Chapter 10
Pricing and Maximizing Profits Within Corporations

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This chapter identifies some of the issues encountered in estimating demand models for corporate clients and then uses related results to suggest pricing strategies that might be more profitable.

The first section provides an illustration of how Professor Taylor's findings and insights can be applied in business settings. The second section discusses—based on pricing decisions within certain businesses—the uneven trend toward the application of demand, cost, and optimization approaches. The next section briefly notes the econometric and other technical challenges that confront companies that are attempting to optimize their prices. The subsequent section explores a number of these econometric challenges through the use of stylized scenarios. The final section concludes the chapter.

10.1 Incorporating Professor Taylor's Insights: Inside the Corporation

To set the stage for the discussion of the issues encountered in estimating demand models for corporate clients, the experience one of us (Tardiff) had in collaborating with Professor Taylor shortly after his update to *Telecommunications Demand* published was informative.[1]

We have benefited from James Alleman's editorial suggestions and Megan Westrum's superb programming of simulations presented in this chapter.

[1] This discussion in this section is based on Tardiff (1999), pp. 97–114.

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During the time in which he was finishing the update, Professor Taylor participated in one of the most hotly debated telecommunications demand elasticity issues of the early 1990s: how price-sensitive were short-distance toll calls (then called intraLATA long-distance calls)? The answer to that question would determine the extent to which the California state regulator reduced long-distance prices (and increased other prices, such as basic local service prices) in a "revenue-neutral" fashion.[2] One side of the debate proposed that the interstate toll price elasticity of approximately −0.7 be used to determine the revenue-neutral price change. The other side—which Professor Taylor supported—suggested smaller elasticities, reflective of the finding that calls within "communities of interest" should be less price-sensitive. The commission more or less "split the difference" by using an elasticity of −0.5 for the incumbent carriers' retail toll calls and −0.44 for the wholesale service (carrier access) they supplied to long-distance carriers that provided intrastate-interLATA retail calling.[3] On the basis of these elasticities and the concomitant expected volume stimulation, the Commission reduced prices for these services on the order of 45–50%, effective January 1, 1995.

Shortly thereafter, Pacific Bell (now AT&T California) asked Professor Taylor and Tardiff to ascertain whether calling volumes had changed as much as the Commission had believed they would (Tardiff and Taylor 1995). Since the specific timing of the price change was Commission-ordered, it provided an exogenous price change and did not suffer from the endogeneity issues that are encountered when companies themselves establish prices based on supply-side considerations. Accordingly, the changes in volumes subsequent to the price reduction were treated as a quasi-experiment, controlling for (1) the growth in volumes experienced in recent years before the price change—a period in which prices had been essentially flat and (2) whether consumers had fully responded to the price change, for example, whether volumes had reached a steady state with respect to that price change. Based on this analysis, Tardiff and Taylor (1995) concluded that the volume changes were much more consistent with the lower proposed price elasticities than with the Commission's adopted values, let alone the even higher elasticities proposed by other parties.[4]

Important insights can be gained from addressing the following questions prompted by this experience: First, can observed price changes be considered as exogenous (rather than jointly determined with supply-side considerations); second can effects other than the price changes be removed from the measures of volume changes attributable to the price change? Third, to the extent that

[2] Technically speaking, the rate rebalancing was profit neutral, that is, to the extent that increased calling also increased calling costs, such "cost onsets" would be included in determining (net) revenue neutrality.

[3] During this time period, the incumbents had not met the requirements that would enable them to provide retail intrastate-interLATA calls.

[4] In ordering a later reduction in toll and carrier access prices, the Commission used elasticities quite similar to those that the incumbent carriers had proposed (but the Commission declined to use) in the earlier proceeding. Tardiff (1999).

consumer demand and a company's pricing changes are jointly determined,[5] can working within a company provide additional information on how that company determines prices, for example, are there "rules of thumb" which can be used to pass through effects such as increased materials costs to product prices?

10.2 Transition to Explicit Profit Maximization

A typical underlying assumption in economic analyses is that companies that survive in the market tend to set prices in order to maximize profits. Of course this does not mean that every company explicitly estimates the demand and marginal cost or sets profit-maximizing prices; or even that every company acts as if they do so. Many successful corporations that make or sell products and services typically do not explicitly use the methods that economists and econometricians use to study how business works.

Economists have been careful to say that businesses "*act as if*" they actually analyze the types of information that economists use when analyzing a business, and again "act as if" businesses make decisions based on the types of maximization methods that economists use when analyzing what decisions business will make. But today increasing numbers of firms are moving toward explicit optimization of prices based on estimated demand curves and estimated, or directly calculated, cost curves.

This section (1) provides a high-level description of how cost and demand information can be used to move toward optimal prices; (2) acknowledges that there may be compelling reasons why particular firms may not yet (or may never) explicitly attempt to set profit-maximizing prices; and (3) describes the trend toward more analytical demand and pricing analysis in other types of companies.

10.2.1 Improving Profitability

The fundamental motivation here is to find prices that have the prospect of improving the profitability (short-run or long-run) of a company's product offerings. If one knew enough about demand, such prices would be produced by the familiar Lerner-like relations:

$$\text{Price} = \frac{\text{Cost}}{1 + \frac{1}{\in}} \tag{10.1}$$

(where $\in$ is the company's own price elasticity).[6]

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[5] In the econometric sense that unspecified demand effects (the error terms or residuals in a demand model) come into play in a company's pricing decisions.

[6] Lerner-like relations are frequently used by economists analyzing competition and antitrust issues, such as in models that simulate the effects of mergers, allegedly anticompetitive behavior,

In many cases, the company may not know enough about the demand for its products to go directly to the pricing exercise. At this point, the question shifts to the following: if the company does not know enough about its demand, how does one collect and analyze the data that will fill in the gaps? Before discussing the possibilities one has to consider, it is useful to review a fundamental econometric challenge involved in using "real-world" price and quantity data to estimate demand models: potential endogeneity between consumer demand and company supply/pricing decisions. A stylized supply/demand system illustrates these issues.[7]

$$\text{Demand}: q = a_1 + b_1\,\text{Price} + c_1\,\text{Cross Price} + d_1 W + \varepsilon_1 \tag{10.2}$$

$$\text{``Inverse supply''}: \text{price} = a_2 + b_2 q + d_2 Z + \varepsilon_2 \tag{10.3}$$

In these equations, W and Z denote exogenous variables (which may overlap to some extent) that affect demand and supply, respectively.

The endogeneity problem arises when the quantity term in the "inverse supply" equation is in equilibrium with demand. In particular, because the error term in the demand equation (ε_1) is a component of price,[8] price and the demand error term are correlated, which in turn would lead to a biased and inconsistent estimate of the price coefficient (b_1). Depending on the nature of the data, there are several possible approaches, depending on the specifics of how the company establishes prices.

