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

Pascal Courty and Mario Pagliero

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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 the 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 demand variations. Holding average price and other variables constant, we find that demand is higher when prices vary more. The evidence suggests that the antagonism effect cannot be first order.

JEL: D01, D12, L86.
Keywords: Consumer demand, responsive pricing, fairness.

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1 Introduction

Economic theory demonstrates that pricing schemes that vary prices in response to demand shocks could reduce rationing and increase welfare. On the other hand, behavioral economics suggests that consumers care about how sellers set prices. In particular, survey evidence shows that, in many contexts, consumers are antagonized by pricing schemes that change prices in response to fluctuations in demand (Kahneman et al., 1986).[3]

These opposite views have 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). Lacking from the debate 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 varying price increase demand?

This paper develops a framework to measure the net impact on demand of introducing more flexible pricing schemes. In contrast with the survey literature, which is based on consumer attitudes, we consider the impact of price variability on actual firm demand. Since price variability may influence aggregate demand through other channels than just fairness, we state the question in terms of a simple trade-off. When prices vary more, holding the overall level of prices and other variables constant, does the quantity demanded change? If so, what is the trade-off (ceteris paribus) between the amount of price variations consumers face and overall quantity sold?

We denote this trade off $dq/d\sigma$ where q stands for average demand and σ for price variability. While data constraints do not allow us to separately identify different sources of

[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

behavioral responses, we can measure the net effect of price variability on demand, and thereby, draw inference on which type of consumer response is unlikely to play a first order role. In addition, the trade-off $dq/d\sigma$ can shed some light on the debate on why firms often do not vary prices in response to demand shocks. If $dq/d\sigma \geq 0$ and prices are correlated with demand, which is the case in situations where prices are used to smooth demand shocks, then revenue increases with the introduction of price variability. Therefore, finding that $dq/d\sigma \geq 0$ would reject the conjecture that the fear of revenue loss due to antagonized consumers is the explanation for the observation that firms do not vary prices.

Measuring the trade-off $dq/d\sigma$ is difficult in practice because one rarely observes consumer responses to pricing schemes that vary prices to different degrees in response to demand shocks. Firms that use different pricing schemes usually differ in other important ways. Moreover, firms rarely modify their pricing policies, and when they do so, it is usually done in conjunction with broader changes (e.g. product offers).

We measure $dq/d\sigma$ using a unique dataset from easyEverything, the largest chain of Internet cafés in the world. While acknowledging that out-of-home Internet access is not of direct interest to economists, we believe that this case study nonetheless provides valuable insights for several reasons. In contrast to the evidence used to support the conjecture that consumers are antagonized by variations in price, which is typically drawn from surveys, our case study provides the first evidence using 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).[4]

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popular goods would be judged unfair" (p.738). See also Xia et al. (2004) for a review with a marketing perspective.

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

In addition, easyEverything has used both peak load pricing and responsive pricing, two pricing rules that have been shown to affect fairness perceptions and that, according to the literature mentioned earlier, should have an impact on demand. Under responsive pricing, the firm updates prices every 5 minutes as a function of the realized occupancy rate in the store. Because it increases price when demand increases, and the magnitude of price changes is large, this pricing rule fits the description of exploitative and unfair firm behavior.

Finally, the firm has experimented, for both peak load pricing and responsive pricing, with different pricing regimes that vary prices to different degrees. Since a large portion of sales involves repeat purchase, the behavioral hypothesis predicts that consumers should care about the pricing rule used (peak load pricing or responsive pricing) and that they should 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 aggregate demand depends positively on the level of price variability while disaggregated (hourly) demand does not depend on the level of price variability. Both findings are inconsistent with the behavioral conjecture that consumer antagonism plays a first order role in determining demand. Instead, the evidence is consistent with a composition effect: when prices vary more, demand increases more when prices are low (off-peak hours) than it decreases when prices are high (peak hours). This channel through which demand may depend on price variations has been largely ignored in the fairness literature. Similarly, we do not find evidence in support of the antagonism hypothesis when we compare peak load pricing and responsive pricing. Taken together, we interpret the finding that price variability increases, rather than decreases demand, as consumers taking advantage of opportunities offered by variation in prices.

This work sheds new light on the role of fairness in explaining pricing policies. Our results do not contradict the vast amount of evidence from surveys showing that consumer care about fairness, but suggest that there are other channels through which aggregate demand may depend on the extent to which 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, the theoretical framework, and outlines the empirical strategy. Section 3 describes the data. Section 4 presents the main evidence and discusses some implications of the results for firm pricing policies. Section 5 presents a brief summary.

2 Background and Empirical Framework

2-2 Literature

The focus in this work is on price variations caused by changes in demand. This choice is motivated by the finding that consumers feel more strongly toward price variability caused by demand than by supply fluctuations (Kahneman et al, 1986). There are many situations in which prices may be linked to demand. When demand is seasonal, for example, a firm can set different prices for different time periods. This corresponds to deterministic peak load pricing. When some component of the change in demand is unpredictable, firms may vary prices in real time, as in responsive pricing (Vickrey, 1971).[5]

Economists hold opposite views on the likely impact of varying prices. Neo-classical models show that firms can use responsive pricing to reduces inefficiencies and/or increase profits. The basic idea is that increasing prices when demand is high reduces congestion and allocates the good to those consumers with highest willingness to pay. Decreasing prices when demand is low stimulates demand, increases sales, and reduces wasted capacity. The overall impact on welfare can be unambiguously positive.

[5] The practice of varying prices could be motivated by the necessity to manage a fixed capacity efficiently in the presence of demand uncertainty but it is important to recognize that

On the other hand, the behavioral literature argues that consumers are antagonized by price adjustments unrelated to changes in cost (Kahneman et al. 1986).[6] As a result, the argument goes, firms prefer to use inflexible allocation schemes, such as first-come first-served, rather than varying prices because consumers would find such practices unfair and would withhold future demand.[7] Coca-Cola's experience with responsive pricing provides an illustration. In 1999, 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 relation 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).[8] Pursuing this line of research, the marketing literature has identified contexts where consumers are more likely to be antagonized (Xia et al., 2004). It is argued that the context (type of product, consumer, and process dictating how prices change...) in which the transaction takes place is likely to influence consumers' fairness perception. For example, Haws and Bearden (2006) show that varying price is more acceptable when consumers play a role in the price determination process (e.g. eBay auction).

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this rationale is often undistinguishable from a pure profit maximization rationale leading to third degree price discrimination.

[6] Fairness in these survey studies refers to the acceptability of the transaction. This notion is different from the use that the word has received later in explicit theories of inter-individual comparisons. In this paper we refer to the former notion.

[7] Kahneman et al., Proposition 2 (p. 738) says "when a supplier provides a family of goods for which there is differential demand without corresponding variation in input costs, shortage of the most valued items will occur". See also Carlton (1986). Consistent with this view, surveys of revenue managers reveal that firms are not willing to change prices because they are afraid to antagonize consumers (Blinder et al. 1998, and Zbaracki et al. 2004). Rotemberg (2004) and Heidhues and Kőszegi (2005) assume that consumers are antagonized by unfair pricing, and propose theoretical models to investigate when firms may benefit from varying prices.

[8] Coca-Cola's chief executive argued that the technology would cater to the basic law of supply and demand, as consumers' desire for cold drinks increases in hot weather and each machine has a fixed capacity. When the news became public, many were shocked by the proposal. Pepsi was quick to state that it was not considering a similar innovation.

