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ABSTRACT

Does Responsive Pricing Increase Efficiency? Evidence from Pricing Experiments in an Internet Café*

Responsive pricing proposes to increase efficiency by introducing a direct linkage between market conditions and changes in prices. This link is established by giving selective discounts that vary in real time as a function of the level of unused capacity. Using data from a unique pricing experiment in Internet cafés, we address the question of whether consumers respond to instantaneous price changes, and whether responsive pricing increases welfare. Our results show that the most responsive scheme in our sample increases occupancy by 11% over peak-load pricing. Welfare increases by an amount that corresponds to 12% of total consumer expenditure.

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1 Introduction

Both academics and policymakers accept the principle that allocating congestible resources efficiently requires varying prices in response to market shocks. One way to implement this principle in practice to is to make prices contingent on the level of congestion. Responsive pricing proposes to increase prices as utilization rates increase—that is, as congestion becomes more likely. Situations where responsive pricing could be applied include telephone use and road use (Vickrey, 1994), electricity markets (Borenstein et al., 2002), Internet pricing (MacKie-Mason and Varian, 1994), and theme park access, to name just a few examples. In these applications, measures of congestion (i.e., the utilization rate) can be used to compute congestion-contingent prices that are communicated to consumers in real time.

To understand the importance of enabling prices to respond to demand shocks, consider what happens when they don't. If prices are set according to the expected level of demand at a given time, the randomness of the arrival process implies that the number of new arrivals sometimes exceeds or falls short of available capacity. If prices do not vary as a function of realized shocks, some potential buyers are denied access when there is a sudden arrival of consumers, and capacity is wasted when there is an unexpected drop in the flow of consumers.

Responsive pricing is useful in applications where variations in demand are difficult to predict, but where it is be possible to influence how much consumers use the service. When this is the case, policymakers can seriously consider using prices to allocate the congestible resource among users more efficiently (Vickrey, 1971; Courty and Pagliero, 2003). However, although the theoretical logic through which responsive pricing raises efficiency is well-understood, there is little evidence as to whether responsive pricing actually works in practice. Are enough consumers willing to monitor prices in real time, and to change their consumption plans according to realized prices? From a policy perspective, the issue is whether the welfare gains from responsive pricing are significant. In fact, assessing their magnitude is essential if implementing responsive pricing and metering consumer use are costly.

In this paper, we estimate the welfare gains to responsive pricing in a unique pricing experiment by easyEverything, the world's largest chain of cafés offering public Internet access. A café has a fixed capacity (number of terminals) and faces demand uncertainty—two features common to all applications where responsive pricing has been proposed. In that sense, our application offers a natural environment to assess the welfare impact of responsive pricing.

EasyEverything has experimented with both peak-load pricing (where the price depends only on the time when use occurs) and responsive pricing. The pricing experiments were part of a company policy to investigate local demand. In our empirical analysis, we treat the changes in pricing policies as a natural experiment, and use the data to study consumers' responses and welfare impacts.

Under responsive pricing, the price is updated every 5 minutes as a function of the level of demand. To illustrate, Figure 1 shows the pricing function for regime 6, regime 11, and regime 17 in our sample. For each regime, the curve shows the price for each level of occupancy. For example, in regime 6 the price is 8.2FF per hour when occupancy is equal to 50 percent of capacity. The curves are upward sloping in all regimes, meaning that consumers receive discounts when store occupancy is low and pay more when occupancy is high: exactly the principle underlying responsive pricing.

Throughout our analysis, we focus on the welfare gains that can be captured if service providers offer discounts in low-demand states of the world where capacity would otherwise go unused. We present a simple model to illustrate the effect of responsive pricing on capacity utilization and efficiency. To capture the idea of demand uncertainty, we assume that demand is randomly drawn from a given population. A demand realization and pricing policy determines the equilibrium price and level of occupancy. Given all possible demand realizations, a pricing regime generates a distribution of occupancy. The model shows that more responsive regimes—that is, regimes that give greater discounts in low-demand states of the world—generate more compressed distributions of occupancy, in that lower deciles get closer to top deciles. Occupancy increases in low-demand states of the world but the probability of congestion remains constant.

In our empirical approach, we observe the distribution of occupancy for different pricing regimes, some of which are more responsive than others. We investigate whether responsive pricing attenuates the impact of unpredictable demand shocks, compresses the realized distribution of occupancy, and ultimately increases capacity utilization rates.

Our main empirical results are as follows:

(a) The distance between the 9th decile and any lower decile of the occupancy distribution decreases as the pricing regime becomes more responsive.

(b) Occupancy varies less not only within hours but also across hours. The standard deviation in occupancy change across hours decreases for more responsive regimes.

(c) The impact of responsive pricing is not uniform across the day. The decrease in inter-decile differences is lowest during the peak. This reflects the fact that peak demand is less price sensitive.

(d) We find evidence that selective discounts increase average occupancy by 5 percent when pricing responsiveness changes from zero (peak-load pricing) to the average level of responsiveness in the sample. Assuming that pricing responsiveness rises to the highest level of responsiveness in our sample, we find an increase in occupancy of 11 percent.

After establishing that consumers respond to responsive pricing, we estimate the welfare gains that result from switching from peak-load pricing to responsive pricing. Welfare calculations are simple in our application, because costs do not change across pricing regimes, and thus welfare gains come exclusively from increases in consumption. When pricing responsiveness increases from zero to the highest value in our sample, welfare rises by an amount that corresponds to12 percent of total consumers' expenditure.

Our evidence contributes to the empirical literature assessing the impact of consumer responses to pricing schemes that are responsive to demand and supply shocks. In spite of the economic relevance of potential applications of responsive pricing, and the importance of responsive pricing in some policy debates, very little evidence exists on consumer responses to such schemes.[3] A large literature in electricity markets shows that users respond to schemes that announce—on a daily basis—the prices for each hour of the following day. These cases include both industrial users (e.g., Patrick and Wolak, 2001; Schwartz et al., 2002) and household users (e.g., Aubin et al., 1995; Herriges et al., 1993). However, these studies focus on substitution responses to announcements of where the peak is likely to be, rather than on the possibility of clearing the market in response to last-minute demand shocks through incentives to consumers to change their intensity of use, as predicated by responsive pricing. To our knowledge, the issue of whether consumers do update their consumption decisions in real time—rather than a day in advance—has not been addressed in the literature.

The remainder of the paper is organized as follows. Section 2 presents a simple framework that illustrates the logic of responsive pricing. Section 3 provides some background information on our pricing experiments and describes the data. Section 4 presents the main empirical results. Section 5 conducts some welfare calculations, and Section 6 summarizes the main findings and discusses policy implications.

2 Model

[3] For example, the California Public Utilities Commission (CPUC) stated that "demand response is a vital resource to enhance electric system reliability, reduce power purchase and individual consumer costs, and protect the environment." (R. 02-06-001, Order Instituting Rulemaking, June 6, 2002, CPUC OIR, p. 1.) The California Energy Commission made similar statements in its 2002-2012 Electricity Outlook Report (http://www.energy.ca.gov/demandresponse/).

What sets responsive pricing apart from more traditional pricing schemes, such as peak-load pricing, is that prices under the former respond to unpredictable changes in demand.[4] Our model presents a framework for investigating how consumers respond to responsive pricing that will guide our empirical analysis. We cast the model from the perspective of a social planner who is maximizing efficiency, and we ask whether responsive pricing can increase welfare above and beyond what peak-load pricing can achieve.[5]

Consider our application to out-of-home Internet access. Assume the service is offered during H hours each day, and that store capacity is Q. Inverse demand in hour h=1…H is

$$P(q;h)=a_h-b_hq,$$

where $a_h-b_hQ\geq 0$, so that it is always possible to fill the store. To simplify the presentation, we assume without loss of generality that there is no substitution between hours.[6] Setting the price in hour h at

$$\alpha_h=a_h-b_hQ$$

sells all capacity and achieves a Pareto efficient outcome.

But, as suggested by Vickrey, unpredictable demand shocks may occur at the last minute—that is, after peak-load prices have been set. In our application, demand shocks could be triggered, for example, by changes in weather conditions that change consumers' relative preferences for joining an Internet café. Consider a simple modification of the demand specification with additive demand shocks that captures the idea of unpredictable demand. Inverse demand in hour h and state i is

$$P_i(q;h)=a_h+u_{h,i}-b_hq$$

where $u_{h,i}$, i=1..I is a zero-mean random demand shock that is realized in hour h. State i occurs with probability $f_{h,i}$. Without loss of generality, we assume that the shocks $u_{h,i}$ are ordered such that $u_{h,i}>u_{h,i'}$ for i>i' and we denote the cumulative density $F_{h,i}=\Sigma_{i'<i}f_{h,i'}$. We assume that the price has to be fixed before the hour-specific demand shock has been realized.