First, in some circumstances, price changes can be established through processes resembling experimental conditions.[9] For example, especially in the case of new products, consumers can be presented prices as part of a structured survey—to the extent that survey responses reasonably approximate market-place behavior, the resulting price/quantity data would not pose endogeneity issues. A similar approach would be to change the price as part of a real-world experiment, most likely administered to a representative group of consumers.

Second, as discussed in greater detail below, examination of how the company in question has changed prices in the past could support the conclusion that such price-setting was essentially random. In particular, historical price changes could be viewed as exogenous if such changes were not driven by changes in *contemporaneous* demand volumes but rather, through administrative rules not resulting

(Footnote 6 continued)
and the like. See, for example, Froeb et al. (1998) pp. 141–148; Tardiff (2010), pp. 957–972; Zona (2011) pp. 473–494.

[7] In the second equation, the quotation marks around "inverse supply" denote the possibility that a company's pricing decisions are not strictly profit maximizing with respect to contemporaneous demand.

[8] Specifically, since q appears in the "inverse supply" equation, $b_2\ \varepsilon_1$ is a component of price.

[9] This would be analogous to how regulators formerly set the prices that were the subject of the bulk of the demand findings reviewed in Taylor's (1980, 1994) seminal books.

from the demand curve.[10] Such data could be analyzed with standard demand modeling techniques, such as ordinary least squares.

Third, examination of previous pricing rules may uncover a systematic price-setting mechanism. For example, if a company sets prices with reference to some measure of cost (not necessarily marginal cost) plus a percentage mark-up and also changes prices in response to increases in critical cost drivers, such as the price of oil,[11] the resulting price/quantity data could be free of the standard endogeneity problem.

Finally, perhaps as a result of learning about demand (e.g., from historical pricing changes that were effectively random) and using such information to set more rational (profit enhancing) prices, the resulting data begin to take on some of the endogeneity problems that require econometric attention. In this situation, the exercise of discovering better prices, for example, through explicit optimization along the lines of Eq. (10.1), above, may well produce independent information that could be used to (1) econometrically identify the structure of the (inverse) supply equation (Greene 1993, p. 595) and/or (2) specify instrumental variables that do not suffer from the properties of weak instruments.[12]

10.2.2 Why Some Companies Do Not Explicitly Optimize

There are many reasons why the powerful tools used to study profit maximization decisions have not been used by many corporate economists.[13]

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[10] In this case, there may still be endogeneity issues with respect to estimating certain cross-price coefficients, e.g., the prices of other firms with competing products.

[11] Such a pricing strategy could reflect the belief that competitors similarly pass through such price increases.

[12] With regard to the possibility of company-specific information providing more effective instruments, one possible avenue of further exploration are cases in which (1) a company's marginal cost is relatively flat with respect to output (possibly locally within the range of likely observations) and (2) the company is setting prices with reference to marginal cost. In such situations, marginal cost measurements (to the extent they vary due to factors such as changing input prices) may serve as effective instruments and/or the typical endogeneity problem with price as an explanatory variable in the demand equation may be mitigated.

[13] Despite the empirical reality that corporate pricing decisions can depart from textbook profit maximization for many reasons, prominent economists nonetheless make legal and policy recommendations based on seemingly literal adherence to the optimizing model. For example, a recent article by Kaplow (2011) on the detection of price fixing observed the following.

"[O]ne would expect firms to have knowledge of their own prices and marginal cost and thus an estimate of price-cost margins. Firms think about which costs are fixed and variable and how joint costs are properly allocated. They know when production is at or near capacity and if marginal cost is rising sharply. When they price discriminate or grant a price concession to a large buyer, they presumably are aware of their costs and their reasons for charging different prices to different customers. If their prices vary across geographic markets, they again have reasons and information on which their reasoning is based. In deciding how much of a cost shift

10.2.2.1 Structure of the Market Does Not Call for Detailed Economic Modeling to Approximate Maximum Profits

In some cases, it could be that the companies or products managed do not require any detailed analysis. This could be because their products are commodities, which make the analysis of the profit optimization decision of relatively little value: optimal profits can be achieved by setting prices to match the market, driving costs down as far as possible, and running the operation with every possible efficiency. Of course this process of running the business efficiently might benefit from methods to help streamline operations and attenuate the effects of turbulence, such as supply shocks and related cost variations. But there may be settings or industries where even these variations and improvements for operational improvement are minimal. These are all hard tasks, requiring skilled management, but in this setting, economic and econometric models are not of great value to corporate managers for maximizing profits, even if economists are developing economic theories and performing econometric analyses that describe the behavior of such markets.

10.2.2.2 Detailed Data Needed to Explicitly Maximize Profits are not Available

In other cases, the detailed cost and demand data needed to perform profit maximization analyses are not available, or at least not easily and/or reliably available on a frequent enough basis.

Even today, there are many large corporations that do not have their data in an electronically accessible form that is captured with adequate frequency on a consistent basis. For example, weekly data for specific sales, along with the cost drivers associated with marginal costs, may be needed to analyze demand, cost, and improve profits.

The time and cost of collecting the data in the format required for this type of analysis may intimidate companies from performing these standard economic and statistical analyses. But in fact the first step need not be inhibited by the initial lack of data. The data required for an initial look at profit maximization topics can be generally captured efficiently and used quickly to produce powerful insights.

Many companies have installed extensive data warehouses or enterprise resource planning (ERP) systems, but even these systems often are not structured in a way that provide easy access to cost or price data that is categorized in the right way for developing strategies to increase profits. Rather than accounting

(Footnote 13 continued)
to pass on to consumers or how to respond to demand fluctuations, they are thinking about whether their marginal costs are constant over the relevant output range, what is the elasticity of the demand they face, and possible interactions with competitors. If they have excess capacity, they have thought about using more of it, which probably involves reducing price, and presumably have decided against it, again, for a reason" (pp. 404–405).

costs, with which businesses are more likely to be familiar, improving profitability must be based on marginal costs that are the additional costs associated with changing production by a marginal unit (or relatively small demand increment). In contrast, accounting costs often include allocations of costs that are fixed over the range of product volumes that one wants to optimize. For example, if a company wanted to maximize short-term profits, say by not considering the wear and tear that additional units of production would cause, the company would exclude these costs from the analysis of what price and quantity result in the largest (short-term) profits.[14] If on the other hand, the company wanted to maximize long-run profits it would take into account the wear that an additional unit of production causes and factor that into the marginal cost of the additional unit even though the cash for that cost may not actually be paid out until sometime in the future.[15]

10.2.2.3 Managers may have the Knowledge and Ability to Maximize Profits Without Explicit Modeling

In some cases, managers have extensive experience with the products, customer base, geography, and the company's costs structure. If these broad supply and demand conditions have been stable enough for long enough, the individuals making pricing decisions may have an accurate idea of how a change in price will change the quantity sold and how a given quantity will alter marginal costs. With this knowledge, whether the pricing manager obtains it from an analytical study of the data or from a long history of observing the process, optimal prices and maximum profits can be approximated. Managers are more likely to have this constellation of cost and consumer-demand knowledge when products they sell and the competitors they face are few in number, and where consumers and costs of production do not change often or greatly.[16] In more dynamic markets, it is harder for managers to maintain accurate perceptions of what can be myriads of changing product features, competitors' offerings, customers' demands by geography and sales channels, customers' demographics, and input costs.