This paper pursues a different although complementary approach. We acknowledge the feature that transaction context may influence the degree of consumer antagonism. Consistent with this literature, we select a context with characteristics that are known to trigger fairness concerns, as we argue shortly. Within this context, we investigate whether there exists a trade-off between the amount of price variation and the level of demand. Because our approach focuses on measuring a trade-off, it could be replicated across contexts, a property regarded as essential by many (Fudenberg, 2006, Roth 2007).

2-2 Empirical Framework

Consider the demand relation

$$q(p,\varepsilon)=F(p)+\varepsilon \qquad (1)$$

where ε is a zero mean demand shock that could either be random, as in the case of a snowstorm, or predictable, as in the case of seasonal changes in weather. Relation (1) corresponds to the textbook demand relation between price and quantity sold. To define the behavioral hypothesis, we restrict without loss of generality to the case where dF/dp is independent of the state of the world. When we later discuss alternative types of consumer responses, we consider state dependent demands.

Assume that prices depend on the demand shock. Specifically, the seller sets price $P(\varepsilon)$ in state ε, where $P()$ is a non-decreasing function. This stylized representation is consistent with a variety of pricing schemes used in practice. If ε is seasonal, for example, prices could depend on the hour of the day, as in deterministic peak load pricing, a class of pricing scheme used in our case study. If there exists an observable random variable τ that is correlated with ε then prices could be a function of τ, as in the Coke example, where τ is temperature. Finally, prices could depend on ε indirectly through q, as would be the case under responsive pricing. easyEverything has also used this class of pricing scheme in our case study: A non-decreasing pricing function specifies a price for each level of store occupancy. Occupancy is measured every 5 minutes and the price is automatically updated according to

$$P(q)=\alpha+\beta q \qquad (2)$$

where P(q) is the price per unit of time and q is the measured level of occupancy (fraction of terminals logged on). A pricing scheme is more responsive if it has a higher slope β. Two pricing schemes are illustrated in Figure 1. Under scheme $P_1(q)$ the price is constant throughout the day independently of demand realizations. Scheme $P_2(q)$ is responsive: Consumers are charged more when there are more consumers logged on.

Behavioral Hypothesis

We modify demand specification (1) to capture the behavioral hypothesis that consumers might care about the properties of the rule that is used to set prices. To do so, we first define a measure of fairness so that pricing regimes can be compared and rated. Following the behavioral literature, we hypothesize that a pricing regime that varies prices more should be perceived as less fair. We denote by σ the measure of how much prices vary under pricing rule P(). For example, one could think of σ as the variance of price (Var[(P(ε)]), but this choice is somewhat arbitrary, and other measures of variability should not be ruled out.[9] The important point is that any measure of price variability, such as σ, captures the notion of exploitation implicit in fairness perception, because more price variability implies, under the assumption that P is increasing in ε, that prices increase more when demand is higher.

[9] Note that fairness considerations may be multi-dimensional. In particular, it may also depend directly on the rule used to set prices (e.g. peak load pricing versus responsive pricing). This would suggest that one may want to supplement our measure of price variability

According to behavioral survey evidence, a consumer should be more likely to buy from sellers that use pricing rules with low σ, holding 'everything else' constant, including the expected price of the good, and other characteristics of the pricing rule such as how it is presented or 'framed' to the consumer. One way to motivate this assumption within the framework of standard utility theory would be to assume that fairness is an additional characteristic of the good that enters the utility function. In the same way that consumers may care about the physical characteristics of a product and about softer dimensions such as brand, convenience, or availability, one could hypothesize that consumers also care about the fairness of the transaction rules that govern how a product is allocated.

We propose to extend relation (1) to the possibility that the demand could depend on the level of price variation,

$$q(P,\varepsilon)=F(P(\varepsilon),\sigma)+\varepsilon \qquad (3)$$

where the function q(.,.) gives the level of demand in state ε when prices are set according to pricing rule P. Demand function $q(P,\varepsilon)$ captures two relations. Holding the level of price variability σ constant, the demand decreases as prices increase, $dF/dP(\varepsilon)\leq 0$. This corresponds to the standard demand relation already present in (2). Functional form (3) also makes it possible to compare pricing regimes that vary prices to different degrees. Translating the behavioral hypothesis to this framework, we say that consumers are *antagonized by price variations*, if the demand responds negatively to an increase in the amount of price variations holding the state price constant, $dF/d\sigma<0$.

Functional form (3) assumes that consumers know the extent to which prices vary. This assumption may be reasonable in the case of deterministic peak load pricing. When prices vary for random reasons, as in the Coke example and in responsive pricing as well,

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σ with additional measures that captures those fairness considerations. We will return to this issue in the context of our case study.

this assumption is obviously a simplification of reality, since in practice different consumers go through different purchasing experiences that may influence their perceptions of how much prices actually vary. Keeping this limitation in mind, the proposed approach rests on the assumption that price variability captures some aspect related to the consumer's perception of fairness.[10]

The parameter of interest is $dF/d\sigma$. Clearly, the variable σ is constant for a given pricing regime. To estimate $dF/d\sigma$, one needs to observe exogenous variations in the pricing function P that generate variations in σ. For example, a firm could change its pricing policies over time, as in our case study, or different firms could adopt different policies. Assume one observes different pricing rules that depend on a parameter vector γ and denote this relation $P(\varepsilon;\gamma)$. For example, $\gamma=(\alpha,\beta)$ in our application (equation (2)). Exogenous variations in γ generate different levels of price variation, opening the possibility to estimate $dF/d\sigma$.

Specification (3) can be restated in terms of expected demand. Let $q(\varepsilon;\gamma)$ denote the consumed quantity in state ε when the price is set according to pricing rule γ. Take a first order approximation of (3) around the mean price $E_\varepsilon P(\varepsilon;\gamma)$ in regime γ (where E_ε is the expectation taken over all realizations of the shock ε). Replacing $F(p,\sigma)\approx F(E_\varepsilon P(\varepsilon;\gamma),\sigma)+(p-E_\varepsilon P(\varepsilon;\gamma))*F_p$ and taking expectations under the assumption that F_p is constant across states gives,

$$E_\varepsilon q(\varepsilon;\gamma)\approx F(E_\varepsilon P(\varepsilon;\gamma),\sigma) \quad (4)$$

where $E_\varepsilon q(\varepsilon;\gamma)$ represents the average level of consumption for regime γ. Specification (4) captures the basic idea that when the average cost of consumption is held constant, the

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[10] An alternative approach to model fairness, which we cannot pursue in this work, would be to assume that a given consumer, with a given consumption profile, cares only about the variation in price she faces. For example, a consumer who consumes only in a subset of the

average quantity demanded should be lower for pricing regimes that vary prices more. To illustrate, consider the Coke example. Interpret q as the number of bottles sold in a given period. Functional form (4) distinguishes between a situation where the price of a bottle is constant, $p=p_0$ and $\sigma=0$ (standard vending machine) with a situation where the price is on average the same, $Ep=p_0$, but is higher on hot days $\sigma>0$ (the innovation proposed by Coke).[11]

Alternative Hypothesis

The reduced form approach implicit in specification (3) and (4) has advantages as well as limitations. The main drawback is that it may not permit to pin down of a unique behavioural mechanism through which demand may depend on price variability. More precisely, behavioral theory is not be the only theory that makes prediction on the sign of $dF/d\sigma$. To illustrate, consider again the example of a vending machine varying prices as a function of temperature. If consumers care about price variations only because they are antagonized by price variations, then one would expect that $dF/d\sigma<0$. There are, however, alternative explanations as to why the demand may depend on unpredictable price variations:

(1) Consumers may be risk averse. Risk aversion would imply that demand should also depend negatively on σ.

states of the world will face a different distribution of prices from a consumer who always consumes.