The social planner faces a trade-off between setting the price too high, and thus having to bear an opportunity loss from unused capacity, and setting it too low, thereby increasing the

[4] Peak-load pricing was first formalized in Boiteux (1956 and 1960). See Crew, Fernando, and Kleindorfer (1995) for a review of the peak-load pricing literature. MacKie-Mason and Varian (1994) and Courty and Pagliero (2003) propose alternative models of responsive pricing that complement the analysis presented here.

[5] The conclusion that a social planner prefers responsive pricing over peak-load pricing extends to a profit maximizing firm---that is, the maximum profits under responsive pricing dominate the maximum peak-load-pricing profits---as long as demand is high enough relative to capacity that additional sales always increase profits. The rationale is the same as for why peak-load pricing maximizes both welfare and profits when demand is high enough relative to capacity.

[6] This is valid if the consumption decision is exogenous, as would be the case if consumers joined the store after work, for example. If consumers substitute, the optimal peak-load price would have to take into account substitution

chances of congestion. This choice will depend on the social cost of congestion. For example, if the social cost of congestion is high, it may be efficient to rule out congestion, and the efficient peak load price is $\alpha_h = a_h + u_{h,I} - b_h Q$, where I denotes the largest-possible shock. The focus of this work is not the choice of the peak-load price. We assume that the peak load price is set at α_h keeping in mind that the following analysis does not depend on this choice. Given α_h congestion occurs in state i such that $u_{h,i} > u_h^c$ where $u_h^c = \alpha_h - a_h + b_h Q$. Unused capacity in state i such that $u_{h,i} < u_h^c$ is

$$Q - q_{h,i} = (u_h^c - u_{h,i})/b_h.$$

Responsive pricing proposes to fine-tune the optimal peak-load price as follows. It maintains the price at α_h when congestion occurs, but gives price discounts when the realized level of demand is low. Consider a simple way to implement responsive pricing where the store gives price discounts that are a function of realized occupancy. Formally, the price in hour h is

$$p_h(q) = \alpha_h - \beta_h(Q_0 - q)$$

if $q < Q_0$ and α_h otherwise. We assume a linear relation between unused capacity and prices, because this corresponds to the typical functional form found in our empirical application but the results generalize to any increasing function p(q).

Responsive pricing has three components. Q_0 is a constant such that $Q_0 \leq Q$ and corresponds to the threshold level of occupancy below which the store starts to give discounts. Q_0 could be set at a level strictly lower than capacity if, for example, consumer inconvenience starts to occur before occupancy has reached capacity. The congestion charge, α_h, deals with predictable demand shocks (peak-load pricing), while the pricing responsiveness parameter, β_h, deals with unpredictable demand shocks (responsive pricing). When $\beta_h = 0$, the store never gives discounts, and the pricing rule boils down to peak-load pricing. When $\beta_h > 0$, the store gives discounts equal to $\beta_h(Q_0 - q)$, and these discounts are a function of realized occupancy. We say that regime 1 is more responsive in hour h than regime 2 if both regimes have the same α_h and Q_0 but regime 1 has a higher β_h.

To understand how responsive pricing works, define the threshold demand shock below which discounts are offered, $u_h^* = \alpha_h - a_h + b_h Q_0$. In states i such that $u_{h,i} > u_h^*$ the demand is greater than Q_0, the price is equal to the congestion charge, and the equilibrium does not change with the introduction of responsive pricing. The interesting case occurs in states i such that $u_{h,i} < u_h^*$.

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responses. However, as will soon become clear, this would not change the rationale for—or the effectiveness of—responsive pricing.

Because consumers make their consumption decisions as a function of the realized price, the equilibrium level of occupancy, $q_{h,i}$, is such that the inverse demand equals the equilibrium price,

$$a_h+u_{h,i}-b_h q=\alpha_h-\beta_h(Q_0- q_{h,i}).$$

Equilibrium occupancy in state i such that $u_{h,i}<u_h^*$ is

$$q_{h,i}=Q_0-(u_h^*-u_{h,i})/(b_h+\beta_h) \qquad (1)$$

The equilibrium is illustrated on Figure 2.[7] Occupancy is higher under responsive pricing than under fixed pricing. This result is actually more general and constitutes our first proposition.

Proposition 1: Capacity utilization increases for more responsive pricing schemes; that is, $\partial(Q_0-q_{h,i})/\partial\beta_h >0$ *for* $u_{h,i}<u_h^*$ *and* $\partial(Q_0-q_{h,i})/\partial\beta_h =0$ *for* $u_{h,i}\geq u_h^*$*.*

More responsive pricing schemes give greater discounts and increase the level of occupancy in each state of the world where occupancy is below the threshold level of occupancy. Figure 3 illustrates this proposition. It assumes that there are two pricing regimes, $p_h(q)$ and $p_h'(q)$, and that the latter regime is more responsive. The realized levels of occupancy are higher in the more responsive pricing regime. But selective discounts do not only increase occupancy; they also reduce occupancy variations. In Figure 3, the difference in occupancy between the high and low states of the world ($q_h(H)-q_h(L)$) is lower in the more responsive regime. To formalize this idea, interpret $u_{h,i}$ as the $F_{h,i}$ percentile of the distribution of demand shocks ($\sum_{i' s.t. u_{h,i'}\leq u_{h,i}} f_{h,i'} = F_{h,i}$), and denote i* as the highest state of the world such that $u_{h,i}<u_h^*$. Consider the distribution of occupancy. The inter-percentile difference in occupancy between percentile $F_{h,i}$ and $F_{h,i}$ is

$$q_{h,i}-q_{h,i'}=(u_{h,i}-u_{h,i'})/(b_h+\beta_h) \quad \text{for } i,i'\leq i^* \qquad (2)$$

Responsive pricing compresses the distribution of occupancy in the sense that the difference between any two percentiles decreases for more responsive regimes.

Proposition 2: For any two percentiles $(u_{h,i},u_{h,i'})$ *such that Min(i,i')<i*, the inter-percentile difference in occupancy decreases for more responsive pricing regimes,* $\partial(q_{h,i}-q_{h,i'})/\partial\beta_h<0$*.*

We show in the appendix that occupancy deviations from the mean decrease as well for more responsive schemes, $\partial(q_{h,i}-q_{h,M})^2/\partial\beta_h<0$, where $q_{h,M}$ is the mean level of occupancy in hour h. This implies that the standard deviation in occupancy decreases for more responsive regimes ($d\sigma_{qh}/d\beta_h<0$). This prediction regarding the distribution of occupancy captures the intuitive notion that responsive pricing makes capacity utilization more predictable. Responsive pricing increases welfare through selective discounts in states of the world where inefficiencies occur.

[7] If q_h is negative because the peak-load price α_h is so large that consumption does not take place even after the introduction of discounts, then q_h should be zero. To simplify the presentation, we do not keep track of that possibility.

One should distinguish the response of average occupancy to the peak-load price, dq_{hM}/α_h, and to the pricing responsiveness parameter, $dq_{h,M}/\beta$. A change in the peak-load price will be equally granted in all states of the world, and one can think of the normalized occupancy response to α_h—that is, $\alpha_h dq_{h,M}/d\alpha_h q_{h,M}$—as a demand elasticity. A change in the responsiveness parameter, however, will not give uniform discounts across states of the world. The level of discounts depends on the level of demand. This implies that a change in pricing responsiveness will have a distortionary effect on the distribution of occupancy, and that these distortions can captured only by keeping track of the distribution of $dq_{h,i}/\beta$.

Measuring these distortions is essential to understanding the welfare impact of responsive pricing, for at least two reasons. First, the social value of an increase in occupancy depends on the state of the world. Prices are by definition lower in lower states of the world and therefore, the marginal social valuation for the service is also lower. Second, responsive pricing has redistribution effects across states of the world, and the level of these effects depends on the distribution of occupancy. To see that, denote the equilibrium price in hour h and state i as $p_{h,i.}$ and note that

$$p_{h,i}-p_{h,i'}=\beta_h(q_{h,i}-q_{h,i'}) \quad \text{for } i,i'\leq i^*.$$

This expression implies that price variations are higher for more responsive regimes, since $\partial(p_{h,I}-p_{h,i'})/\partial\beta_h>0$. Although occupancy variations decrease for more responsive pricing regimes, price variations increase. While peak-load pricing reduces the impact of within-day demand differences, and also possibly the impact of other predictable changes in demand, responsive pricing reduces the impact of *unpredictable* demand shocks. Peak-load pricing introduces deterministic price variations. Responsive pricing, on the other hand, introduces random price variations. Consumers find out the realized price only when they arrive at the store and the hourly shock is realised.

