Price Variation Antagonism and Firm Pricing Policies[1,2]

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Abstract: Pricing schemes that vary prices in response to demand shocks may antagonize consumers and reduce demand. At the same time, consumers may take advantage of the opportunities offered by price changes. Overall, the net impact of varying price on demand is ambiguous. We investigate this issue empirically, exploiting a unique dataset from a firm that has experimented with different pricing schemes. Each scheme is characterized by how much prices respond to fluctuations in demand and generates different amounts of price variability. We find that greater variability in prices does not lead to diminished demand. We discuss the implications of our findings in terms of the consumer antagonism hypothesis.

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1 Introduction

Economic theory demonstrates that pricing schemes varying prices in response to demand shocks could reduce rationing and increase welfare. Yet survey evidence shows that, in many contexts, consumers are antagonized by pricing schemes that modify prices in response to fluctuations in demand (Kahneman et al., 1986).[3] Consumers seem to care about how sellers set prices. This contrast between theory and evidence has fueled a debate on the use and prevalence of innovative schemes that vary prices (e.g. Blinder et al., 1998; Borenstein et al., 2002; Rotemberg, 2004; Seidel et al., 2004). Missing from the debate, however, is systematic evidence from any industry of the impact of varying price on consumer demand. Are consumers more likely to withhold consumption when firms vary prices in response to demand fluctuations? Or does price variation increase demand?

This paper measures the net impact on demand of increasing price variability by introducing more flexible pricing schemes. In contrast with the survey literature, which focuses on consumer attitudes, we consider the impact of price variability on actual demand. We state the question in terms of a simple trade-off. When prices vary more, but the overall level of prices and other variables are held constant, does the quantity demanded change? If so, what is the trade-off (ceteris paribus) between the magnitude of price variations consumers face and the overall quantity sold?

We denote this trade off dq/dv where q stands for average demand and v for price variability. Measuring this trade-off is a natural starting point for studying the hypothesis that consumers care about firms' choices about pricing policies. It must be kept in mind,

[3] In an early contribution based on a survey of managers, Hall and Hitch (1939, p.22) summarize that "changes in price ... are disliked by merchants and consumers." Later, Okun (1981, p.151) argues that "suppliers must beware of rocking the boat with their price actions". Kahneman et al. (1986) conclude that "charging the market-clearing price for the most popular

however, that consumers may respond to other aspects of pricing than changes in price variability. Survey studies have considered, for example, consumer response to the introduction of price variability and framing effects. These alternative channels are not investigated in this paper, because we can only measure dq/dv for positive v and because we do not observe changes in the way the pricing policy is made known to consumers.

Measuring the trade-off dq/dv is difficult in practice because one rarely observes consumer responses to pricing schemes that vary prices to different degrees in response to demand shocks. Moreover, firms that use different pricing schemes also usually differ in other important ways. In addition, firms rarely modify their pricing policies, and when they do, it is usually in conjunction with broader changes, such as product offers.

We measure dq/dv using a unique dataset from an Internet café that is part of the easyEverything chain, and that has experimented with different pricing schemes. We believe that this case study provides valuable insights for several reasons. Firstly, evidence supporting the conjecture that consumers are antagonized by variations in price is typically drawn from surveys, whereas our case study furnishes the first evidence drawn from actual demand responses. Because the demand for Internet access varies over the day and is also unpredictable at any given hour, an Internet café fits the description of contexts where it has been argued that consumers may demonstrate price variation antagonism (Xia et al., 2004).

In addition, easyEverything has used both peak load pricing and responsive pricing. These two pricing rules have been shown to affect perceptions of fairness and, according to the literature, should influence demand. Under peak load pricing, the price per minute of use varies as a function of the hour of day. Under responsive pricing, the firm updates prices every 5 minutes as a function of the realized occupancy rate in the store. This pricing rule fits the description of exploitative and unfair firm behavior: it increases the price when demand

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goods would be judged unfair" (p.738). See also Xia et al. (2004) for a review with a increases. Swings in prices are large (the highest prices charged by easyEverything are much higher than those of competitors), and consumers were not used to such price changes.

Another pertinent aspect of our case study is that easyEverything has experimented, for both peak load pricing and responsive pricing, with different pricing regimes that vary prices to different degrees. Given that so many of their sales involve repeat purchase, we are able to investigate whether consumers care about which pricing rule is used (peak load pricing or responsive pricing) and whether they withhold demand when prices vary more. These unique pricing experiments provide ideal conditions for measuring the impact of price variability on demand.

We find that demand never depends negatively on the level of price variability and that, for some specifications, it depends positively. This latter finding can be explained if price elasticity is negatively correlated with the level of demand. For more responsive regimes, prices will diminish for low levels of demand and increase for high ones. But the demand increase in the former case will be higher than the decrease in the latter one. This channel through which demand may depend on price variations has been largely ignored in the literature on consumer antagonism.

Our results shed new light on the role of fairness in explaining pricing policies. They do not contradict the vast amount of evidence from surveys showing that consumers care about fairness, suggesting instead that there are other channels through which demand may depend on how prices respond to shocks. The net impact of these different channels on demand is more complex than previously thought.

The rest of this paper is organized as follows. The next section presents our case study, describes the data, and outlines the empirical strategy. Section 3 presents the main evidence. Section 4 discusses some implications of the results, and Section 5 concludes.

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marketing perspective.

2 Overview of the pricing experiment and the data

Our data set consists of the pricing policies and the average hourly occupancy for one of the easyEverything Internet cafés in Paris (Paris Sebastopole) from the day the store opened on January 19, 2001, to July 23, 2001. During this period, store capacity remained fixed at 373 terminals, and the store's competitive environment did not change. The firm has used two different pricing rules: peak-load pricing from January 19 to February 21, and, later, a combination of responsive pricing from 8 am till midnight and peak load pricing at night. Our sample comprises the store's experiments with 17 consecutive pricing regimes: 5 under peak-load pricing and 12 under responsive pricing. Each peak-load pricing regime specifies a day cycle of up to 24 prices. Under responsive pricing, occupancy is measured every 5 minutes and the price is automatically updated according to

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

where P(q) is the price per unit of time and q is the measured level of occupancy (fraction of terminals logged on).[4] Consumers are charged in real time the minimum of the current price and their logon price. A pricing scheme is more responsive if it has a higher slope β. Two pricing schemes are illustrated in Figure 1. Scheme $P_1(q)$ is less responsive than scheme $P_2(q)$: consumers are charged more when there are more consumers logged on under the latter than under the former scheme.