[11] Specification (4) and the above illustration highlight the distinction between price variation antagonism as defined in this paper and the concept of fairness introduced in Kahneman et al. (1986). We ask a different question from those typically posed in consumer surveys. Our study focuses on consumer responses to changes in the level of price variability when holding the level of price constant, rather than on a single price increase triggered by a positive demand shock.

(2) Consumers may update their consumption decisions after observing the realized price. A risk neutral consumer values price variability.[12] If this were the only channel through which consumers respond, it could be possible that $dF/d\sigma > 0$.[13]

(3) Most importantly, demand may be state dependent, a possibility not allowed by specification (1). For example, consider the more general specification,

$$q(p,\varepsilon)=F(p,\sigma;\varepsilon) \qquad (5)$$

and assume that demand is less elastic in higher states: F is increasing in ε and dF/dp decreases with ε, a reasonable assumption in our application as we will argue later. When prices vary more across states (an increase in σ), demand increases more in low states than it decreases in high ones. This implies that average demand responds positively to price variations.

2-3 Summary

Specifications (3-5) serve three purposes well. First, they provide a descriptive tool to characterize (aggregate) demand responses to pricing policies that generate different levels of price variability. Arguably, the extent to which price variations affect the demand function is of interest in itself. We can measure the sign of $dF/d\sigma$ and establish the existence of a trade-off between the level of price and price variability.

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

[13] To illustrate that this conclusion does not always follow, assume that only consumers with positive expected utility ($E(V(p))$) consume. Total consumption is the sum of individual consumption $EX(p)$ for all consumers who have positive utility. Although the number of consumers increases with the variance of price, actual consumption may increase or decrease. $dF/d\sigma>0$ is possible but not necessary.

Second, specifications (3) and (4) can be used to test whether consumer antagonism toward price variation plays 'a first order role' as suggested by the behavioral literature. We will interpret the finding that $dF/d\sigma<0$ as consistent with the behavioral hypothesis of consumer antagonism. Alternatively, the finding that $dF/d\sigma\geq 0$ implies that the consumer antagonism hypothesis cannot be first order.

Third, the measure $dq/d\sigma$ can shed some light on the hypothesis that firms do not vary prices because they fear antagonizing consumers. Say that one finds that $dq/d\sigma\geq 0$ in an industry where firms typically do not vary prices. Since the pricing schemes we consider generate a positive correlation between occupancy and price, expected revenues must increase with the introduction of price variations. To illustrate this point, consider the class of pricing rules used in our case study corresponding to specification (1). Firm revenues can be expressed as

$$R=E[q(\varepsilon;\gamma)P(\varepsilon;\gamma)]=Cov(q(\varepsilon;\gamma),P(\varepsilon;\gamma))+Eq(\varepsilon;\gamma)EP(\varepsilon;\gamma)$$

$$=\beta Varq(\varepsilon;\gamma)+Eq(\varepsilon;\gamma)EP(\varepsilon;\gamma)$$

If $dEq(\varepsilon;\gamma)/d\sigma\geq 0$, the introduction of price variations that holds the level of price constant clearly increases revenues, R, since the first term becomes positive (it is zero under constant price ($\beta=0$)) and the second increases by assumption.[14] To summarize, the finding that firms' demand is such that $dEq(\varepsilon;\gamma)/d\sigma\geq 0$ in an industry where firms do not vary prices implies that the fear of demand withholding by antagonized consumers cannot be an explanation for the observation that prices do not vary.

3 Data

[14]The prediction $dR/d\sigma|_{EP}\geq 0$ holds more generally for any increase in price variation that holds the level of price constant as long as the covariance $Cov(q(\varepsilon;\gamma),P(\varepsilon;\gamma))$ also increases with the increase in price variations, a reasonable assumption since we restrict the analysis to schemes that increase/decrease prices when demand is high/low.

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 store opening 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 during the 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. Each responsive pricing regime is characterized by its intercept α and slope β as in equation (2).[15] Under responsive pricing, prices are communicated to consumers, who are charged in real time the minimum of the current price and their logon price.

After opening a new store, the company experiments with different pricing functions, typically starting off with peak load pricing and then introducing responsive pricing, to learn the specific characteristics of the local demand before attempting to optimise the pricing scheme (Courty and Pagliero, 2001). Table 1 shows that the firm has changed 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 level of price variation 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.

[15] Because of implementation constraints, the store had to use step functions instead of continuous functions. On average there are 30 steps per curve, with a minimum of 15. We compute linear approximations of the pricing curves by regressing the price at each step on the occupancy rate at the midpoint. Steps that are never reached during the regime are excluded from the regression. The average slope, corresponding to β, is 17.1—meaning that the price decreases by 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 more than 95 percent of the variation. In regimes 12, 13, and 14, the R^2 is between 0.75 and

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.[16] 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.[17] 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 never binds in our sample. This implies that quantity demanded equals quantity consumed.

The average price per hour is FRF 10.7 (€ 1.63) and the price variance is 28.7 FRF^2/hour. This amount of price variability is significant. In fact, the standard deviation of price is 51% of the average price. The difference between the 90th and 10th percentile is FRF 14.8 (€ 2.26). 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,

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0.87. These regimes are piecewise linear, with a kink at 60 percent. These non-linearities do not affect our results.

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

[17] 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

the snowstorm question in Kahneman et al. (1986) related to an increase in price of 33 percent.

Do consumers face price variation?

The type of price variation introduced by easyEverything falls within our empirical framework and qualifies to test the behavioral hypothesis that consumers are antagonized by schemes that increase prices in response to demand shocks. To illustrate, 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 over the day cycle and also that they vary across days for the same hour due, for example, to changes in weather, start of school vacation, occurrence of strike and so on...

In principle, consumers may assess fairness on basis of the variability of billed price, which may differ from the login price due to the price cap feature, but computing this figure would require consumer level data. The difference in the variability of the two prices, however, is likely to be small for most consumers because prices do not vary much over the typical length of stay. (The level of price at the start of a session may still be uncertain because it depends on the level of demand on that day.) In fact, a smaller dataset on length of stay shows that consumers remain connected on average for 65 minutes. In addition, prices vary little across consecutive hours, compared to the overall price variability. Table A1 in Appendix I shows that the average price increase between adjacent hours is 1.73FRF,

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sudden drop. Using an additional data set on downtime periods, we removed all corresponding observations.

that is only 1/3 of the overall standard deviation of price.[18] In the rest of the analysis, will use the variations in login price as our measure of the price variation.

Should consumers respond to changes in pricing regimes?

Two types of changes have taken place during our sample period. First, the distribution of price changes from regime to regime. Second, the store has switched from peak load pricing to responsive pricing after regime 5. Because there was no other change in the pricing policies during our sample period, we can focus exclusively on these two dimensions holding constant other behavioral considerations such as framing.

The level of price variation changes from regime to regime. In fact, the differences in variance across regimes, reported in Table 1, are large and statistically significant (see Table A2 in Appendix I). 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 is enough repeat purchase which is the case 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.

Comparing different pricing regimes, for a given type of pricing rule (peak load or responsive), falls within our empirical framework. Changes in the level of price variability across regimes of the same type, allow us to estimate $dF/d\sigma<0$. Comparing demand across pricing regimes that belong to a different type may involve additional considerations such as the possibility that framing may have changed from peak load to responsive pricing. We will take this possibility into account in the empirical analysis.

[18] Table 1 reports the overall price variance, 28.73 FRF^2, which implies a standard deviation of 5.36 FRF.