3 Internet Café and Dataset

3.1 EasyEverything

EasyEverything, the largest chain of Internet cafés in the world,[8] offers broadband out-of-home Internet access in convenient central locations. All stores share the same pricing model. During the first few weeks after opening, a new store typically prices Internet access according to a fixed schedule, where the price depends only on the hour of the day (i.e., time-of-use or peak-load pricing). After that, the store introduces responsive pricing. Under responsive pricing,

[8] The company changed its name to easyInternetCafe in October 2001 (Courty and Pagliero, 2001).

the price is updated every 5 minutes as a function of the number of consumers logged on. Although the logon price varies, it is capped for each consumer, in that it cannot exceed the price at which the consumer starts a session.[9]

The billing system under responsive pricing is simple. At the entrance of the store a screen shows the price per hour at which consumers can logon. Each consumer buys a ticket with a given nominal monetary value from a vending machine. The consumer uses this ticket to logon at any available terminal and surf the Internet. In practice, the billing system is very similar to those used for many prepaid telephone cards. The instantaneous price is posted in a small window on the terminal, and consumers are charged—in real time—the minimum of the realized price and their logon price. (There is no evidence that the quality of the service—that is, Internet speed—depreciates as occupancy increases.)

Discussions with easyEverything management suggest that stores typically experiment with different schemes. The pricing schemes used early on are unlikely to be optimal, or to be selected in response to changes in the local environment. Rather, the purpose of experimentation is to explore different features of local demand.[10] We treat these experiments as exogenous and measure consumer responses and welfare gains, keeping in mind that the company was clearly not conducting these experiments to maximize welfare.

3.2 Data

Our data set consists of the pricing policies and the average hourly occupancy for one of the Paris stores (Paris Sebastopole) from January 19, 2001, until July 23, 2001. During this period, store capacity remained fixed at 373 terminals, and the store's competitive environment did not change. The store used peak-load pricing from January 19 to February 21 and responsive pricing from then on. In our sample, the store has experimented with 17 different pricing regimes: 5 under peak-load pricing, and 12 under responsive pricing. Each peak-load pricing regime specifies a price structure over a 24-hour cycle. Prices vary over this day cycle from 2 FF per hour in the early morning to 10 FF per hour in the afternoon, when the store is typically more crowded.

The occupancy data consist of hourly average occupancy rates for 186 days. Although the store was open 24 hours a day, we restricted our analysis to the period 8 a.m. to 12 p.m. because

[9] Stores also offer complementary services, such as web cams, browsing, word-processing software, and various beverages, but the revenues from these additional services are small relative to Internet access, and the prices of these other services remained constant during the period covered in our sample.

[10] Shortly after the period covered in our sample, the company started to experiment with more complex pricing strategies, introducing daily, weekly, and monthly passes in addition to responsive pricing.

the store never used responsive pricing during night hours. Overall, our dataset consists of 2,758 hourly observations, of which 446 occurred under fixed pricing and 2,312 occurred under responsive pricing.[11]

Table 1 reports summary statistics. The average occupancy rate in the sample is 54 percent, with a standard deviation of 17 percent. The average price is 12.9FF, with a standard deviation of 4.7FF. Table 1 also reports the responsiveness parameter and the congestion charge for each pricing curve. The responsiveness parameter is measured by the slope of the 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 are excluded from the regression. The average congestion charge over responsive pricing regimes, corresponding to α in the model, is 22.3FF, while the average slope, corresponding to β, is 17.1—meaning that the price decreases by 1.71FF each time occupancy decreases by 10 percent (or 37 computers). In all but three regimes, a linear approximation of the pricing curve explains more than 95 percent of the variation (the R^2 in table 1 is higher than 0.95). In regimes 12, 13, and 14, the R^2 is between 0.75 and 0.87. These regimes are piecewise linear, with a kink at 60 percent. As we will show later, however, these non-linearities do not affect our main findings.

4 Occupancy Responses

To demonstrate that responsive pricing works, we show that the distance between any two occupancy deciles is smaller for more responsive regimes. We also present some evidence on the standard deviation of occupancy showing that more responsive pricing curves decrease the standard deviation of the occupancy distribution. The evidence on standard deviation is complementary, and provides a measure of the overall change in the occupancy distribution.

4.1 Inter-Decile Regressions

In this section we use a quantile-regressions framework to measure the effect of the responsiveness parameter on the distribution of occupancy (Koenker and Basset, 1978). In particular, the objective of this section is to test Proposition 2. We estimate the effect of the responsiveness of the pricing regime on the difference between the 9th and the Yth decile,

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

$$q_{0.9} - q_Y = \gamma_{0,Y} + X\gamma_{X,Y} + \beta\gamma_{\beta,Y} + \varepsilon_Y \quad \text{(A)}$$

where q_Y is the Y^{th} decile of the occupancy distribution and γ are the coefficients to be estimated. The variables in X control for independent sources of variation in deciles that could come from hour fixed effect, day-of-week fixed effect, holiday effect, and weekend-cycle effects (hour dummies for Saturday and Sunday).

One interpretation of this regression is the following. The 9th decile could be interpreted as the threshold level of occupancy below which the store offers discounts (Q_0 in the model). The model shows that the number of empty terminals should decrease as the regime is more price responsive. This implies that, holding the 9^{th} decile constant, all deciles should increase for more responsive regimes. Stated differently, the inter-decile difference should decrease. We test the hypothesis that γ_β is negative.

Table 2 shows the estimated coefficients for model (A) when *Y=0.1, 0.3, 0.5,* and *0.7*. Panel A reveals the two main findings. First, the coefficients γ_β are negative and significantly different from zero. Increasing the responsiveness parameter by 10 percent implies a decrease in the distance between the 9^{th} and the 1^{st} decile of almost 3 percent. Second, reading Table 2 from left to right, these coefficients decrease as *Y* increases. The effect of a change in responsiveness on the distance between the 9^{th} and the 7^{th} decile is 1/4 of the effect on the distance between the 9^{th} and the 1^{st} decile, and this difference is significant.[12]

We interpret the results in Table 2 as follows. If we take a given decile—for example, the 9^{th}—as a reference point, an increase in the responsiveness of the pricing function moves all deciles closer to the reference decile. Moreover, lower deciles move more than higher ones. This implies that the inter-decile differences decrease for any two deciles, as predicted by proposition 2. To interpret this second finding, it helps to consider equation (2). We rewrite this equation assuming that the two states of the world correspond to the 9^{th} and Y^{th} deciles, $q_{h,0.9}-q_{h,Y}=(u_{h,0.9}-u_{h,Y})/(b_h+\beta_h)$. The effect of a change in responsiveness is greater on lower deciles because these deciles are located further away from the 9^{th} decile—that is, $u_{h,0,9}-u_{h,Y}$ decreases with Y.[13]

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[12] By jointly estimating the effect of responsiveness on the deciles of the occupancy distribution, we can test for the equality of coefficients across equations. Coefficients in the first row of Table 2 are significantly different from each other.

[13] Another possibility is that the slope of the demand curve, b_h, could depend on the state of the world. We can investigate that possibility by using the coefficient estimates from Table 2 to compute the implied demand slopes. The demand slope at the Y^{th} quantile of the distribution of shocks is $dq_Y/dp_Y=\gamma_{\beta,Y}/(Q_{0.9}-q_Y)$, where $\gamma_{\beta,Y}$ is the coefficient of responsiveness in model (A). This expression is obtained by replacing $dp_{h,Y}/d\beta_h=-(Q_{h,0.9}-q_{h,Y})$ and $dq_{h,Y}/d\beta_h=-\gamma_{\beta,Y}$ in $dq_{h,Y}/d\beta_h=(dq_{h,Y}/dp_{h,Y})(dp_{h,Y}/d\beta_h)$. Using the estimates in Table 2, we find slopes that vary from 0.018 to 0.024, depending on the quantile considered, corresponding to demand elasticities ranging from 0.64 to 0.47 (evaluated using the average responsiveness in the sample). Jointly estimating model (A) for each quantile, we find that demand slopes evaluated using the average responsiveness in the sample are not significantly different across quantiles (at a 5 percent

Panels B, C, and D show that the results are robust even if we rely on different methods to construct the measure of responsiveness. Panel B excludes fixed-pricing regimes, in which the responsiveness parameter is zero. The coefficients do not change, suggesting that our results are not driven by these regimes. Panel C excludes the 3 responsive pricing regimes that are not linear and again the results do not change, showing that the 3 non-linear pricing curves are not driving the results. Panel D considers only hours 8, 9, and 10 a.m., during which occupancy never reaches 60 percent, which corresponds to the kink in the three non-linear pricing curves. During these three hours, we can assume that the pricing curve is linear for all regimes. Again, the results do not change substantially.

Another test of robustness is to allow for regime-fixed effects. Regime-fixed effects control for other regime-specific effects that may not be captured by the responsiveness variable. Panel E shows the results of the same specification as Panel A but with regime-fixed effects. The estimates of the responsiveness coefficient are again of the right sign and significant, and they remain within the range of previous estimates.

