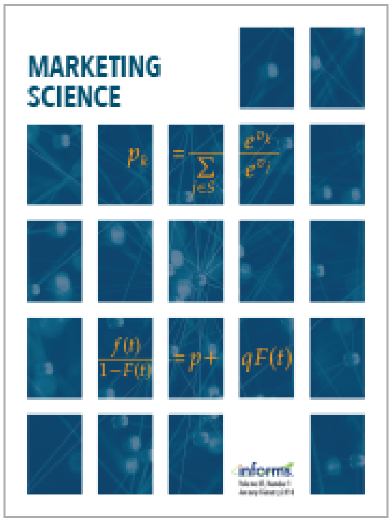


Marketing Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

Empirical Analysis of Metering Price Discrimination: Evidence from Concession Sales at Movie Theaters

Ricard Gil, Wesley R. Hartmann,

MARKETING SCIENCE
Vol. 28, No. 6, November–December 2009, pp. 1046–1062
ISSN 0732-2399 | EISSN 1526-548X | 09 | 2806 | 1046
DOI 10.1287/mksc.1090.0494

Empirical Analysis of Metering Price Discrimination: Evidence from Concession Sales at Movie Theaters

Ricard Gil
University of California, Santa Cruz, Santa Cruz, California 95064, rgil@ucsc.edu
Wesley R. Hartmann
Stanford Graduate School of Business, Stanford University, Stanford, California 94305, hartmann_wesley@gsb.stanford.edu

Prices for goods such as blades for razors, ink for printers, and concessions at movies are often set well above cost. Theory has shown that this could yield a profitable price discrimination strategy often termed "metering." The idea is that a customer's intensity of demand for aftermarket goods (e.g., the concessions) provides a meter of how much the customer is willing to pay for the primary good (e.g., admission). If this correlation in tastes for the two goods is positive, a high price on the aftermarket good allows firms to extract a greater total price (admissions plus concessions) from higher-type customers. This paper develops a simple aggregate model of discrete-continuous demand to motivate how this correlation can be tested using simple regression techniques and readily available firm data. Model simulations illustrate that the regressions can be used to predict whether aftermarket prices should be above, below, or equal to their marginal cost. We then apply the approach to box office and concession data from a chain of Spanish theaters and find that high-priced concessions do extract more surplus from customers with a greater willingness to pay for the admission ticket.

Key words: metering; price discrimination; empirical industrial organization; entertainment; concession sales; movie theaters
History: Received: June 15, 2008; accepted: February 16, 2009; processed by Pradeep Chintagunta. Published online in *Articles in Advance* May 19, 2009.

1. Introduction

When a variable unit good is sold after the purchase of a single unit good, the price of the variable unit good is often observed to be well above cost. For instance, popcorn purchased after entering a movie theater, sports stadium, or other venue charging admission is priced much higher than in grocery stores, small shops, or restaurants.[1] A common presumption is that the venues exploit the fact that customers have little if any choice between sellers of the aftermarket good (i.e., the concessions). Although this presumption is probably accurate, it is important to recognize that high aftermarket prices might reflect a shift in profits to aftermarket goods to extract more surplus from the customers that buy more of them. This strategy has been termed metering price discrimination because the surplus extracted from a customer is "metered" by how much of the aftermarket good they demand. It is an attractive price discrimination scheme because it falls within the category of second-degree price discrimination such that the firm does not need to identify specific customers or groups of customers to offer tailored menus of prices. Among all second-degree price discrimination schemes, this is also one of the simplest to implement because the firm only needs to set two prices.

Like other forms of price discrimination, metering has the ability to increase efficiency because it can open access of a good to customers that would otherwise be priced out of the market. For example, if a venue priced concessions at or near marginal cost, its admission price would likely be set higher and some customers would be left out. Therefore, although the surplus of some consumers may be reduced by high concession prices, total surplus, producer surplus, and the surplus of other consumers may be increased.[2]

[1] Sources used in Gil and Hartmann (2007) indicate that costs of nonadmission items amount to only 15% of the revenue that they produce.

[2] One condition under which total surplus could decrease even though movie admission increases is if the reduced concession sales from high concession prices reduces surplus more than the surplus increase for admission. We doubt this is possible in this case and many other similar examples because the aftermarket goods (concessions) are of substantively less consequence than the primary good (movie admission). Specifically, concessions could be purchased without ever attending a movie, so it seems reasonable to weight the surplus effects of the movies much greater than those of the concessions.

For high aftermarket prices to be associated with efficiency increases, the primary good price must be predicted to be lower than it would be under a competitive aftermarket. However, primary good prices are only lower because of metering if customers that demand more aftermarket goods (e.g., concessions) also place a greater value on the primary good (e.g., admission). This demand condition has been shown by Oi (1971), further explored by Schmalensee (1981), and applied to the case of admission tickets and concessions by Rosen and Rosenfield (1997). More recently, Ellison (2005) contrasts the case of metering with add-on pricing. He explicitly uses the example of concessions in movie theaters as one where consumers are fully informed of ticket and popcorn prices, implicitly allowing firms to use metering to price discriminate among customers.[3] The explanation of metering has been applied to many goods such as razors and blades or Polaroid cameras and film among others,[4] and has been a common efficiency rationale for the decision to tie aftermarket goods to the purchase of primary goods (see Peltzman 2005, Klein 1996).

Despite the awareness of metering and its demand conditions, there has yet to be any work estimating whether these demand conditions are met and therefore testing whether metering price discrimination occurs in practice.[5] This paper fills this void by developing a simple test that can be applied to market-level data where customers repeatedly buy the primary and aftermarket goods. The intuition for our approach is that increases in primary good demand typically involve more low willingness-to-pay customers, such that decreases (increases) in aftermarket demand per buyer would indicate a positive (negative) correlation between aftermarket demand and willingness to pay for the primary good. The test therefore involves evaluating whether percentage changes in aftermarket demand or revenue are less than, greater than, or equal to percentage changes in primary demand. For illustration purposes, we define a model and simulate data assuming different demand relationships and find that log aftermarket revenue on log primary demand regressions predict whether aftermarket prices should be above, below, or equal to marginal cost.

Next, we apply our approach to aggregate weekly data from a chain of Spanish movie theaters and find that concession demand does meter willingness to pay for admission. This has two positive implications. First, the finding validates that demand conditions do support metering in one of the most commonly cited examples. Second, even if the firm is not aware of metering price discrimination incentives, it is in fact benefiting from metering price discrimination because its high concession prices are extracting a higher total margin from those willing to pay more for admission.

The managerial implications of this paper are directed to other firms because the observed chain's concession price is already above cost. To other theater chains and venues such as stadiums and arenas, we suggest that these regressions should be run to also validate that they are not incorrectly pricing concessions high relative to cost. There is potentially even more value in applying this approach in industries where there is or has been variation in whether aftermarket prices are above, below, or equal to cost. For example, the airline industry has recently gone through this change, and the hotel industry exhibits substantial variation in Internet and phone call pricing.[6]

When applying our approach, it is important to control for factors other than the metering demand relationship that could lead to a relationship between percentage changes in aftermarket and primary demand. Some obvious controls can be applied in all contexts, whereas other controls are application specific. Fixed effects are particularly useful. We use them to control for systematic differences across locations and systematic differences across time. We also test for the relationship of interest within each decile of primary good demand. This allows us to remove confounding factors that might be specific to either high or low primary demand observations. For example, in our application, this allows us to account

[3] Ellison (2005) focuses on showing that in the presence of add-on pricing, firms may have an incentive to raise prices on the primary good to screen consumers with high valuation for a secondary good. This strategy would only apply to concessions in movie theaters if moviegoers had no information on prices for popcorn. He rules out add-on pricing for the particular case of concession pricing in movie theaters.

[4] Other examples of items where metering may be applied is consoles and video games, rental cars and per-mile charges, or amusement park tickets and per-ride charges.

[5] The closest empirical papers are the following: Hartmann and Nair (2009) empirically analyze the pricing of razors and blades. Although they note that metering is a likely explanation for manufacturer pricing in that industry, they focus on the retailers' pricing incentive, where the blades are not tied so as to allow metering. Two papers from the sports economics industry (Marburger 1997, Fort 2004) consider that concession sales might explain inelastic ticket pricing, but neither paper actually analyzes data on concession sales.

[6] The "Armchair Economist" at *Slate* recently pointed out the variation in these hotel pricing policies and questioned why we do not also see variation in concession pricing across different movie theaters (Landsburg 2006). This likely arises because there is much more product differentiation in the types of hotels, whereas most movie theaters are quite similar. In fact, we conducted our tests with theater-specific effects and found that all theaters in the data exhibit the same relationship between concession revenue and ticket sales.

for the fact that in very high attendance weeks, the length of concession lines systematically reduces concession sales. We are able to verify that the queuing effect is restricted to the top decile of attendance weeks and can measure its effect on the correlation of interest. In fact, a supplementary variable measuring how actual demand differed from forecasted demand illustrates that the queuing effect only arises in the top decile when unexpectedly high demand overwhelmed staffing that was based on underpredictions of actual attendance. We also control for the composition of movies (e.g., genre) in case there are differences in concession demand across customer groups that prefer particular types of movies. However, we find few of these to be significant because the fixed effects above account for most of the differences. Other applications will have other potential confounds, but we hope that our extensive robustness checks provide a benchmark.