[14] Determining whether certain types of cost are included in a particular marginal cost estimates can be illustrated by costs associated driving a car and additional mile. There is gas, which is a short-run marginal cost. Oil might be considered a medium-term marginal cost. Wear and tear on the car engine transmission, etc., also happens with each mile. So it also has a marginal cost, but one that is only paid for far into the future, when a new car has to be purchased.

[15] Indeed, the cash expenditure may occur even months or years into the future when repairs resulting from operating production facilities at higher levels of output in the earlier period are made.

[16] That is, whether corporate decisions comport with the textbook description in footnote 13, above likely varies by industry and by company within particular industries.

10.2.2.4 Advances in Computing Power Needed for Large-Scale Elasticity Estimation and MultiProduct Optimization

Another reason these scientific analytical methods have not been used is that the computing power needed to perform such analysis on a regular basis for a large array of a manufacturer's products was expensive and difficult to obtain. Twenty-five years ago, scientific measurements of the sensitivity of product sales to a change in prices for an entire portfolio of products could take many hours, even days, to run on a major university research mainframe computer. Today, the same analysis would require a computer or server that could fit under a desk and could complete the same calculation in a matter of minutes.

10.2.3 Movement Toward Explicit Modeling of Optimal Prices Based on Estimated Price Elasticities

As data collection and computing power advance, and the benefit of rapidly adjusting prices increases, a growing number of companies are explicitly developing demand and marginal cost models for the products they offer. Obviously, the ability to accurately model the company's supply and demand curves is a significant advantage in maximizing profits. Those firms that do not have this ability have a greater chance of being weeded out of the competitive field.[17]

These improvements in data availability and computing power have been accompanied by advances in the analytical methods used to measure consumer sensitivity to changes in prices and to optimize prices. These technological changes along with the growing familiarity among corporate managers with these analytical techniques have produced an expanding use of these powerful scientific methods—in some cases, on a daily basis—in manufacturing, wholesaling, retailing, and service companies.

In addition, the ranks of CEO and corporate leaders are now from a generation who have been exposed to these more powerful analytical models and computing technology through coursework at universities and from practical experience. These resources can accommodate the estimation of own price elasticities, cross-price elasticities and marginal cost functions for hundreds or even thousands of products within a corporation. Further, advances in computing power and optimization software then allows these elasticities and costs to be combined with other corporate strategic and logistical restrictions to optimize profits within the broader context of corporate strategic goals.[18]

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[17] These abilities are analogous to cost advantages or disadvantages.

[18] Corporate strategic goals can be thought of as a component of marginal cost, but here they are simply noted as additional constraints on the optimization process.

Even with this evolution in data warehousing, computing power and modeling techniques, most manufacturing, retail and service companies have not performed the detailed economic and econometric analysis to know how to maximize their profits, or even whether they are close to maximizing profits.

In fact, even in large companies, there may be relatively few formally trained/PhD-level economists that perform significant economic and econometric analyses to help companies determine such fundamental economic decisions as what price and quantity should be sold to maximize profit.[19] Certainly PhD-level economists, many of whom are capable of performing such analyses, do work, or in some cases, even run large segments or even entire corporations. But still decisions about fundamental components of profit maximization are rarely if ever explicitly analyzed in many industries using standard tools that economists use to analyze the behaviors of those same businesses.

10.3 Path to Profit Maximization in a Corporate Setting

Maximizing profits in a corporate setting, particularly one where explicit profit maximization has not occurred before, presents a unique set of analytical concerns. While the expanded use of advanced economic concepts and econometric models to observe and scientifically measure the behavior of consumers, competitors, and suppliers often relies heavily on standard economic and econometric concepts and the latest academic developments, the application of these techniques in the business setting presents a different set of challenges and opportunities than is the case in academic settings. Furthermore, applying optimization techniques presents an additional set of technical economic and econometric issues that academic economists rarely have to deal with when studying the same set of businesses. These differences go far beyond the obvious, albeit important, differences that typically come to mind: The analysis for corporate purposes typically has to have practical implications and must lead to implementable results.

More profoundly, the results produced by corporate economists about fundamental business decisions, such as product pricing and quantity determination are often actually used in the market. (That was the whole purpose for the business to perform the analysis in the first place.) This means that the observed empirical behavior and resulting data in the market is altered by corporate decisions that are, in turn, based on the empirical econometric analysis of the market data. In this way, corporate economic research of fundamental decisions interacts with the data

[19] For example, the trend towards reducing the number of economists and demand analysts within large telecommunications companies that Professor Taylor noted in the 1990s has resulted in many fewer such specialists than there were when the industry was regulated. Similarly, we have analyzed demand and profitability for companies that have billions of dollars of annual sales. In many cases, minimal resources had been assigned to price setting and profit improvement before they asked us to analyze their business.

being analyzed in ways that are rarely observed in academic research of corporate behavior. Academic analysis of consumer demand and costs has rarely made it into the actual pricing and production decision of corporation on an ongoing basis, but now they do.[20] This close interaction between the analysis of the behavior in the market and this influence that the economic research and resulting corporate decision have on the data that is being analyzed creates some important econometric challenges that must be recognized and accounted for in order to understand and scientifically estimate the impact that corporate decisions about pricing and production will have on consumer demand, competitor behavior and corporate profits.

At the same time, economic analysis performed within a corporate setting provides some enormous advantages, not only in data quality, but also in the ability to access data almost continuously over time as it is produced by the market. Economic analysis within a corporate setting also provides access to certain types of data which are rarely if ever in the market, including detailed company-specific cost data, by product, region, customer, etc. Furthermore, and perhaps more importantly, in the corporate setting economists may have access to the specific implicit or explicit rules companies use to set prices (even to the point of having participated in their development). Use of this data (and even more so the optimization function that corporate decision-makers use to set prices and quantities) changes the estimation strategy required to get the best estimate of customers', competitors', and suppliers' reactions in the market.

The remainder of the chapter shows the effect of the use of these differing estimation strategies on the observed demand and supply curves and ultimately on the prices, quantities, and profits achieved by the firm. Further, the chapter shows how the use of certain standard approaches in an applied corporate setting, without recognizing how explicit efforts to optimize profits can affect the resulting price and quantity data, can lead to a path of pricing decisions that are far from optimal and in fact could even be worse than using alternative naïve pricing rules.