A final issue is that under responsive pricing, consumers do not observe directly when the pricing function changes, or the overall distribution of price. Prices, however, are posted on a small window on each terminal, and are updated every 5 minutes. Consumers can observe occupancy in the store and up to 12 prices every hour, so they have sufficient information for inferring the pricing function. For linear pricing functions, in principle 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 4.3.

4 Demand Responses to Price Variations

The empirical objective is to describe the relationship between quantity demanded, price, and price variability (relations (3) and (4)) in a way that is robust to the specification used. 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 opens up the possibility of estimating how variations in these variables affect the level of demand.

As mentioned earlier, the price elasticity of demand for Internet access is likely to be hour dependent. Therefore one needs to consider the possibility of hour heterogeneity (specification 5). 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. Our primary specification corresponds to a linearization of model (4)

$$q_{j,i} = a_0 + a_1 p_j + a_2 \sigma_j + a_3' x_{j,i} + u_{j,i} \qquad j = 1,...,17,\ i = 1,...,I_j \qquad (6)$$

where $q_{j,i}$ is the i^{th} occupancy observation in regime j, p_j is a price index for regime j, and σ_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 error term.[19]

We later consider a more disaggregated specification than (6), introducing hour fixed effects ($a_{0,h}$) and hour-specific average prices ($p_{j,h}$). We also explore non-linear specifications. Finally, there are many ways to construct the right-hand side variables in specification (6). We present the main results (Table 2) using a first set of right-hand side variables that we describe shortly. In subsection 4.3 we then show that these results are robust.

The price index p_j is computed as follows. We use the subscript h=0,...,23 to denote hours. Define $p_{j,h}$ as the average price in hour h in regime j and w_h as the fraction of total consumption in the sample that takes place in hour h. The price index in regime j is $p_j=\Sigma_h w_h p_{j,h}$. Consider next the measure of fairness, σ_j. We use the variance in price computed at the regime level to measure how fair a pricing regime is. Under peak load pricing, this corresponds to the variance in the daily price cycle. Under responsive pricing, it mixes night hourly prices, when prices are fixed, and the realized prices during the day. As suggested earlier, there is no perfect measure of fairness in our case study because consumers are characterized by unique purchase histories that influence their perceptions of fairness. Having said this, however, it also seems plausible that price variance should capture some common aspect of fairness that consumers are likely to be concerned with.

The two right-hand side variables p_j and σ_j in specification (6) may not depend only on the parameters of the pricing function. They may also depend on the error term. To illustrate, recall that the variables p_j and σ_j are computed using observed prices. Under

[19] Model (4) says that average occupancy (over all observations in a given regime) should be a function of average price (p_j) and price variability (σ_j). However, observations in model (6)

responsive pricing, these variables are a function of the occupancy observations (through relation (2)) and may be correlated with the error term. In addition, because we use a finite number of observations for each regime, these variables are imperfect measures of the true p_j and σ_j which should be based on the distribution of the demand shocks (ε in the model). Measurement error in p_j and σ_j may also generate correlation between the regressors and the error term. 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.[20] Table A3 in Appendix I reports the first stage regression results. The instruments are highly correlated with the price level and the price variability.

4-1 Main Results

Overall Response (TABLE 2, COLUMN 1)

Table 2, column 1 presents the results of specification (6). Consistent with standard economic theory, the coefficient estimating the response to the price index is negative and significant, giving a price elasticity of 0.26. Allowing for hourly price responses (column 2) implies price elasticities as high as 0.9.[21] This rules out the possibility that one should not expect antagonism responses in our case study because consumers are price insensitive.

However, the focus of this work is on a_2. The coefficient estimating the response to price variations is positive and significant. Holding the price index constant, higher

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are not averaged at the regime level because the control variables $x_{j,i}$ are hour and day specific.

[20] The variables p_j and σ_j are likely to depend not only on the parameters of the pricing function α and β but also on their square α^2 and β^2. To demonstrate this point, solve (2) and (3) for the price in state ε as $P(\varepsilon)=\alpha+\beta q(P(\varepsilon),\varepsilon)$. For example, if the function q is linear in both its argument, the solution $P(\varepsilon)$ is non linear in β. Clearly, the variance is a non-linear function of P and therefore of α and β.

[21] 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%.

variability of prices is associated with higher consumption. Consider a switch from a hypothetical regime that generates the minimum price variance observed in our sample (0.17 FRF^2/hour) to another hypothetical regime that generates the largest price variability observed in our sample (57.5 FRF^2/hour). At the aggregate level, the results in Table 2, column 1, suggest that consumption increases by 5.6 percent of store capacity, or 12 percent of average observed occupancy.

We rule out an obvious explanation for this effect. The increase in consumption could be due to a binding capacity effect. If the capacity binds, then increasing price variations while maintaining a constant average price increases consumption in low demand states, but does not decrease consumption in high demand states. We rule out this interpretation because the capacity never binds in our sample. To conclude, the positive demand response to increases in price variation rules out the hypothesis that antagonism responses play a first order role in our data.

Disaggregate Specification (TABLE 2, COLUMN 2)

Table 2, column 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 (6),

$$q_{j,h,i} = a_0 + a_{0,h} + a_{1,h} p_{j,h} + a_2 \sigma_j + a_{3,h}' x_{j,h,i} + u_{j,h,i} \qquad j = 1,...,17,\ h = 0,...,23,\ i = 1,..., I_j \tag{7}$$

where $p_{j,h}$ is the average price in regime j and hour h; $x_{j,h,i}$ includes the same control variables as before along with the weekend-specific hourly price cycle.[22] To motivate this specification, write model (5) as $q_h(p,\varepsilon)=F_h(p,\sigma)+\varepsilon$ and take a first order approximation.

The coefficient on price variation a_2 is smaller and not significantly different from zero. This suggests that the estimate of a_2 in column 1 captured a demand composition effect similar to the one described as an illustration of specification (5). To explain this effect in the context of our case study, assume that different consumers come at the peak and at the trough (demand heterogeneity) and that peak consumers are less price sensitive than off-peak consumers (a realistic assumption as we argue next). More responsive pricing regimes increase the difference between peak and off-peak prices. Therefore, 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 at the peak. In fact, consumption is highest in our sample from 4pm to 7pm (peak hours), and the marginal effect of a change in the hourly average price is lower than during off-peak hours – morning or late evening. Varying price stimulates consumption more during off-peak hours than it chokes off demand during peak hours.

Summary

Aggregate 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). This is inconsistent with the hypothesis that consumer antagonism to price variations plays a first order role. The positive effect of price variability on aggregate consumption is consistent with a composition effect due to demand heterogeneity. In the rest of this section, we show that this conclusion is robust to the way we capture price variation antagonism and to different demand specifications.

4-2 Controlling for Different Sources of Price Variability

Specification (6) focuses exclusively on the role of price variability. This implicitly rules out the possibility that demand could depend directly on the pricing rule used. Recall

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[22] Under peak load pricing, the average price $p_{j,h}$ corresponds to the predetermined price for

that two pricing rules, peak load pricing and responsive pricing, were used in our sample. Consumers may perceive these two 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 make the distinction between: "How do you evaluate a price rise when a hot day was completely unforeseeable?" and "Do you consider a price rise ... to be more, equally, or less acceptable than when hot days normally occur in the season 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 subjects find the former rule more acceptable than the latter). This suggests that we should treat peak load pricing and responsive pricing differently.[23] In this section, we explore variations of model (6) and (7), allowing for the demand to depend in more general ways on the pricing rule.