After opening a new store, the company generally experiments with different pricing functions to learn the specific characteristics of local demand before attempting to optimise

[4] Implementation constraints forced the store to use step functions instead of continuous functions. On average there are 30 steps per curve, with a minimum of 15. We compute linear approximations of the pricing curves by regressing the price at each step on the occupancy rate at the midpoint. Steps that are never reached during the regime are excluded from the regression. The average slope, corresponding to β, is 17.1, meaning that the price decreases by FRF 1.71 each time occupancy decreases by 10 percent (or 37 computers). In all but three regimes, a linear approximation of the pricing curve explains over 95 percent of the variation.

the pricing scheme (Courty and Pagliero, 2001). They usually start off with peak load pricing and later introduce responsive pricing. Table 1 shows that the firm has changed both the price cycle under peak load pricing and the slope of the pricing functions under responsive pricing. Changes to the pricing functions provide the exogenous variability in the level of price variability that is used in the estimation. In fact, Table 1 shows that there is no predictable pattern in the timing of change of regimes or in the length of the regimes. Given the strong cyclical patterns in demand in our sample (according to time of day and day of the week), one would have expected to find clear patterns (such as daily or weekly regime changes) if the introductions had indeed responded to demand fluctuations.[5] 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 186 days. (easyEverything did not collect consumption information at the individual level). Overall, our dataset consists of 4,143 hourly observations.[6] Table 1 reports summary statistics. The average occupancy rate in the sample is 46 percent of store capacity, with a standard deviation of 19 percent. A feature that will play a role in interpreting the results is that the capacity is never binding in our sample. This implies that quantity demanded equals quantity consumed.

In regimes 12, 13, and 14, the R^2 is between 0.75 and 0.87. These regimes are piecewise linear, with a kink at 60 percent. These non-linearities do not affect our results.

[5]Shortly after the end of our sample period, the company decided to change its pricing strategy and store layout because it could not maintain high levels of occupancy while also holding prices above a level that would cover average costs. According to the managers, this decision was deliberately taken after the end of the experimentation period and was based on the information collected during this first phase.

[6] 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 dip. Using an additional data set on downtime periods, we removed all corresponding observations.

The average price per hour is FRF 10.7 (€ 1.63) and the price variance is 28.7. This amount of price variability is significant. In fact, the standard deviation of price is 51% of the average price. The 90th percentile (FRF 18.18 or € 2.77) of the price distribution is more than five times higher than the 10th percentile (FRF 3.33 or € 0.51). These levels of price variability are also high relative to those discussed in the literature. As a comparison, the celebrated snowstorm question in Kahneman et al. (1986) related to a 33 percent increase in price.

The variance in price by regime presented in Table 1 can be interpreted as the variability in logon price experienced by a consumer who joins the store at a random hour every day. These variances capture the fact that prices vary both over the day cycle as well as from day to day at the same hour, in relation to circumstances such as weather, school vacation periods, or strikes.

Two types of changes took place during our sample period: first, the distribution of prices changed from regime to regime and, second, the store switched from peak load pricing to responsive pricing after regime 5. Because there was no other change in pricing policies, we can focus exclusively on these two dimensions, while holding all other dimensions, such as framing, constant.

The differences in variance across regimes, reported in Table 1, are large and statistically significant. This implies that a consumer who joins the store at a random hour every day will face more price uncertainty under more responsive pricing regimes. Although consumers may not join the store every day, we would expect a response if there were enough repeat purchase, which indeed proves true in our case study. Based on survey data, the store manager reported that a large fraction of users come regularly to the store and, on average, half of them visit the store at least 3 times a week.

Under responsive pricing, consumers do not directly observe when the pricing function or the overall distribution of prices changes. However, prices are posted in a small window on each terminal, and are updated every 5 minutes. Since consumers can observe occupancy in the store and up to 12 prices every hour, they have sufficient information for inferring the pricing function. For linear pricing functions, it takes only two non-identical observations on price and occupancy to back up the parameters (α,β). In practice, however, consumers may not immediately respond to changes in regime. We investigate the possibility of transition periods between regimes in Section 3.3.

2-1 Identification of dq/dv

The exogenous variations in the level of prices under peak load pricing and in the parameters of the pricing function (α, β) under responsive pricing generate exogenous variations in the level of prices and the level of price variation. This makes it possible to estimate how variations in these variables affect the level of demand. Our primary specification is

$$q_{j,i} = a_0 + a_1 p_{j,i} + a_2 v_j + a_3 ' x_{j,i} + u_{j,i} \quad j = 1,...,17, i = 1,..., I_j \qquad (2)$$

where $q_{j,i}$ is the i[th] occupancy observation in regime j, $p_{j,i}$ is the corresponding price observation, and v_j is a measure of price variability in regime j; $x_{j,i}$ is a vector of control variables including indicator variables for day of the week (Tuesday to Sunday) and national holidays; $u_{j,i}$ is an econometric error term. Relation (2) describes how consumption varies as prices and price variability change. It can be interpreted as a system of state demand functions, with unobservable random shifters $u_{j,i}$, that specify that the quantity demanded depends on the realized price and the level of price variability in a given regime. To keep matter simple, we have assumed that the demands were linear in price, but we show in a robustness section that the results do not change with non-linear demands.

There are many ways to construct the measure of price variability. We present the main results (Table 2) using the variance in price computed at the regime level. Under peak load pricing, this corresponds to the variance in the daily price cycle. Under responsive pricing, it mixes the fixed prices during the night and the realized prices during the day. Since prices increase with the level of demand, it seems plausible that price variance should capture some common aspect of fairness that consumers are likely to be concerned with.[7] In subsection 3.3 we show that these results are robust to other measures of price variability. In principle, a change in price may affect consumption directly through a_1 as well as indirectly, because $p_{j,i}$ enter v_i, but we can ignore this second channel because the average number of observations per regime is 244 and each $p_{j,i}$ has a negligible impact on v_i.

Under responsive pricing, the two right-hand side variables $p_{j,i}$ and v_j in specification (2) are endogenous. In fact, in equilibrium, the pair ($q_{j,i}$, $p_{j,i}$) is the solution to (1) and (2) and therefore $p_{j,i}$ and v_j are a function of the unobserved demand shifter $u_{j,i}$.[8] To deal with this endogeneity problem, we use the parameters of the pricing function and their square values (α, α^2, β, β^2) as instruments.[9] Table A1 in the Appendix reports the first stage regression results. The instruments are highly correlated with the level and variability of prices.[10]

To highlight the novel elements in the estimation of (2), consider the benchmark case with no antagonism effect (a_2=0) and with a flat pricing function (β=0). In this case, the exogenous variations in the level of price α allow estimation of the parameters of the demand

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[7] We have shown in a previous study that consumers perceive pricing schemes with greater variation in prices as more unfair (Courty and Pagliero 2008, p. 35).

[8] Measurement error in p_j and σ_j may also generate a correlation between the regressors and the error term; our instrumental variable approach also addresses this problem.

[9] To demonstrate that $p_{j,i}$ and v_j depend non-linearly on α and β, rewrite (1) for observation (j,i) as $p_{j,i} =\alpha+\beta q_{j,i}$ and solve jointly with (2) for ($p_{j,i}$,$q_{j,i}$). The solution $p_{j,i}$ is non linear in (α,β) and so is the variance v_j.