10.4 Empirical Evidence of Methods Based on Business Requirements

In some cases, managers responsible for setting prices report that prices are set with little or no regard for marginal costs, or even costs in general. Instead, the focus is on revenues or sales. This claim is not inconsistent with the possibility that the price variation created by a corporate pricing department is within a small enough range to approximate the optimal price during some period of time.

[20] Some notable examples that are exceptions are the airlines industry where some forms of fare optimization has been in use for years; and more recently the hotel and hospitality industry, where pricing systems have been used to price "excess" capacity.

Perhaps when some larger price changes occur, managers do tend to move prices in the expected direction. But if corporate managers are right, there may be a range of time when the price changes trace out the demand curve. If this is the case, the variation in the prices over this range could be sufficient to estimate the demand curve. And further, if it is appropriate to estimate the demand curve directly, the precision of the estimates will be greater than if estimated through a two-stage process. However, as one will see, once the company starts to explicitly maximize profits, the classic problem of endogeneity may kick in, requiring some other identification strategy.

To illustrate the analytical issues and challenges, several scenarios are developed, described in the following seven subsections.

10.4.1 Marginal Costs are Not Volume-Sensitive

A simple, but not necessarily unrealistic example, illustrates the potential power of understanding costs. Suppose a marginal costs do not vary significantly with volume over the range of variation, but can be different from period to period, for example, as input prices change. The firm, which faces a linear demand curve—that in turn may shift in and out from period to period—sets prices to maximize profits in each period.

In particular, suppose one observes 100 periods of volume, price, and marginal cost outcomes generated as follows:

- Demand curve slope: -1.5.
- Marginal cost: Mean $= 25$, standard deviation $= 20$.
- Intercept of demand curve: Mean $= 200$, standard deviation $= 50$.

Figure 10.1 displays the prices and quantities observed from the firm's profit-maximizing pricing decisions. The square points reflect the actual demand curve.

Figure 10.1 illustrates the fundamental endogeneity issue: the diamond points—representing the market equilibrium prices—suggest almost no relationship between the volume demanded and price. If anything, the Figure suggests a weak positive relation between price and volume.

It turns out that with a linear demand curve and volume-insensitive marginal costs, knowing costs in every period—along with the price and volume data typically used in demand analysis—allows exact recovery of the slope of the demand curve by means of basic algebra.[21] Table 10.1 compares this algebraic result with ordinary least squares and instrumental variables estimation.

[21] The slope is calculated from the following equation: $b = \frac{\bar{V}}{\bar{p}-\bar{c}}$, where $\bar{V}$, $\bar{p}$, $\bar{c}$ are the sample averages for volume, price, and marginal cost, respectively. The estimate of the intercept is: $\hat{A} = \frac{\bar{V}(2\bar{p}-\bar{c})}{\bar{p}-\bar{c}}$.

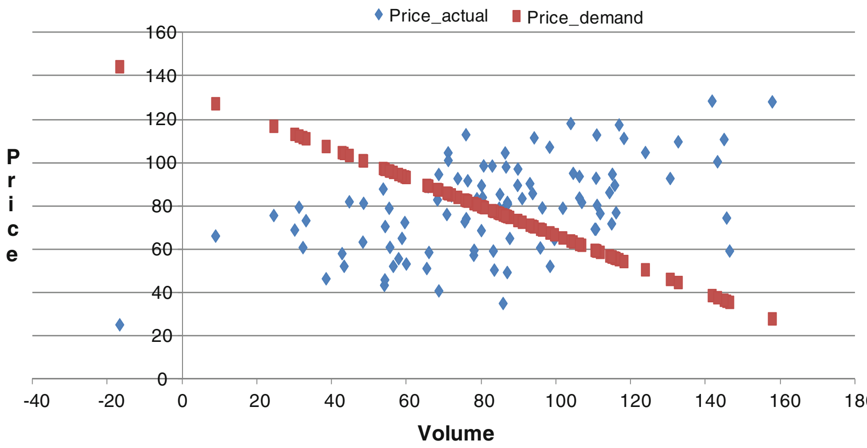


Fig. 10.1 Price and volume data: volume-insensitive marginal cost scenario

As anticipated, the algebraic solution exactly reproduces the slope, while the intercept is close to the mean of the assumed distribution (202.8 vs. 200). The instrumental variables (IV) results are also quite close to actual. On the other hand, as depicted in Fig. 10.1, ordinary least squares does a poor job of uncovering the demand curve.

10.4.2 Pre-optimization Demand Model Estimation

The scenarios in this and the subsequent two subsections are based on the following simplified example:[22]

Demand Equation

$$Q = 550 - 0.5 * \text{price} - \text{oil} + \varepsilon. \tag{10.4}$$

Marginal Cost Equation

$$MC = \frac{Q + \text{oil} + \text{steel}}{0.5}. \tag{10.5}$$

In Eq. (10.4), the quantity of the firm's output demanded by consumers is a linear function of the product's price and the price of oil (which can be viewed as a

[22] For each of the scenarios described below, observations are generated for price, quantity, oil, and steel using the following distributional assumptions:

oil—(mean = 100, standard deviation = 5)

steel—(mean = 50, standard deviation = 15)

ε—(mean = 0, standard deviation = 75).

Table 10.1 Demand model estimation: Volume-insensitive marginal costs

	Actual	Algebraic	Instrumental variables (IV)	Ordinary least squares (OLS)
Intercept	200	202.8	203.7 (43.96)	19.6 (10.56)
Slope	−1.5	−1.5 Exact	−1.51 (0.55)	0.80 (0.13)

Standard errors are in parentheses
Source authors' simulation

proxy of economic conditions). Equation (10.5), the parameters of which in this example the company knows with certainty, indicate that the marginal cost of the company's product increases by two dollars for each dollar increase in the price of critical production inputs (oil and steel) and by \$2 for additional unit of output.

If the company is attempting to maximize profits, it will select prices and quantities that equate marginal revenue (derived from Eq. 10.4) with marginal cost Eq. (10.5). Because the resulting prices may be a function of demand, possibly including its error term, even if the business knows the parameters of its marginal cost function with certainty—the only source of error (ε) comes from the demand function, the use of observed prices to estimate the demand equation could result in biased and inconsistent estimates.

Consider the possibility that the company in question has not been optimizing its prices, but will do so in the future, based on what it can learn about the demand for its product. If prices were previously set for some period of time without regard to the marginal costs, the demand curve can be estimated directly from the historical price, quantity, and exogenous variables, for example, with ordinary least squares.

Table 10.2 lists the coefficients of the demand equation for this scenario. The results represent two years of historical weekly observations (100 weekly data points). The estimated coefficients are quite close to the parameters of the true demand equation.