Responsive Pricing Fixed Effect

Table 3, column 1 introduces a fixed effect for responsive pricing. The motivation for the fixed effect is that consumers may respond differently to peak load pricing and responsive pricing. In fact, responsive pricing explicitly links prices to demand realizations, making prices unpredictable. 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 first order.

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that hour.

[23] 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. Assuming additional

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. This is again inconsistent with the hypothesis that antagonism responses play a first order role in our data. In Table 3, column 2, the coefficient of price variability is again positive and significantly different from zero. As before, we find that after controlling for hourly heterogeneity, this effect is not significantly different from zero (as in Table 2).

Results in Table 3 raise the question of why the fixed effect is positive. A potential interpretation for this finding follows the line of the explanation for why price variability influences aggregate, and not disaggregated, consumption, in Table 2. Holding the expected hourly price constant, 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 would have to disaggregate the hourly demand and estimate the price response in different states of the world.[24,25]

Peak Load versus Responsive Price Variability

One could argue that consumption may respond differently to price variation generated by different pricing rules. The results of Table 2 may confound two opposing effects

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variables (such as day of the week and National Holiday fixed effects) are used by consumers to predict prices reduces only marginally the amount of unpredictable price variability.

[24] 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.

[25] Another possible explanation is that the introduction of responsive pricing was framed differently than peak load pricing, for example, emphasizing differently consumer benefits and losses. Although we cannot explore this hypothesis with our data, there is no indication that this was the case from reviewing store posters and advertising pamphlets.

generated by peak load pricing and responsive pricing. Therefore, we 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.

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. Again, the evidence is not consistent with the hypothesis that price variability (however it is generated) has a negative impact on consumption.

4-3 Robustness

In this section we explore a set of variations of model (6) and (7) in order to investigate the robustness of the baseline results reported in Table 2. We deal with substitution effects, functional form assumptions, the definition of right-hand side variables (weighted price and price variability), sample definition, and time trend.

Substitution effects

Table 5 accounts for substitution across hours by extending specification (7). In principle, it might be desirable to include in the specification for each hour the average price in every other hour, since substitution may occur between any hour. However, due to data limitations, we have to aggregate different hours to limit the number of coefficients that need to be estimated.

We group observations in our sample into two broad periods: "peak", from 11am to 10 pm, and "off-peak", from 11pm to 10 am such 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 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.

Specification (7), there is one additional variable capturing substitution between peak and off-peak hours,

$$q_{j,h,i} = a_0 + a_{0,h} + a_{1,h} p_{j,h} + a_2 \sigma_j + a_{3,h}' x_{j,h,i} + a_4 \tilde{p}_{j,h} + u_{j,h,i} \qquad j = 1,...,17,\ h = 0,...,23,\ i = 1,..., I_j \tag{8}$$

$\tilde{p}_{j,h}$ is equal to the average off-peak price if $11 \le h \le 23$ and to the average peak price otherwise; a_4 is a parameter to be estimated. Clearly, the new variable $\tilde{p}_{j,h}$ 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 model (9). 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 and not significantly different from zero. The main results discussed in the previous section, however, are unchanged.

Other Robustness Results

Tables 6 and 7 report aggregate and disaggregate specifications respectively. The former reports variations of model (6) and the latter reports variations of model (7).

(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 signs of the coefficients of price variability are not different from the results in Table 2.

(2) In column 2, Table 6, p_j^2 is included to control for non-linear effects of the price level. This specification allows for more general demand heterogeneity. In column 2, Table 7, the specification includes p_{jh}^2. 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. 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 and significant in Table 6, and non significant in Table 7.

These first three robustness checks also show that it is unlikely that, in Table 2, the variance in price captured non-linear price effects.

(4) In column 4, Tables 6-7, hourly observations in the 24 hours after each regime change are excluded from the sample. Such deletion is motivated by the possibility that it may take time for consumers to adjust to a regime change. In fact, our empirical analysis assumes that consumers know the average level of price and 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) Table 6, column 6 reports the results when the price index p_j is constructed as the (un-weighted) average price within each regime.

(7) 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.[26] The results are not affected.

4-4 Implications for Firm Pricing Policies

Our case study presents a situation where prices change significantly in response to demand shocks, but these variations in price have no negative impact on aggregate demand. Our evidence suggests that varying prices can influence overall demand through several channels. While survey evidence demonstrates the importance of antagonism responses, we show that in practice the demand composition effect can dominate. To repeat, this does not imply that the antagonism effect does not exist, nor that it never plays a first order role.

We recognize that our approach has limitations. First, the evidence presented is specific to our case study, and consumer attitude toward price variations may be different in different markets so one must be cautious in generalizing our results to different contexts. However, our case fits the description of situations where it has been conjectured that antagonism caused by demand driven price variation should be significant. Second, it is possible that only a small proportion of consumers is not antagonized by price variability and that this

[26] The coefficients imply an average decrease in occupancy of 0.7 percent per week.

group is over-represented in our case study. Still, we find no margin from increasing the amount of price variation, and 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 surveys. Third, our findings do not imply that firms should necessarily introduce responsive pricing. Profits do not necessarily increase with price variability. In fact, it could be the case that the costs of implementing responsive pricing schemes outweigh the benefits.

Our evidence does not support the hypothesis that *increasing* price variation in response to demand shocks would necessarily alienate consumers and decrease revenue. This leaves at least two candidates behavioral 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, there may be a discontinuity between constant price and variable price 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. Second, 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 a way that was acceptable to consumers, a public relation exercise that Coke failed. We cannot address this issue either, because there is no variation in framing in our case study.

With all of this in mind, an implication of our work is that even if the initial introduction of price variation decreases demand, once price variation has been introduced there may not be any further negative demand responses from further increases in price variation. This suggests that one should observe that firms either do not vary prices at all or vary prices a lot, an observation that seems consistent with casual observations from the airline industry, and hotel industry, for example.

5 Summary

This work develops a framework to study whether consumers care about how much a seller varies prices in the presence of demand fluctuations. Are consumers antagonized by pricing policies that vary prices more? Or do increases in price variation increase demand? What is the trade-off between the amount of price variations consumers face and the level of demand?

We find that aggregate demand depends positively on price variability, holding all other dimensions of the pricing rule constant. The positive response disappears when we allow for demand heterogeneity across hours, suggesting that this response was due to an aggregation effect over hourly demands. We also compare the demand under peak load pricing and responsive pricing. Survey evidence suggests that consumers are more likely to be antagonized by responsive pricing, since it varies prices not only over the day cycle but also as a function of unpredictable demand shocks; also in this case, however, we find that demand is higher under responsive pricing. We interpret this result as an aggregation effect due to different demand elasticities in different demand realizations.

To conclude, we want to emphasize that the framework presented in section 2 is general and that it can be applied elsewhere. We argue that varying price as a function of demand may influence demand through several channels, including the antagonism channel emphasized in the behavioral literature, and we propose to measure the net impact of these responses as a simple the trade-off. This work establishes a first step toward understanding how consumer demand depends on the rule governing how prices are set.