One valuable aspect of specifying an approach that draws on theory but can be tested with regressions is that we can uncover the correlation of the underlying taste distributions of consumers for primary and aftermarket goods without many of the parametric assumptions required in a structural approach to estimation. Most empirical demand analyses of price discrimination use a structural approach in which a utility function is specified as a function of parameters, and then the population distributions of the parameters are estimated from the data (e.g., Leslie 2004, McManus 2007, Cohen 2008, Mortimer 2007, Hartmann and Viard 2006). In our case, we motivate our empirical approach with a flexible utility function defined over the two goods. In other words, our estimates hold for various utility functions.

Our nonstructural approach is related to "reduced-form" empirical analyses of price discrimination but is substantively different in emphasis. The disadvantage of a nonstructural approach is that although we can predict whether aftermarket prices should be above, below, or equal to marginal cost, we do not have estimates of model parameters that allow us to predict exact pricing levels. This inability to do such counterfactuals is common to other nonstructural approaches that have been used to empirically analyze price discrimination (e.g., Shepard 1991, Miravete and Röller 2004, Seim and Viard 2004, Busse and Rysman 2005, Borzekowski et al. 2009). However, our work differs from these papers in that most of these relate the incidence of price discrimination to market structure.

Although the primary goal of the paper is to explore the phenomenon of metering price discrimination, the paper also contributes to a growing empirical literature on the movie industry. Papers in this area have considered a wide array of topics such as the vertical structure of movie exhibition (Gil 2004), the location of theaters (Davis 2006), release decisions (Krider and Weinberg 1998, Elberse and Eliashberg 2003, Einav 2007), run-length decisions (Swami et al. 1999, Ainslie et al. 2005), financing decisions (Goettler and Leslie 2005), risk and uncertainty (De Vany 2004), and post-box office distribution (Mortimer 2007, 2008). Eliashberg et al. (2006) provide an excellent summary of the state of current research in this area. The present paper contributes to this broader literature by linking an empirical analysis of concession sales data to the pricing incentives of exhibitors.

The rest of the paper is organized as follows. The next section describes the motivation behind our empirical analysis. Section 3 describes the data. Section 4 discusses our empirical approach and results, and §5 concludes the paper.

2. Motivation for Empirical Analysis

The existing theoretical work (e.g., Oi 1971, Littlechild 1975, Schmalensee 1981, Rosen and Rosenfield 1997) is instructive about the joint distribution of demands required for sales of an aftermarket good to profitably meter the variation in willingness to pay for the associated primary good. However, these theoretical models do not provide intuition about how to uncover this joint distribution from available data. In this section, we illustrate how variation in vertical attributes specific to the primary good can uncover the correlation between willingness to pay for the primary good and demand for the aftermarket good.

2.1. General Utility Function

We define $u(y, z, x \mid \xi; I, \theta)$ to be a utility function over a primary good y, an aftermarket good z, and a composite commodity x. y can only take values one or zero, whereas x and z can take on any nonnegative values. ξ is a mean zero vertical attribute or demand shock to the primary good that is common to all consumers relative to the value of not consuming the primary good. θ is a vector of preference parameters. We assume consumers spend their entire budget or income I on the three goods such that $x = I - py - wz$, where p and w are the respective prices of the primary and aftermarket goods. We consider a specific example of this utility function and the following analysis in §2.4 below.

Utility maximization subject to this budget constraint implies a demand function for the aftermarket good of $z(w; \theta)$. This demand function reveals two assumptions of our model and analysis:

Assumption 1. *Aftermarket demand is not affected by the price of the primary good p.*

Assumption 2. *Aftermarket demand is not affected by changes in the vertical demand shock ξ.*

The first assumption is satisfied by assuming away income effects, as is common in the discrete-choice demand literature. The second assumption requires that changes in primary good quality or outside options do not increase or decrease the marginal utility of the aftermarket good. This arises if ξ and z are separable in the utility function. In practice, this implies, for example, that an idiosyncratic shock to the demand for a flight, hotel, or movie does not affect the meals, pay-per-view movies, or concessions consumed upon entry. We show below that a common quasi-linear utility function satisfies these assumptions. Assumption 1 is common in the theoretical literature on metering price discrimination and is generally considered reasonable for "small ticket" items like admission tickets and concessions. Assumption 2 is specific to our empirical approach. We therefore include an appendix that illustrates and discusses the sensitivity of our analysis to this assumption.

Given the demand function for the aftermarket good $z(w;\theta)$, the choice of the primary good is determined by evaluating whether or not there is positive surplus from purchasing the primary good. We define the consumer surplus from purchasing the primary good to be

$$v(p,w,\xi;\theta)=v_1(p,w,\xi,\theta)-v_0(\xi,\theta), \qquad (1)$$

where v_1 and v_0 are, respectively, the indirect utilities of consuming and not consuming the primary good. The marginal consumer for a given demand shock ξ is therefore defined by setting the above equation equal to zero. We define $\theta^*(\xi)$ to denote the preference parameters of this marginal consumer of the primary good. The consumers of the primary good are therefore defined to be all θ such that $v(p,w,\xi,\theta)\geq v(p,w,\xi,\theta^*(\xi))$.

2.2. Demand Conditions for Metering Price Discrimination

We now consider the demand conditions for metering price discrimination as defined in Rosen and Rosenfield (1997). They show that firms should charge a premium on aftermarket goods if the aftermarket demand of the marginal consumer is less than the average aftermarket demand of all primary good consumers:

$$z(w;\theta^*(\xi)) < E\big[z(w;\theta)\mid v(p,w,\xi;\theta)\geq v(p,w,\xi;\theta^*(\xi))\big]. \qquad (2)$$

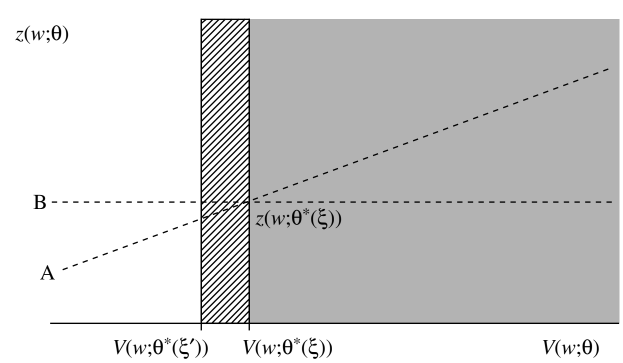
The only difference between our model and that of Rosen and Rosenfield (1997) is that their theoretical model only considers a single market such that there is no demand shock ξ. The consideration of observed data with varying aggregate demands for the primary and aftermarket goods requires such a shock. Moreover, it is exactly this shock that will allow us to test for the condition in Equation (2).

To motivate our empirical test, it is first important to note that Equation (2) is equivalent to saying that there is a positive correlation between $z(w;\theta)$ and $v(p,w,\xi,\theta)$; i.e., a positive correlation implies that Equation (2) will be satisfied and that Equation (2) cannot hold without a positive correlation. One other useful thing to note is that because ξ is a vertical shock that does not change the ordering of consumers' valuations, Equation (2) also holds if $z(w;\theta)$ and $V(w;\theta)$ are positively correlated, where $V(w;\theta)$ is a time-invariant measure of a consumer's willingness to pay for the primary good. $V(w;\theta)$ is obtained by setting price and the demand shock in Equation (1) equal to zero. To see a practical example of how this arises, please refer to the section below when we apply this to a quasi-linear utility function.

We now graphically illustrate the metering price discrimination intuition. Figure 1 plots $V(w;\theta)$ on the horizontal axis and $z(w;\theta)$ on the vertical axis. ξ enter the diagram by shifting the marginal consumer along the horizontal axis. For example, an increase in the quality of the aftermarket good from ξ to ξ' increases the region of consumers buying the primary good from the gray shaded area to the gray shaded area plus the region with the diagonal lines. Line A in Figure 1 represents a positive correlation between aftermarket demand and willingness to pay for the primary good. For line A, we see that the aftermarket demand of a marginal consumer $z(w;\theta^*(\xi))$ is clearly less than the average aftermarket demand of all consumers (to the right) that do purchase the primary good. The price discrimination is evident in recognizing that the total margin contributed by the marginal consumer $p+(w-c)\cdot z(w;\theta^*(\xi))$ is less than that contributed by higher willingness-to-pay customers

$$p+(w-c)z\big(w;\theta\mid V(w;\theta)>V(w;\theta^*(\xi))\big).$$

Figure 1 **Relationship Between Aftermarket Demand per Person and Primary Good Demand**



However, if line B describes the relationship between aftermarket demand and willingness to pay for the primary good, the marginal consumer would consume exactly the same amount of the aftermarket good as the rest of the consumers, and all consumers would contribute the same margin: $p+(w-c)z(w;\theta^*(\xi))$.

2.3. An Empirical Test for Metering Price Discrimination

Figure 1 also provides an intuitive way to learn about the correlation from the relationship between total primary good demand $Q=\sum_i y_i$ and average aftermarket sales

$$\bar{z} = E\big[z(w;\theta)\mid u(y,z\mid p,w;\theta) > u(y,z\mid p,w;\theta^*)\big] = \frac{\sum z}{\sum y} = \frac{Z}{Q}.$$

Total demand is increasing as the marginal consumer shifts to the left in the diagram. We also see that as total demand shifts, the average aftermarket demand changes depending on our correlation of interest. For example, if the quality of a primary good increases such that primary demand increases (i.e., a move from ξ to ξ'), line A would indicate that average aftermarket demand for purchasers of the primary good should fall while line B implies that it should remain the same. Therefore, a negative correlation between primary good demand Q and aftermarket demand per buyer of the primary good $\bar{z}$ indicates that the demand conditions for metering price discrimination exist and support a premium on the aftermarket good. Alternatively, no correlation between primary good demand and aftermarket demand per buyer rejects the fact that the demand conditions for metering price discrimination are in place. We discuss the implications of a positive correlation in §2.5.

