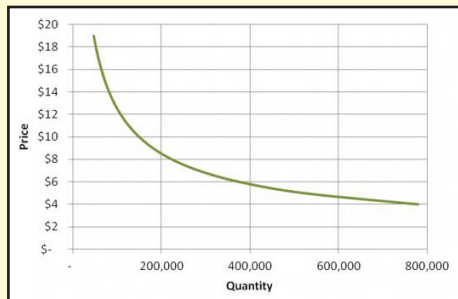


# Is Economic Price Optimization Optimal?



Economic price optimization is both a theory that is deceptively beautiful but also one that requires caution in its engagement. In this paper, the authors attempt to bridge the gap between the abstract and the concrete as it relates to economic price optimization. Tim J. Smith is the managing principal at Wiglaf Pricing, adjunct professor at DePaul University, a frequent PPS speaker, instructor and presenter, and the Academic Advisor for the Certified Pricing Professional designation. His most recent book is *Pricing Strategy: Setting Price Levels, Managing Price Discounts, & Establishing Price Structures* (South-Western Cengage Learning, 2012). He can be reached at [tsmith@wiglafpricing.com](mailto:tsmith@wiglafpricing.com). Brian C. Lowe greatly contributed to the development of this article. He can be reached at [bclowe@wiglafpricing.com](mailto:bclowe@wiglafpricing.com).

**E**conomic price optimization is a seductive concept. The name of it alone implies that it delivers the best answer to the difficult question of what the best price to charge is. But digging beneath the surface, one uncovers a theory not unlike many others in economics: one that is deceptively beautiful but that requires caution in its engagement.

Like other good theories, economic price optimization makes predictions of cause and effect that enables humans to manage complex challenges, but does so only in tightly constrained situations. For most pricing challenges, economic price optimization is associated with insurmountable limitations. For some pricing challenges, economic price optimization is a useful workhorse. And across the board, theoretical examinations of economic price optimization can be used to clarify corporate strategy. The simple matter of fact is that there exists no single formula or program one can plug her firm's data into to obtain an optimal pricing solution across all industries.

In this paper, we will attempt to bridge the gap between the abstract and the concrete as it relates to economic price optimization. Specifically, we will be addressing the questions of:

- What is economic price optimization *really*?
- What are the dominant approaches to economic price optimization and how can firms execute these approaches?
- What is the price determination value of the various approaches to economic price optimization?
- What are the strategic implications of economic price optimization?
- How has the concept of economic price optimization from historical market data been extended to address a wider variety of price determination challenges?
- What are the alternative price determination approaches and why are they superior for many price determination challenges?

We write this missive as a guide specifically for managers within firms in competitive markets so that they can know when economic price optimization is useful versus useless, and which form is useful in which situation. Our hope is that this will help execu-

tives—those in real firms competing for real business—manage price better.

For clarity, when we refer to economic price optimization, we are referring specifically to methods which rely on historical market data, be it internal sales transactions or externally gathered market data, to manage the pricing of goods and services for a current or future period, and are not referring to the overall concept of price optimization which may or may not require the use of any of the techniques described herein. In doing so, we treat economic price optimization as a subtopic of the more general theory of price optimization.

To address these questions at the executive level, Part 1 refreshes reader's recall of Microeconomics 101 with the simple case of economic price optimization using linear demand functions. Part 2 examines economic price optimization using elasticity of demand. Part 3 takes a far more advanced approach by clarifying the realistic firm-level demand function and its implications for economic price optimization. Part 4 clarifies the practice of economic price optimization through A/B testing. We conclude with Part 5 where we place economic price optimization within a broader framework of price determination.

## Part 1: Linear Demand Functions and Economic Price Optimization

Economic price optimization relies on a defined demand curve, the simplest of which is a straight line. We start by examining economic price optimization with a globally linear demand function. Taking a simplified view is helpful in determining a baseline judgment for the utility of this technique.

