminal contribution, Vickrey (1971) introduced the concept of responsive pricing to advocate that the access price to a congestible resource should be directly linked to congestion levels. This paper presents the first evidence on responsive pricing from a unique pricing experiment by easyEverything, a chain of cafés offering public Internet access. We investigate whether consumers respond to responsive pricing and whether responsive pricing smoothes demand shocks as conjectured by Vickrey.

easyEverything updates prices every 5 minutes as a function of the level of store occupancy. The price per minute when q percent of computer terminals are used is $p(q)=P_0+\beta(q-Q_0)$, where P_0 is a base level of price corresponding to a target level of utilization $q=Q_0$, and β measures how much price responds to deviations from Q_0. According to Vickrey, the target level of occupancy Q_0 is set to 'maintain the quality of service at a "satisfactory" level' (p. 339). 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 $q<Q_0$. The pricing function $p(q)$ offers discounts when utilization is below Q_0 and raises prices when it is above Q_0.

A given pricing function, characterized by (Q_0,P_0,β), generates a distribution of capacity utilization rates. If responsive pricing works, as Vickrey conjectured, the percentiles of the distribution of occupancy rates should cluster around Q_0 for more responsive schemes (with a higher β holding Q_0 and P_0 constant). In other words, occupancy should become more predictable and the distribution of occupancy should be more concentrated around Q_0.[3]

Figure 1 shows two pricing schemes $p(q)$ in our sample. The curves specify a price for each level of store occupancy q. Consider the flatter of the two curves. The price increases/decreases by 1.4FF/hour when occupancy is 10 percent above/below the target level of

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[3] Vickrey acknowledged that increasing the level of price, P_0, also reduces the chance of congestion but he argued that this was a very inefficient solution because it also increases the events of unused capacity. Vickrey argued that using

consumption. The more responsive curve implies a price change of 4.2FF/hour for the same deviation in occupancy. Figure 2 plots the cumulative distribution of occupancy rates observed for 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. This finding is consistent with the hypothesis that increasing the responsiveness parameter smoothes demand shocks. This paper generalizes this finding by aggregating information from many pricing functions and controlling for a variety of other factors.

This study contributes to the empirical literature assessing the impact of pricing schemes that vary prices in real time. 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, such as those announcing 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, Barbose et al., 2004, Taylor et al 2005). Our work differs from these previous studies in important ways.

Firstly, previous empirical research has 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] There are some significant differences between responsive pricing and day-in-advance pricing. Day-in-advance pricing does not introduce the immediate feedback loop between current congestion conditions and prices proposed by Vickrey. Consequently, day-in-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,

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price responsiveness, β, is a more efficient solution because it influences the variance (not the mean) of the distribution of occupancy.
[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.

prices may vary for reasons unrelated 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 prices vary more, would possibly not hold.

A second point distinguishing this from previous studies is its novel empirical focus. 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. This is in line with Vickrey's conjecture, which is not couched in terms of unobservable parameters, but in terms of observable outcomes (distribution of occupancy). Another significant difference between this and previous research is in the results, which differ greatly from previous studies. For example, we find much larger responses than those reported in the literature.[5]

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 discusses policy implications and Section 6 concludes.

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 13 days on average. Prices are updated

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

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.

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 (depending on 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 introduction of responsive pricing had indeed responded to demand fluctuations.[6] 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. Table 1 reports summary statistics. The average 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. There is a pronounced day cycle. 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. One 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

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[6] Consistent with the experimentation view, the company decided shortly after the end of our sampling period 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. The managers report that this decision was deliberately taken after the end of the experimentation period, based on the information collected during this first phase.

rationing in estimating the impact on responsive pricing of the distribution of occupancy rates. In addition, there is no evidence that service quality degrades as occupancy increases.