4.2 Standard Deviation

In this section we look at the effect of responsiveness on the standard deviation of the occupancy distribution. The main finding is illustrated in Figure 3, which plots the standard deviation in occupancy—computed by hour and regime—as a function of the responsiveness of the pricing curve, measured on the horizontal axis. Each of the 272 points in the graph corresponds to the standard deviation in occupancy for a given hour and regime.[14] As expected, the standard deviations of occupancy under fixed pricing (the points on the vertical axis, since $\beta=0$) appear to be higher—and the difference is significant—than the standard deviations under responsive pricing. In addition, Figure 3 suggests the existence of a negative relationship between the responsiveness of the pricing regime and the standard deviation of occupancy. Column 1 in Table 3 reports the estimates of a regression of standard deviation of occupancy on the responsiveness variable. These estimates show that the negative relation suggested by Figure 3 is indeed significant.

The standard deviation in occupancy rates shown in Figure 1 does not control for independent sources of variation in standard deviation. We compute standard deviation in

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confidence level). The test of the equality of slopes is a test of a nonlinear function $R(\gamma)$ of the estimates. The test can be written as a Wald test $W=R(\gamma)'[GVG']^{-1}R(\gamma)$, where G is the vector of first derivatives of $R(\gamma)$ with respect to γ, and V is the estimated variance covariance matrix of the parameters.

[14] There are 5 regimes under fixed pricing and 12 regimes under responsive pricing, with 16 hour observations per regime. This amounts to 272 observations.

occupancy by hour and regime $\sigma_{h,r}$ after controlling for the predictable source of variations in occupancy:

$$q = \widetilde{\gamma}_0 + \widetilde{X}\widetilde{\gamma} + \widetilde{\varepsilon} \quad \text{(B)}$$

where q represents occupancy rates and $\widetilde{X}$ includes hour- and regime-specific fixed effects, day-of-the-week fixed effects, holiday fixed effects, and weekend-cycle fixed effects. The residuals—which have zero mean for each combination of hour and regime—are used to compute the dependent variable $\sigma_{h,r}$.[15] We regress $\sigma_{h,r}$ on the responsiveness measure, controlling for hour fixed effects:

$$\sigma_{h,r} = \hat{\gamma}_0 + \hat{X}\hat{\gamma}_1 + \hat{\gamma}_\beta \beta_r + \hat{\varepsilon} \quad \text{(C)}$$

β_r is the measure of discount responsiveness for regime r and $\hat{X}$ includes and hour and regime fixed effects. The results of estimation (OLS) of model (C) are reported in Table 3. The estimate of $\hat{\gamma}_\beta$ in column 2 is negative (-0.00046), and significantly different from zero (at 1 percent confidence level). The magnitude of the coefficient does not change with respect to the coefficient in column 1.

We follow the same procedure as in the previous subsection to test if our results are robust regarding our construction of the responsiveness variable. Column 3 presents the same specifications as column 2 but excludes all fixed-price regimes, column 4 excludes the three non-linear regimes, and column 5 considers only hours between 8 and 11 a.m. The coefficients in columns 3, 4, and 5 show that our estimates do not depend on the method used to construct the slope variable. Given an estimated coefficient for the responsiveness variable of –0.00046, the elasticity of standard deviation in occupancy to responsiveness— computed for the average slope (17.1) and the average $\sigma_{h,r}$ (0.045)—is 0.18. This implies that doubling the pricing responsiveness parameter reduces the standard deviation of unexplained variations in occupancy by 18 percent.

4.3 Additional Evidence

Impact of Responsive Pricing over the Day Cycle

The inter-decile regressions in Table 2 do not allow for different impacts of the responsiveness parameter on different hours. The results in Table 2 could be driven by only a single hour or a couple of hours. To address this issue, we allow for hour-specific responsiveness effects in model (A). In addition, investigating the impact of responsive pricing over the day cycle is interesting for policy reasons.

Table 4 presents the estimates for the hour-specific responsiveness effects. Table 4 shows that our main findings generalize at the hour level. For example, column 1 reports the coefficient estimates of γ_β for the distance between the 9th and the 1st deciles. These coefficient estimates are negative, and significantly different from zero, for all hours but 4 p.m. This finding holds for the other 3 inter-decile differences, with the caveat that fewer hour coefficients are significant for deciles that are closer to the 9th one. Only 7 coefficient estimates of γ_β are significant at the 10 percent confidence level for the distance between the 9th and the 7th deciles. The explanation for the finding that the significance decreases for deciles closer to the 9th decile is that the level of discount is lower for higher levels of occupancy. Higher deciles move less, and the impact of responsiveness on the inter-decile differences is smaller and less likely to be statistically different from zero.

Table 4's findings are displayed in Figure 5, which plots the coefficient estimates for the hour-specific responsiveness effects over the day cycle. The four points at 10 a.m., for example, measure how much the distance between the 9th decile and the 1st, 3rd, 5th, and 7th deciles decreases for a unitary change in responsiveness at that hour.

Figure 5 reveals two findings. First, the impact of an increase in responsiveness is larger for the distance between the 9th and the 1st decile than for any other inter-decile distance for each hour of the day. Moreover, the effect of responsiveness tends to decrease for smaller inter-decile differences for each hour of the day. This is consistent with the model (and Table 2's results), which predicts that the coefficient estimates for γ_β should decrease for smaller inter-decile distances.

Second, Figure 5 shows that the effect of responsive pricing is smallest at 4 p.m—the peak hour of the day cycle. To see that, consider the lowest curve on the figure that corresponds to the effect of the responsiveness parameter on the distance between the 9th and 1st decile.[16] This curve reaches its peak at 4 p.m., and is then not significantly different from zero (see Table 4). Figure 5 suggests that responsive pricing is less effective at reducing the impact of sudden demand

[15] Column 1 in Table 3 used the residuals of model (B) with only hour and regime fixed effects to compute the dependent variable $\sigma_{h,r}$.

[16] The 4 p.m. peak in estimated coefficients cannot be explained by the fact that demand for Internet access is highest at that hour, implying lower average discounts. Our dependent variable—inter-decile differences—controls for hour-specific, demand-fixed effects .

shocks at the peak.[17] The model suggests two reasons why this may be the case. Consumers may be less price-sensitive at the peak, or variability in demand may be lower at the peak. In fact, equation 2 suggests that $d(q_{h,0.9}-q_{h,Y})/d\beta_h$ depends on the slope of the hourly demand functions (b_h), and also on the dispersion of demand shocks at each hour ($u_{h,0.9}-u_{h,Y}$).

We explore these two alternative explanations. We estimate b_h for each hour by using a simple linear demand system.[18] We find that the slope of the inverse demand is significantly steeper at the peak. In addition, the correlation between the estimated slope at each hour and the coefficients reported in table 4 is large, and significantly different from zero. For example, if we consider the coefficients for the distance between the 9th and the 1st decile, the correlation is 0.70. This suggests that the variations in the slope do explain at least part of the day-cycle variations in the impact of responsive pricing.

We also compute the standard deviation—by hour—of the occupancy residuals obtained from the simple linear demand system. We use these hourly standard deviations as a proxy for the standard deviation in hourly demand shocks ($u_{h,.}$). We find that the standard deviation in occupancy is not significantly smaller at the peak. In addition, the correlation between the hourly standard deviation of the occupancy residuals and the coefficients reported in Table 4 is not significantly different from zero.[19] Overall, the evidence suggests that consumers respond less to an increase in the responsiveness parameter at the peak of the day cycle.

Hourly Changes in Occupancy

So far we have investigated the impact of responsive pricing on the hourly distributions of occupancy, and we have shown that more responsive regimes reduce the dispersion of the occupancy distributions. This suggests that occupancy is likely to vary less over time—that is, from one hour to the next—under responsive pricing, although that does not *necessarily* follow from the results presented so far. In this section, we present evidence from occupancy time

[17] Another feature of Figure 5 is that the impact of pricing responsiveness on inter-decile differences varies over the day cycle, with local peaks at 8 a.m. and 10 p.m. However, the nature of these local peaks is different from the 4 p.m. peak. Although the coefficients on the 9th and 1st deciles are lower at these local peaks in absolute value, they are significantly different from zero. At these hours, consumers still respond to responsive pricing, albeit to a lesser extent.

[18] The demand function is specified as $q = \delta_{1,h} + \delta_{2,h} p + X\delta_3 + \varepsilon$, where q is the hourly occupancy rate and p is the hourly price. $\delta_{1,h}$ and $\delta_{2,h}$ are estimated hour-specific coefficients that correspond to a_h and b_h in the model. ε corresponds to unpredictable demand uncertainty, or u in the model. X is a matrix of exogenous variables, including day fixed effects, national holiday fixed effects, and weekend hour-cycle fixed effects. δ_3 is a vector of parameters. Variations in the pricing curve allow us to estimate the hourly demand functions, and we use the congestion charge and the responsiveness of the pricing curves as instruments for p.