### Step 1: The Firm's Profit Equation

Economic price optimization refers to finding the price that will maximize the firm's profits. It does so by taking the first derivative of the firm's profit equation with respect to price, setting this equal to zero, and finding the price which satisfies the resulting

equation. To demonstrate, start with the standard form of the firm's profit equation:

$$\pi = Q \cdot (P - V) - F$$

where  $\pi$  stand for the firm's profit,  $Q$  stands for the quantity sold,  $P$  stands for the price of the product,  $V$  stands for the variable costs to make the product, and  $F$  stands for the firm's fixed costs. There is nothing new in this equation. It is taught in freshman business classes.

### Step 2: Set the Derivative with Respect to Price Equal to Zero

As freshman calculus tells us, the profit function for normal products is maximized where the first derivative of the profit with respect to price equals zero. The price which delivers the maximum profits is clearly the optimal price from the firm's perspective.

In looking at the profit equation of the firm, we can see that a price change affects the firm's profit directly through the variable  $P$ . We can also expect that a price change influences the quantity sold and so indirectly affects the firm's profit through the variable  $Q$ . As for  $F$  and  $V$ , fixed and variable costs are constants with respect to a pure price change.

Taking the first derivative of the firm's profit equation with respect to price, and setting this equal to zero yields

$$\frac{\partial \pi}{\partial P} = \frac{\partial Q}{\partial P} \cdot (P - V) + Q = 0$$

### Step 3: Use the Demand Function

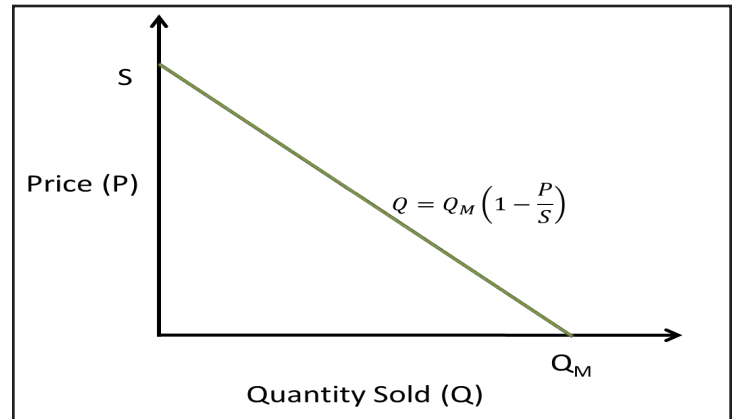
The derivative of the firm's profit equation depends upon the relationship between price ( $P$ ) and quantity sold ( $Q$ ). The demand function defines this relationship.

Economists often make a simplifying assumption of the shape of the demand function to both demonstrate the approach and uncover strategic implications. Given that higher prices are associated with lower sales volumes, and lower prices deliver higher sales volumes for normal goods, we know the demand function must slope downward. The simplest method for approximating a general, downward sloping, demand curve is a straight line. Hence, economists often assume a globally linear downward sloping line when demonstrating economic price optimization in freshman economics classes.

No decent economist actually believes demand curves are globally linear, but we all like them because they are simple and instructive. Hence, whatever follows from here must be taken not from the viewpoint of 'This will give us the definitive and quantitatively accurate best price.' It will not. But it can be taken from the viewpoint of 'This might give us some insights into pricing and corporate strategy.'

A globally linear demand function is defined as that which the quantity demanded by the market varies linearly with the price extracted by the firm. It would look like:

Figure 1: Globally Linear Demand Function



or be described mathematically as:

$$Q = Q_M \cdot \left(1 - \frac{P}{S}\right)$$

Where  $Q_M$  is the maximum demand possible in the market (the quantity demanded when the price is zero, i.e. free) and  $S$  is the maximum price at which any one unit can be sold. Conceptually,  $S$  is a very powerful issue. It represents simultaneously the maximum utility or benefits delivered by any one item to anyone in the market and the maximum willingness to pay by any customer within the market.

### Step 4: Insert, Simplify, & Identify

Inserting the demand function into the above questions and simplifying reveals the following identities:

**The optimal price is:**

$$\hat{P} = \frac{1}{2}(S + V)$$

**The quantity sold at this price is:**

$$\hat{Q} = \frac{Q_M}{2S}(S - V)$$

**And the firm's profit at this price is:**

$$\hat{\pi} = \frac{Q_M}{4S}(S - V)^2 - F$$

(For fun, try deriving these equations on your own.)