Table 1 also reports the responsiveness parameter (the slope) for each pricing curve. 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). Table 1 shows that prices vary within and across regimes. The changes in the pricing curves generated significant differences in the level of price variability. Overall, the magnitude of price variability in our sample is in line with other studies.[7]

The standard deviation presented in the last column corresponds to the variability in price that a consumer would face when entering the store at a random time in a given regime. These standard deviations capture the fact that prices vary systematically over the day cycle and also that they are to some extent unpredictable at any given hour. These two sources of price variation should give consumers an incentive to adjust their consumption decisions through two different channels. First, 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. 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. One may argue that announcing hourly prices a day in advance could offer the same incentives. Only responsive pricing, however, can smooth demand shocks that take place after the daily prices have been set, leading to the second response channel. Consumers have an incentive to adjust their length of stay once they arrive in the store and learn the actual price. Price may also change in unexpected ways while in the

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[7] The expected absolute price difference for two hours selected at random in our sample is 30 percent of the average price, which is comparable to what Borenstein and Rose (1994) found in their study of airline fares.

store, and consumers have an incentive to increase their length of stay in the event of a decrease in price.[8]

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

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

represent the jth 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 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

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

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 above. Assume that consumers either consume one hour or nothing and that they have heterogeneous valuation for consumption. To illustrate the 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 scenario, 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 who values consumption more than the posted price actually consumes. Equilibrium occupancy at hour h takes place at the point where the downward sloping hour h

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[8] The price cap mitigates the incentive for incumbent consumers to reduce their length of stay when the price increases. This may introduce a delay in response. Our results can be interpreted as a lower bound of the potential impact of responsive pricing on occupancy variability.

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 the channel two response, assume that a random number of consumers join the store every hour. 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.

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 prices vary over the day cycle. Expectations about future prices could play an important role to the extent that there is much demand uncertainty. One can construct counterexamples, where there are multiple equilibria 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 is an empirical issue.

4 Estimation and Results

We provide both non-parametric and parametric evidence supporting hypothesis H_0. 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 4.4).[9]

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 two directions: (a) we generalize this result to a larger set of pairs of pricing functions; and (b) we present a formal test of H_0.

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. Comparing pricing functions with similar slopes produces tests of low power, with the risk of failing to reject the null when it is false. To obtain conclusive results on whether the slope affects the distribution of occupancy, 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. The threshold we

use is such that each pricing function in our sample occurs at least once. These pairs of pricing functions cross at between 8 percent and 33 percent of capacity. The average crossing point is 20 percent. Increasing the threshold would reduce the number of tests, but would not affect the results of the statistical tests. Decreasing the threshold would increase the number of tests, but would add tests with relatively low power.

The 10 panels in Figure 4 complement the evidence in Figure 2. 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 $0 \leq q \leq 1$.[10]

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 (or is dominated by) the less responsive one if Q_0 lies to the left (or right) of the support. Vickrey's conjecture still holds - the more responsive regime is more concentrated around Q_0 - but this can be observed only on one side of Q_0. In Panel 1, for example, the distribution corresponding to regime 12 lies closer to Q_0 than that corresponding to regime 1.

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[9] We also sometimes refer to further robustness checks, which can be consulted in the separate Additional Materials section available on the authors' web pages.

[10] The P-values for the D statistic are computed using the first five terms of the asymptotic distribution

$$\lim_{m,n \to \infty} \Pr[((mn/(m+n))^{1/2} D \leq a] = 1 - 2\sum_{i=1}^{\infty} (-1)^{i-1} \exp(-2i^2 a^2)$$, where n and m denote the size of the two samples.

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, for example, in Figure 4 Panel 7 displaying pairs (7, 12). 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.

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 jth 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 5th percentile and the nine deciles using the standard Least Absolute Deviations (LAD) method (Koenker and Basset 1978 and Koenker 2005). 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 $q_{k(x,y)} = Q_0(x, y)$.[11] If regime x is more responsive than y, H^{np}_0 implies that

$$b_{y,j} < b_{x,j} \text{ if } j<k(x,y) \text{ and } b_{x,j} < b_{y,j} \text{ if } j>k(x,y).[12]$$

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

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[11] 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.

[12] 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.

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.

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).

4.2 Parametric Test 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

$$q''_j(P_0,\beta|Q_0). \tag{3}$$

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

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

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 using data on occupancy rates and the pricing policies for the 12 regimes in the sample. 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.

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 measures 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.