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FIGURE 1

Examples of responsive pricing functions

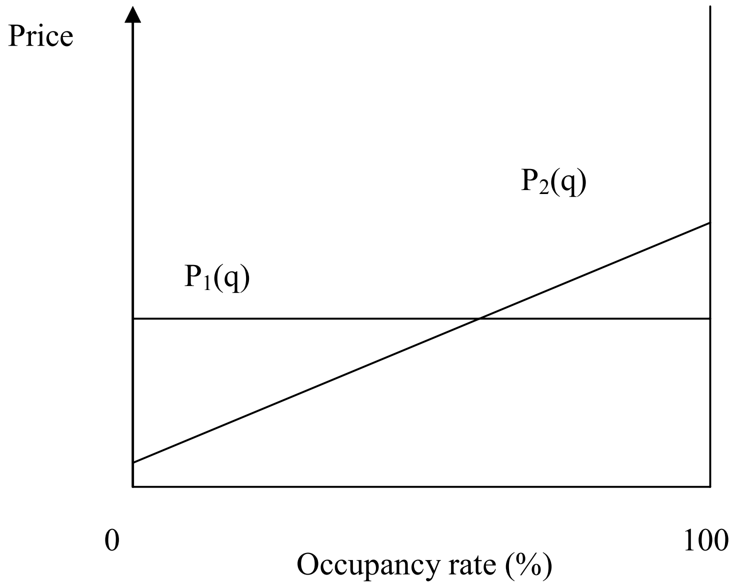

TABLE 1

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

TABLE 2

Baseline Results

	(1)	(2)
Price index (p_j)	-1.120***	
	(0.267)	
Price Variance (σ)	0.097**	0.006
	(0.048)	(0.020)
Price 0-1 am		-1.940***
		(0.288)
Price 1-2 am		-2.184***
		(0.326)
Price 2-3 am		-3.430***
		(0.565)
Price 3-4 am		-3.545***
		(0.477)
Price 4-5 am		-4.128***
		(0.528)
Price 5-6 pm		-3.608***
		(0.413)
Price 6-7 am		-2.842***
		(0.308)
Price 7-8 am		-0.872***
		(0.139)
Price 8-9 am		-1.587***
		(0.196)
Price 9-10 am		-2.803***
		(0.273)
Price 10-11 am		-2.949***
		(0.288)
Price 11-12 am		-2.092***
		(0.227)
Price 12 am-1 pm		-1.618***
		(0.211)
Price 1-2 pm		-1.429***
		(0.210)
Price 2-3 pm		-1.507***
		(0.218)
Price 3-4 pm		-0.734***
		(0.156)
Price 4-5 pm		-0.409***
		(0.140)
Price 5-6 pm		-0.403***
		(0.126)
Price 6-7 pm		-0.286**
		(0.121)
Price 7-8 pm		-0.609***
		(0.161)
Price 8-9 pm		-0.818***
		(0.162)
Price 9-10 pm		-1.096***
		(0.165)
Price 10-11 pm		-1.071***
		(0.165)
Price 11-12 pm		-1.278***
		(0.198)
Centered R^2	0.03	0.87
Observations	4,143	4,143

Note: The dependent variable is the mean occupancy rate x 100. Price denotes the average price (computed by hour and regime). Price level 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), 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 index (p_j)	-1.192***	-2.109***	
	(0.207)	(0.441)	
Responsive Pricing Fixed Effect	4.226**	7.646***	4.470***
	(2.081)	(2.588)	(1.385)
Price Variance (σ)		0.184***	-0.027
		(0.059)	(0.019)
Price 0-1 am			-2.388***
			(0.226)
Price 1-2 am			-2.657***
			(0.255)
Price 2-3 am			-4.026***
			(0.525)
Price 3-4 am			-4.057***
			(0.453)
Price 4-5 am			-4.466***
			(0.541)
Price 5-6 pm			-3.845***
			(0.425)
Price 6-7 am			-3.097***
			(0.325)
Price 7-8 am			-1.020***
			(0.130)
Price 8-9 am			-1.844***
			(0.193)
Price 9-10 am			-3.178***
			(0.260)
Price 10-11 am			-3.356***
			(0.263)
Price 11-12 am			-2.444***
			(0.217)
Price 12 am-1 pm			-1.946***
			(0.207)
Price 1-2 pm			-1.706***
			(0.195)
Price 2-3 pm			-1.747***
			(0.206)
Price 3-4 pm			-0.934***
			(0.142)
Price 4-5 pm			-0.584***
			(0.133)
Price 5-6 pm			-0.593***
			(0.123)
Price 6-7 pm			-0.477***
			(0.115)
Price 7-8 pm			-0.805***
			(0.147)
Price 8-9 pm			-1.022***
			(0.147)
Price 9-10 pm			-1.326***
			(0.149)
Price 10-11 pm			-1.313***
			(0.145)
Price 11-12 pm			-1.575***
			(0.176)
Centered R^2	0.03	0.04	0.87
Observations	4,143	4,143	4,143

Note: The dependent variable is the mean occupancy rate x 100. Price denotes the average price (computed by hour and regime). Price level 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), 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 index (p_j)	-1.072***	
	(0.322)	
Price Variance (Responsive Pricing)	0.106**	0.032
	(0.051)	(0.024)
Price Variance (Peak Load Pricing)	0.276	0.320
	(0.263)	(0.278)
Price 0-1 am		-1.871***
		(0.277)
Price 1-2 am		-2.113***
		(0.320)
Price 2-3 am		-3.358***
		(0.568)
Price 3-4 am		-3.491***
		(0.491)
Price 4-5 am		-4.070***
		(0.541)
Price 5-6 pm		-3.534***
		(0.422)
Price 6-7 am		-2.769***
		(0.320)
Price 7-8 am		-0.841***
		(0.141)
Price 8-9 am		-1.560***
		(0.198)
Price 9-10 am		-2.776***
		(0.280)
Price 10-11 am		-2.912***
		(0.304)
Price 11-12 am		-2.054***
		(0.240)
Price 12 am-1 pm		-1.577***
		(0.221)
Price 1-2 pm		-1.411***
		(0.209)
Price 2-3 pm		-1.495***
		(0.225)
Price 3-4 pm		-0.739***
		(0.158)
Price 4-5 pm		-0.434***
		(0.140)
Price 5-6 pm		-0.418***
		(0.126)
Price 6-7 pm		-0.301**
		(0.121)
Price 7-8 pm		-0.613***
		(0.160)
Price 8-9 pm		-0.814***
		(0.161)
Price 9-10 pm		-1.086***
		(0.166)
Price 10-11 pm		-1.062***
		(0.163)
Price 11-12 pm		-1.257***
		(0.197)
Centered R^2	0.03	0.87
Observations	4,143	4,143

Note: The dependent variable is the mean occupancy rate x 100. Price denotes the average price (computed by hour and regime). Price level 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), 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 (σ)	0.039	0.090***	
	(0.034)	(0.033)	
Substitution (Peak/ Off-peak) ($\tilde{p}_{j,h}$)	-0.213	-0.925***	-0.167
	(0.170)	(0.182)	(0.203)
Responsive Pricing Fixed Effect		8.626***	
		(1.662)	
Price Variance (Responsive Pricing)			0.057
			(0.035)
Price Variance (Peak Load Pricing)			0.299
			(0.297)
Price 0-1 am	-1.754***	-2.021***	-1.744***
	(0.216)	(0.203)	(0.207)
Price 1-2 am	-1.996***	-2.304***	-1.986***
	(0.238)	(0.228)	(0.232)
Price 2-3 am	-3.155***	-3.440***	-3.170***
	(0.447)	(0.446)	(0.451)
Price 3-4 am	-3.257***	-3.310***	-3.286***
	(0.388)	(0.375)	(0.393)
Price 4-5 am	-3.891***	-3.783***	-3.899***
	(0.500)	(0.465)	(0.507)
Price 5-6 pm	-3.424***	-3.285***	-3.399***
	(0.409)	(0.378)	(0.412)
Price 6-7 am	-2.648***	-2.516***	-2.628***
	(0.313)	(0.281)	(0.316)
Price 7-8 am	-0.764***	-0.688***	-0.759***
	(0.113)	(0.108)	(0.117)
Price 8-9 am	-1.428***	-1.403***	-1.438***
	(0.156)	(0.159)	(0.149)
Price 9-10 am	-2.582***	-2.584***	-2.611***
	(0.224)	(0.235)	(0.214)
Price 10-11 am	-2.728***	-2.795***	-2.750***
	(0.197)	(0.200)	(0.189)
Price 11-12 am	-2.103***	-2.841***	-2.075***
	(0.232)	(0.253)	(0.259)
Price 12 am-1 pm	-1.638***	-2.354***	-1.604***
	(0.221)	(0.247)	(0.244)
Price 1-2 pm	-1.454***	-2.083***	-1.439***
	(0.224)	(0.240)	(0.233)
Price 2-3 pm	-1.534***	-2.104***	-1.524***
	(0.234)	(0.255)	(0.253)
Price 3-4 pm	-0.739***	-1.152***	-0.750***
	(0.160)	(0.172)	(0.169)
Price 4-5 pm	-0.413***	-0.772***	-0.441***
	(0.142)	(0.154)	(0.147)
Price 5-6 pm	-0.412***	-0.820***	-0.430***
	(0.131)	(0.148)	(0.136)
Price 6-7 pm	-0.298**	-0.720***	-0.316**
	(0.127)	(0.142)	(0.133)