### Price Determination Shortfall of Linear Demand Assumptions

Here again, these aren't equations an executive can actually use to set prices, set production, or predict profits. They were derived using an expression for the demand function which we know is

a lie. So what good is it? Does it have any practical implication? Should we throw it away along with this whole approach? In regard to actually setting prices, the answer is yes; with respect to strategic corporate insights, emphatically *no*.

### Strategic Implications Arising from This Simplistic Investigation

These equations may not tell us the optimal price nor predict profit, but they do tell us a lot about competitive strategy.

Starting with the equation for optimal price: Notice that optimal price (P) increases with the maximum benefits delivered (S) and the variable costs (V), and has no relation to fixed costs. That is perhaps the most consistent and important implication economic price optimization has to reveal about pricing: the firm's fixed costs should not affect pricing decisions. Having clarified that the relationship between fixed costs and pricing decisions should not exist; we can turn to the issue of benefits (S) and variable costs (V). Let's focus on the benefits (S).

The firm's optimal price increases when the value of the product to its market increases—that is when S increases. Hence, when a firm wants to charge higher prices, it should seek to enhance the benefits of their offerings and make their customers aware of these benefits. This is precisely why product managers need to focus on identifying the goals of their customers and developing solutions to their needs. It is also why sales executives are smart to practice value-based selling and marketing communications executives should spend money on messaging to convince customers of the benefits of their products.

As for the variable costs, V: executives often focus on cost reductions in order to ensure their prices are in line with the markets. The above equations support this approach, and firms do in fact need to manage costs to compete. But this is only half of the story, as told by these equations. Benefits are the other half—benefits delivered to customers.

Now, let's turn to the firm's profits at the optimal price. Notice that profits are dependent on the difference between S and V, squared. That is, the greater the difference between the benefits a product delivers to a customer and the cost to produce the product at the firm, the more the firm makes. And the profits aren't just linearly dependent upon the difference between the benefits delivered and the costs to create, they are quadratically dependent, that is, for every doubling of difference there is a quadrupling of profit.

This relation between profit and the difference between benefits delivered (S) and costs to produce (V) clarifies much of modern competitive strategy. Modern competitive strategy often takes a resource-based view that claims:

- A firm has a competitive advantage if it can earn more profit than its competitors in the same market.
- If a firm wants a competitive advantage over its competitors, it needs some strategic resource that its competitors do not and cannot have (rare and inimitable).
- Moreover, that strategic resource will be strategic precisely because it enables the firm to deliver more benefits to its customers than its competitors without increasing costs, or

it enables the firm to reduce costs without reducing benefits, or do both concurrently.

Put in relation to our equations, a strategic resource delivers a competitive advantage precisely because it increases the difference between S and V—that is, the difference between the maximum benefits delivered and the costs to produce, in comparison to its competitors.

### Part 2: Locally Measured Elasticity of Demand and Economic Price Optimization

Theoretically, if you know the elasticity of a market's demand for a service or product, you can optimize the price of that offering through economic price optimization. Yet this statement overlooks the basic problem: how can you measure the elasticity of demand with sufficient accuracy to make the endeavor worthwhile? Making an errant assumption of elasticity is both a common and efficient method of decimating a firm's profitability and market standing.

To clarify, we will define elasticity of demand en route to identifying the economically optimized price around a locally known elasticity of demand. We will then demonstrate the sensitivity of the derived optimal price to the uncertainty in the elasticity of demand.

#### Step 1: Know what the elasticity of demand describes

Price optimization requires knowing the relationship between price (P) and quantity sold (Q). If we know how many units are sold at a given price and the elasticity of demand around that price, we can then identify the local demand function.

By definition, the elasticity of demand, denoted by epsilon, is the ratio of the percent change in quantity sold to the percent change in price. Mathematically, we would write this as

$$\varepsilon \equiv \frac{\% \Delta Q}{\% \Delta P}$$

#### Step 2: Express the elasticity of demand for the case of infinitesimally small changes in price and quantity sold

The definition of the elasticity of demand uses the percent delta Q (%ΔQ) and the percent delta P (%ΔP).