[10] In our specifications, the F-test of the significance of the excluded instruments in the first stage rejects the null that the instruments are weak (in the sense that the nominal 5 percent

equation (a_0,a_1,a_3) by OLS. Consider now the case in which the pricing function is upward sloping ($\beta>0$). This implies that the price is endogenous, since it is now determined jointly by (1) and (2). The demand function is still identified, and exogenous changes in the pricing function allow estimation of the parameters (a_0,a_1,a_3) using instrumental variables, where intercept α and slope β are the instruments. Finally, adding the antagonism effect does not change the problem. Now the demand function has two endogenous variables, but changes in the pricing function still allow estimation of the parameters (a_0,a_1,a_2,a_3) by instrumental variables.

3 Results

3-1 Main Results

The price elasticity of demand for Internet access is likely to be hour dependent. We consider both a specification where we aggregate all hours of the day and also a disaggregated specification. The former specification gives the overall impact of price variation on demand, while the latter gives the net impact after controlling for hour heterogeneity.

Overall Response (Table 2, column 1)

Column 1 of Table 2 presents the results of specification (2). Consistent with economic theory, the coefficient estimating the response to the price is negative and significant, giving a price elasticity of 0.28. Allowing for hourly price responses (column 2) implies price elasticities as high as 0.9 at some hours of the day.[11] Consumers significantly respond to changes in price.

2SLS test of the hypothesis that price and price variability do not affect demand has size potentially exceeding 5 percent, Stock and Yogo 2005).

[11] At 9am, $dq/dp=-2.8$ (see Table 2, column 2), the average price is 9.15FF and the average occupancy rate is 27.98 percent.

However, the focus of this work is on a_2. The coefficient estimating the response to price variations is positive and significantly different from zero at 13 percent confidence level. In Tables 3 and 4, column 2 we treat separately peak load pricing and responsive pricing and the impact price variability is again positive, and significantly from zero at 10 percent confidence level. Holding the price constant, higher variability of prices is associated with constant or higher consumption. We rule out an obvious explanation for an increase in consumption: if the capacity were binding, then an increase in price variability while maintaining a constant average price would increase consumption in low demand states, but would not decrease consumption in high demand states. We rule out this interpretation because the capacity never binds in our sample.

Hour Level Response (Table 2, column 2)

Column 2 in Table 2 controls for heterogeneity across hours by including hour specific fixed effects $a_{0,h}$ and hour specific price coefficients $a_{1,h}$ in model (2),

$$q_{j,i} = a_{0,h} + a_{1,h} p_{j,i} + a_2 v_j + a_{3,h}' x_{j,i} + u_{j,i} \qquad j = 1,...,17,\ h = 0,...,23,\ i = 1,..., I_j \tag{3}$$

where $x_{j,i}$ includes the same control variables as before along with the weekend-specific hourly price cycle.[12]

The coefficient of price variation a_2 is much smaller. This suggests that the estimate of a_2 in column 1 captured a demand composition effect. Different consumers come at the peak and at the trough (demand heterogeneity) and peak consumers are less price sensitive than off-peak consumers. Since more responsive pricing regimes increase the difference between peak and off-peak prices, peak consumers consume less and off-peak consumers more, but the latter effect dominates the former, holding the price index constant. Consistent with this interpretation, we find that demand is more sensitive off-peak than during peak hours. In fact, consumption is highest in our sample from 4 pm to 7 pm (peak), and the marginal effect of a change in price is lower than during off-peak hours in the morning or late evening. Variation in price stimulates consumption more during off-peak hours than it reduces demand during peak hours. [13]

Summary

We do not find a negative impact of price variability on demand. If anything, average daily demand depends positively on the level of price variability, while disaggregated demand does not. Pricing schemes that vary prices more do not reduce consumption (Table 2, columns 1 and 2). In the rest of this section, we show that our results are robust to the way we capture price variation antagonism and to different demand specifications.

3-2 Controlling for Different Sources of Price Variability

Specifications (2) and (3) focus exclusively on the role of price variability. This implicitly rules out the possibility that demand might depend directly on the pricing rule used. Recall that two pricing rules, peak load pricing and responsive pricing, were used in our sample. Consumers may perceive these rules in different ways. In fact, survey evidence suggests that consumers care about the rule that generates price variability. For example, Frey and Pommerehne (1993, p.303) consider the case of a sightseeing point where a limited supply of cool drinking water is sold to thirsty hikers. Assuming excess demand due to hot weather, they asked consumers: “How do you evaluate a price rise when a hot day was completely unforeseeable?” and “Do you consider a price rise ... to be more, equally, or less acceptable than when hot days normally occur in the season considered?” Their findings suggest that consumers are less likely to be antagonized by predictable price variations (as in peak load pricing) than by unpredictable price variations generated by unpredictable demand shocks (as in responsive pricing); (64% of those surveyed found the former rule more

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[12] Under peak load pricing, the price $p_{j,i}$ corresponds to the predetermined price for that hour.

acceptable than the latter). This suggests that we should treat peak load pricing and responsive pricing differently.[14] In this section, we explore variations of model (2) and (3), allowing for the demand to depend on the pricing rule in more general ways.

Responsive Pricing Fixed Effect

Column 1 of Table 3 introduces a fixed effect for responsive pricing. According to the conclusion of Frey and Pommerehne (1993, p.303), one would expect the fixed effect for responsive pricing to be negative if fairness concerns are predominant. Table 3, column 2 includes a measure of price variability as well, as in Table 2, column 1. Table 3, column 3 allows for hourly heterogeneity as in Table 2, column 2. The fixed effect is positive and significant in all three specifications. This suggests that varying price in real time does not decrease demand. In Table 3, column 2, the coefficient of price variability is positive and now significantly different from zero. Its magnitude is similar to Table 2, column 1. After controlling for hourly heterogeneity, this effect is not significantly different from zero (as in Table 2).

The results reported in Table 3 raise the question of why the fixed effect is positive. One possible interpretation for this finding is similar to the argument made to explain the drop in the coefficient on price variability once we controlled for hourly prices in Table 2. Responsive pricing increases prices when demand is higher and, presumably, less price sensitive. This generates a positive effect of increasing price variability on demand. In order to test the hypothesis that the demand is less price sensitive when the demand is higher, one

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[13] We discuss possible substitution effects across hours in Section 3.3.

[14] In responsive pricing regimes the amount of unpredictable price variability is significant: 7 percent of price variance (corresponding to approximately 25% in terms of standard deviation) cannot be explained by a regime-specific daily price cycle. Adding variables (such as day of the week and national holiday fixed effects) to predict prices only marginally reduces the amount of unpredictable price variability.

would have to disaggregate the hourly demand and estimate the price response in different states of the world.[15,16]

Peak Load versus Responsive Price Variability

One could argue that consumption may respond differently to price variation generated by different pricing rules. The results in Table 2 may confound two opposing effects generated by peak load pricing and responsive pricing. We therefore allow price variability to have a different impact on demand during the peak load pricing and the responsive pricing periods. Table 4, columns 1 and 2 report the aggregate and disaggregate results respectively.

Table 4 tells the same story as Table 2 and 3. The effect of price variability is never negative. During responsive pricing regimes, it is significantly different from zero in the aggregate specification (column 1). In the disaggregated specification (column 2), the effect of price variability is not significant for responsive pricing nor for peak load pricing

3-3 Robustness

In this section we explore a set of variations of model (2) and (3) in order to investigate the robustness of the baseline results reported in Table 2. We deal with substitution effects, non-linearities and functional form assumptions, the definition of price variability, sample definition, and time trend.