2.3.1. Discussion. We now discuss a few of the valuable aspects of this approach. First, we only need vertical attributes to vary over time to trace out the correlation between willingness to pay for the primary good and demand for the aftermarket good. Second, we can measure the sign of this correlation directly from the joint distribution of demand for the primary good and aftermarket demand per buyer of the primary good. Finally, as a consequence of the last point, we need not observe the vertical attribute. In our application of concession sales at movies, the vertical attribute indexes changes in the quality of the selection of movies at the theater and changes in the consumers' outside options. These variables are generally not observable and there is typically not observed price variation from week to week (Orbach and Einav 2007). Therefore, our approach allows us to test the relationship by only observing the aggregate demands of the two goods. We illustrate in our simulations that our approach also works when prices endogenously vary with ξ.

One other important issue to consider is the presence of variation in horizontal attributes that may change the selection of consumers arriving across different observations of the aggregate primary and aftermarket good demands. Because our analysis relies on variation in vertical attributes tracing out the relationship between concession demand and willingness to pay, we require that the vertical dimension that drives primary good demand does not have a systematic relationship with the presence of horizontal attributes. The standard assumption in discrete-choice demand models that unobserved product quality is not correlated with other product characteristics would be sufficient. More generally, if horizontal attributes exist in the data, there are two ways to address this. First, horizontal attributes can be controlled for if observed, or if they are common across multiple observations but unobserved, fixed effects can be used. We use both approaches in our empirical application. Second, we can test the relationship of interest throughout multiple regions on the horizontal axis of Figure 1. If horizontal attributes lead to different types of consumers systematically arriving at different primary good demand levels, it is likely that they will be concentrated in certain parts of the primary good demand distribution (otherwise, the horizontal attributes would have to be almost perfectly correlated with primary good demand). If so, a misinterpreted correlation would only be found in some regions and researchers would know this is a problem. In our analysis, we find that the same correlation holds throughout 10 deciles representing primary good demand along the horizontal axis in Figure 1.

2.4. An Illustrative Utility Function

We now consider a quasi-linear utility function that fits within the general model to clarify the utility function discussion and provide a basis for some model simulations. A consumer's utility depends on whether or not the primary good is consumed $y\in\{0,1\}$ and, if consumed, how much of the aftermarket good is consumed z:

$$\begin{aligned} u(y,z\mid p,w;\theta) &= (\beta+\xi+\eta z^{\gamma})y+\alpha x \\ &= (\beta+\xi+\eta z^{\gamma})y+\alpha(I-py-wz). \end{aligned} \tag{3}$$

The consumer's preference parameters, $\theta=\{\beta,\gamma,\eta,\alpha,\xi\}$, are defined as follows. $\beta+\xi$ is the consumer's utility for the primary good. β is a consumer's time-invariant preferences for the primary good, and ξ is the time-varying primary good demand shock that is common to all consumers. Aftermarket goods enter utility in a concave function such that $\gamma\in(0,1)$. η is a time-invariant preference for concessions that may vary across consumers. α is the price sensitivity or marginal utility of income I as in common discrete-choice models.

Maximization of this utility function involves solving for z given $y = 1$ and then comparing the indirect utility of each option. The demand function for concessions is therefore

$$z = \left(\frac{\alpha w}{\eta\gamma}\right)^{1/(\gamma-1)}. \tag{4}$$

By normalizing the utility of not buying the primary good to zero, the payoffs in the discrete choice over the primary good become

$$u(y \mid p, w; \theta) = \begin{cases} \beta + \xi + \eta\left(\dfrac{\alpha w}{\eta\gamma}\right)^{\gamma/(\gamma-1)} \\ \qquad -\alpha\left(py + w\left(\dfrac{\alpha w}{\eta\gamma}\right)^{1/(\gamma-1)}\right) \\ \qquad \text{if } y = 1, \\ 0 \quad \text{if } y = 0. \end{cases} \tag{5}$$

The time-invariant measure of willingness to pay for the primary good is

$$V(w; \theta) = \frac{1}{\alpha}\left[\beta + \eta\left(\frac{\alpha w}{\eta\gamma}\right)^{\gamma/(\gamma-1)} - \alpha w\left(\frac{\alpha w}{\eta\gamma}\right)^{1/(\gamma-1)}\right], \tag{6}$$

where $V(w; \theta)$ is derived by setting the primary good price p and the primary good shock ξ in the first line of (5) to zero and dividing by the marginal utility of income α.

2.5. Model Simulations to Illustrate Correlation Patterns

We now illustrate how different distributions of model parameters can lead to positive, zero, or negative correlations in Figure 1 (i.e., between $z(w; \theta)$ and $V(w; \theta)$) by simulating the variables at hypothetical parameter values. Obviously, there must be some heterogeneity in model parameters or there will only be a mass of consumers at a single point in the diagram. We therefore define the variables to be joint normal or log-normally distributed as follows:

$$\begin{bmatrix} \beta \\ \ln\eta \\ \ln\alpha \end{bmatrix} \sim N\left(\begin{bmatrix} 2 \\ 0.35 \\ -1.2 \end{bmatrix}, \begin{bmatrix} \sigma_\beta^2 & \sigma_{\beta\eta} & \sigma_{\beta\alpha} \\ \sigma_{\beta\eta} & \sigma_\eta^2 & \sigma_{\eta\alpha} \\ \sigma_{\beta\alpha} & \sigma_{\eta\alpha} & \sigma_\alpha^2 \end{bmatrix}\right).$$

γ is assumed homogenous across consumers at a value of 0.35. We consider three different heterogeneity structures that can drive the correlation to be positive, zero, or negative. First, suppose that there is only heterogeneity in the marginal utility of income. This is depicted in Figure 2(a) and gives us the upward sloping relationship resembling line A in Figure 1. Under these parameters and a constant marginal cost of the aftermarket good equal to 0.4, the optimal aftermarket price is just less than 0.56, i.e., a 39% markup. In other words, the firm is engaging in metering price discrimination. Second, suppose there is only heterogeneity in the tastes for the primary good. This is depicted in Figure 2(b) and gives us the flat line resembling B in Figure 1. Under these parameters, the optimal aftermarket price is exactly 0.4, implying no markup. This pricing is consistent with a typical two-part tariff in which all surplus is extracted on the primary good. Finally, suppose there is a positive correlation between tastes for the primary good and the marginal utility of income. This is depicted in Figure 2(c) and gives us a distribution of tastes that are negatively correlated such that the marginal consumers would pay the largest total price despite having the smallest willingness to pay. One way in which this pattern might arise is if consumers with the lowest opportunity costs of time were also the most price-sensitive consumers. Under these parameters, the firm's optimal aftermarket price is 0.37, implying a 6% markdown below cost. Essentially, the firm meters in the opposite direction. Marginal customers would not be willing to buy the primary good at the high primary good price targeted to the high willingness-to-pay customers, so the firm lures them in with aftermarket subsidies that are disproportionately favored by lower willingness-to-pay customers.

Other forms of heterogeneity could also bring rise to similar plots. For example, a negative correlation between β and η also leads to a plot similar to that in Figure 2. Also, if heterogeneity only exists in η, a plot similar to Figure 2(a) would arise. Plots similar to Figure 2(a) could also arise if β and η are positively correlated, if β and α are negatively correlated, and if all correlations are zero and either η or α are heterogeneous. Once again, it is useful to point out that only in the case of plots resembling Figure 2(a) does metering price discrimination favor charging a premium on aftermarket goods.

2.6. Testing for the Relationships Using Log-Log Regressions

As we described in §2.3, the relationship of interest can be tested by evaluating the correlation between average aftermarket good demand Z/Q and aggregate primary good demand Q. In other words, one could test this with the following simple regression equation:

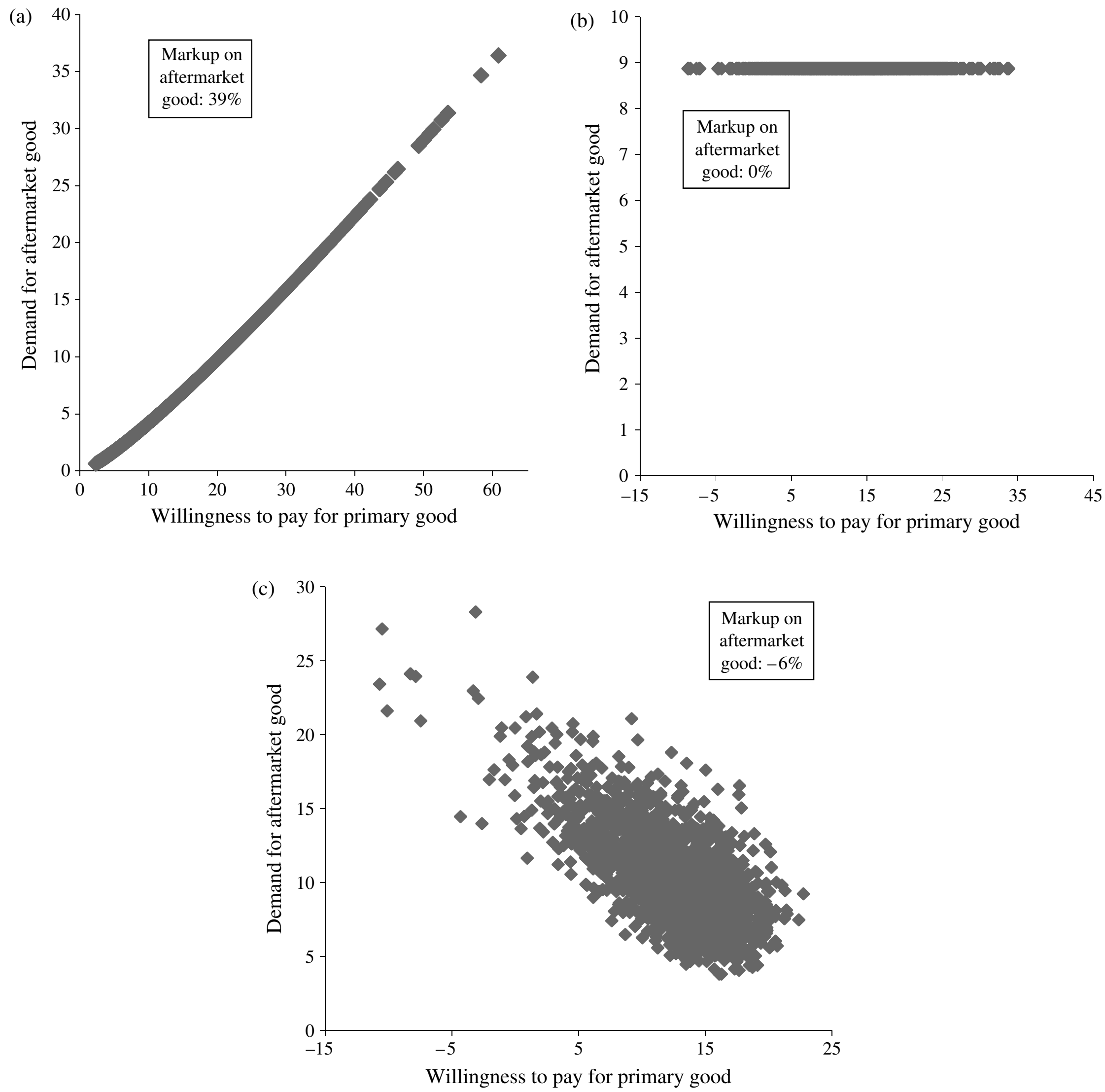
$$Z/Q = \delta_0 + \delta_1 Q + e. \tag{7}$$

For practical purposes, we transform this by taking logs of the variables and actually run the regression:

$$\log Z = d_0 + d_1 \log Q + \varepsilon \tag{8}$$

and test whether d_1 is greater than, equal to, or less than one. To illustrate the ability of this simple

Figure 2 Simulations of Aftermarket Demand and Willingness to Pay



regression to uncover the relationship of interest, we apply it to the aggregate primary and aftermarket good demands that came from the simulated data in Figures 2(a), 2(b), and 2(c). Note that in our application we only observe aftermarket revenue, so we actually substitute wZ in place of Z in the regression.

We can see in Table 1 that when metering demand conditions supporting an aftermarket premium exist (Figure 2(a) and specification A in Table 1), our regression predicts a coefficient statistically significantly less than one. When demand conditions are such that metering should not exist and a two-part tariff with aftermarket good prices equal to marginal cost should arise (Figure 2(b) and specification B in Table 1), the coefficient is found to be exactly one. Finally, when a negative correlation between aftermarket good demand and willingness to pay exists, and firms should actually use metering to subsidize low willingness-to-pay customers, our regression finds a coefficient statistically greater than one.

These regressions and the simulations in Figure 2 are comparable to our empirical example because prices are assumed to be fixed despite temporal variation in ξ. As we stated previously, our test should also hold when the prices are endogenously set by the firm. We therefore reran the simulations from Figure 2 and solved for the prices at each realization of ξ. Regressing the log of aggregate aftermarket revenue on the log of aggregate primary good sales, we obtain the regression results in Table 2.

We can see from Table 2 that, even with endogenously set prices, the same pattern in the coefficients holds. The coefficient in specification B in Table 2 is slightly greater than one, but this is not statistically significant given the standard error reported below it. Specifications A and C in Table 2 are, respectively, below and above one as in Table 1.

Table 1 Regressions on Simulated Data

	(A)	(B)	(C)
Dependent variable: log(Aftermarket revenue)			
log(Primary demand)	0.62	1.00	1.15
	(0.01)***	(0.00)	(0.00)***
Constant	4.80	2.18	1.16
	(0.04)***	(0.00)***	(0.03)***
Observations	100	100	100

Notes. Standard errors are in parentheses.
Asterisks indicate significance from one for log(primary demand): *Significant at 10%; **significant at 5%; ***significant at 1%.

Table 2 Regressions on Simulated Data, Endogenously Set Prices

	(A)	(B)	(C)
Dependent variable: log(Aftermarket revenue)			
log(Primary demand)	0.27	1.01	1.32
	(0.03)***	(0.01)	(0.01)***
Constant	6.73	1.16	−1.05
	(0.22)***	(0.07)***	(0.10)***
Observations	100	100	100

Notes. Standard errors are in parentheses.
Asterisks indicate significance from one for log(primary demand): *Significant at 10%; **significant at 5%; ***significant at 1%.

2.7. Discussion of Identification in the Context of Movies and Concessions

We intuitively describe the identification in the context of our empirical application as follows. If a theater has a poor set of movies that lowers its attendance below average or if the outside alternative improves, then the marginal customer from the average week will no longer attend. If we also observe average concession sales per attendee to increase, it tells us that the customers opting not to attend in the week with below average attendance must have consumed fewer concessions per person than those individuals that still attend. In other words, marginal attendees would have lower concession spending than average attendees (the condition from Equation (2)). Identification of this relationship would imply that firms should charge premiums on concessions rather than extracting all consumer value through admission prices.

3. Empirical Application and Data Description

We evaluate whether high margins on aftermarket goods result in metering price discrimination by analyzing the case of concession sales at movie theaters. In the introduction we note a growing literature studying the economics of the movie industry, but Gil and Hartmann (2007) is the only other paper that analyzes actual concession sales data. That paper documents stylized facts and trends in concessions but does not consider the economic incentives behind concession pricing.

The data we use consist of weekly concession sales, box office revenues, and attendance from a Spanish exhibitor. The data span from January 2002 to June 2006 and contain information on 43 different theaters during that time. These 43 theaters are in 30 different cities in 17 provinces.

Even though we observe 43 different theaters during the five years of data, we do not observe 43 theaters at all times because the Spanish exhibitor sold a few theaters, built up new theaters, and acquired theaters from other exhibitors that exited the market. The sample starts with 24 theaters and ends with 37 theaters. The missing six theaters at the end of the sample were mainly old theaters located in Barcelona and Madrid downtown. Most of these missing six theaters were only operated and not directly owned by the exhibitor. In these cases, the owners of the property decided to sell the locations for other uses (housing, supermarkets, or even nightclubs). Theaters that show up in the middle of our panel consist of both newly constructed theaters and newly acquired theaters.[7]

Because we focus on the study of concession sales, we exclude from our analysis those theaters for which the concession sales are outsourced and hence unobserved. After dropping those theaters, we are left with 6,206 weekly observations from 43 different theaters. These theaters differ in size and seating capacity. The theaters in our sample have from 1 to 24 screens and range from 396 to 5,300 seats. Detailed summary statistics are available in Table 3.

Table 3 also provides summary statistics for other variables used in our analysis. Weekly attendance varies from 348 to a bit over 40,000 attendees with an average close to 8,900. These numbers denote the skewness of the distribution of attendance across theaters. Table 3 also summarizes the forecast error and weekly weather for each theater. The forecast error is defined as the actual attendance minus the week-ahead forecast that is used to determine staffing of concession stands. Large positive forecast errors should therefore proxy for long concession lines. We observe the weather data for most of the observations; however, our data source was missing data for many cities during the month of January 2004. Rain days

[7] To put this in a historical perspective, the Spanish market was no different than other Western economies in the late 1990s and early 2000s in that it experienced a rapid growth in number of theaters (and screens). This growth came from both new developments and new exhibitors coming in the market. After such rapid growth, movie demand did not respond as industry managers had first anticipated, and exhibitors were required to cut losses and investment. This manifested in the closing of older theaters, cancellation of new projects, and firm exit. The latter two caused a major consolidation in the industry where surviving firms acquired a number of theaters that had been operated until that moment by other exhibitors.

Table 3 Summary Statistics

Variable	Obs.	Mean	Std. dev.	Min	Max
Box office data					
Concession sales per person	6,206	1.59	0.29	0.24	2.94
Box office per person	6,206	4.68	0.59	2.60	6.26
Weekly attendance	6,206	8,864.27	5,698.95	348	40,303
Theater characteristics					
No. of screens	43	9.65	5.20	1	24
No. of seats	43	2,344.86	1,248.13	396	5,300
Other variables					
Forecast error	4,024	−652.37	2,109.63	−18,182	11,405
Average temperature	6,117	60.15	11.49	33.86	92.29
Rain days	6,120	1.62	1.64	0	8

Notes. Forecast error is equal to the weekly attendance minus the theater's week-ahead forecast of the attendance. There are only 4,024 observations for this variable because we do not observe the forecasts for the first 62 weeks of the data.

within the week vary from zero to eight, with the eight arising because the final week of one year is classified to have eight days and rain was observed on all eight days.