[19] We performed a simple OLS regression (with 16 observations) of the coefficients reported in Table 4 for the impact of responsiveness on the distance between the 9th and the 1st decile on the hourly measures of demand slope and

series that suggests that responsive pricing reduces the change in occupancy rates across adjacent hours.[20] We compute the standard deviation of the change in occupancy across hours (by hour and regime), and we test whether the responsiveness variable affects this new measure of occupancy variability.

As before, we use the residuals of model (B) to compute a variable that measures how much occupancy changes between adjacent hours. The average standard deviation of the first differences in the residuals of model (B) is 0.036 for responsive pricing and 0.049 for peak-load pricing regimes, and this difference is significant. This suggests that occupancy varies less across hours under responsive pricing. Columns (7) and (8) in Table 3 present results analogous to those in columns (2) and (3), but where the dependent variable is the standard deviation of the change in occupancy across hours. We again find that occupancy varies less over time as the pricing curve becomes more responsive. The elasticity of the standard deviation with respect to the slope varies between 0.18 and 0.23, depending on the specification. This implies that doubling the pricing responsiveness parameter reduces the standard deviation of unexplained variations in hour-to-hour occupancy by 18 to 23 percent.

5 The Welfare Impact of Responsive Pricing

Responsive pricing increases welfare by increasing consumption in states of the world where capacity would otherwise be wasted. Consider our Internet café application, and assume that the store switches from peak-load pricing to responsive pricing. In particular, consider a responsive pricing regime that sets the level of pricing responsiveness (β in the model) at the average level of responsiveness in our sample. The threshold level of occupancy below which discounts are offered (Q_0 in the model) is set at a level that corresponds to the average realized 9^{th} decile in our sample—implying that discounts are given in only 90 percent of the states of the world where inefficiencies occur. This choice of Q_0 is justified by the fact that estimates of the effect of the responsiveness parameter become less accurate for very high quantiles of the distribution. In our sample, the 9^{th} decile is located at 74 percent of total capacity. Accordingly, the peak-load price (α in the model) is set at the 9^{th} decile of the distribution of prices. Under peak-load pricing, store occupancy is by definition lower than Q_0 90 percent of the time.

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demand uncertainty. This regression shows that only the slope measure is significant, and that it explains 54 percent of the impact variations.

[20] Assuming that the joint distribution of arrival rates across hours does not change with the pricing regime, the model presented in section 2 predicts that the standard deviation in occupancy differences across hours decreases for more responsive regimes.

The first step in estimating welfare gains from responsive pricing is to compute the increase in occupancy that stems from responsive pricing. The effect of an increase in the responsiveness parameter on the 1st, 3rd, 5th, and 7th deciles relative to the 9th decile of the occupancy distribution is simply given by the coefficients in Table 2. For example, the coefficient in column (1)—corresponding to the change in the 9th minus 1st decile—measures the increase in occupancy that would occur, on average, in the 10 percent lowest states of the world. The impact of an increase in the responsiveness parameter on expected occupancy is the weighted sum of the effects at each decile of the distribution.[21]

We find that increasing the responsiveness of the pricing curve from zero (peak-load pricing) to the mean level of responsiveness in our sample (17.1) increases occupancy by 11 terminals, on average. To put this figure into perspective, we compare it with the average occupancy under peak-load pricing. The impact of responsive pricing corresponds to 5 percent of the average peak-load-pricing occupancy. Assuming that the responsiveness parameter corresponds to the highest value in our sample (41.8), we find an increase in occupancy of 27 terminals that corresponds to 11 percent of the average peak-load-pricing occupancy.

Knowing the occupancy increase that is due to responsive pricing, we can estimate the welfare gains created by the additional consumption. Under the assumption that all costs are fixed, we can focus on changes in consumer welfare and producer revenue, since a change in pricing regime that changes total consumption will not change producer costs. Following the model, the welfare change from regime r to regime r' is:

$$\tfrac{1}{2} \Sigma_i f_i(q_i(r) - q_i(r'))(p_i(r)+p_i(r'))$$

where $q_i(r)$ and $p_i(r)$ are the quantity and price in state i under regime r, and f_i is the weight associated with state i. To understand the intuition underlying this expression, recall that when demand is linear, the welfare gains from a change in price from p to p'—which implies a change in consumption from q to q'—is ½(q-q')(p+p'). In the case of responsive pricing, a change in price responsiveness implies a change in the distribution of prices and quantities. The overall welfare change is equal to the weighted average of the welfare change in each state of the world.

To give more meaning to the welfare figures, we normalize the increase in welfare by the average consumer expenditure under peak-load pricing. The welfare gain deriving from the introduction of responsive pricing is 5 percent of consumer expenditure under peak-load pricing, when the responsiveness of the pricing regime is set at the average level in our sample. The same

[21] In our calculations, the weights on the coefficients for the 1st, 3rd, 5th and 7th deciles are.2, .2, .2 and .3. The weights add up to .9 because discounts are given in 90 percent of the states of the world.

figure rises to 12 percent when the responsiveness parameter is set to the maximum level observed in our sample.

6 Conclusions

Responsive pricing proposes to reduce the inefficiencies that result from unpredictable demand shocks by shortening the feedback loop between market shocks and adjustments in market prices, thereby providing more efficient consumption incentives. This paper exploits a unique experiment in an Internet café to assess the welfare impact of responsive pricing. In this situation, prices change as a function of demand realizations: prices increase when demand is high—that is, when the store edges closer to congestion—and prices fall when demand is low: that is, when unused capacity increases.

First, we show that responsive pricing significantly decreases the variability in occupancy caused by unpredictable demand shocks. The results show that occupancy varies less under more responsive regimes. Occupancy also varies less across hours. This evidence is consistent with the hypothesis that responsive pricing increases occupancy in low-demand states of the world, holding the probability of congestion constant. As a result, responsive pricing reduces the amount of wasted capacity that occurs under peak-load pricing.

Second, we show that our estimates of the impact of responsive pricing on the distribution of occupancy imply significant welfare gains. We estimate that the welfare gains from moving from peak-load pricing to the average responsive pricing in our sample equal 5 percent of average consumer expenditure. The welfare gains from increasing the responsiveness parameter to the highest level observed in our sample are equal to 12 percent of consumer expenditure. These welfare gains are specific to responsive pricing and cannot be obtained under peak-load pricing.

Our results show that consumers do respond to fairly sophisticated pricing schemes. Consumers are willing to monitor prices in real time, and they do adjust their behavior in response to market conditions. This suggests that policymakers should seriously consider introducing self-regulating pricing schemes such as responsive pricing in other contexts. Our results show that responsive pricing could be particularly effective in situations with highly unpredictable demand and price elastic consumers. Although we find substantial welfare gains from responsive pricing in our application, an important consideration in policy applications is whether these welfare gains justify implementation and metering costs.

In this work, we have focused on the possibility of using responsive pricing to reduce inefficiencies that stem from wasted capacity, because this was the main source of inefficiency in our application. In other applications, an important source of inefficiency is not unpredictable overcapacity but rather unpredictable excess demand, which results in rationing. Responsive pricing can also decrease the inefficiencies that result from rationing. The intuitive notion is that responsive pricing raises prices when the resource approaches congestion, thereby reducing both the chance that congestion will occur and the waiting lines if it does occur. We show in a different paper that full efficiency can be achieved under pricing regimes that are sufficiently responsive (Courty and Pagliero, 2003).

Appendix

Proposition: Standard deviation decreases as discount responsiveness increases, $d\sigma_{qh}/d\beta_h<0$.

Proof: Let $q_{h,M}$ represent the mean level of occupancy in hour h,

$$q_{h,M}=Q_0-1/(b_h+\beta_h)[\Sigma_{u<uh*}f_{h,i'}(u_h*-u)].$$

Define i_h* as the highest state of the world such that $u_i \leq u_h*$. Deviation from mean occupancy in state i is

$$q_{h,i}-q_{h,M}=\begin{cases}\dfrac{1}{b_h+\beta_h}\displaystyle\sum_{i\leq i_h^*} f_{h,i}\left(u_h^*-u_{h,i}\right) & if\ i\geq i_h^* \\ \dfrac{1}{b_h+\beta_h}\left(\displaystyle\sum_{i\leq i_h^*} f_{h,i}\left(u_h^*-u_{h,i}\right)-\left(u_h^*-u_{h,i}\right)\right) & if\ i\leq i_h^*\end{cases}$$

Responsive pricing reduces deviations from the mean, $\partial(q_{h,i}-q_{h,M})^2/\partial\beta_h<0$. This implies that standard deviation decreases for more responsive pricing schemes ($d\sigma_{qh}/d\beta_h<0$). QED

References

Aubin, Christophe, Denis Fougere, Emmanuel Husson and Marc Ivaldi (1995). "Real-Time Pricing of Electricity for Residential Customers: Econometric Analysis of an Experiment." Journal of Applied Econmetrics, Vol 10, p. S171-S191.