Substitution

Table 5 accounts for substitution across hours by extending specification (3). In principle, it might be desirable to include in the specification for each hour the price in every

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[15] Under some functional assumption on the state demands, one can use a quantile framework to estimate the state demands. Consistent with the above interpretation, Courty and Pagliero (2003) find that the state demands are less price sensitive when demand is higher.

[16] Another possible explanation is that the introduction of responsive pricing was framed differently than peak load pricing, for example, through a different emphasis on consumer benefits and losses. Although we cannot explore this hypothesis with our data, a review of store posters and advertising pamphlets gives no indication that this was the case.

other hour, since substitution may occur between any hour. However, due to data constraints, we aggregate different hours to limit the number of coefficients to be estimated.

We group observations in our sample into two broad periods: "peak", from 11 am to 10 pm, and "off-peak", from 11 pm to 10 am, so that the actual peak and trough are roughly in the middle of these two periods. We allow consumption in each of the two groups to be a function of the average price (during each regime) in the other group. In order to further reduce the number of parameters to be estimated, we assume symmetry in the substitution effects across groups. Of course there are other ways of aggregating the observations, but the results are not significantly affected.

Relative to specification (3), there is one additional variable capturing substitution between peak and off-peak hours, $\tilde{p}_{j,h}$ which is equal to the average off-peak price if $11 \leq h \leq 23$ and to the average peak price otherwise; a_4 is a parameter to be estimated. Clearly, this new variable may be correlated with the error term. Exogenous variation in the pricing function provides exogenous variation in the relative price across periods. This allows estimation of a_4.

Table 5, column 1 reports the results of this model. Table 5, columns 2 and 3 are the extension of the results in Table 3, column 3 (responsive pricing fixed effect), and Table 4, column 2 (different sources of price variability). The substitution effect in Table 5 tends to be negative. The main results discussed in the previous section, however, are unchanged.

Non-Linearities

We check whether the variance in price in Table 2 captured non-linear price effects. Tables 6 and 7 report aggregate and disaggregate specifications respectively. The former reports variations of model (2) and the latter reports variations of model (3).

(1) In column 1, Tables 6-7, price variability is measured by its standard deviation, rather than its variance, to check robustness to different measures of variability. The coefficient of price variability is never negative.

(2) In column 2, Tables 6 and 7, the specification includes $p_{j,h,i}^2$. Similarly to the interpretation given to relation (2), the interpretation of this specification is that the state demands could be non-linear in price. The signs of the effects of total variance are the same.

(3) In column 3, Tables 6-7, the dependent variable is the log of the occupancy rate (and prices are also measured in logs, so the estimated coefficients can be interpreted as elasticities). This specification tests the robustness of the results to a non-linear specification. The marginal effect of a change in variance on occupancy rate is still positive in both Table 6 and 7.

Other Robustness Results

(4) In column 4, Tables 6-7, hourly observations in the 24 hours after each regime change are excluded from the sample. This is motivated because it may take time for consumers to adjust to a regime change. In fact, our empirical analysis assumes that consumers know the amount of price variability. This is a realistic assumption in our case study, as consumers tend to visit the store regularly. Still, we test the robustness of the results by excluding those observations for which transition effects could play a role. Both aggregate and disaggregate results are not significantly affected.

(5) In column 5, Tables 6-7, the sample is restricted to the responsive pricing regimes (regimes 6-17). This is because peak load pricing may be perceived differently from responsive pricing, and the results in Table 2 may be driven by the aggregation of the two different time periods. The coefficient of price variability is again positive and significant in the aggregate specification, and non significant in the disaggregate specification.

(6) Another concern is that there may be a trend in demand during our sample period. Column 5, Tables 6-7, which excludes the first month following the launch of the store and focuses on the following five months, already suggests that the results are not driven by a change in demand after the first month. To further investigate the effects of a possible trend in demand, in column 6, Table 7, we use the same specification as in column 5, Table 7, but we also include a linear-quadratic trend (the week number from the beginning of the sample and its square). The marginal effect of the trend is negative and relatively small.[17] The results are not affected.

4 Implications for Firm Pricing Policies

dq/dv provides a descriptive tool for characterizing demand responses to pricing policies that generate different levels of price variability. Price variability does not negatively impact consumer demand. If anything, higher variability implies higher consumption. This can be explained if the level of demand is negatively correlated with price elasticity. While survey evidence demonstrates the importance of antagonism responses, we do not find any evidence of such responses in our case study.

Our estimates of dq/dv could still aggregate different responses. Consumers could be antagonized by price variations, or they may be risk averse. Risk aversion implies that demand depends negatively on v. In addition, consumers may update their consumption decisions after observing the realized price. In this case, a risk neutral consumer values price variability. Overall, we find that the net effect of these responses is zero.

Since the pricing schemes we consider generate a positive correlation between occupancy and price, expected revenues cannot decrease with the introduction of price

[17] The coefficients imply an average decrease in occupancy of 0.8 percent per week.

variations.[18] The implication is that easyEverything did not lose revenue due to antagonized consumers. More generally, in any industry where dq/dv≥0 antagonism cannot be an explanation for the lack of variation in prices.

Consumer heterogeneity

It is possible that only a given proportion of consumers is not antagonized by price variability and that this group is over-represented in our case study. Still, we find no margin from increasing the amount of price variation. In addition, we find no additional impact from switching to a pricing rule that changes prices in real time, although both changes are perceived as exploitative in Frey and Pommerehne (1993).

Relevance to other industries

As the evidence presented is specific to a given firm and market, and consumer attitude toward price variations may be different for other firms or in other markets, one must be cautious in generalizing our results. However, our case fits the description of situations where it has been conjectured that antagonism caused by demand driven price variation should be significant. Both Okun (1981) and Kahneman et al. (1986) use data from the hotel industry to illustrate the conjecture that consumers may be antagonized by price variation (see Proposition 2, p.738). Out of home Internet access is a service industry facing capacity management problems similar to those in the hotel industry: fixed capacity, zero (or very low) marginal costs, and variable demand. These characteristics are common to other industries where it has been argued that responsive pricing could reduce the occurrence of stoking-out, rationing, or queues. For example, road pricing and electricity pricing offer important applications that are debated in policy circles (Vickrey, 1971; Borenstein et al.,

[18] Firm revenues can be expressed as E[qP(q)]=Cov(qP(q))+EqEP(q). If dEq/dv≥0, the introduction of price variations that hold the level of price constant leads to an increase in revenue if price is positively correlated with demand.

2002; Seidel et al., 2004), rationing is common in sports events and rock concerts, and waiting for popular rides is a common problem for theme parks and ski-resorts.