Table 10.2 Demand model estimation: Pre-optimization (initial) results

	Actual	Initial Estimation
Intercept	550	519.27 (137.12)
Price	-0.5	-0.43 (0.03)
Oil	-1	-0.94 (1.36)

Standard errors are in parentheses
Source authors' simulation

10.4.3 Potential Endogeneity Problems Stemming from Price-Optimizing Efforts: Ordinary Least Squares

Because the company estimated the demand curve for the purpose of selecting profit-maximizing prices, the company's new price-setting process may cause the standard endogeneity problem to creep into subsequent estimation of the demand curve. For example, if prices are reset weekly based on a demand curve that is re-estimated weekly, it may take less than a year for the estimated demand curve to become severely biased. This can be seen in Figs. 10.2, 10.3, 10.4 and Table 10.3.

These results represent the following process: (1) start with the original 100 historical data points; (2) estimate an initial demand model; (3) based on the known parameters of the marginal cost function, observed values of the exogenous variables, and estimated parameters of the demand model determine the quantity that maximizes expected profits; (4) based on this production decision, the company then adjusts it price to clear the market—a price response that will be based in part of the unobserved component of the demand function; (5) record the quantity produced and the resulting price for that period; and (6) re-estimate the demand model, using the 100 most recent observations. Steps 3 through 6 are repeated for each production decision period (e.g., weekly). As the following three Figures show, the estimated demand curve rotates with successive periods of optimization, in this case becoming more inelastic.

The hollow circles in the three graphs are the price and quantity points that were generated before the firm started optimizing. The crosshair symbols are the price and quantity points that were generated after the firm started optimizing. Even though OLS was the most appropriate method to use prior to the optimization

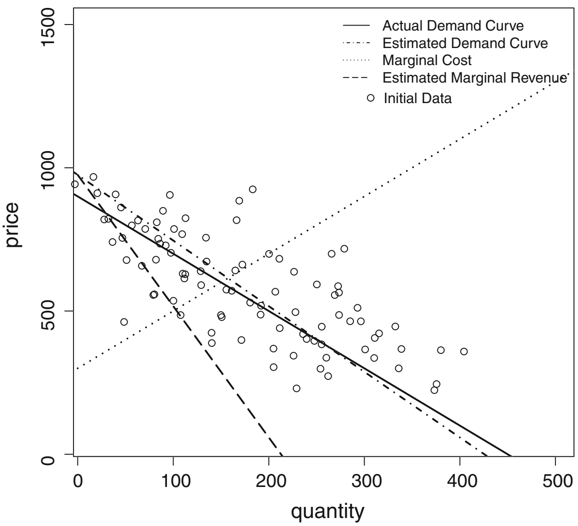


Fig. 10.2 Initial estimate (OLS)

Fig. 10.3 After one year (OLS)

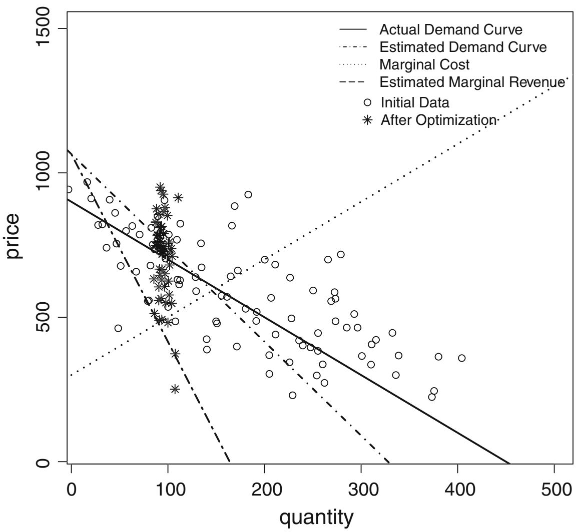


Fig. 10.4 After two years (OLS)

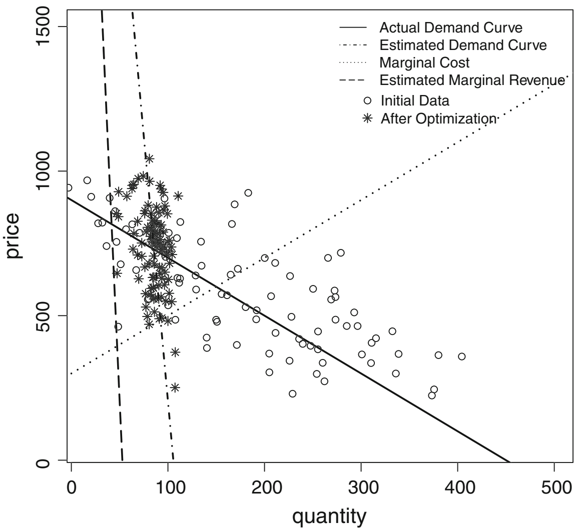


Table 10.3 Demand model estimation: Initial and two-years of post-optimization (Ordinary least squares (OLS))

	Actual	Initial Estimation	After 1 Year (OLS)	After 2 Years (OLS)
Intercept	550	519.27 (137.12)	329.91 (127.24)	125.16 (24.16)
Price	-0.5	-0.43 (0.03)	-0.31 (0.03)	-0.03 (0.01)
Oil	-1	-0.94 (1.36)	-0.02 (1.25)	-0.20 (0.23)

Standard errors are in parentheses
Source authors' simulation

process, over time the estimated demand curve diverges from the true demand curve. Table 10.3 shows that the estimated price coefficient changes from its initial value of −0.43 to an almost completely inelastic −0.03 after two years.

10.4.4 Postoptimization Estimation: Instrumental Variables

Typically, economists will look for an identifying variable to include in the two equation model to solve for endogeneity. Here, one can use the variable, steel, which is found in the marginal cost equation but is not in the demand equation. As in the prior example, re-estimating the demand curve weekly for two years is simulated, using the evolving 100 most recent observations. The results are shown in Figs. 10.5, 10.6, and 10.7 and Table 10.4.

The last two columns of Table 10.4 show the OLS estimates and the instrumental variable (IV) estimates after 100 periods. The OLS estimate has become more inelastic than the actual demand curve, at −0.03, while the IV estimate provides a relatively good estimate of the slope of the demand curve, −0.47, which is close to the actual value of −0.50 listed in the first column. It is interesting to note that in this specific example, the IV estimates have a much large standard error than the OLS estimates after one year of re-estimation. At this time, in the estimation process, the demand curve is being estimated on 50 data points generated pre-optimization (where there was no endogeneity) and 50 data points postoptimization (where endogeneity exists in the data). After two years of re-estimation, the standard error of the IV estimates has reduced greatly.