The data also show that the average concession spending per attendee is close to €1.6 and ranges from €0.24 to almost €2.94. Box office per person averages €4.7 and ranges from €2.6 to €6.3. This variable deserves further clarification because it provides information on what type of customer is entering the theater in any given week.

This firm follows a rather distinct pricing schedule. The firm charges three different prices throughout the week. We can call these different prices a high price p^H, a nonpeak price p^L, and a discount price p^S. The firm charges p^H to all individuals attending theaters on Saturdays and Sundays (and festive days). On Wednesdays, the theater charges the discounted price p^S to all attendants. Finally, on the other days during the week (Monday, Tuesday, Thursday, and Friday), the theater enforces third-degree price discrimination. During these days, the theater charges the discounted price p^S to students and seniors and the nonpeak price p^L to all attendants who do not identify themselves as students or senior citizens.

Therefore, variation in box office per person brings information on the types of individuals attending the theater in any given week compared to other weeks. For example, an increase in box office per person (average ticket price) means that a higher share of attendants arrives during the weekend or that a lower share of students and senior citizens is attending the theater, and therefore tells us information on the average willingness to pay of individuals attending the theater.

We also use screening data from Gil (2004). These data provide information on what movies each theater is playing for the first 26 weeks during the year 2002. During those weeks, we only have data for 24 theaters that differ in size from 2 to 16 screens and in seating capacity from 396 to 3,875. See Table 4 for detailed summary statistics. We use information on movie characteristics such as movie genre, rating classification, weeks after release, and U.S. box office revenue of the movie. To merge these into weekly theater observations, we weight each movie's characteristics by its total Spanish box office revenue across all weeks. We see that theaters typically have more adventure movies and PG-13 movies than other genres or classifications. We also see that the weighted average weeks after release are 6.21, the weighted average share of opening films is 0.13 and that on average two movies open in a given theater week. U.S. box office revenue is reported in millions and theaters' weekly movie offerings have a weighted U.S. box office revenue average of $185.75 million.

Table 4 Summary Statistics for Sample When Movie Characteristics Are Available

Variable	Mean	Std. dev.	Min	Max
Concession sales per person	1.41	0.26	0.44	2.90
Box office per person	4.32	0.48	2.70	4.98
Weekly attendance	8,522.99	5,932.78	408	37,565
No. of screens	7.64	3.21	2	16
No. of seats	1,849.28	771.21	396	3,875
Genre, classification, and weeks after release (weighted by Spanish box office revenue of each movie)				
Action	0.06	0.08	0.00	0.41
Adventures	0.34	0.24	0.00	1.00
Science fiction	0.14	0.23	0.00	0.96
Comedy	0.08	0.12	0.00	1.00
Animated	0.14	0.14	0.00	0.93
Drama	0.13	0.14	0.00	1.00
Fantasy	0.02	0.04	0.00	0.57
Terror	0.01	0.02	0.00	0.39
Thriller	0.10	0.14	0.00	1.00
PG-13	0.40	0.21	0.00	1.00
PG-18	0.10	0.13	0.00	1.00
PG-7	0.06	0.09	0.00	1.00
All audiences	0.43	0.21	0.00	0.96
U.S. box office revenue	185.75	64.07	0.00	390.06
Weeks after release	6.21	2.84	1.00	14.89
Fraction opening	0.13	0.17	0.00	1.00
Number of openings*	2.04	1.32	0.00	7.00

Notes. This table describes summary statistics for a sample of weekly theater observations for which movie screenings are available. This sample is made of 622 observations that cover the first 26 weeks of 2002. The sample contains information on 24 different theaters; we observe the complete time series for all except one.

*Number of openings is the only movie characteristic that is not a weighted average of the Spanish box office revenue.

4. Empirical Methodology and Results

We now analyze the data to evaluate the efficacy of using concession sales to price discriminate across customers with different valuations for movies. The work of Rosen and Rosenfield (1997) and Schmalensee (1981) documented that if marginal attendees demand fewer concessions, then firms would have an incentive to price concessions above marginal cost. We therefore assess how concession sales per person vary as demand shocks lure or deter the marginal theater attendee. We use a variety of fixed effects or other explanatory variables to assure that this relationship is not driven by composition effects. Specifically, we want to be sure that movie-specific effects or other demand shocks are not altering the entire composition of attendees.

4.1. Empirical Methodology

In this section, we describe how traditional price discrimination in movie admission tickets (e.g., student and senior discounts as well as discount days or shows) both affects the identification intuition described in §2 and provides an additional test for whether customers with a greater willingness to pay for admission also demand more concessions.

Our primary variable of interest is average concession revenue per attendee $AR^{CO} = pZ/Q$. Given that this aggregates over the pricing classes $j \in \{L, H, S\}$ described above, it is useful to decompose AR^{CO} as follows:

$$AR_{it}^{CO} = \frac{p^{CO}[Z^H(Q^H) + Z^S(Q^S) + Z^L(Q^L)]}{Q^H + Q^S + Q^L}. \qquad (9)$$

p^{CO} is the price of concessions. For simplicity and due to data limitations, we will assume that there is a single uniform price for concessions. Recall from the data description that there are three types of customers that enter a theater: Q^L is the demand from customers who do not have third-degree price discrimination discounts but do elect to visit the theater in nonpeak periods to pay lower ticket prices, Q^H is the demand from customers who elect to visit the theater in a peak-demand period such as a weekend and may or may not have access to third-degree discounts in other periods, and Q^S is the demand from customers such as students or seniors who attend in periods when they can realize their discounts. $Z^j(Q^j)$ is the total concession demand from customers who paid price j, where the function allows this demand to be increasing or decreasing with the total number of attendees in price category j. By the arguments described in §2, if $\partial(Z^j(Q^j)/Q^j)/\partial Q^j$ is less than zero, then the marginal customer of type j does consume fewer concessions, and it will be profitable to charge a premium for concessions.

In our data, we do not observe the demand of each type of customer Q^j, but we do have information about the relative size of each group as observed through the box office revenue per person AR^{BO}, where

$$AR_{it}^{BO} = \frac{p^H Q^H + p^S Q^S + p^L Q^L}{Q^H + Q^S + Q^L} = p^H \alpha^H + p^S \alpha^S + p^L(1 - \alpha^H - \alpha^S). \qquad (10)$$

α^j is the share of attendees who paid price j. Although we also do not directly observe the α^js, AR^{BO} informs us whether there is a relatively larger or smaller fraction of customers that pay the full price p^H. We now redefine our dependent variable in terms of the α^js as well:

$$AR_{it}^{CO} = p^{CO}\big[AQ^{CO,H}(Q^H)\alpha^H + AQ^{CO,S}(Q^S)\alpha^S + AQ^{CO,L}(Q^L)(1 - \alpha^H - \alpha^S)\big], \quad (11)$$

where $AQ^{CO,j}(Q^j) = Z^j(Q^j)/Q^j$ is the quantity of concessions averaged across attendees. Under this specification, if $\partial AQ^{CO,j}/\partial Q^j$ is less than zero, charging a premium on concessions to price discriminate will be profitable.

Using Equation (11), we can more specifically define the relevant empirical relationships in the data. Our primary relationship of interest is the correlation between AR^{CO} and attendance. If $\text{Corr}(AR^{CO}, Q) = 0$, then we can infer that customers of each type consume a constant amount of concessions, Ω^j, such that $AQ^{CO,j}(Q^j) = \Omega^j Q^j$.[8] Under this null hypothesis, it would not be profitable to raise the price of concessions to extract more revenue from customers with higher movie values.

If this null hypothesis is rejected, a negative sign of this correlation will support the use of a premium on concessions to price discriminate, whereas a positive sign will suggest that the practice may not be appropriate for the purposes of price discrimination. Once again, although we cannot measure the sign of each $\partial AQ^{CO,j}/\partial Q^j$, we will evaluate the average effect. This could be rationalized by an assumption that the signs are identical for all types, but this assumption is not necessary for the average effect to indicate the profitability of the price discrimination practice. Clearly, a very negative $\partial AQ^{CO,j}/\partial Q^j$ could offset a modestly positive $\partial AQ^{CO,k}/\partial Q^k$ to make the price discrimination profitable.

Finally, as in §2.4, we estimate the model in logs:

$$\ln(R^{CO}) = \beta_Q \ln(Q) + \beta_R AR^{BO} + \beta_x X + \varepsilon. \qquad (12)$$

β_Q is therefore interpreted as the percentage increase in concession revenue resulting from a 1% increase in attendance. If $\beta_Q < 1$, we infer that concession revenue per person is decreasing with attendance and that theaters should, in fact, price concessions above marginal cost.

The presence of AR^{BO} in the above specification serves two purposes. First, it controls for differences

[8] One exception to this would be if increasing concession consumption for one type of customer was perfectly offset by decreasing concession consumption from another type of customer. This coincidence seems unlikely and could be ruled out by assuming that $\partial AQ^{CO,j}/\partial Q^j$ had the same sign for all types j.