Different industries have had varying experiences with responsive pricing. While responsive pricing is common in the airline industry, some firms in other industries have failed to or chosen not to introduce it (Courty and Pagliero, 2008). For example, in an attempt to deal with the problem of stocking out, Coca-Cola began testing a vending machine with a temperature sensor and computer chip to determine when to automatically raise prices for its drinks in hot weather. A public relations fiasco followed, "causing Coke to promptly deny that it would ever have a vending machine do any such thing." (Washington Post, Wednesday 27 2000, p. A1).

Our evidence does not support the hypothesis that *increasing* price variability in response to demand shocks would necessarily alienate consumers and decrease revenue. This leaves at least three candidate explanations for the observation that firms do not vary prices and that consumers show significant fairness concerns when asked to give their opinion about price variations. First, it could be that firms do not use responsive pricing because the costs of doing so outweigh the benefits. Second, there may be a discontinuity between constant prices and variable prices, and all antagonism responses may take place there. We cannot test this hypothesis because the firm in our case study has never experimented with constant prices. Finally, consumers may be sensitive to the means of communicating the rules used to set prices. For example, easyEverything may have framed the introduction of responsive pricing in such a way that was acceptable to consumers, whereas Coca-Cola failed to do so. We cannot address this issue either, because there is no variation in framing in our case study. With all of this in mind, one implication of our work is that, even if the initial introduction of price variation decreases demand, once price variation has been introduced, there may be no further negative demand responses from further increases in price variation. This seems to imply that that firms will either not vary prices at all or vary prices a lot, as casual observations from the airline industry, for example, would seem to confirm.

5 Summary

Increasing prices when demand increases may influence average demand through several channels, including antagonism, as emphasized in the survey literature. In our case study, average demand does not depend negatively on price variability, when all other dimensions of the pricing rule are held constant. In some specifications, we find a positive effect of price variability on demand which can be explained if the level of demand is negatively correlated with price elasticity. Evidence from this study provides a first step toward understanding how consumer demand depends on the rules governing how prices are set.

References

Blinder, A. S., Canetti, E. R. D., Lebow, D. E., and Rudd, J. B., 1998. Asking About Prices: A New Approach to Understanding Price Stickiness. New York, NY: Russell Sage Foundation.

Borenstein, S., Jaske, M., and Rosenfeld, A., 2002. Dynamic Pricing, Advanced Metering and Demand Response in Electricity Markets. The Energy Foundation.

Courty, P., Pagliero, M., 2001. easyEverything Pricing Policies (ECCH case). London: London Business School.

Courty, P., Pagliero, M., 2003. Does Responsive Pricing Increase Efficiency? Evidence from Pricing Experiments in an Internet Cafè. CEPR Discussion Paper 4149

Courty, P., Pagliero, M., 2008. Do Consumers Care about how Prices are Set?. International Journal of the Economics of Business 15:1, 27-43.

Frey, B., Pommerehne, W., 1993. On the Fairness of Pricing - An Empirical Survey among the General Population. Journal of Economic Behavior and Organization 20, 295-307.

Fudenberg, D., 2006. Advancing Beyond Advances in Behavioral Economics. Journal of Economic Literature 44:3, 694-711.

Hall, R., Hitch, C., 1939. Price Theory and Business Behaviour. Oxford Economic Papers os-2, 12-45.

Heidhues, P., Kőszegi, B., 2005. The Impact of Consumer Loss Aversion on Pricing. CEPR Discussion Paper 4849.

Kahneman, D., Knetsch, J., Thaler, R., 1986. Fairness as a Constraint on Profit Seeking: Entitlements in the Market. American Economic Review 76, 728–741.

Okun, A. M., 1981. Prices and Quantities: A Macroeconomic Analysis. Washington, DC: The Brookings Institution.

Rotemberg, J., 2004. Fair Pricing. NBER Working Paper 10915.

Seidel, T., Matthes, A., Wieland, B., Schlag, B., Schade, J., Verhoef, E., Ubbels, B., Tánczos, K., Kosztyó, Á., Mészáros, F., 2004. Political Acceptability and Perceived Legitimacy of Transport Policy Implementation. TIPP working paper.

Stock, J., Yogo, M., 2005. Testing for weak instruments in linear IV regression. In: Andrews, D., Stock, J. (Eds.), Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothemberg. Cambridge: Cambridge University Press.

Vickrey, W., 1971. Responsive Pricing of Public Utility Services. The Bell Journal of Economics and Management Science 1, 337-346.

Xia, L., Monroe, K. B., Cox, J. L, 2004. The Price is Unfair! A Conceptual Framework of Price Fairness Perceptions, Journal of Marketing 68, 1-15.

FIGURE 1

Examples of responsive pricing functions

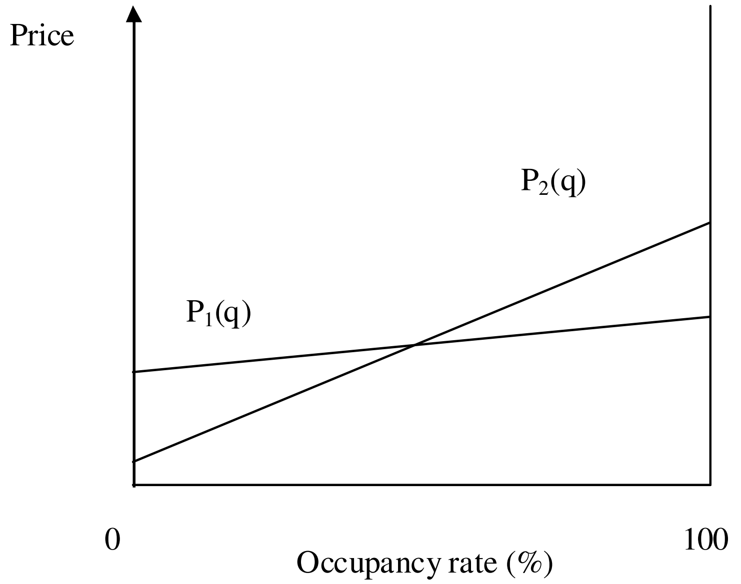

TABLE 1

Summary Statistics

	Regime	Number of Observations	Responsiveness (β)	Mean Occupancy Rate	Mean Price	Price Variance
	(1)	(2)	(3)	(4)	(5)	(6)
	1	170	0	0.44	3.00	0.17
Peak-load	**2**	72	0	0.48	5.17	9.06
	3	94	0	0.53	5.15	1.26
Pricing	**4**	217	0	0.55	5.73	3.60
	5	126	0	0.51	7.44	8.43
	6	132	10.73	0.55	7.75	10.97
	7	166	12.24	0.52	8.69	13.90
	8	336	15.10	0.53	9.59	19.38
	9	304	15.14	0.50	10.16	18.28
Responsive	**10**	268	16.09	0.48	11.09	15.59
	11	344	15.54	0.45	11.59	16.41
Pricing	**12**	667	12.67	0.40	13.02	12.45
	13	518	14.08	0.41	12.36	29.16
	14	291	17.27	0.45	12.22	28.93
	15	135	33.72	0.45	14.02	48.73
	16	168	32.78	0.44	14.16	54.48
	17	135	41.88	0.41	14.76	57.50
	All regimes	4,143	17.11	0.46	10.67	28.73

Note: Mean price and price variance are computed by regime.