Continued on next page

TABLE 5 (continued)

	(1)	(2)	(3)
Price 7-8 pm	-0.630***	-1.094***	-0.636***
	(0.172)	(0.175)	(0.178)
Price 8-9 pm	-0.840***	-1.322***	-0.839***
	(0.171)	(0.165)	(0.180)
Price 9-10 pm	-1.118***	-1.651***	-1.113***
	(0.175)	(0.170)	(0.186)
Price 10-11 pm	-1.092***	-1.644***	-1.088***
	(0.175)	(0.171)	(0.183)
Price 11-12 pm	-1.138***	-1.258***	-1.159***
	(0.163)	(0.166)	(0.159)
Centered R^2	0.87	0.87	0.87
Observations	4,143	4,143	4,143

Note: The dependent variable is the mean occupancy rate x 100. Price denotes the average price (computed by hour and regime); $\tilde{p}_{j,h}$ 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)	(6)
Dependent Variable:	Occupancy Rate	Occupancy Rate	Ln(Occupancy Rate)	Occupancy Rate	Occupancy Rate	Occupancy Rate
Price index (p_j)	-1.706***	2.728***		-1.246***	-3.995***	
	(0.379)	(0.910)		(0.274)	(0.289)	
Price Standard Deviation	2.174***					
	(0.707)					
Price index squared		-0.235***				
		(0.055)				
Price Variance		0.417***	0.002**	0.103**	0.417***	0.070*
		(0.090)	(0.001)	(0.051)	(0.041)	(0.041)
Ln (Price index)			-0.220***			
			(0.058)			
Average Price						-1.237***
						(0.285)
Centered R^2	0.04	0.05	0.02	0.04	0.05	0.03
Observations	4,143	4,143	4,143	3,774	3,464	4,143

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 index, price index 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), 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) Occupanc y Rate
Price Standard Deviation	0.356					
	(0.236)					
Price Variance		0.018	0.001	0.006	-0.018	0.167***
		(0.025)	(0.001)	(0.023)	(0.020)	(0.044)
Price 0-1 am	-2.058***	-1.301	-0.045***	-2.061***	-2.982***	0.034
	(0.263)	(1.373)	(0.006)	(0.316)	(0.490)	(0.407)
Price 1-2 am	-2.313***	5.398**	-0.054***	-2.365***	-7.021***	-2.435***
	(0.293)	(2.199)	(0.007)	(0.360)	(0.732)	(0.639)
Price 2-3 am	-3.554***	0.962	-0.098***	-3.576***	-3.595***	-2.229***
	(0.552)	(2.638)	(0.015)	(0.601)	(0.510)	(0.377)
Price 3-4 am	-3.685***	1.821	-0.118***	-3.638***	-5.109***	-3.040***
	(0.464)	(2.397)	(0.016)	(0.504)	(0.546)	(0.404)
Price 4-5 am	-4.204***	-5.508*	-0.161***	-4.201***	-4.482***	-2.882***
	(0.540)	(3.103)	(0.021)	(0.542)	(0.540)	(0.395)
Price 5-6 pm	-3.657***	-9.996***	-0.172***	-3.694***	-3.646***	-2.359***
	(0.426)	(3.585)	(0.020)	(0.414)	(0.392)	(0.288)
Price 6-7 am	-2.896***	-6.166**	-0.181***	-2.959***	-3.037***	-1.680***
	(0.323)	(2.822)	(0.020)	(0.306)	(0.304)	(0.219)
Price 7-8 am	-0.901***	1.374	-0.056***	-1.023***	-1.240***	-0.244**
	(0.133)	(0.901)	(0.009)	(0.140)	(0.122)	(0.106)
Price 8-9 am	-1.638***	2.913	-0.081***	-1.746***	-1.830***	-0.495***
	(0.195)	(1.970)	(0.010)	(0.200)	(0.202)	(0.153)
Price 9-10 am	-2.923***	-9.268***	-0.098***	-2.975***	-2.896***	-0.826***
	(0.263)	(3.071)	(0.009)	(0.251)	(0.256)	(0.252)
Price 10-11 am	-3.115***	-3.432	-0.078***	-3.089***	-3.906***	-1.538***
	(0.270)	(2.187)	(0.007)	(0.282)	(0.345)	(0.305)
Price 11-12 am	-2.245***	-1.928*	-0.047***	-2.221***	-3.142***	-1.664***
	(0.218)	(1.085)	(0.005)	(0.239)	(0.388)	(0.279)
Price 12 am-1 pm	-1.761***	-1.615*	-0.035***	-1.708***	-2.070***	-1.013***
	(0.205)	(0.950)	(0.004)	(0.211)	(0.305)	(0.238)
Price 1-2 pm	-1.560***	-1.317	-0.028***	-1.593***	-1.859***	-0.979***
	(0.199)	(0.859)	(0.004)	(0.206)	(0.256)	(0.207)
Price 2-3 pm	-1.628***	-1.011	-0.027***	-1.739***	-1.978***	-1.161***
	(0.207)	(0.870)	(0.004)	(0.197)	(0.245)	(0.220)
Price 3-4 pm	-0.825***	1.827***	-0.012***	-0.837***	-1.545***	-0.597***
	(0.144)	(0.608)	(0.002)	(0.134)	(0.186)	(0.203)
Price 4-5 pm	-0.493***	1.458***	-0.007***	-0.430***	-1.039***	-0.207
	(0.133)	(0.516)	(0.002)	(0.156)	(0.147)	(0.173)
Price 5-6 pm	-0.495***	0.649	-0.008***	-0.366**	-0.904***	-0.132
	(0.121)	(0.486)	(0.002)	(0.143)	(0.169)	(0.182)
Price 6-7 pm	-0.380***	0.686	-0.006***	-0.280**	-0.908***	-0.144
	(0.114)	(0.452)	(0.002)	(0.140)	(0.149)	(0.142)
Price 7-8 pm	-0.712***	-0.931	-0.011***	-0.667***	-0.818***	-0.167
	(0.152)	(0.639)	(0.003)	(0.161)	(0.168)	(0.147)
Price 8-9 pm	-0.914***	-1.591***	-0.014***	-0.924***	-0.642***	-0.020
	(0.154)	(0.530)	(0.003)	(0.162)	(0.158)	(0.128)
Price 9-10 pm	-1.199***	-1.822***	-0.020***	-1.119***	-0.945***	-0.232
	(0.157)	(0.565)	(0.003)	(0.188)	(0.192)	(0.158)
Price 10-11 pm	-1.179***	-1.051*	-0.021***	-1.113***	-1.130***	-0.327*
	(0.152)	(0.588)	(0.003)	(0.184)	(0.213)	(0.194)
Price 11-12 pm	-1.399***	0.689	-0.028***	-1.326***	-2.250***	-0.952***
	(0.182)	(0.845)	(0.003)	(0.220)	(0.341)	(0.304)