Percent delta Q is the change in quantity sold (ΔQ) expressed as a percentage of the quantity sold. That is,

$$\% \Delta Q \equiv \frac{\Delta Q}{Q}$$

For infinitesimal changes in quantity sold, ΔQ is replaced with δQ where the lowercase delta denotes a very small (infinitesimal) change. In this case, we write

$$\% \Delta Q = \frac{\partial Q}{Q}$$

Similarly, percent delta P is the change in price expressed as a percentage of the price. We can write it in either form as

$$\% \Delta P \equiv \frac{\Delta P}{P} = \frac{\partial P}{P}$$

Using the infinitesimal forms of the percent change in quantity sold and percent change in price in the definition of the elasticity of demand and we find

$$\varepsilon \equiv \frac{\partial Q / Q}{\partial P / P}$$

### Step 3: Integrate to find the local demand function

We can integrate the above equation to find the local demand function. Simply rearrange the definitional equation of the elasticity of demand equation to separate the Ps and Qs to other sides of the equality

$$\varepsilon \cdot \frac{\partial P}{P} = \frac{\partial Q}{Q}$$

then integrate both sides, starting at the known price and quantity sold and going up to the price and quantity sold that we want to investigate:

$$\varepsilon \int_{P_i}^P \frac{\partial P}{P} = \int_{Q_i}^Q \frac{\partial Q}{Q}$$

to yield

$$\varepsilon \cdot \ln \left( \frac{P}{P_i} \right) = \ln \left( \frac{Q}{Q_i} \right)$$

Using both sides of this equation as the exponent of the natural number e, and some properties of exponents and logarithms we may recall from high school algebra, we find the demand as a function of price around a known quantity demanded at a known price to be

$$Q = Q_i \cdot \left( \frac{P}{P_i} \right)^\varepsilon$$

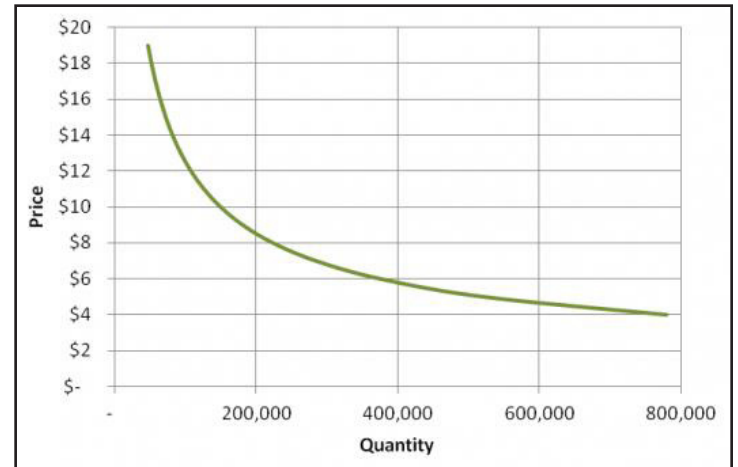
This is the demand function with a locally known elasticity.  $Q_i$  and  $P_i$  are the known quantity sold at the known price.  $\varepsilon$  is the elasticity in demand around that price.

The elasticity of demand is known to not be constant across all

prices, yet that is not a fatal flaw to this approach. So far, we have assumed that the elasticity is locally constant, and have used the subscript  $i$  on both price (P) and quantity sold (Q) to imply the local measurement of the elasticity around some known initial price and quantity sold. As long as we are considering price changes near that locally measured point, we can accept this approximation and continue our analysis.

A plot of this demand function can be found below given an elasticity of -1.8 (an average elasticity of demand for consumer products) around the price of \$10 where 150,000 units are sold. Notice that lower prices are associated with higher sales volumes and higher prices are associated with lower sales volumes.

Figure 2: Demand Curve with Constant Elasticity



### Step 4: Use the demand function to optimize the price against the firm's profit function

From here, prices can be optimized against the firm's profit equation. We begin as before with the standard form of the firm's profit equation

$$\pi = Q \cdot (P - V) - F$$

Once again, we take the first derivative of the firm's profit equation with respect to price and set this equal to zero to find the profit maximizing price.

$$\frac{\partial \pi}{\partial P} = \frac{\partial Q}{\partial P} \cdot (P - V) - Q = 0$$

Q is defined above in relation to P through the elasticity equation and similarly the derivative of Q with respect to P is defined by the elasticity equation as

$$\frac{\partial Q}{\partial P} = \varepsilon \cdot \frac{Q}{P}$$

Inserting and simplifying, we find the optimal price for elasticities  $>1$  to be

$$\hat{P} = \frac{\varepsilon \cdot V}{1 + \varepsilon}$$



Notice that the optimal price is dependent on the variable costs and elasticity alone. That is, once again, *fixed costs have no effect on the optimal price*, only variable costs.