TABLE 2

Baseline Results

	(1)	(2)
Price (p_{ji})	-1.217***	
	(0.272)	
Price Variance (v_j)	0.0696	0.00266
	(0.0463)	(0.0250)
Price 0-1 am		-1.934***
		(0.293)
Price 1-2 am		-2.198***
		(0.342)
Price 2-3 am		-3.399***
		(0.651)
Price 3-4 am		-3.496***
		(0.543)
Price 4-5 am		-4.090***
		(0.640)
Price 5-6 pm		-3.609***
		(0.516)
Price 6-7 am		-2.818***
		(0.390)
Price 7-8 am		-0.856***
		(0.136)
Price 8-9 am		-1.578***
		(0.204)
Price 9-10 am		-2.793***
		(0.283)
Price 10-11 am		-2.930***
		(0.293)
Price 11-12 am		-2.074***
		(0.234)
Price 12 am-1 pm		-1.598***
		(0.218)
Price 1-2 pm		-1.415***
		(0.218)
Price 2-3 pm		-1.495***
		(0.227)
Price 3-4 pm		-0.728***
		(0.158)
Price 4-5 pm		-0.400***
		(0.142)
Price 5-6 pm		-0.391***
		(0.129)
Price 6-7 pm		-0.275**
		(0.124)
Price 7-8 pm		-0.598***
		(0.163)
Price 8-9 pm		-0.808***
		(0.163)
Price 9-10 pm		-1.085***
		(0.168)
Price 10-11 pm		-1.059***
		(0.168)
Price 11-12 pm		-1.265***
		(0.201)
Observations	4,143	4,143

Note: The dependent variable is the occupancy rate x 100. Price and price variance are treated as endogenous. Coefficients are estimated using instrumental variables. Instruments are the slope and the intercept of the pricing functions and their squares (interacted with hour indicator variables in column 2). Day-of-the-week fixed effects (Tuesday to Sunday, Monday omitted), the national holiday fixed effect and a constant are included in both specifications. Hour specific fixed effects (omitted 8-9 am) and weekend cycle fixed effects are included in column 2. Robust standard errors (clustered by observation day) are reported in parentheses.

TABLE 3

Direct Response to Pricing Rule

	(1)	(2)	(3)
Price (p_{ij})	-1.376***	-1.697***	
	(0.264)	(0.393)	
Responsive Pricing Fixed Effect	4.016*	4.523*	4.407***
	(2.268)	(2.445)	(1.447)
Price Variance (v_j)		0.0802*	-0.0308
		(0.0486)	(0.0245)
Price 0-1 am			-2.375***
			(0.233)
Price 1-2 am			-2.668***
			(0.273)
Price 2-3 am			-3.969***
			(0.648)
Price 3-4 am			-3.989***
			(0.540)
Price 4-5 am			-4.419***
			(0.669)
Price 5-6 pm			-3.846***
			(0.540)
Price 6-7 am			-3.077***
			(0.420)
Price 7-8 am			-0.994***
			(0.129)
Price 8-9 am			-1.831***
			(0.203)
Price 9-10 am			-3.162***
			(0.275)
Price 10-11 am			-3.329***
			(0.278)
Price 11-12 am			-2.419***
			(0.230)
Price 12 am-1 pm			-1.920***
			(0.215)
Price 1-2 pm			-1.684***
			(0.206)
Price 2-3 pm			-1.730***
			(0.219)
Price 3-4 pm			-0.923***
			(0.146)
Price 4-5 pm			-0.571***
			(0.136)
Price 5-6 pm			-0.578***
			(0.127)
Price 6-7 pm			-0.462***
			(0.119)
Price 7-8 pm			-0.790***
			(0.151)
Price 8-9 pm			-1.007***
			(0.150)
Price 9-10 pm			-1.311***
			(0.153)
Price 10-11 pm			-1.296***
			(0.150)
Price 11-12 pm			-1.556***
			(0.180)
Observations	4,143	4,143	4,143

Note: The dependent variable is the occupancy rate x 100. Price and price variance are treated as endogenous. Coefficients are estimated using instrumental variables. Instruments are the slope and the intercept of the pricing functions and their squares (interacted with hour indicator variables in column 3). Day-of-the-week fixed effects (Tuesday to Sunday, Monday omitted), the national holiday fixed effect and a constant are included in all specifications. Hour specific fixed effects (omitted 8-9 am) and weekend cycle fixed effects are included in column 3. Robust standard errors (clustered by observation day) are reported in parentheses.

TABLE 4
Different Sources of Price Variability

	(1)	(2)
Price (p_{ij})	-1.210***	
	(0.302)	
Price Variance (Responsive Pricing)	0.0875*	0.0290
	(0.0469)	(0.0287)
Price Variance (Peak Load Pricing)	0.255	0.323
	(0.279)	(0.284)
Price 0-1 am		-1.862***
		(0.281)
Price 1-2 am		-2.122***
		(0.333)
Price 2-3 am		-3.320***
		(0.653)
Price 3-4 am		-3.432***
		(0.553)
Price 4-5 am		-4.029***
		(0.648)
Price 5-6 pm		-3.530***
		(0.520)
Price 6-7 am		-2.734***
		(0.394)
Price 7-8 am		-0.834***
		(0.138)
Price 8-9 am		-1.549***
		(0.205)
Price 9-10 am		-2.763***
		(0.289)
Price 10-11 am		-2.891***
		(0.309)
Price 11-12 am		-2.036***
		(0.245)
Price 12 am-1 pm		-1.556***
		(0.226)
Price 1-2 pm		-1.395***
		(0.217)
Price 2-3 pm		-1.483***
		(0.233)
Price 3-4 pm		-0.734***
		(0.160)
Price 4-5 pm		-0.424***
		(0.142)
Price 5-6 pm		-0.407***
		(0.129)
Price 6-7 pm		-0.292**
		(0.123)
Price 7-8 pm		-0.604***
		(0.162)
Price 8-9 pm		-0.805***
		(0.163)
Price 9-10 pm		-1.077***
		(0.168)
Price 10-11 pm		-1.049***
		(0.165)
Price 11-12 pm		-1.242***
		(0.199)
Observations	4,143	4,143

Note: The dependent variable is the occupancy rate x 100. Price and price variance are treated as endogenous. Coefficients are estimated using instrumental variables. Instruments are the slope and the intercept of the pricing functions and their squares (interacted with hour indicator variables in column 2). Day-of-the-week fixed effects (Tuesday to Sunday, Monday omitted), the national holiday fixed effect and a constant are included in all specifications. Hour specific fixed effects (omitted 8-9 am) and weekend cycle fixed effects are included in column 2. Robust standard errors (clustered by observation day) are reported in parentheses.