Fig. 10.5 Initial estimates

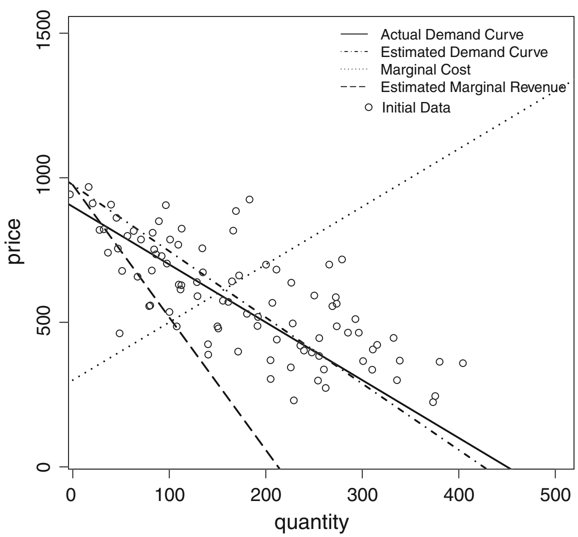


Fig. 10.6 After one year (IV)

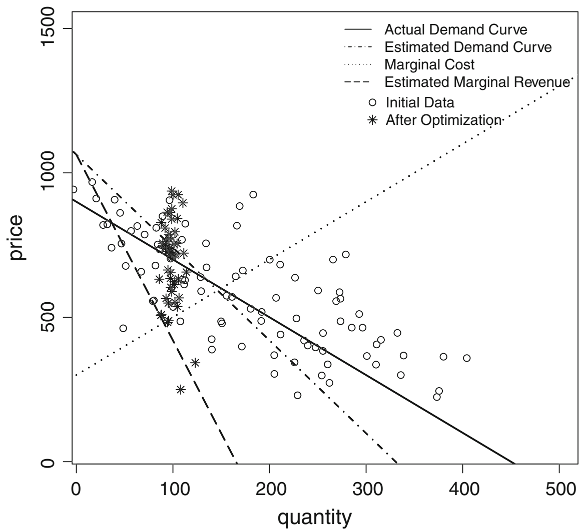
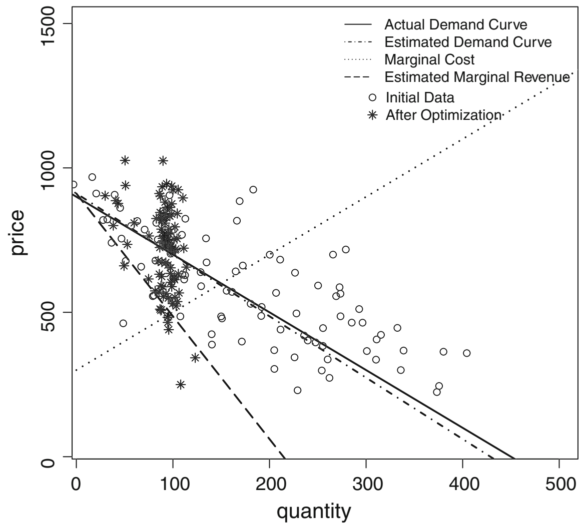


Fig. 10.7 After two years (IV)



Comparing Figs. 10.2, 10.3, 10.4 with Figs. 10.5, 10.6, 10.7 demonstrates that using steel as the identifying variable results in a much more accurate estimate of the demand curve. The estimated demand curves in Figs. 10.5, 10.6, 10.7 diverge much less from the true demand curve than the estimated demand curves in Figs. 10.2, 10.3, 10.4. Additionally, as shown in Table 10.4, using the identifying variable produces less biased estimates of the price coefficient than the first set of estimates in which one did not use the identifying variable. In both cases, OLS was the best method to estimate the initial regression, for data generated prior to price optimization.

Table 10.4 Demand model estimation: Initial and two-years post-optimization Ordinary least squares (OLS) v. (Instrumental variables (IV)

	Actual	Initial Estimation	After 1 Year (OLS)	After 1 Year (IV)	After 2 Years (OLS)	After 2 Years (IV)
Intercept	550	519.27 (137.12)	329.91 (127.24)	329.22(219.01)	125.16 (24.16)	545.17 (236.75)
Price	−0.5	−0.43 (0.03)	−0.31 (0.03)	−0.31 (0.23)	−0.03 (0.01)	−0.47 (0.12)
Oil	−1	−0.94 (1.36)	−0.02 (1.25)	0.01 (1.28)	−0.2 (0.23)	−1.17 (1.64)

Standard errors are in parentheses
Source authors' simulation

10.4.5 Postoptimization Estimation: Inside Supply Curve Information

The economist in the corporate setting can take this one step further and actually capture the marginal cost curve from the corporate processes. In this case, one can directly observe the marginal cost equation, for example, Eq. (10.5) above, which may provide significant advantages.

In many cases, locating an effective instrumental variable to identify the demand curve is a problem. Without knowing how the company sets prices and what inputs or factors the company considers when setting price, the researcher actually does not know what variables will make suitable instruments. With complete knowledge of which variables explain costs, and more importantly which variables influence the companies supply curve, the corporate economist knows whether or not there is a viable instrumental variable approach.

In situations where there is not an informative instrumental variable approach, explicit knowledge of how the variables considered in the cost curve and the price-setting process can still identify the demand curve based on the knowledge that error term in the corporate supply curve used is uncorrelated with the error in the demand curve. The corporate economist can know that the error term in the supply curve is not correlated with any other factors because she/he knows all of the factors in that supply curve, leaving the error term to be pure measurement error rather than some result of misspecification or omitted variables.

The significant advantage here is that where an economist outside the company may not be able to identify an instrument or an identification strategy, the economist inside the firm often can. This can often lead the economist outside the company to instrument with a variable that is not actually used by the company in the supply curve or perhaps a weak instrument. Here, a scenario is considered in which there is a weak instrument as compared to the situation where the same supply and demand is identified based on the knowledge that the error terms in the supply and demand are not correlated. (Technical details, which are based on Kmenta (1986), pp. 668–678, are available from the principal author).

In this example, the supply curve and the demand curve underlying the pre-optimization data are as follows:

$$S: Q^S = 100 + 3 * \text{price} - .01 * \text{Steel} + \varepsilon_s$$

$$D: Q^D = 550 - 2 * \text{price} + \varepsilon_D$$

$$\varepsilon_S \sim N(0, 1)$$

$$\varepsilon_D \sim N(0, 10).$$

Note that the steel instrument is weak. In addition, there is no correlation between the error terms in the demand and supply equations.

Data for this scenario were generated as follows. First, similar to the previous scenarios, assume that 100 price/quantity data points were the result of an essentially random price-setting process. Ordinary least squares was then used to estimate an initial demand curve. Then, for the next (101st) period (e.g., the following week), the firm produces a quantity of output based on (1) the parameters of the estimated demand curve, (2) draws from the distributions for the exogenous variable (steel) and the supply and demand curves error terms, and (3) the intersection of the supply and demand curves based on those values. Price then adjusts, based on the true demand curve. The resulting price and quantity are recorded and the demand model is re-estimated (using either an instrumental variable without an error term restriction or a restricted instrumental variable estimation) with the most recent 100 observations, that is, the new observation replaces the first observation of the original data. These steps are repeated for periods 102 through 204. Table 10.5 shows these results for demand models estimated from this process.