**Price Determination Value of Economic Price Optimization from Elasticity Metrics**

A numerical example will help us see the value of the resultant equations.

Suppose a firm makes an item for \$5, sells it for \$10, and at \$10, the firm sells 150,000 units. Furthermore, the firm has a fixed cost of \$500,000. (V=\$5, Pi=\$ 10, Qi=150,000, F=\$500,000)

Managers then go out and measure the elasticity of demand to optimize prices. Perhaps they use NPD data or they use their own transactional history. Either way, suppose they find the elasticity is about -1.8. I say about because they weren't able to measure the elasticity exactly. Statistically, they may only know that it is -1.8 +/- 0.5. That is, they know it is around -1.8, but aren't sure if it is higher or lower. It has a 95% probability of being somewhere between -2.3 (= -1.8 - 0.5) and -1.3 (= -1.8 + 0.5), and it is rather unlikely that it is exactly -1.8, but that is the manager's best expectation.

(A note about statistics and measurements: the 95% confidence interval around a measurement is defined to be 1.96 standard deviations above and below the measurement.)

This is the nature of elasticity measurements. We rarely are able to measure elasticity precisely. We may be able to narrow our uncertainty down to some range, but will never know it exactly. In studying years of transactional history on various specific products, there have been many cases where the elasticity of demand was completely immeasurable and many cases where it could be measured to only one significant digit. Elasticity can rarely be measured with any real precision – that is, to two or more significant digits.

So what happens when we use our elasticity measurements to identify the “optimal” price? Well, since we can't measure the elasticity exactly, we only know it falls within some range; we should similarly suspect we won't find the optimal price exactly, only that it falls within some range. We may be partially satisfied with this, given that a range is better than nothing. So let's find the range of prices associated with the expected range of elasticity found in the measurement. While we are at it, let's also calculate the quantity sold and profit at each potential price.

We find the following for different expectations for price, quantity sold, and profits for the range of the elasticity of demand identified: (see figure 3)

If you review the table in figure 3 carefully, the challenge should become clear.

In this example, we stated managers were able to measure elasticity to be -1.8 +/- 0.5, which would be a very good measurement as measuring these things goes. With this measurement and level of precision, they would predict the optimal price to be \$11.25

Figure 3

	Low Expectation	Expected Value	High Expectation
Elasticity of Demand (ε)	-1.3	-1.8	-2.3
Optimal Price (P)	\$ 21.67	\$11.25	\$ 8.85
Quantity Sold (Q)	54,899	121,344	198,864
Profit	\$414,977	\$258,397	\$265,861

and should report that it could lie anywhere between \$8.85 and \$21.67. Now what should an executive do with this result?

The executive is likely to interpret the analytical results with the following logic: “This pricing analyst thinks the price should be \$11.25, but acknowledges the best price could be as low as \$9 and as high as \$21. Given he can't narrow it down inside a range of roughly a factor of 2, he is effectively saying he doesn't know.”

Now if the executive is managing thousands-to-millions of products and is able to identify the elasticity of demand for each product, even with some high level of uncertainty, relatively cheaply and time-efficiently, then, as a future argument will show, perhaps going with the suspected optimal price for each of product, while acknowledging some prices will be too low and others too high, is better than guessing or more cost-effective than the alternative pricing methodologies.

But, in most situations, the executive will be forced to conclude the effort was costly and fruitless.

Now, if this approach isn't good for pricing in most cases, what does it tell us? Examining the results of the numerical example reveals that a firm's profits increase as the demand for their products become more inelastic. This in turn implies firms should focus on making the market demand for their offerings somewhat inelastic, and on finding customers whose demand for their offerings is somewhat inelastic. And how can firms do that? At this point, we have reentered the realm of market segmentation, branding, and value-based selling, the core of sales, marketing, and entrepreneurship.