Table 5 Relationship Between Concession Revenues and Attendance

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: log(Concession revenue)					
log(Attendance)	1.080	0.996	0.961	0.913	0.866	0.848
	(0.004)***	(0.005)	(0.004)***	(0.004)***	(0.005)***	(0.007)***
Box office revenue per attendee	0.023	−0.005	0.106	0.114	0.122	0.142
	(0.004)***	(0.004)	(0.005)***	(0.004)***	(0.008)***	(0.013)***
No. of screens		0.029				
		(0.001)***				
No. of seats per screen		0.00008				
		(0.00004)*				
Constant	−0.374	0.235				
	(0.033)***	(0.040)***				
Fixed effects						
Week	No	No	No	Yes	No	No
Week – Year	No	No	No	No	Yes	Yes
Quarter – Year – Theater	No	No	No	No	No	Yes
Theater	No	No	Yes	Yes	Yes	Yes
Observations	6,206	6,206	6,206	6,206	6,206	6,206
R-squared	0.94	0.95	0.98	0.99	0.99	0.99

Notes. Standard errors are in parentheses.
Asterisks indicate significance from zero for all variables, except log(attendance), which is the difference from one: *Significant at 10%; **significant at 5%; ***significant at 1%.

in the composition of ticket prices paid to avoid confounding estimates of β_Q. Second, the coefficient β_R is itself indicative of whether customers with a greater willingness to pay, as identified by paying a higher ticket price, consume more concessions than those customers paying a lower ticket price.

4.2. Results

We now begin to analyze this relationship. The first column of Table 5 reports the simple regression of $\ln(R^{CO})$ on $\ln(Q)$ and AR^{BO}. In this and all other specifications, asterisks indicate significance from zero for all variables except $\ln(Q)$, in which case the asterisks indicate significance from one. The estimated coefficient on $\ln(Q)$ is significantly greater than one, but this is primarily due to systematic differences in theaters as is clear from specification (2), which controls for the number of screens and the number of seats per screen at each theater. To account for other unobservable theater characteristics such as local demographics, specification (3) includes theater fixed effects and reveals a coefficient on $\ln(Q)$ that is significantly less than one. This is the primary result suggesting that theaters should charge premiums on concessions to meter willingness to pay for admission. Note that the coefficient on AR^{BO} is also positive, suggesting that groups with identifiably greater willingness to pay for admission consume more concessions per person. The remainder of the specifications illustrates the robustness of these results to a variety of potentially confounding factors.

Specification (4) in Table 5 includes week fixed effects to account for seasonality factors such as annually recurring summer or holiday weeks. We see that the signs of the coefficients of interest are unchanged and the effects become stronger in magnitude. Specification (5) interacts the week fixed effects with year fixed effects. This allows us to control for specific market characteristics in any given time period. For example, if a very unique movie was released in a given week across many theaters, this would account for the fact that customers with demand for this movie may be systematically different than customers arriving in other weeks. Once again, the estimated effects only become stronger. The final set of fixed effects is added in specification (6). We interact the theater fixed effects with quarter and year fixed effects. This controls for factors specific to a given theater within a time period. One advantage of this is that it can account for theaters periodically increasing prices to keep up with inflation. The results are also robust to this specification.

Table 6 describes specifications accounting for the potentially confounding factors such as concession lines being longer when attendance is greater. In specification (1), we drop all observations in which the attendance for the week is greater than the average attendance at the theater. This removes occasions when lines should be longest (i.e., the highest demand weeks). In this sample of 3,524 theater weeks, we see that the relationship still holds. In specification (2), we include a variable that measures how much actual demand differed from what the theater forecast it to be the week before. Such forecasts are used for staffing purposes such that concession line length should be correlated with how far actual demand differs from forecasted demand. This variable is not

Table 6 Robustness to Queuing and Other Confounding Factors

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: log(Concession revenue)				
log(Attendance)	0.881 (0.018)***	0.853 (0.018)***	0.848 (0.029)***	0.847 (0.029)***	0.824 (0.026)***
Box office revenue per attendee	0.119 (0.021)***	0.151 (0.027)***	0.145 (0.025)***	0.145 (0.025)***	0.141 (0.024)***
Attendance − Forecasted attendance (in millions)		1.10 (1.04)	0.76 (1.02)	0.66 (1.04)	
Attendance − Forecasted attendance (Positive)					−0.0001 (0.005)
(Attendance − Forecasted attendance) × (90 to 100 pctl)					−0.003 (0.001)**
log(att) × Percentiles of att					
less than 10 percentile			−0.011 (0.011)	−0.009 (0.011)	0.128 (0.013)
10 to 20			0.008 (0.009)	0.010 (0.009)	0.012 (0.011)
20 to 30			−0.008 (0.010)	−0.006 (0.010)	−0.003 (0.010)
30 to 40			−0.001 (0.010)	0.001 (0.010)	0.023 (0.015)
50 to 60			0.012 (0.011)	0.016 (0.012)	0.008 (0.010)
60 to 70			0.017 (0.016)	0.020 (0.016)	0.025 (0.011)
70 to 80			0.003 (0.012)	0.003 (0.012)	0.008 (0.013)
80 to 90			−0.008 (0.018)	−0.007 (0.018)	0.016 (0.013)
90 to 100			−0.031 (0.011)***	−0.029 (0.012)**	0.014 (0.013)
Number of days with rain				0.000 (0.001)	0.0005 (0.001)
Average temperature				0.000 (0.001)	0.001 (0.001)
Number of days with rain × Summer				0.001 (0.002)	0.001 (0.002)
Average temperature × Summer				0.002 (0.001)***	0.002 (0.001)***
Observations	3,524	4,024	4,024	4,024	3,946
R-squared	0.90	0.95	0.95	0.95	0.95

Notes. Standard errors are in parentheses.

Asterisks indicate significance from zero for all variables, except log(attendance), which is the difference from one: All specifications above include quarter, week, year, and theater fixed effects. *Significant at 10%; **significant at 5%; ***significant at 1%.

significant and does not alter the relationship between concession sales and attendance. We have also tried including the forecast error in percentage terms and including the forecasted attendance in logs; neither alters the coefficients of interest.

Specification (3) explores the robustness to queuing and other confounding factors further by interacting the coefficient of interest, log(attendance), with deciles of the attendance distribution at the theater. We see that the coefficient is not significantly different than the 40 to 50 decile (which is excluded) except for the top decile in which the coefficient is 0.03 lower. This likely picks up the effect of queuing resulting from fixed inputs such as soda machines rather than the variable inputs such as staffing that we proxy for with forecasted attendance. The notion is that when the theater is very busy, there may not be any level of variable inputs that can avoid long concession lines. The encouraging factor about this is that it picks up an additional drop in concession sales per person in these high-attendance weeks without washing out the effect across all other levels of attendance.

Specification (3) is also useful because it narrows the scope of any factor that could confound our estimated relationship. It essentially suggests that whatever confounding factor might exist, it must be equally relevant at all attendance levels. This removes the possibility that our findings reflect systematically different types of movies with different concession demand across broadly different levels of attendance. Even within a decile of attendance, the variation in attendance reflects a negative relationship with concession demand per person. The positive relationship between willingness to pay for admission and concession demand is exactly the phenomenon that can explain this within decile relationship.

In specification (4), we control for weather, which also can affect demand for concessions. The only weather variable that has a significant effect is the average temperature during the summer. It appears that attendees might be consuming more cold beverages, for instance, on hot summer days than on cooler summer days. This also does not alter the estimated relationship between concession sales and attendance.

Finally, specification (5) of Table 6 examines the possible role of interactions between attendance forecast error and attendance decile. The results in this specification show that weeks with positive attendance forecast error do not lower average concession revenue by themselves. Only those weeks with positive attendance forecast error that are within the 90 to 100 decile of attendance seem to have lower average concessions sales. Moreover, because the negative coefficient on the 90 to 100 decile dummy disappears, it seems adequate to conclude that the impact of queuing on average concession sales is not common to all high-demand weeks but rather those high-demand weeks with high unforecasted demand.

Before closing the discussion of our main results and first round of robustness checks, it is worth a discussion of where our identification comes from; most of the controls used in Table 6 have come out as statistically insignificant and one may wonder what is the source of the underlying variation in demand in our study. Our data set is comprised by theaters belonging to a same theater chain located across cities within Spain, a relatively small country when compared to the United States. This relative homogeneity across observations in our data causes that once we introduce quarter-year-theater fixed effects along with week-year fixed effects we are basically controlling for all weekly common trends across theaters in movie programming or weather. For example, changes in weather may surely drive movie attendance, but as long as weather in Spain is correlated across regions within a week, our weather variables will add little to the presence of week-year fixed effects. The same argument will apply to the results shown in our next section where we control for heterogeneity across time and theaters in movie composition and movie programming. Therefore, any variation left in attendance across weeks and theaters must be due to exogenous shocks that are uncorrelated with unobservable factors fixed across weeks, theaters, and within a quarter and a theater. These would essentially be the ξs in a Berry, Levinsohn, and Pakes style demand model (Berry et al. 1995), but instead of worrying about how ξs endogenously determine prices, we are able to exploit fixed prices to allow ξs to tell us about how the willingness to pay of theater attendees changes across weeks.

4.3. The Relation Between Concession Sales and Movie Types

Although our results in Table 6 suggest that estimates are not confounded by other factors, we verify this by also analyzing the characteristics of movies at the theater, which we observe during the first 26 weeks of the general sample. Table 7 shows results of five different regressions using the weighted average movie characteristics (genre, rating classification, U.S. box office revenue, and weeks since release) in a given week at a given theater. Specification (1) replicates the regression in Table 5's specification (6) using theater and week fixed effects. From the results in specification (1), we observe that log of attendance is still significantly less than one and, therefore, the marginal consumer left outside the theater values concessions less than the average consumer inside the theater. This result holds in specifications (2) to (5) when we control by movie composition in each theater in any given week.