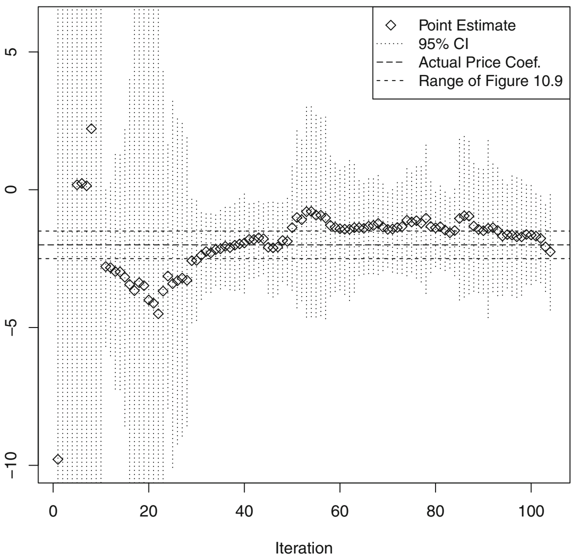
The first column reports the actual slope and intercept for the demand equation. The second column shows the ordinary least squares estimated for the initial 100 observations. The next six columns contrast (a) the OLS estimate (OLS2); (b) the simple IV estimate (IV2); and (c) the constrained estimate (cov = 0) estimated with (1) observations 53–152 (most recent 100 observations after the first year of price optimization) and (2) estimated with observations 105–204 (most recent 100 observations after the second year of price optimization). In particular, the last column of Table 10.5 shows the results for the identification by the error structure

Table 10.5 Demand model estimation: Ordinary least squares (OLS2), weak instrument (IV2), and uncorrelated errors (cov=0)

	Actual	Initial estimate	After 1 year	After 1 year	After 1 year	After 2 years	After 2 years	After 2 years
			(OLS2)	(IV2)	(cov=0)	(OLS2)	(IV2)	(cov=0)
Intercept	550	547.920	539.273	458.400	553.955	276.580	558.373	536.703
		(8.406)	(8.406)	(158.427)	(11.576)	(24.960)	(74.220)	(18.174)
Price	−2	−1.981	−1.863	−1.008	−2.011	1.048	−2.077	− 1.940
		(0.083)	(0.090)	(1.673)	(0.040)	(0.277)	(0.825)	(0.182)

Standard errors are in parentheses
Source authors' simulation

Fig. 10.8 Price coefficients—IV2



after two years of optimization. The second-to-last column shows the estimates based on a weak instrument after two years of optimization. The third-to-last column shows the estimates based on the OLS estimates. The estimated slope of the IV estimate has a large standard error relative to both the OLS estimate and the (cov = 0) estimate.

Figure 10.8 illustrates the practical effect of the large variance in the IV estimate. With the weak instrument, the variance of the estimated price coefficient is large and the estimated price coefficient tends to drift significantly over time.

Such instability in the estimated price coefficient could cause a significant practical problem in establishing profit-improving prices, as suggested by the two dashed horizontal lines representing the much tighter bounds of the estimated price coefficient when the identification is based on the more detailed understanding of the supply curve used in the (cov = 0) model.

Figure 10.9 displays the progression of the estimated price coefficient over time that results from the constrained (cov = 0) estimation.[23] These results make use of the fact that one knows that the error in the supply curve is not correlated with the demand, which follows from understanding the company's production process. Here, the precision of the estimates is much greater, ranging from −2.1 to −1.95, and with much tighter 95% confidence intervals.

Figure 10.9 shows some variation in the estimated price over time, but the range of the variation is much smaller. In fact, while both the IV and the (cov = 0) estimates reveal that the random draw of the exogenous and error term data used in

[23] These results are based on the same historical pattern of exogenous variables and error terms used to generate the results shown in Fig. 10.8.

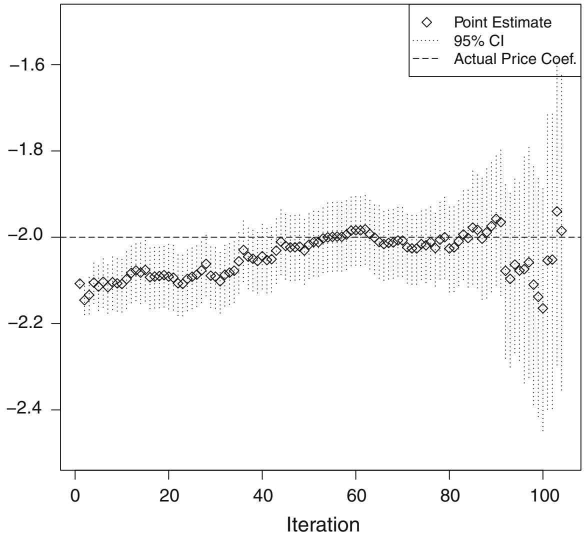


Fig. 10.9 Price coefficient estimates—(Cov = 0)

these simulations had a rather extreme combination around month 88, the estimated price coefficient of the (cov = 0) model was considerably more stable than the estimated price coefficient based on the IV method. This outcome illustrated the potential advantage that knowing the structure of the supply curve can afford. Simply by knowing how the company sets its prices can allow the economist to know whether the error in the supply curve is correlated with the error in the demand curve. With this knowledge, which would be hard for economists outside

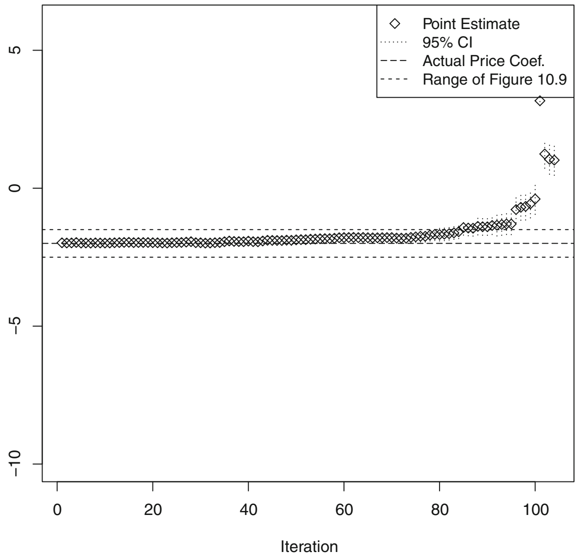


Fig. 10.10 Price coefficient estimates—OLS2

the company to obtain, one can obtain better estimates of the demand curve than would otherwise be available—in great part because this knowledge opens up the use of a broader set of estimation techniques.

Finally, Fig. 10.10 shows the pattern of OLS estimates of price coefficient over time. Not surprisingly, the OLS estimates show a pattern of bias and moves outside the bounds of the estimates provided by the (cov $=$ 0) estimates.