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

$$a_{2,j}>0 \text{ if } j<k \text{ and } a_{2,j}<0 \text{ if } j>k \qquad\qquad (H^P_0)$$

for any percentile j. 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 $q_k(P_0,\beta\,|\,Q_0)=Q_0$. 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⁺].[13]

Consistently with Vickrey's conjecture, the impact of responsiveness ($a_{2,0.1}$) is not significantly different from zero (Table 4, column 1). On the contrary, the coefficient $a_{2,0.9}$, in

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[13] An additional complication arises with the determination of k. In theory, k should be independent of β. Given our linear approximation, k solves $Q_0= a_{1,k}+a_{1,k}P_0+a_{2,k}\beta$, and it obviously depends on β (because the non-linear terms in P_0 and β are missing). This poses no problem because k=0.1 falls within the range of k that solves $q_k(P_0,\beta\,|\,Q_0)=Q_0$ for any slope within the range observed in our sample.

column 5, is negative and significant. To illustrate, an increase in 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.[14]

4.3 Conditional Responses

One may argue that the responses measured so far capture to a large extent a reduction in consumption variability over the day cycle. But does consumption also vary less in a given hour? To answer this question, we consider the distribution of occupancy conditional on the hour of the day. Denoting $q'_j(Q_0,P_0,\beta|h,X)$ the jth percentile of the distribution of occupancy conditional on hour h and other demand shifters summarized by X (such as day of the week and holiday), hypothesis H_0 generalizes to

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

By focusing on conditional distributions, one eliminates the reduction in day cycle variation (channel one response), allowing a focus on the reduction in occupancy variations that are driven by channel two response. We estimate a modified version of (4),

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

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

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[14] 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.

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.

The distribution of occupancy at 9 a.m. reveals a slightly different story (Figure 6, Panel 2), because demand at 9 a.m. is on average higher (occupancy typically increases in the 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 latter. 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 times of day.

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.

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.

4.4 Robustness

We discuss two robustness checks and for the sake of conciseness we report the results only in the Additional Materials section. We first 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. 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. 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. Consistent with Vickrey's conjecture, we find that increasing the responsiveness of the pricing function has a negative impact on all deciles.

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.

5 Economic Implications

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 $x^+=Max(x,0)$. 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'

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

ΔD^q measures the percentage change in inefficiencies and captures the compression effect hypothesized by Vickrey.[15] Consider again the pairs of pricing functions compared in Figure 4.

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

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.

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, extensive 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)).[16]

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

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

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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 $D^p(\beta)=(1/10)\Sigma_t|p(q_i(Q_0,P_0,\beta),\beta) - p(Q_0, \beta)|$. 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 extraordinarily so. 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.

6 Concluding Remarks

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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."

This paper contributes to the empirical literature studying whether congestion pricing can smooth demand shocks.[17] 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. 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).

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 is to incorporate welfare calculations in order to investigate, for example, how welfare depends on the responsiveness parameter.

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[17] Congestion pricing could be implemented in a variety of industries. For example, de Marin de Montmarin (2007) and Laih et al. (2007) discuss applications to port access and computer network pricing.

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Figure 1: Examples of Pricing Functions (regime 8 and 12)
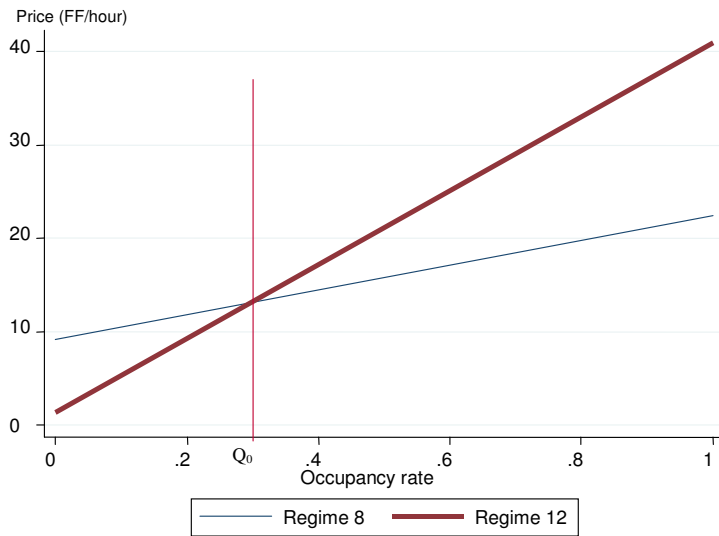
Note: The figure reports the pricing curves for regime 8 and 12 (see Table 1). The price is measured in French Francs / hour. The occupancy rate is the hourly average number of computers used divided by the total number of computers in the store.