Boiteux, M. (1956). "Sur la Gestion des Monopoles Publics Astreints a l'Equilibre Budgetaire." Econometrica, 24:1, pp. 22-40.

Boiteux, M. (1956). "Sur la Gestion des Monopoles Publics Astreints a l'Equilibre Business 33 (April 1960), 157-179.

Borenstein, Severin, Michael Jaske, and Arthur Rosenfeld. (2002) "Dynamic Pricing, Advanced Metering and Demand Response in Electricity Markets." The Energy Foundation.

Crew, Michael, Fernando, Chitru, Kleindorfer, Paul. (1995) "The Theory of Peak-Load Pricing: A Survey". Journal of Regulatory Economics v8, n3: 215-48.

Courty, Pascal and Pagliero, Mario (2001). "easyEverything Pricing Policies." ECCH case.

Courty, Pascal and Pagliero, Mario (2003). "Responsive Pricing." CEPR Discussion Paper 4036.

Herriges, Joseph, Mostafa Baladi, Douglas Caves, and Bernard Neenan. (1993). "The Response of Industrial Customers to Electricity Rates Based Upon Dynamic Marginal Costs." The Review of Economics and Statistics. p. 446-454.

Koenker, R, Basset, G (1978). "Regression Quantiles", Econometrica, 46, 33-50.

MacKie-Mason, Jeffrey and Hal Varian (1994). "Some Economics of the Internet" Mimeo, University of Michigan.

Patrick, Robert and Frank Wolak. (2001) "Estimating the Customer-Level Demand for Electricity Under Real-Time Market Prices." Mimeo, Stanford University.

Schwartz, Peter, Thomas Taylor, Matthew Birmingham, and Shana Dardan. (2002) "Industrial Response to Electricity Real-Time Prices: Short Run and Long Run. Economic Inquiry, 40 (4), p. 497-610.

Vickrey, William. (1971). "Responsive Pricing of Public Utility Services." The Bell Journal of Economics and Management Science, 1(2), p. 337-346.

William Vickrey (1994). Public Economics. Edited by Richard Arnott, Anthony B. Atkinson, Kenneth Arrow, Jacques H. Drèze. Cambridge University Press.

Table 1. Summary Statistics

Regime	Number of observations	Length of the regime (days)	Responsiveness (R^2)	Congestion charge	Mean occupancy rate	S.d. occupancy rate	Mean Price	S.d. Price
	(1)	(2)	(3)	(4)	(5)	(6)	(6)	(7)
1	109	9	0	3.277	0.541	0.148	3.277	0.204
2	48	3	0	6.625	0.572	0.112	6.625	2.671
3	68	5	0	5.648	0.606	0.162	5.648	0.697
4	143	10	0	6.625	0.644	0.156	6.625	1.435
5	78	7	0	9.141	0.584	0.218	9.141	1.785
Peak-load pricing	446	6.8	0	6.098	0.595	0.168	6.098	2.402
6	85	6	10.733 (0.99)	13.629	0.618	0.160	9.616	1.757
7	110	7	12.235 (0.99)	15.766	0.596	0.149	10.773	1.794
8	221	15	15.098 (0.99)	18.072	0.600	0.150	12.085	2.320
9	208	15	15.141 (0.99)	18.638	0.578	0.159	12.344	2.518
10	183	11	16.090 (0.95)	20.462	0.550	0.171	12.906	2.747
11	224	16	15.536 (0.96)	20.938	0.539	0.159	13.642	2.463
12	444	28	12.670 (0.75)	21.236	0.492	0.161	14.477	2.887
13	342	22	14.082 (0.83)	22.486	0.501	0.165	15.419	3.010
14	196	13	17.272 (0.87)	23.445	0.516	0.148	15.176	3.168
15	94	6	33.722 (0.96)	33.950	0.513	0.152	17.519	5.151
16	112	7	32.782 (0.95)	33.983	0.509	0.154	18.306	5.189
17	93	6	41.879 (0.99)	41.018	0.461	0.131	18.714	5.492
Responsive Pricing	2,312	12.66667	17.112	22.264	0.533	0.163	14.174	3.808
All regimes	2,758	9.7333	17.112	19.65	0.543	0.165	12.868	4.683

Note: The table reports the mean value of the variables by regime (from 1 to 17), and also reports the average for the peak-load pricing period (regimes 1–6), the responsive pricing period (regimes 6–17), and the entire sample. 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 observed occupancy rate and price. The table includes observations for hours between 8 am and 12 pm.

Table 2. Relationship Between Inter-Decile Differences of Occupancy and Pricing Responsiveness

	$q_{0.9}$-$q_{0.1}$	$q_{0.9}$-$q_{0.3}$	$q_{0.9}$-$q_{0.5}$	$q_{0.9}$-$q_{0.7}$
	(1)	**(2)**	**(3)**	**(4)**
A) The sample includes all regimes				
Responsiveness	-0.0032***	-0.0025***	-0.0016***	-0.0008***
	(0.0002)	(0.0002)	(0.0003)	(0.0002)
Const	0.1891***	0.1494***	0.0983***	0.0576***
	(0.0138)	(0.0166)	(0.0113)	(0.0067)
N	2758	2758	2758	2758
Regime fixed effects?	No	No	No	No
B) The sample includes responsive pricing regimes only				
Responsiveness	-0.0028***	-0.0024***	-0.0017***	-0.0009***
	(0.0003)	(0.0002)	(0.0003)	(0.0002)
Const	0.1819***	0.1420***	0.0987***	0.0578***
	(0.0129)	(0.0127)	(0.0098)	(0.0107)
Regime fixed effects?	No	No	No	No
N	2312	2312	2312	2312
C) The sample excludes regimes 12,13, and 14				
Responsiveness	-0.0027***	-0.0016***	-0.0010***	-0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Const	0.1737***	0.1178***	0.0815***	0.0462***
	(0.0142)	(0.0155)	(0.0095)	(0.0105)
Regime fixed effects?	No	No	No	No
N	1776	1776	1776	1776
D) The sample includes observations between 8 am and 11 am only				
Responsiveness (see note)	-0.0037***	-0.0031***	-0.0021***	-0.0008***
	(0.0004)	(0.0003)	(0.0004)	(0.0003)
Const	0.1946***	0.1562***	0.1023***	0.0481***
	(0.0151)	(0.0168)	(0.0194)	(0.0175)
Regime fixed effects?	No	No	No	No
N	525	525	525	525
E) The sample includes all observations				
Responsiveness	-0.0030***	-0.0022***	-0.0018**	-0.0018**
	(0.0008)	(0.0008)	(0.0007)	(0.0008)
Const	0.2384***	0.1771***	0.1438***	0.1266***
	(0.0278)	(0.0323)	(0.0280)	(0.0343)
Regime fixed effects?	Yes	Yes	Yes	Yes
N	2758	2758	2758	2758

NOTE: The dependent variable is the inter-decile distance ($q_{0.9}$-q_y), y=0.1, 0.3, 0.5, 0.7. Responsiveness is the slope of the pricing curve in each regime. Hour fixed effects (9am–12pm), day fixed effects (Tuesday to Sunday), weekend-cycle fixed effects (9am–12pm during weekend days), and national holiday fixed effects are included in each regression. In Panel D the sample includes observations between 8am and 11am, during which time occupancy never reached 60 percent. In panel D, the slope of the pricing function is estimated for levels of occupancy below 60 percent only. Specification in Panel E is the same as in Panel A, but it includes regime-specific fixed effects. N is the number of observations in the sample. Standard errors are estimated using the bootstrap resampling routine in Stata7 (with 20 replications), and are reported in parentheses.

* Significant at the 10 percent level.

** Significant at the 5 percent level.

*** Significant at the 1 percent level.

Table 3. Relationship Between Standard Deviation of Occupancy and Pricing Responsiveness

	sd(occupancy)	sd(q)	sd(q)	sd(q)	sd(q)	sd(q)	sd(q_t -q_{t-1})	S.d.(q_t -q_{t-1})
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Responsiveness	-0.00058***	-0.00046***	-0.00046***	-0.00046***	-0.00048***	-0.00086***	-.00049***	-0.00049***
	(0.00014)	(0.00010)	(0.00011)	(0.00010)	(0.00010)	(0.00015)	(0.00008)	(0.00011)
Const	0.06022***	0.04101***	0.04296***	0.04191***	0.04125***	0.05741***	0.0150***	0.0280***
	(0.00320)	(0.00247)	(0.00343)	(0.00277)	(0.00261)	(0.00182)	(0.0043)	(0.0031)
Hour fixed effects?	No	yes	yes	yes	yes	yes	Yes	Yes
Regime fixed effects?	No	no	no	no	no	yes	no	No
N	272	272	192	224	51	272	269	189
R2	0.1	0.17	0.23	0.17	0.3	0.35	0.29	0.38
Hours in the sample	8am–12pm	8am–12pm	8am–12pm	8am–12pm	8am–11am	8am–12pm	8am–12pm	8am-12pm
Regimes excluded from the sample	-	-	1–5	12,13,14	-	-	-	1-5

NOTE: The dependent variable in specification (1)—sd (occupancy)—is the standard deviation of the occupancy rate computed by hour and regime. The dependent variable in specifications (2) to (6) is the standard deviation (computed by hour and regime) of the unpredictable component of occupancy rates, computed from model (B). The dependent variable in specifications (7–8)—sd (q_t -q_{t-1})—is the standard deviation of the first difference of the unpredictable component of occupancy rates, computed by hour and regime. Responsiveness is measured by the estimated slope of the pricing curve. In specification (5), the responsiveness of the pricing regime is estimated for levels of capacity below 60 percent. N is the number of observations in the sample. Newey-West robust standard errors appear in parentheses.