**Part 3: Firm-Level Demand Functions and Economic Price Optimization**

In the two prior sections, we examined standard models for price optimization taught in freshman economics. In both cases, these models yielded some fruit, but proved questionable when it came to actually identifying prices. We reached the conclusion that all competitive advantage derives from exploiting a rare and inimitable resource that enables a firm to deliver greater value at a lower cost to its customers. This is a significant accomplishment and should not be overlooked.

However, this conclusion is not what most executives think about when they think of economic price optimization. Instead, they think of it as a concrete and self-sufficient method for pricing. And we have seen that simplistic approaches are of questionable value when it comes to actually pricing a product or service.

We also posited that firms seeking pricing power should seek to reduce their customers' price sensitivity, usually implying the firm should seek to increase its customers' sensitivity to differences in benefits. Again, this is an accomplishment and should guide

strategy decisions, but the wide range of returned results limits its utility for the vast majority of companies.

One major fault with both of these models derives from a common shortcoming, and this shortcoming can be overcome—*theoretically*.

### Identifying the Shortcoming

Economic price optimization relies upon an accurate depiction of the market demand function. Neither of the above approaches uses a demand curve that is observed in actual markets. They may approximate demand curves for small changes in price, but they do not describe the real, observed demand curves.

Real markets don't generally face a linear demand function, nor a power-law demand function. The assumption that elasticity is part-wise constant may be true for small changes in price and quantity sold, but this assumption doesn't describe the observed demand at all prices for any known market. Both of the previous models have more utility in the classroom than the boardroom, as while they do simplify derivations and the demonstration of the underlying concepts, they don't capture the full beauty and complexity of market behavior. Elasticity is useful for describing the market's reaction to a small price change, and therefore managerially useful for evaluating the potential for a small price change. Yet while this model is useful for small price changes, it isn't the best approach for describing the market's reaction to all possible prices. In fact, it is generally the wrong mental model to use when trying to describe the full range of prices possible.

### Describing Firm-Level Demand

We need a better model of demand. Fortunately, they do exist. But first, let's think about how real markets react to real prices offered by firms.

Please note: This paper is examining firm-level decisions in competitive markets, not the 'whole market'-level issues. This approach is necessary to address the challenges faced by real executives that manage real businesses, not economists or governmental agencies describing and regulating entire industries. As a point of clarification for classically trained economists: you may wish to think of this as the decisions of a firm engaged in monopolistic competition moving to the extreme of perfect competition. This does describe most real firms in real competitive markets under free-market capitalism as it is practiced today.

### Maximum Prices

For a firm serving customers in a market with competitors, there is a price so high that it can expect all of its customers to abandon it and choose to purchase from a competitor. Let this be defined as  $P_{Max}$ . At any price above  $P_{Max}$ , the firm's demand drops to zero. At a price below  $P_{Max}$ , at least one customer will purchase something.

### Minimum Prices

For a firm serving customers in a market with competitors, there is a price so low that it can expect all customers to purchase from

it, with all competitors losing their business. Let this be defined as  $P_{Min}$ . At any price below  $P_{Min}$ , the firm's demand increases to reach the full demand of the entire industry.

In competitive markets,  $P_{Min}$  is likely to lie at a point below variable costs. That is, it is likely to be so low that the firm cannot sell at that price and make a profit, and since it is the price at which competitors won't sell either, it is likely to be below the minimum variable costs of even the most efficient competitor.

Since the firm makes no profits at  $P_{Min}$ , and is likely to achieve losses at  $P_{Min}$ , no rational firm should choose to price at  $P_{Min}$ .

### The Range in the Middle

At a price between  $P_{Max}$  and  $P_{Min}$ , some customers will purchase from the firm and other customers will purchase from competitors. This is the range of prices where a firm usually operates.

The demand function that we would want to use to describe the market's response to prices between  $P_{Max}$  and  $P_{Min}$  is some smooth function that describes the case of zero demand at  $P_{Max}$  and the entire industry demand at  $P_{Min}$ .