Figure 2. Empirical Cumulative Distribution Functions (regimes 8 and 12)
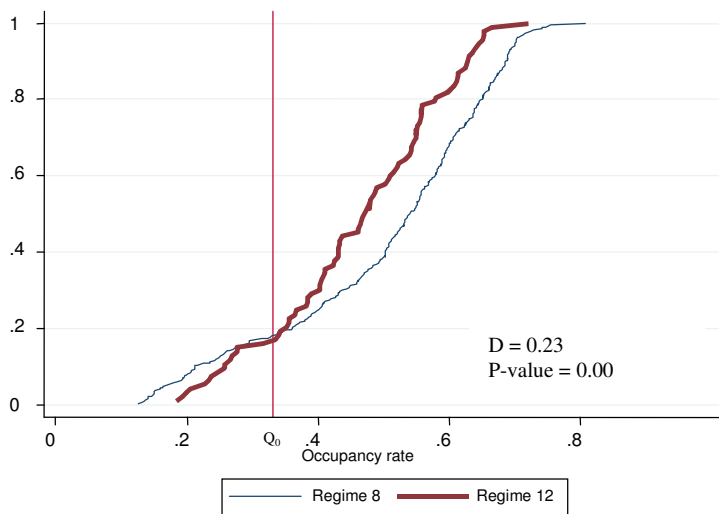
Note: The figure reports the empirical cumulative distribution function of the occupancy rate for regimes 8 and 12. The occupancy rate is the hourly average number of computers used divided by the total number of computers in the store. D is the maximum vertical distance between the two empirical distributions (Kolmogorov-Smirnov statistic).

Figure 3. Pricing Curves

Note: The figure reports 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.
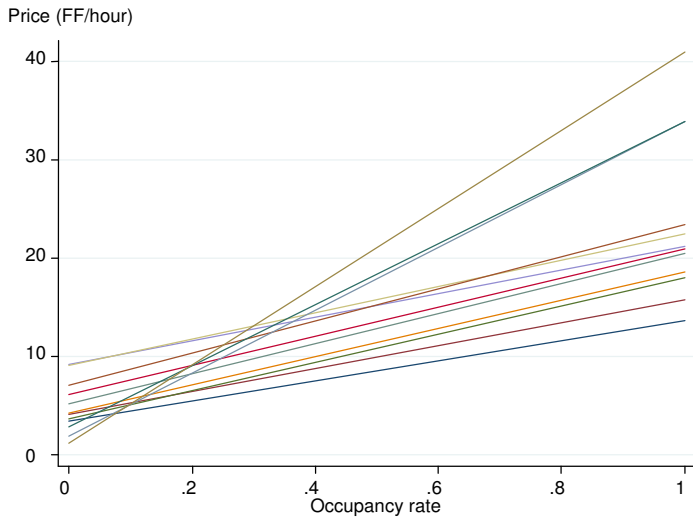
Figure 5. Simulated Quantiles ($Q_0 = 0.28$)