* Significant at the 10 percent level.

** Significant at the 5 percent level.

*** Significant at the 1 percent level.

Table 4. Relationship Between Inter-Decile Differences of Occupancy and Pricing Responsiveness at Hour Level

	$q_{0.9}$-$q_{0.1}$	$q_{0.9}$-$q_{0.3}$	$q_{0.9}$-$q_{0.5}$	$q_{0.9}$-$q_{0.7}$
	(1)	(2)	(3)	(4)
Responsiveness *h8	-0.0029***	-0.0021***	-0.0011*	-0.0003
	(0.0011)	(0.0008)	(0.0006)	(0.0005)
Responsiveness *h9	-0.0050***	-0.0042***	-0.0028***	-0.0015**
	(0.0010)	(0.0007)	(0.0011)	(0.0008)
Responsiveness *h10	-0.0058***	-0.0033***	-0.0023***	-0.0012**
	(0.0021)	(0.0010)	(0.0006)	(0.0006)
Responsiveness *h11	-0.0048***	-0.0031***	-0.0014***	-0.0013**
	(0.0018)	(0.0012)	(0.0005)	(0.0005)
Responsiveness *h12	-0.0031**	-0.0020**	-0.0013	-0.0009
	(0.0013)	(0.0010)	(0.0010)	(0.0006)
Responsiveness *h13	-0.0046***	-0.0033***	-0.0020***	-0.0010
	(0.0008)	(0.0006)	(0.0005)	(0.0007)
Responsiveness *h14	-0.0032***	-0.0027***	-0.0016**	-0.0003
	(0.0009)	(0.0011)	(0.0008)	(0.0005)
Responsiveness *h15	-0.0023**	-0.0014	-0.0004	-0.0006
	(0.0012)	(0.0010)	(0.0009)	(0.0011)
Responsiveness *h16	-0.0003	-0.0005	0.0004	0.0003
	(0.0013)	(0.0009)	(0.0008)	(0.0008)
Responsiveness *h17	-0.0024***	-0.0012*	-0.0004	-0.0010
	(0.0009)	(0.0007)	(0.0009)	(0.0008)
Responsiveness *h18	-0.0028***	-0.0017**	-0.0006	-0.0010
	(0.0010)	(0.0008)	(0.0013)	(0.0010)
Responsiveness *h19	-0.0030***	-0.0031**	-0.0020**	-0.0012*
	(0.0010)	(0.0013)	(0.0008)	(0.0007)
Responsiveness *h20	-0.0046***	-0.0042***	-0.0029***	-0.0017**
	(0.0011)	(0.0009)	(0.0006)	(0.0007)
Responsiveness *h21	-0.0043***	-0.0035***	-0.0029***	-0.0017**
	(0.0012)	(0.0006)	(0.0008)	(0.0008)
Responsiveness *h22	-0.0035***	-0.0027***	-0.0019**	-0.0002
	(0.0010)	(0.0007)	(0.0009)	(0.0008)
Responsiveness *h23	-0.0049***	-0.0048***	-0.0036***	-0.0025***
	(0.0012)	(0.0009)	(0.0007)	(0.0008)
Constant	0.1756***	0.1265***	0.0894***	0.0490***
	(0.0149)	(0.0186)	(0.0176)	(0.0139)
N	2758	2758	2758	2758

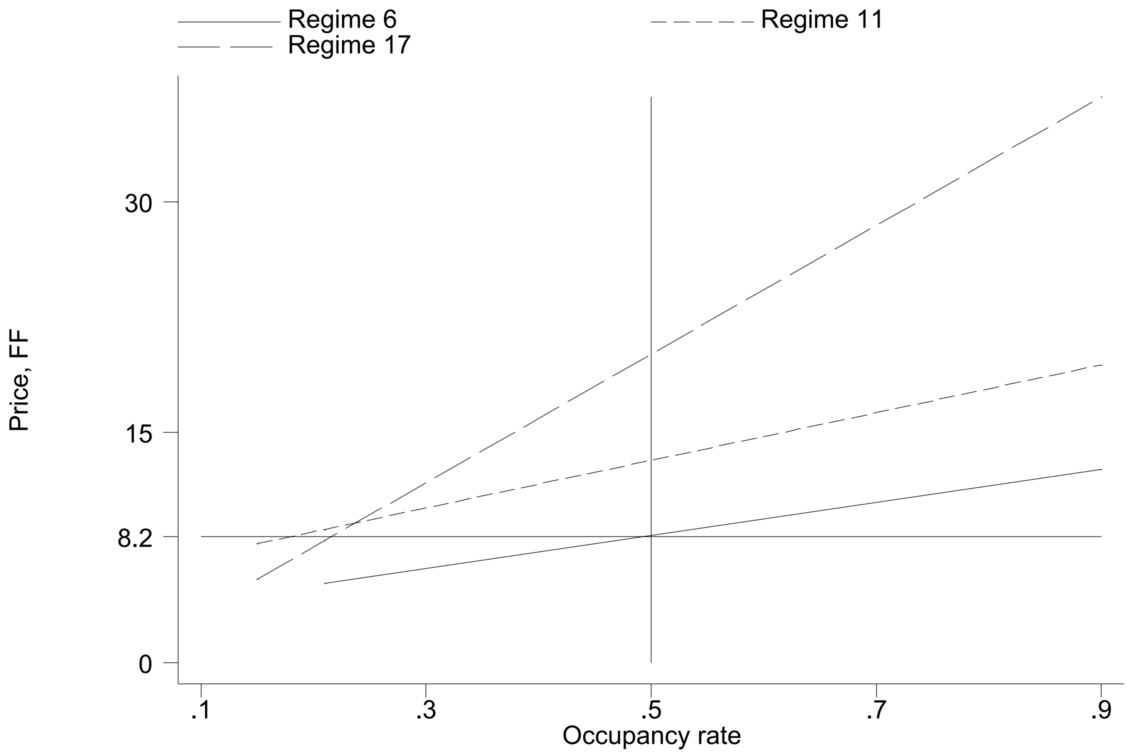
NOTE: The dependent variable is the inter-decile distance ($q_{0.9}$-q_y), y=0.1, 0.3, 0.5, 0.7. Responsiveness*hx is the slope of the pricing curve interacted with the indicator variable for hour x (8am–12pm). Hour fixed effects (9am–12pm), day fixed effects (Tuesday to Sunday), weekend-cycle fixed effects (9am–12pm during weekend days), and national holiday fixed effects are included in each regression. N is the number of observations in the sample. Standard errors are estimated using the bootstrap resampling routine in Stata7 (with 20 replications), and are reported in parentheses.

* Significant at the 10 percent level.

** Significant at the 5 percent level.

*** Significant at the 1 percent level.

Figure 1. Representative Pricing Curves



NOTE: The figure reports linear approximations of the pricing curves used in regimes 1, 11, and 17 (see Table 1). In computing the linear approximation, we do not consider occupancy levels that are not reached in the sample. Thus the pricing functions in the graph do not necessarily have the same support.