Specification (4) replicates the regression in specification (1), adding genres present in each theater. Science fiction, comedy, and animated seem to have larger concession spending than the excluded genre fantasy. Drama and action genres are not statistically different than fantasy. Specification (3) replicates the exercise of specification (2) but controls for rating classification. We see that "all audience" and PG-13 movies have lower concession spending than the excluded group PG-7 movies. In specification (4), we combine these variables into one regression and find effects for a subset of the characteristics with effects in specifications (2) and (3). The relationship of interest remains significant throughout.

Specification (5) in Table 7 adds some additional variables: Weeks after release, Fraction in opening week, Number of openings, and U.S. box office revenue are intended to capture the phenomenon that there could be different types of customers showing up in opening weeks than nonopening weeks. The introduction of these variables allows us to identify the effect of recent changes in the stock of movies in

Table 7 Relationship Between Concession Revenue and Attendance, Accounting for Movie Genre, Classification, and Weeks After Release

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: log(Concession revenue)				
log(Attendance)	0.858	0.874	0.858	0.878	0.870
	(0.052)***	(0.053)**	(0.052)***	(0.054)**	(0.053)**
Box office revenue per attendee	0.321	0.279	0.302	0.272	0.271
	(0.139)**	(0.129)**	(0.131)**	(0.126)**	(0.125)**
	Characteristics weighted by Spanish box office revenue of each movie				
Action		0.240		0.287	0.263
		(0.235)		(0.252)	(0.242)
Adventure		0.223		0.339	0.305
		(0.136)		(0.137)**	(0.169)*
Science fiction		0.269		0.232	0.230
		(0.121)**		(0.141)	(0.153)
Comedy		0.432		0.432	0.424
		(0.155)***		(0.149)***	(0.164)***
Animated		0.272		0.286	0.281
		(0.148)*		(0.181)	(0.194)
Drama		0.046		0.144	0.126
		(0.170)		(0.164)	(0.171)
Terror		0.202		0.262	0.213
		(0.191)		(0.193)	(0.189)
Thriller		0.138		0.188	0.160
		(0.136)		(0.134)	(0.141)
PG-13			−0.285	−0.187	−0.179
			(0.087)***	(0.088)**	(0.090)**
PG-18			−0.050	0.086	0.087
			(0.102)	(0.104)	(0.099)
All audience			−0.171	−0.051	−0.065
			(0.076)**	(0.108)	(0.126)
Weeks after release (in millions)					21.600
					(18.400)
Fraction in opening week					0.004
					(0.004)
U.S. box office revenue					−0.00002
					(0.0003)
Number of openings					−0.013
					(0.009)
R-squared	0.99	0.99	0.99	0.99	0.99

Notes. All regressions contain 622 observations and use theater and week fixed effects. We drop two variables to avoid multicollinearity: fantasy and PG-7 movies. Standard errors are in parentheses.
*Significant at 10%; **significant at 5%; ***significant at 1%.

a theater, after controlling for week-year fixed effects across theaters and within a quarter in every theater. The two opening week measures allow us to identify the relationship of interest within opening weeks and outside of opening weeks. The weighted average Weeks after release further assists in this issue by controlling for effects common to many of the movies postrelease. None of these variables is significant and the estimated relationship between concession sales and attendance does not change. The most likely reason that these are significant is because similar compositions of movies occur across many theaters such that week fixed effects control for these issues. This final specification also includes weighted average U.S. box office revenue of the movies, which also does not affect concession revenue.

The specifications throughout Tables 5, 6, and 7 account for most factors that could confound the relationship between concession revenues and attendance. The outstanding result is that when marginal customers are lured into a theater (i.e., attendance increases), the average revenues from concessions decreases. This indicates that these marginal customers consume fewer concessions, which is the necessary condition identified by

Rosen and Rosenfield (1997) and Schmalensee (1981) to justify charging a premium on concessions to price discriminate.

5. Summary

In this paper, we define an empirical approach for analyzing metering price discrimination incentives. We use a general discrete-continuous demand model to show how metering incentives can be assessed by regressing aggregate aftermarket demand or revenue on aggregate primary good demand. To illustrate the ability of the model to recover a firm's aftermarket pricing incentives, we simulate data for a variety of hypothetical distributions of consumer preferences and show that the regressions accurately predict when the price should be above, below, and equal to marginal cost. We then apply our approach to a new and unique data set of weekly concession sales, box office revenues, and theater attendance from a large Spanish exhibitor and find that demand conditions support charging a premium on concessions.

Despite our results confirming the presence of the demand conditions for metering, we are not certain whether theaters are indeed consciously trying to discriminate across consumers with their aftermarket good pricing strategies. Nevertheless, our empirical results confirm that regardless of the theaters' motivations, high valuation customers end up paying higher total prices (movie ticket and concessions) than low valuation customers, and therefore they are extracting more surplus from high valuation customers. In other words, the theater chain may be engaging in a profitable metering price discrimination strategy even though it is unaware of the strategy.

The ease of implementation of our approach should make it accessible to managers at other firms to analyze their data to test whether aftermarket prices should be set above cost or not. Although our analysis confirmed the pricing strategy of the chain from which we obtained data, we expect that some markets or industries may not exhibit the same demand conditions. In fact, industries such as hotels and airlines either exhibit variation in whether aftermarket goods are priced at a premium or have recently gone through a regime shift in which formerly free aftermarket goods are now sold at high prices. We hope our analysis and empirical approach can provide guidance in these industries as well.

Acknowledgments

The authors thank Steve Berry, Latika Chaudhary, J.-P. Dubé, Liran Einav, Phillip Leslie, Julie Mortimer, Raphael Thomadsen, Brian Viard, and participants at the 13th Annual IO Fest at University of California, Berkeley; the Winter Business Economics Conference; and seminars at University of California, Santa Cruz and Yale University for valuable comments. The authors also thank John Johnson for valuable research assistance. Any errors are the authors'.

Appendix

Complementarities Between Primary Good Quality and Aftermarket Demand

Our quasi-linear utility function defined in the text satisfies Assumption 2 because ξ is fully separable from all terms relating to aftermarket demand. Relaxing the separability of ξ and z violates Assumption 2. We illustrate this below in a simple Cobb-Douglas example. However, it is useful to point out that the way ξ enters the demand function biases against a metering finding in which prices are predicted to be above cost.

Suppose that u_1 took the Cobb-Douglas form in the quality of the primary good ξ and the quantity of the aftermarket good z:

$$u_1 = \beta + \xi^{\eta} z^{\gamma} + \alpha (I - p - wz), \tag{13}$$

where η and γ are both between zero and one. We retain the linearity in the outside good, as opposed to making it part of the Cobb-Douglas function, because we need consumers to be able to not consume z, and it is easier to ignore income effects as most of the discrete-choice literature does. In Equation (13), ξ is not a choice by the consumer but rather adjusts the utility (and marginal utility) of z up or down. The demand function for the aftermarket good in this case is

$$z = \left(\frac{\alpha w}{\xi^{\eta} \gamma}\right)^{1/(\gamma-1)}. \tag{14}$$

We readily see that Equation (14) violates Assumption 2. This implies that the regression analysis we propose would be biased. However, it is useful to point out that the bias is against a finding that aftermarket prices should be above marginal cost. This direction of the bias arises because increases in ξ increase z such that higher primary demand periods would have more aftermarket sales per person. We illustrate this bias by simulating data in which all consumers have the same aftermarket demand but the regression coefficient for our analysis is significantly greater than one. We set parameters to obtain a plot similar to Figure 2(b). We use the same covariance matrix as Figure 2(b) and set the mean parameters as follows: $\beta = 2$, $\eta = 0.35$, $\gamma = 0.35$, and $\alpha = -1.2$. We also change ξ to be log-normally distributed. The resulting plot (not shown here) looks like Figure 2(b), but when we run the regression we obtain a coefficient on log primary demand of 3.34. This implies that if, in practice, a researcher finds a coefficient significantly less than one and suspects a utility function similar to Equation (13), then the researcher can be quite sure that aftermarket prices should be above marginal cost. On the other hand, a coefficient above one would only suggest below-cost aftermarket pricing if the researcher is sure the utility function does not imply that increases in primary good quality increase the marginal utility of the aftermarket good.

There is one interesting point related specifically to ticket pricing that comes from the simulation of this utility function. When the firm is committed to not adjusting the primary good price to changes in ξ, as is the case for most movie theaters and many sports teams, the optimal uniform price for the aftermarket is above cost. Even though all customers demand the same amount of the aftermarket good in a given time period, the fact that they demand more when there is a higher willingness to pay for the primary good implies that a premium on concessions allows the total margin per customer to be greater in peak demand periods, even when prices and costs per unit remain fixed.