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 4. Empirical Cumulative Distribution Functions
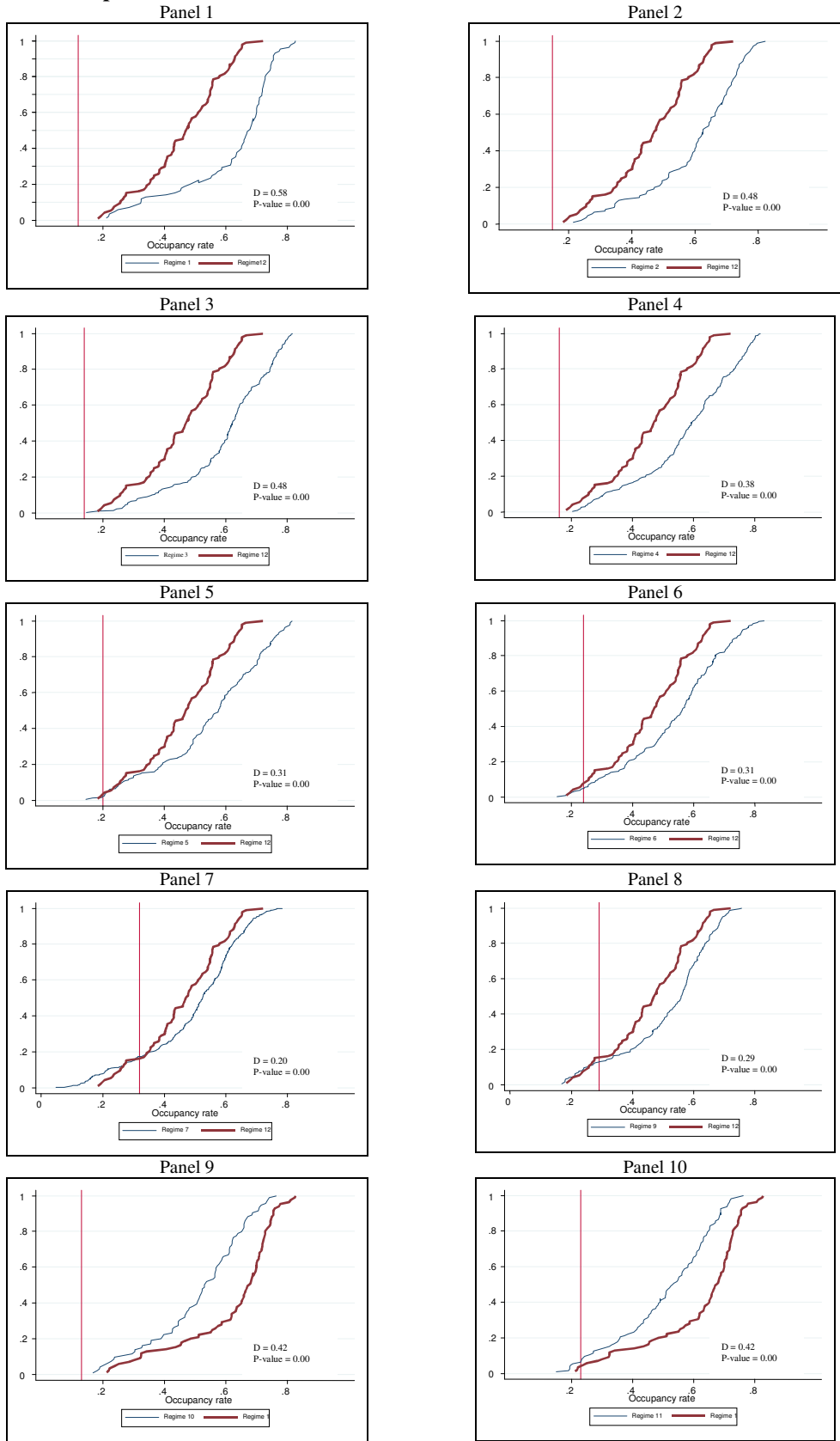
Note: The figure compares pairs of regimes for which the difference in responsiveness is larger than 22. This singles out 11 pairs: regimes 1 to 9 crossed with regime 12, and regimes 10 and 11 crossed with regime 1. The comparison of regimes 8 and 12 is reported in Figure 2. Each pricing function in 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).
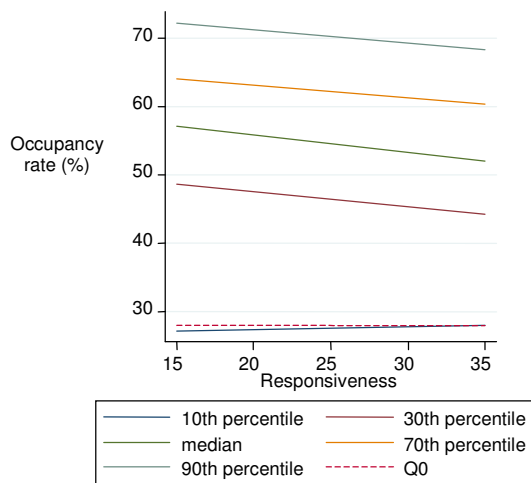
Figure 6. Simulated Quantiles (Hour of Day Interactions and $Q_0 = 0.28$)

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 corresponds to Thursday, with no national holiday.