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Figure 2. Equilibrium Under Responsive Pricing

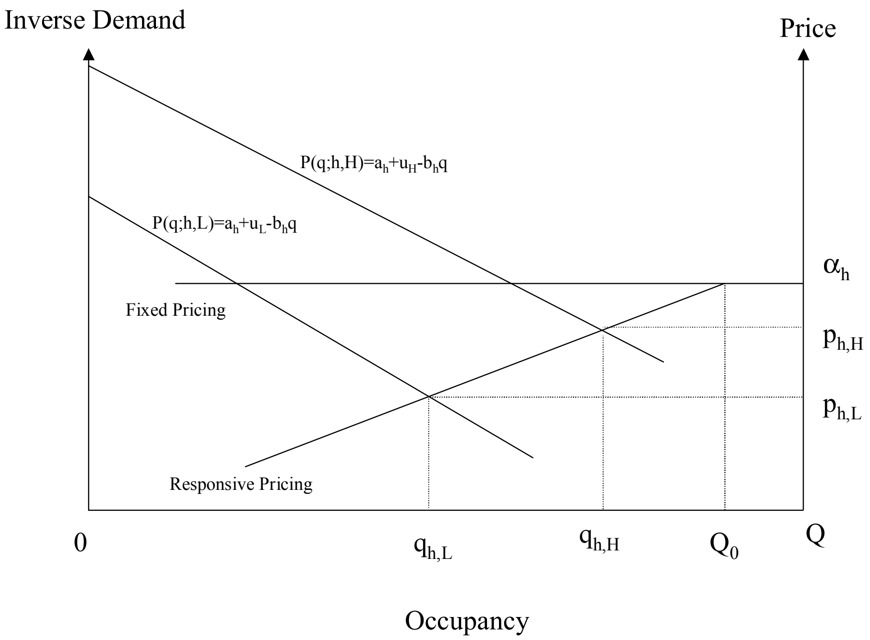


Figure 3. Occupancy Response to Changes in Pricing Responsiveness

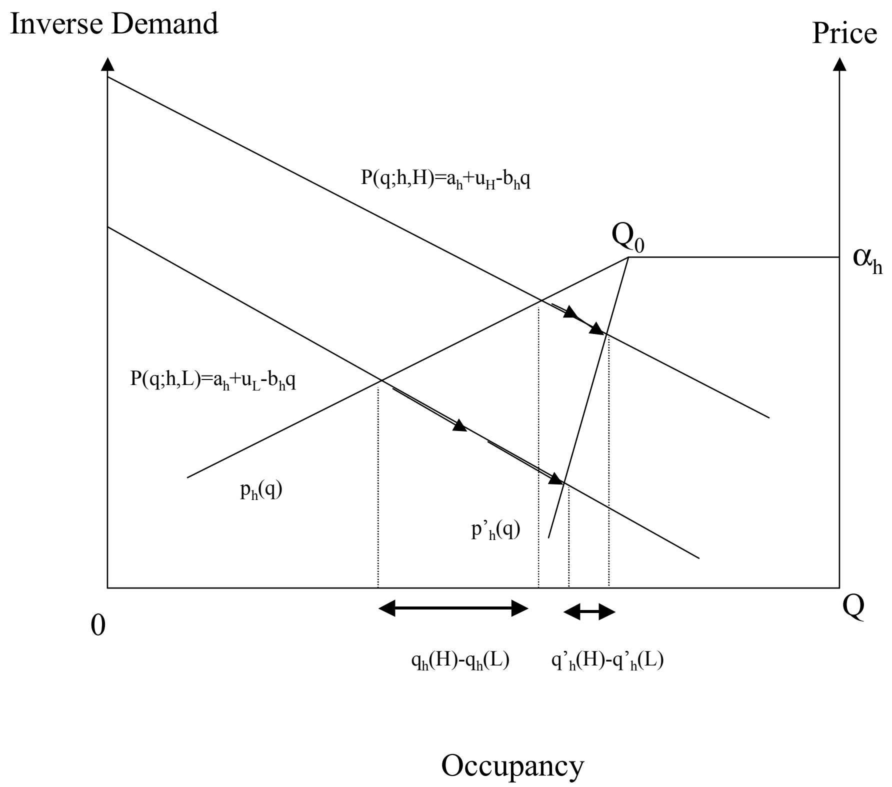


Figure 4 Occupancy Standard Deviation and Pricing Responsiveness

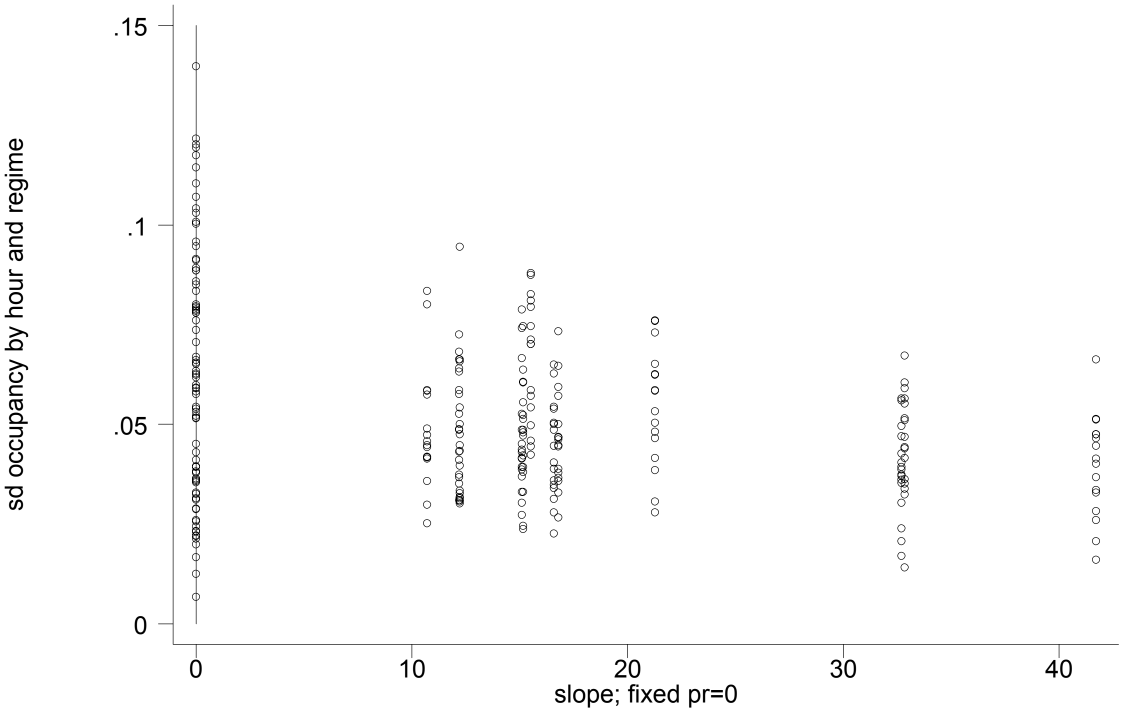
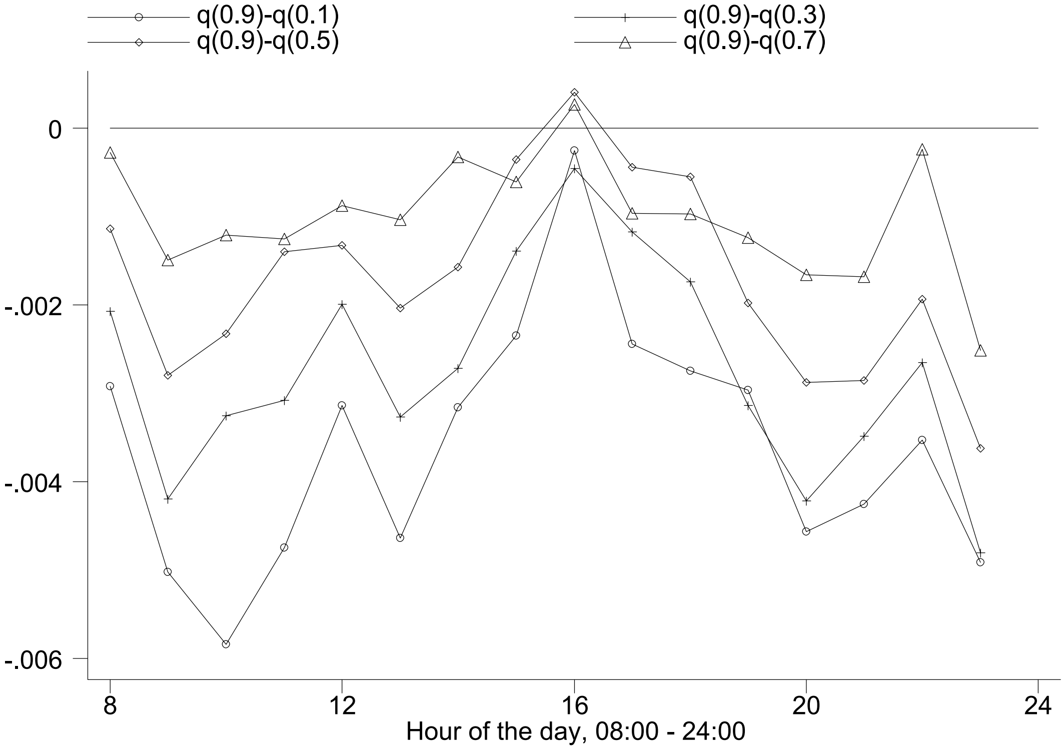


Figure 5. Impact of Pricing Responsiveness on the Distribution of Occupancy



NOTE: The figure plots the coefficients of Table 4 by hour of the day.