Continued on next page

TABLE 7 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
Price Squared 0-1 am		-0.043				
		(0.084)				
Price Squared 1-2 am		-0.546***				
		(0.156)				
Price Squared 2-3 am		-0.327*				
		(0.187)				
Price Squared 3-4 am		-0.475**				
		(0.208)				
Price Squared 4-5 am		0.113				
		(0.251)				
Price Squared 5-6 pm		0.533*				
		(0.300)				
Price Squared 6-7 am		0.277				
		(0.234)				
Price Squared 7-8 am		-0.161**				
		(0.062)				
Price Squared 8-9 am		-0.286**				
		(0.121)				
Price Squared 9-10 am		0.384**				
		(0.172)				
Price Squared 10-11 am		0.024				
		(0.120)				
Price Squared 11-12 am		-0.010				
		(0.051)				
Price Squared 12am-1pm		-0.002				
		(0.040)				
Price Squared 1-2 pm		-0.007				
		(0.032)				
Price Squared 2-3 pm		-0.021				
		(0.030)				
Price Squared 3-4 pm		-0.095***				
		(0.021)				
Price Squared 4-5pm		-0.067***				
		(0.017)				
Price Squared 5-6 pm		-0.039**				
		(0.016)				
Price Squared 6-7 pm		-0.036**				
		(0.015)				
Price Squared 7-8 pm		0.011				
		(0.020)				
Price Squared 8-9 pm		0.031*				
		(0.018)				
Price Squared 9-10 pm		0.031				
		(0.021)				
Price Squared 10-11 pm		-0.002				
		(0.023)				
Price Squared 11-12 pm		-0.103***				
		(0.040)				
Trend (week)						-1.338***
						(0.341)
$Trend^2$						0.018
						(0.011)
Centered R^2	0.87	0.87	0.84	0.87	0.89	0.92
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). Price denotes the average price (computed by hour and regime). 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 I

TABLE A1

Price Increase Between Adjacent Hours

Regime	Average price increase between adjacent hours	Variance of price increases between adjacent hours
6	1.33	0.46
7	1.40	1.16
8	1.54	1.76
9	1.46	1.55
10	1.47	1.99
11	1.63	3.17
12	1.38	3.68
13	2.13	6.84
14	2.05	5.44
15	2.34	3.27
16	2.24	1.92
17	2.42	1.58
All	1.73	3.38

Note: Define the price difference between adjacent hours as $d_i = p_i - p_{i-1}$, and the number of price increases across hours as I^+. The first column of the table reports $\bar{d} = (1/I^+)\sum_i (d_i \mid d_i > 0)$, the second $(1/I^+)\sum_i (d_i - \bar{d} \mid d_i > 0)^2$.

TABLE A2

Tests for Equality of Variance of Price (F-tests)

Regime	1	2	3	4	5	6	7	8	9	10
2	0.019									
	(.00)									
3	0.13	7.17								
	(.00)	(.00)								
4	0.05	2.517	0.351							
	(.00)	(.00)	(.00)							
5	0.02	1.075	0.149	0.427						
	(.00)	(.72)	(.00)	(.00)						
6	0.015	0.826	0.115	0.328	0.768					
	(.00)	(.37)	(.00)	(.00)	(.14)					
7	0.012	0.652	0.091	0.259	0.606	0.789				
	(.00)	(.04)	(.00)	(.00)	(.00)	0.157				
8	0.009	0.467	0.065	0.186	0.434	0.566	0.717			
	(.00)	(.00)	(.00)	(.00)	(.00)	(0.00)	(.02)			
9	0.009	0.495	0.069	0.197	0.461	0.6	0.760	1.060		
	(.00)	(.00)	(.00)	(.00)	(.00)	(0.00)	(.05)	(.60)		
10	0.011	0.581	0.081	0.231	0.540	0.704	0.892	1.243	1.173	
	(.00)	(.00)	(.00)	(.00)	(.00)	0.02	(.40)	(.06)	(.18)	
11	0.010	0.552	0.077	0.219	0.513	0.669	0.847	1.181	1.114	0.950
	(.00)	(.00)	(.00)	(.00)	(.00)	(0.00)	(.20)	(0.12)	(.33)	(.65)
12	0.013	0.727	0.101	0.289	0.676	0.881	1.116	1.556	1.469	1.252
	(.00)	(.09)	(.00)	(.00)	(.00)	0.37	(.35)	(.00)	(.00)	(.02)
13	0.006	0.311	0.043	0.123	0.289	0.376	0.477	0.664	0.627	0.535
	(.00)	(.00)	(.00)	(.00)	(.00)	(0.00)	(.00)	(.00)	(.00)	(.00)
14	0.006	0.313	0.044	0.124	0.291	0.379	0.480	0.670	0.632	0.539
	(.00)	(.00)	(.00)	(.00)	(.00)	(0.00)	(.00)	(.00)	(.00)	(.00)
15	0.003	0.186	0.026	0.074	0.173	0.225	0.285	0.398	0.375	0.320
	(.00)	(.00)	(.00)	(.00)	(.00)	(0.00)	(.00)	(.00)	(.00)	(.00)
16	0.003	0.166	0.023	0.066	0.154	0.201	0.255	0.356	0.336	0.286
	(.00)	(.00)	(.00)	(.00)	(.00)	(0.00)	(.00)	(.00)	(.00)	(.00)
17	0.003	0.158	0.022	0.063	0.147	0.191	0.242	0.337	0.318	0.271
	(.00)	(.00)	(.00)	(.00)	(.00)	(0.00)	(.00)	(.00)	(.00)	(.00)

(continued)

Regime	11	12	13	14	15	16
12	1.318					
	(.00)					
13	0.563	0.427				
	(.00)	(.00)				
14	0.567	0.430	1.008			
	(.00)	(.00)	(.94)			
15	0.337	0.255	0.598	0.594		
	(.00)	(.00)	(.00)	(.00)		
16	0.301	0.228	0.535	0.53	0.895	
	(.00)	(.00)	(.00)	(.00)	(0.50)	
17	0.285	0.216	0.507	0.503	0.848	0.948
	(.00)	(.00)	(.00)	(.00)	(.34)	(.74)

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

TABLE A3

First Stage Regression Results

	(1) Price index (p_j)	(2) Price Variance (σ)
Responsiveness (β)	0.514***	0.822***
	(0.013)	(0.076)
Level of the pricing function (α)	0.656***	1.955**
	(0.096)	(0.805)
Responsiveness Squared (β^2)	-0.003***	0.020***
	(0.000)	(0.003)
Level of the pricing function squared (α^2)	-0.003	-0.099
	(0.008)	(0.073)
Observations	4143	4143
R-squared	0.97	0.87
Partial R-squared of excluded instruments	0.96	0.86

Note: Day-of-the-week fixed effects (Tuesday to Sunday, Monday omitted), National Holiday fixed effect and a constant are included in all specifications. Robust standard errors (clustered by observation day) are reported in parentheses. Robust standard errors (clustered by observation day) are reported in parentheses.