Table 1. Summary Statistics

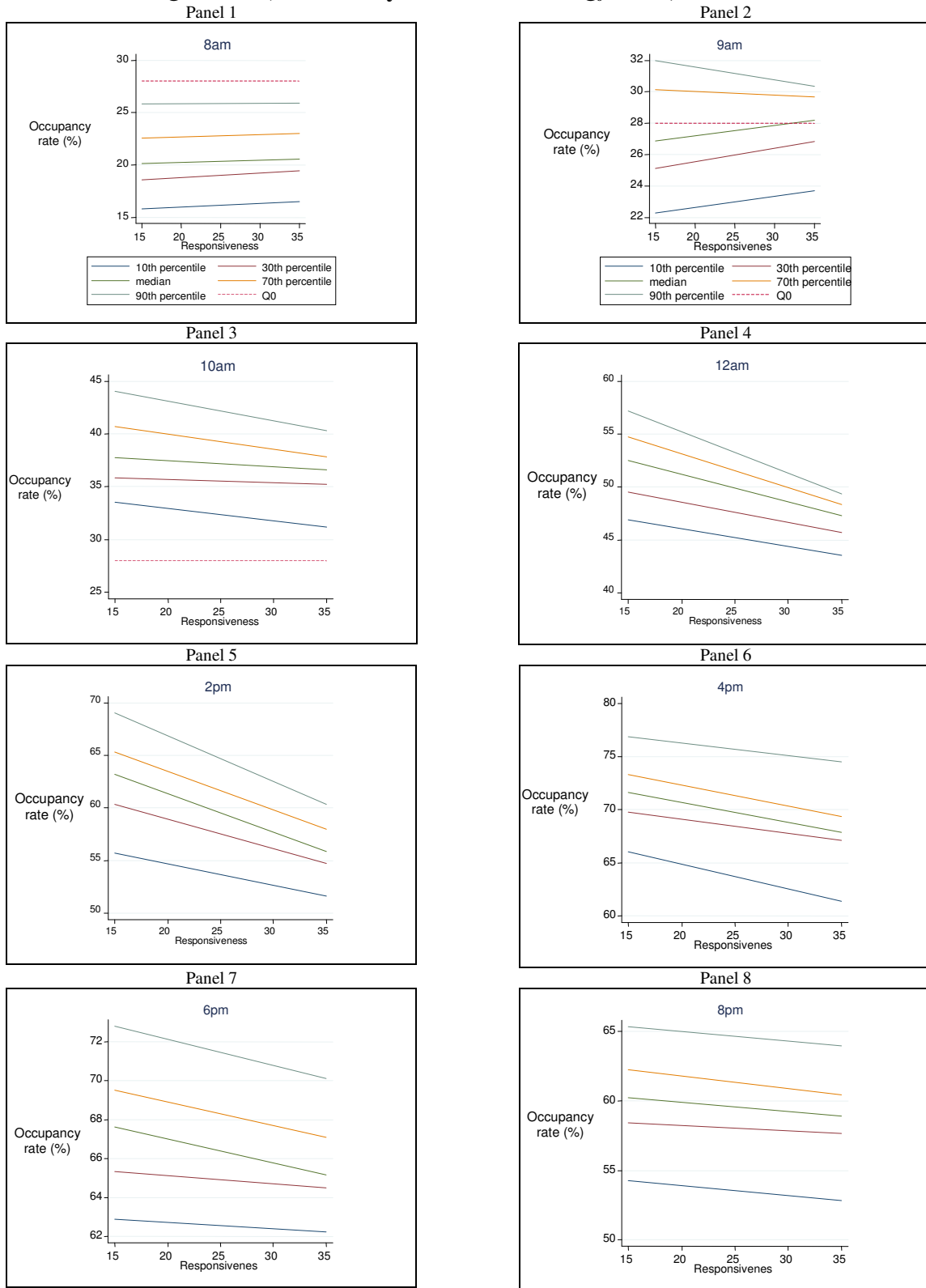| Regime	Number of observations	Length of the regime (days)	Responsiveness	Mean occupancy rate	S.d. occupancy rate	Mean Price	S.d. Price
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1	85	6	10.733	0.618	0.160	9.616	1.757
2	110	7	12.235	0.596	0.149	10.773	1.794
3	221	15	15.098	0.600	0.150	12.085	2.320
4	208	15	15.141	0.578	0.159	12.344	2.518
5	183	11	16.090	0.550	0.171	12.906	2.747
6	224	16	15.536	0.539	0.159	13.642	2.463
7	444	28	12.670	0.492	0.161	14.477	2.887
8	342	22	14.082	0.501	0.165	15.419	3.010
9	196	13	17.272	0.516	0.148	15.176	3.168
10	94	6	33.722	0.513	0.152	17.519	5.151
11	112	7	32.782	0.509	0.154	18.306	5.189
12	93	6	41.879	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. "S.d. occupancy rate" and "s.d. price" are the standard deviation of the occupancy rate and the price. The table includes observations for hours between 8 a.m. 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 on our website.

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.