TABLE 5

Robustness Results (Substitution Effects)

	(1)	(2)	(3)
Total Price Variance (v_i)	0.0365	0.0885**	
	(0.0395)	(0.0388)	
Substitution (Peak/ Off-peak) ($\tilde{p}_{j,h}$)	-0.217	-0.934***	-0.171
	(0.177)	(0.198)	(0.210)
Responsive Pricing Fixed Effect		8.621***	
		(1.759)	
Price Variance (Responsive Pricing)			0.0548
			(0.0403)
Price Variance (Peak Load Pricing)			0.301
			(0.302)
Price 0-1 am	-1.746***	-2.012***	-1.734***
	(0.217)	(0.205)	(0.207)
Price 1-2 am	-2.006***	-2.314***	-1.992***
	(0.245)	(0.238)	(0.239)
Price 2-3 am	-3.127***	-3.399***	-3.133***
	(0.527)	(0.539)	(0.533)
Price 3-4 am	-3.207***	-3.251***	-3.224***
	(0.448)	(0.436)	(0.452)
Price 4-5 am	-3.849***	-3.731***	-3.855***
	(0.600)	(0.564)	(0.606)
Price 5-6 pm	-3.418***	-3.272***	-3.390***
	(0.499)	(0.463)	(0.499)
Price 6-7 am	-2.619***	-2.486***	-2.588***
	(0.378)	(0.345)	(0.378)
Price 7-8 am	-0.750***	-0.670***	-0.752***
	(0.111)	(0.106)	(0.116)
Price 8-9 am	-1.417***	-1.390***	-1.425***
	(0.164)	(0.169)	(0.157)
Price 9-10 am	-2.568***	-2.568***	-2.594***
	(0.233)	(0.245)	(0.223)
Price 10-11 am	-2.705***	-2.770***	-2.726***
	(0.212)	(0.217)	(0.204)
Price 11-12 am	-2.088***	-2.831***	-2.061***
	(0.239)	(0.271)	(0.266)
Price 12 am-1 pm	-1.621***	-2.342***	-1.586***
	(0.228)	(0.260)	(0.251)
Price 1-2 pm	-1.442***	-2.076***	-1.426***
	(0.234)	(0.255)	(0.243)
Price 2-3 pm	-1.525***	-2.100***	-1.515***
	(0.244)	(0.272)	(0.263)
Price 3-4 pm	-0.735***	-1.153***	-0.746***
	(0.163)	(0.180)	(0.172)
Price 4-5 pm	-0.404***	-0.767***	-0.434***
	(0.145)	(0.161)	(0.149)
Price 5-6 pm	-0.402***	-0.813***	-0.421***
	(0.135)	(0.156)	(0.140)
Price 6-7 pm	-0.290**	-0.714***	-0.309**
	(0.131)	(0.150)	(0.137)

Continued on next page

TABLE 5 (continued)

	(1)	(2)	(3)
Price 7-8 pm	-0.621***	-1.088***	-0.628***
	(0.175)	(0.184)	(0.181)
Price 8-9 pm	-0.832***	-1.316***	-0.832***
	(0.174)	(0.173)	(0.183)
Price 9-10 pm	-1.109***	-1.644***	-1.105***
	(0.179)	(0.178)	(0.189)
Price 10-11 pm	-1.082***	-1.636***	-1.077***
	(0.179)	(0.180)	(0.187)
Price 11-12 pm	-1.124***	-1.242***	-1.143***
	(0.166)	(0.168)	(0.162)
Observations	4,143	4,143	4,143

Note: The dependent variable is the occupancy rate x 100. $\tilde{p}_{j,h}$ is equal to the average off-peak price if $11 \le h \le 23$ and the average peak price otherwise; prices and price variance are treated as endogenous. Coefficients are estimated using instrumental variables. Instruments are the slope and the intercept of the pricing functions and their squares (interacted with hour indicator variables). Day-of-the-week fixed effects (Tuesday to Sunday, Monday omitted), national holiday, hour specific (omitted 8-9 am), weekend cycle fixed effects and a constant are included in all specifications. Robust standard errors (clustered by observation day) are reported in parentheses.

TABLE 6

Robustness Results (Aggregate Specification)

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	Occupancy Rate	Occupancy Rate	Ln(Occupancy Rate)	Occupancy Rate	Occupancy Rate
Price (p_{ij})	-1.534***	3.555*		-1.308***	-3.811***
	(0.351)	(1.855)		(0.275)	(0.428)
Price Standard Deviation	1.264**				
	(0.605)				
Price Squared		-0.297***			
		(0.111)			
Price Variance		0.550***	0.00227**	0.0564	0.263***
		(0.173)	(0.00101)	(0.0452)	(0.0604)
Ln(Price)			-0.257***		
			(0.0586)		
Observations	4,143	4,143	4,143	3,774	3,464

Note: The data is comprised of 4,143 hourly observations in columns 1-3 and 6, of 3,774 observations in column 4 (observations within 24 hours from a regime change are excluded), and of 3,464 in column 5 (responsive pricing regimes only). The price, price squared, price variance and price standard deviation are treated as endogenous. Coefficients are estimated using instrumental variables. Instruments are the slope and the intercept of the pricing functions and their squares. Day-of-the-week fixed effects (Tuesday to Sunday, Monday omitted), the national holiday fixed effect and a constant are included in all specifications. Robust standard errors (clustered by observation day) are reported in parentheses.

TABLE 7

Robustness Results (Disaggregate Specification)