10.4.6 Both the Wrong and the Right Marginal Costs Need to be Used

Even when inside a company, some may wonder whether the precise cost curves can be known. When estimating the demand curve, it is important to recognize that the supply curve that the company *used* to set prices is the one that should be used to estimate the demand curve. The supply curve used by the company to set prices may not be the actual supply curve derived from the marginal cost curve. In fact, the supply curve used by the company often does depart significantly from that derived from marginal costs. There are a wide range of reasons accounting for why this can be the case. For example, corporate managers may have strategic goals to increase volume in certain market segments. Or it simply could be that corporate managers have not measured costs with sufficient accuracy. Regardless of the reason, the marginal cost curve that the corporate managers use to set prices is the one that should be used to recover the demand curve. However, even if this is the case, in extracting an estimate of the demand curve from the market price and quantity pairs, the supply curve that should be used is the one the company actually used to set prices. This type of information is unlikely to be available to any researcher outside the company and it can greatly improve the precision of the estimates and eliminate bias.

By not using the accurate marginal cost curve in setting prices, corporate managers are foregoing maximum profits. This problem must be addressed in the optimization process and not during recovery of the demand curve. This leads to the interesting result that as a company moves toward the more explicit process of optimization, the supply curve used for estimating the demand curve will be the one that managers used historically. However, once the demand curve has been estimated, the marginal cost curve used to optimize prices should reflect as closely as possible actual marginal costs. This means that as a company makes the transition to explicit price optimization, corporate managers will have to use two different sets of supply curves. The first “functional” supply curve will be whatever supply curve was used during the historical period over which the demand curve is estimated; the second supply curve is based on the actual marginal cost curve measured as precisely as possible for use in optimizing future prices.

10.4.7 *Approximate Optimization Approaches and the Endogeneity Problem*

Under certain circumstances, information from initial demand equation estimation could be used to change prices in a way that does not introduce the usual endogeneity problem, that is, the price and quantity data could be used with standard econometric methods such as ordinary least squares. This scenario proceeds as follows.[24] First, based on an earlier period in which prices were set in an essentially random fashion, a company produced estimates of the structural demand parameters close to the actual values (550 for the intercept, −0.5 for price and −1.0 for oil). The estimated parameters are shown in Table 10.2 above. Second, since the company does not know the precise value of the error term for a particular period, suppose the company set prices going forward based on the non-random components of an estimated price equation, which represents price optimization, given (1) the results of the demand study and (2) lack of knowledge of the error term.[25] Since the price-setting process does not include the demand equation error term (but does incorporate exogenous supply-side shifts and *expected* demand reaction), the price/quantity data can be used with standard ordinary least squares.

To illustrate this process, one hundred such data points are generated, representing approximately two years of weekly price changes to pass through the price of steel, based on the previous demand model and optimization to expected demand levels. Table 10.6 reports the results of this illustrative estimation.[26]

Because the prices set by the company are (by construction) not endogenous with demand, the resulting coefficients are reasonably close to their true values. Of course, if the company were reasonably satisfied with the model previously developed from pre-optimization observations, the exercise depicted here is at best a validation of the previous demand results. However, because (1) there is variation in the data, due to the effect of exogenous shifts in supply and (2) these prices

[24] This scenario differs from the early one in which the company first determined a quantity that was expected to maximize profits and then was able to adjust price in "real time" to sell just that volume. In this alternative example, assume that while prices can be adjusted for exogenous factors, the business is not able to respond to the random fluctuations in demand introduced by factors not explicitly included in the estimated model.

[25] In particular, the estimated coefficients from Table 10.2 and the known marginal cost curve are used to determine prices that equate expected marginal revenue with marginal cost, given observations for the exogenous variables.

[26] The data are the second 100 observations from a random draw of 1,000 sets of values for the prices of oil, steel, and the error term of the demand equation. The distributions are assumed to be independently normal with means and standard deviations of (100, 5), (50, 15), and (0, 10) for oil, steel, and the error term, respectively. For each of these sets, prices were generated by applying the demand equation in Table 10.2, without the error term. Quantities were generated using the structural parameters of the demand equation with the values for price, oil, and the error term. Results for the other nine sets (e.g., observations 1 through 100, etc.) are similar.

Table 10.6 Demand model estimation after 100 periods of expected price optimization

	Actual	Estimated coefficients
Intercept	550	592.14 (80.97)
Price	−0.5	−0.540 (0.094)
Oil	−1	−1.118 (0.245)

Standard errors are in parenthesis
Source authors' simulation

Table 10.7 Demand model estimation after 100 periods of expected price optimization: price sensitivity trend

	Actual	Estimated Coefficients
Intercept	550	594.22 (81.52)
Initial Price	−0.5	−0.538 (0.095)
Oil	−1	−1.138 (0.252)
Price*Period	0.001	0. 000983 (0.0000465)

Standard Error in Parenthesis
Source authors' simulation

are not correlated with the errors in the demand equation, the data can be used to explore possible shifts in demand parameters.

For example, suppose consumers are gradually becoming less price sensitive. To represent this possibility, the quantities used to produce Table 10.6 are adjusted for consistency with the price parameter decreasing (in absolute value) by 0.001 per week, so that at the end of the 100 periods represented in the data, it is reduced in magnitude from its original value of −0.5 to −0.4. Table 10.7 presents the results.[27]

Again, because of the facts that (1) the prices for this example are uncorrelated with the demand equation error term and (2) the supply-side shifts produce variability in prices and quantities, the trend in price sensitivity is properly detected. In particular, the coefficient of the price/time period interaction term is close to the true price sensitivity trend of a 0.001 per period reduction in magnitude. At the same time, the coefficients of the other two variables, the initial price sensitivity and oil are close to the values estimated in Table 10.6.

10.5 Conclusion

Motivated by Professor Taylor's advice and the realization that working with companies to apply these principles may not only improve short-term performance (if successful), but also affect how the company subsequently improves its

[27] The results are not sensitive to whether the trend in the price coefficient is assumed to be the same constant reduction each period, or whether there is variability in the period-to-period reduction in price sensitivity.

understanding of how customers respond to its product and pricing decisions, some of the econometric issues that may arise in the process are explored. As more experience is gained along the path toward explicit price optimization, additional issues are likely to emerge. For example, to the extent that ever-present proprietary concerns permit, further identification of the ways in which issues such as data availability, choice of estimation approaches, for example, IV, and identification issues differ between academic and business settings would be valuable information for businesses and their demand analysts. Along these lines, more analysis of how detailed knowledge of cost processes—for example, to the extent of obtaining cost relations with minimal error—can be used in improving the demand estimation process with respect to identifying structural equations, selecting powerful instruments, and the like has the prospect of adding to the analytical tool kit of practical demand analysts.

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