Substitutability Between Primary Good Quality and Aftermarket Demand

The above illustrates that complementarity between primary good quality ξ and aftermarket demand z biases against a finding supporting aftermarket price premiums, and we now show that substitutability biases in favor of finding aftermarket price premiums. Although the following identifies the type of utility function that could invalidate our result, it is important to recognize that if the two were substitutable, why do we often see them sold together? If substitutability exists between these two, it also suggests the odd incentive that, under admission prices that do not vary across movies, a theater might want to select very poor-quality movies to raise revenue by selling more concessions. Nevertheless, the assumption may perhaps be valid in some instances of metering price discrimination, so we illustrate its bias here. We redefine u_1 as follows:

$$u_1 = \beta + (\xi + z)^{\gamma} + \alpha(I - p - wz). \tag{15}$$

The additivity of ξ and z inside the parentheses implies perfect substitutability between the two. If consumers could choose ξ and if it were priced per unit of quality, they would spend their entire budget for the system on either primary good quality or aftermarket quantity. However, we assume, as above, that consumers cannot choose ξ. The demand function for the aftermarket good when a positive amount is consumed is therefore

$$z = \left(\frac{\alpha w}{\gamma}\right)^{1/(\gamma-1)} - \xi. \tag{16}$$

Using exactly the same parameter values as in the complementarity case above, we once again simulate a plot (not shown here) like Figure 2(b). The optimal price for the aftermarket is at cost, as expected, but the regression coefficient for our analysis is significantly less than 1 (-1.315). The coefficient itself reveals how odd this utility function and demand function is. The greater the attendance at a movie, the lower the concession revenue, implying that in low-demand weeks, a few people eat a lot of popcorn, but when movie quality and attendance increase, people stop eating popcorn.

Using an Instrument to Relax Assumption 2

Finally, if researchers are unable to satisfy Assumption 2, it can be avoided by using an instrument for primary good demand. The instrument needs to be correlated with primary good demand but uncorrelated with aftermarket demand. In other words, only the instrument needs to satisfy Assumption 2 as opposed to all vertical quality shocks satisfying Assumption 2. The predicted primary demand from the first stage in a two-stage least-squares procedure would trace out variation in primary good demand that does satisfy Assumption 2. The second stage would involve regressing log aftermarket demand or revenue on the predicted log primary demand from the first stage. To implement the instrumental variable strategy in the two examples above, we added an additional vertical attribute ξ_2 that satisfies Assumption 2:

$$u_1 = \beta + \xi_2 + \xi^{\eta} z^{\gamma} + \alpha(I - p - wz) \quad \text{and}$$
$$u_1 = \beta + \xi_2 + (\xi + z)^{\gamma} + \alpha(I - p - wz). \tag{17}$$

In both cases, the ordinary least-squares (OLS) regression is biased when applied to preferences like Figure 2(b), but when the instrumental variables (IV) strategy is used, the coefficient on log primary demand is not significantly different from one. These simulations are reported in Table A.1.

Table A.1 Relationship Between Aftermarket Revenue and Primary Demand

	$E[\xi z] > 0$		$E[\xi z] < 0$	
	OLS	IV	OLS	IV
Dependent variable: log(Aftermarket revenue)				
log(Primary demand)	2.09	1.03	−0.28	1.13
	(0.05)***	(0.12)	(0.04)***	(0.14)
Constant	−5.85	1.42	11.06	0.90
	(0.35)***	(0.82)	(0.31)***	(0.99)
	Mean	Variance	Mean	Variance
True values				
Population means				
β	2.00	2.00	2.00	2.00
η	0.50	0.00	0.50	0.00
α	−1.20	0.00	−1.20	0.00
γ	0.50	0.00	0.50	0.00
Demand shocks				
ξ	0.00	1.00	0.00	0.50
ξ_2	0.00	1.00	0.00	0.05
Constant marginal costs				
Primary good	0.00		0.00	
Aftermarket good	0.40		0.40	
Optimal prices				
Primary good	11.85		11.34	
Aftermarket good	0.56[a]		0.40	

Notes. Simulations are based on 2,000 individuals across 500 time periods. Regressions are at the aggregate levels, so there are 500 observations in each specfication. Standard errors are in parentheses.

*Significant at 10%; **significant at 5%; ***significant at 1%.

[a]The aftermarket price in this specification is above cost despite no correlation between customers' willingness to pay and aftermarket demand within a period, because the complementarity of the primary good demand shock and aftermarket demand across periods leads this pricing to be optimal. This arises because of the constraint that the firm must price the same in every period. Setting the aftermarket price above cost effectively allows the firm to "meter" its pricing across time periods. This is only possible if the primary demand shocks really are positively correlated with aftermarket demand.

References

Ainslie, A., X. Drèze, F. Zufryden. 2005. Modeling movie life cycles and market share. *Marketing Sci.* **24**(3) 508–517.

Berry, S., J. Levinsohn, A. Pakes. 1995. Automobile prices in market equilibrium. *Econometrica* **63**(4) 841–490.

Borzekowski, R., R. Thomadsen, C. Taragin. 2009. Competition and price discrimination in the market for mailing lists. *Quant. Marketing Econom.* **7**(2) 147–179.

Busse, M., M. Rysman. 2005. Competition and price discrimination in Yellow Pages advertising. *RAND J. Econom.* **36**(2) 378–390.

Cohen, A. 2008. Package size and price discrimination in the paper towel market. *Internat. J. Indust. Organ.* **26**(2) 502–516.

Davis, P. 2006. Spatial competition in retail markets: Movie theaters. *RAND J. Econom.* **37**(4) 964–982.

De Vany, A. 2004. *Hollywood Economics*: *How Extreme Uncertainty Shapes the Film Industry*. Routledge, Taylor & Francis Group, London.

Einav, L. 2007. Seasonality in the U.S. motion picture industry. *RAND J. Econom.* **38**(1) 127–145.

Elberse, A., J. Eliashberg. 2003. Demand and supply dynamics for sequentially released products in international markets: The case of motion pictures. *Marketing Sci.* **22**(3) 329–354.

Eliashberg, J., A. Elberse, M. A. A. M. Leenders. 2006. The motion picture industry: Critical issues in practice, current research, and new research directions. *Marketing Sci.* **25**(6) 638–661.

Ellison, G. 2005. A model of add-on pricing. *Quart. J. Econom.* **120**(2) 585–637.

Fort, R. 2004. Inelastic sports pricing. *Managerial Decision Econom.* **12**(2) 87–94.

Gil, R. 2004. Contracting in the Spanish movie industry. Ph.D. dissertation, University of Chicago, Chicago.

Gil, R., W. Hartmann. 2007. The role and determinants of concession sales in movie theaters: Evidence from the Spanish exhibition industry. *Rev. Indust. Organ.* **30**(4) 325–347.

Goettler, R., P. Leslie. 2005. Cofinancing to manage risk in the motion picture industry. *J. Econom. Management Strategy* **14**(2) 231–261.

Hartmann, W. R., H. S. Nair. 2009. Retail competition and the dynamics of demand for tied goods. *Marketing Sci.*, ePub ahead of print September 22, http://mktsci.journal.informs.org/cgi/content/abstract/mksc.1090.0518v1.

Hartmann, W. R., V. B. Viard. 2006. Quantity-based price discrimination using frequency reward programs. Working paper, Stanford University, Stanford, CA.

Klein, B. 1996. Market power in aftermarkets. *Managerial Decision Econom.* **17** 143–164.

Krider, R. E., C. B. Weinberg. 1998. Competitive dynamics and the introduction of new products: The motion picture timing game. *J. Marketing Res.* **35**(1) 1–15.

Landsburg, S. 2006. How much should hotel Web access cost? *Slate* (February 1), http://www.slate.com/id/2135226/.

Leslie, P. 2004. Price discrimination in Broadway theatre. *RAND J. Econom.* **35**(3) 520–541.

Littlechild, S. C. 1975. Two-part tariffs and consumption externalities. *Bell J. Econom.* **6** 661–670.

Marburger, D. 1997. Optimal ticket pricing for performance goods. *Managerial Decision Econom.* **18**(5) 375–381.

McManus, B. 2007. Nonlinear pricing in an oligopoly market: The case of specialty coffee. *RAND J. Econom.* **38**(2) 512–532.

Miravete, E., L.-H. Röller. 2004. Competitive nonlinear pricing in duopoly equilibrium: The early U.S. cellular telephone industry. Working paper, University of Texas at Austin, Austin.

Mortimer, J. H. 2007. Price discrimination, copyright law, and technological innovation: Evidence from the introduction of DVDs. *Quart. J. Econom.* **122**(3) 1307–1350.

Mortimer, J. H. 2008. Vertical contracts in the video rental industry. *Rev. Econom. Stud.* **75**(1) 165–199.

Oi, W. 1971. A Disneyland dilemma: Two-part tariffs for a Mickey Mouse monopoly. *Quart. J. Econom.* **85**(1) 77–96.

Orbach, B., L. Einav. 2007. Uniform prices for differentiated goods: The case of the movie-theater industry. *Internat. Rev. Law Econom.* **27**(2) 129–153.

Peltzman, S. 2005. Aaron Director's influence on antitrust policy. *J. Law Econom.* **48**(2) 313–330.

Rosen, S., A. Rosenfield. 1997. Ticket pricing. *J. Law Econom.* **40**(2) 351–376.

Schmalensee, R. 1981. Monopolistic two-part pricing arrangements. *Bell J. Econom.* **12**(2) 445–466.

Seim, K., V. B. Viard. 2004. The effect of entry and market structure on cellular pricing tactics. NET Institute Working Paper 03-13, http://ssrn.com/abstract-618221.

Shepard, A. 1991. Price discrimination and retail configuration. *J. Political Econom.* **99**(1) 30–53.

Swami, S., J. Eliashberg, C. Weinberg. 1999. SilverScreener: A modeling approach to movie screen management. *Marketing Sci.* **18**(3) 352–372.