Dependent Variable:	(1) Occupancy Rate	(2) Occupancy Rate	(3) Ln(Occupancy Rate)	(4) Occupancy Rate	(5) Occupancy Rate	(6) Occupancy Rate
Price Standard Deviation	0.317					
	(0.278)					
Price Variance		0.0299	0.000978	-0.00569	-0.0243	0.171***
		(0.0333)	(0.000759)	(0.0297)	(0.0303)	(0.0511)
Price 0-1 am	-2.046***	-2.001	-0.296***	-2.041***	-2.923***	0.181
	(0.274)	(1.420)	(0.0447)	(0.322)	(0.587)	(0.403)
Price 1-2 am	-2.321***	4.624**	-0.318***	-2.388***	-6.876***	-2.075***
	(0.316)	(2.151)	(0.0469)	(0.380)	(1.287)	(0.776)
Price 2-3 am	-3.504***	-7.104**	-0.543***	-3.634***	-3.467***	-1.977***
	(0.661)	(2.834)	(0.0970)	(0.738)	(0.716)	(0.465)
Price 3-4 am	-3.621***	-2.422	-0.550***	-3.582***	-5.060***	-2.871***
	(0.548)	(2.267)	(0.0836)	(0.579)	(0.720)	(0.479)
Price 4-5 am	-4.156***	-5.440*	-0.832***	-4.072***	-4.478***	-2.762***
	(0.664)	(2.832)	(0.129)	(0.649)	(0.691)	(0.467)
Price 5-6 pm	-3.653***	-10.20***	-0.952***	-3.510***	-3.673***	-2.283***
	(0.537)	(3.407)	(0.132)	(0.490)	(0.509)	(0.334)
Price 6-7 am	-2.869***	-7.251***	-0.991***	-2.789***	-3.035***	-1.594***
	(0.411)	(2.639)	(0.133)	(0.370)	(0.398)	(0.240)
Price 7-8 am	-0.882***	1.606*	-0.303***	-1.000***	-1.237***	-0.212*
	(0.132)	(0.926)	(0.0553)	(0.140)	(0.133)	(0.111)
Price 8-9 am	-1.625***	3.620	-0.546***	-1.733***	-1.833***	-0.442***
	(0.206)	(2.308)	(0.0886)	(0.215)	(0.237)	(0.165)
Price 9-10 am	-2.907***	-10.76***	-0.754***	-2.935***	-2.894***	-0.715**
	(0.280)	(4.069)	(0.0896)	(0.273)	(0.353)	(0.282)
Price 10-11 am	-3.090***	-3.873*	-0.626***	-3.062***	-3.863***	-1.371***
	(0.284)	(2.183)	(0.0724)	(0.302)	(0.479)	(0.363)
Price 11-12 am	-2.222***	-2.186*	-0.420***	-2.204***	-3.087***	-1.541***
	(0.231)	(1.127)	(0.0525)	(0.256)	(0.447)	(0.315)
Price 12 am-1 pm	-1.737***	-1.595	-0.324***	-1.673***	-2.016***	-0.933***
	(0.216)	(1.029)	(0.0479)	(0.226)	(0.353)	(0.259)
Price 1-2 pm	-1.542***	-1.291	-0.272***	-1.566***	-1.800***	-0.904***
	(0.212)	(0.935)	(0.0457)	(0.227)	(0.309)	(0.231)
Price 2-3 pm	-1.614***	-0.839	-0.277***	-1.721***	-1.935***	-1.083***
	(0.222)	(1.046)	(0.0508)	(0.222)	(0.322)	(0.257)
Price 3-4 pm	-0.817***	1.962**	-0.130***	-0.811***	-1.517***	-0.538**
	(0.149)	(0.777)	(0.0312)	(0.142)	(0.220)	(0.212)
Price 4-5 pm	-0.481***	1.619**	-0.0745**	-0.402**	-1.017***	-0.151
	(0.138)	(0.640)	(0.0291)	(0.162)	(0.179)	(0.178)
Price 5-6 pm	-0.481***	0.818	-0.0775***	-0.335**	-0.875***	-0.0754
	(0.127)	(0.574)	(0.0259)	(0.149)	(0.191)	(0.186)
Price 6-7 pm	-0.367***	0.821	-0.0604**	-0.250*	-0.875***	-0.0915
	(0.120)	(0.508)	(0.0258)	(0.146)	(0.173)	(0.148)
Price 7-8 pm	-0.698***	-0.878	-0.123***	-0.633***	-0.790***	-0.120
	(0.157)	(0.690)	(0.0343)	(0.164)	(0.188)	(0.151)
Price 8-9 pm	-0.901***	-1.545***	-0.140***	-0.900***	-0.614***	0.0244
	(0.158)	(0.559)	(0.0281)	(0.168)	(0.174)	(0.129)
Price 9-10 pm	-1.186***	-1.791***	-0.183***	-1.095***	-0.918***	-0.181
	(0.162)	(0.600)	(0.0266)	(0.195)	(0.215)	(0.166)
Price 10-11 pm	-1.164***	-1.022	-0.178***	-1.085***	-1.099***	-0.265
	(0.158)	(0.633)	(0.0258)	(0.191)	(0.242)	(0.204)
Price 11-12 pm	-1.382***	0.675	-0.215***	-1.284***	-2.215***	-0.862**
	(0.188)	(0.969)	(0.0320)	(0.226)	(0.411)	(0.339)

Continued on next page

TABLE 7 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
Price Squared 0-1 am		2.61e-05				
		(0.0883)				
Price Squared 1-2 am		-0.482***				
		(0.154)				
Price Squared 2-3 am		0.269				
		(0.191)				
Price Squared 3-4 am		-0.0948				
		(0.189)				
Price Squared 4-5 am		0.0981				
		(0.212)				
Price Squared 5-6 pm		0.488*				
		(0.256)				
Price Squared 6-7 am		0.327*				
		(0.197)				
Price Squared 7-8 am		-0.177***				
		(0.0648)				
Price Squared 8-9 am		-0.332**				
		(0.143)				
Price Squared 9-10 am		0.473**				
		(0.235)				
Price Squared 10-11 am		0.0459				
		(0.119)				
Price Squared 11-12 am		8.49e-05				
		(0.0522)				
Price Squared 12am-1pm		-0.00491				
		(0.0447)				
Price Squared 1-2 pm		-0.00954				
		(0.0368)				
Price Squared 2-3 pm		-0.0293				
		(0.0383)				
Price Squared 3-4 pm		-0.100***				
		(0.0279)				
Price Squared 4-5pm		-0.0727***				
		(0.0222)				
Price Squared 5-6 pm		-0.0459**				
		(0.0199)				
Price Squared 6-7 pm		-0.0421**				
		(0.0173)				
Price Squared 7-8 pm		0.00749				
		(0.0225)				
Price Squared 8-9 pm		0.0274				
		(0.0193)				
Price Squared 9-10 pm		0.0277				
		(0.0228)				
Price Squared 10-11 pm		-0.00533				
		(0.0259)				
Price Squared 11-12 pm		-0.104**				
		(0.0476)				
Trend (week)						-1.396***
						(0.369)
$Trend^2$						0.0186
						(0.0125)
Observations	4,143	4,143	4,143	3,774	3,464	3,464

Note: The data is comprised of 4,143 hourly observations in columns 1-3, of 3,774 observations in column 4 (observations within 24 hours from a regime change are excluded), and of 3,464 in columns 5 and 6 (responsive pricing regimes only). In column 3, the prices are measured in logs. The price, price squared, price variance and price standard deviation are treated as endogenous. Coefficients are estimated using instrumental variables. Instruments are the slope and the intercept of the pricing functions and their squares (interacted with hour indicator variables). Day-of-the-week fixed effects (Tuesday to Sunday, Monday omitted), national holiday, hour specific (omitted 8-9 am) and weekend cycle fixed effects, and a constant are included in all specifications. Robust standard errors (clustered by observation day) are reported in parentheses.

APPENDIX

TABLE A1

First Stage Regression Results

	(1) Price (p_{ij})	(2) Price Variance (v_j)
Responsiveness (β)	0.432***	0.822***
	(0.0161)	(0.0757)
Level of the Pricing Function (α)	0.542***	1.955**
	(0.161)	(0.805)
Responsiveness Squared (β^2)	-0.00247***	0.0202***
	(0.000710)	(0.00328)
Level of the Pricing Function Squared (α^2)	0.0169	-0.0994
	(0.0137)	(0.0728)
Observations	4143	4143
Partial R-squared of excluded instruments	0.32	0.87
F-test excluded instruments	1234.82	427.09
(p-value)	(0.000)	(0.000)

Note: The table reports the first stage regression results for the results in Table 2, column 1. Day-of-the-week fixed effects (Tuesday to Sunday, Monday omitted), the national holiday fixed effect and a constant are included in all specifications. Robust standard errors (clustered by observation day) are reported in parentheses.