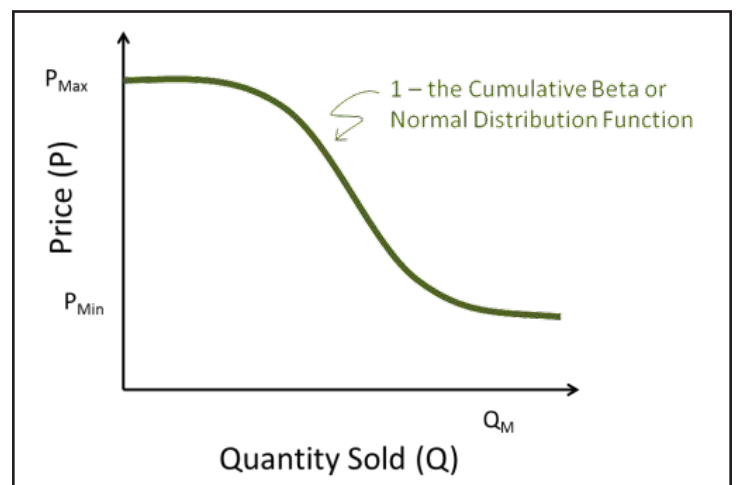
There are two commonly used functions that meet these goals. Most economists and marketers use the cumulative beta distribution function. Some use the cumulative normal distribution function. In either case, they produce demand curves like that shown below.

Now, given this demand function, where should a firm set prices?

Economic price optimization can be done with this model for demand and produce reasonably useful results after making appropriate measurements of various parameters required for defining the demand function. The math behind such an approach is the same as that described in our prior two models, but the equations get rather long and intractable with pencil and paper. As such, it is common to program a spreadsheet or software system to identify the optimal price for a given product and market.

### Mental Modeling

Figure 4: Observed Firm-Level Demand Function



Despite the increased precision of this last model, for most pricing problems, there are more efficient and accurate approaches to pricing optimization—approaches that start not with an abstract model of market demand but rather with concrete data gathered from customers and prospects regarding their perceptions of differential benefits and willingness to pay. For others, we find we want precision around a point rather than precision for the market overall. This implies that while this model of demand is superior to the linear or constant elasticity model, it still isn't perfect.

If the above demand curve can be used for subset of pricing problems only, what does it reveal to the rest of us?

Three strategic pricing concepts are revealed through the describing demand with a cumulative beta or cumulative normal distribution function.

### Number One: Shoot High, Explore Low

If a product has to have one list price for the market, where should it be on the Observed Firm-Level Demand Function? High.

Consider that most firms practice discounting. Discounting is a good method for exploring demand at prices below list. As a rule, a well-managed discounting policy enables the firm to capture marginal sales at marginally lower but still profitable prices. Since discounts are made from higher list prices, and since discounting can enable the firm to price an offer selectively for certain customers, we come to the conclusion that list prices should be set high on the demand curve while discounting policy is used to explore lower price points on the demand curve.

The key to pricing lies in understanding market demand, understanding what customers want and what they will pay for it, understanding that no two customers are alike and that each may have a different willingness to pay.

### Number Two: Most Firms Don't Sell Commodities

If someone claims their market is being commoditized, examine the range of prices in the market before you accept their claim.

$P_{Max}$  and  $P_{Min}$

In a fully commoditized market, the difference between  $P_{Max}$  and  $P_{Min}$  is zero. Using economics-speak, one would say "Under perfect competition, all firms are price takers. The industry-clearing price is the one price all firms must accept to be in the market."

Now most firms see some difference between the price at which demand collapses to zero ( $P_{Max}$ ) and the price at which they could capture the entire industry ( $P_{Min}$ ). The size of that difference, the difference between  $P_{Max}$  and  $P_{Min}$ , is a measure of the commodity nature of the industry.

**Not that there are hard rules about this, but one can pretty safely state the following:**

- If the same product is sold by multiple firms and the differ-

ence between the maximum price and minimum price of the product in the market is less than 5%, then that product is probably best described as a commodity.

- Alternatively, if similar products are sold by multiple firms and the difference between the maximum price of a product and minimum price of a product within the category is more than 50%, then that product should not be considered a commodity.

Some markets, like oil, wood, chemicals, gasses, and ingredient vitamins, are best described as commodity markets. In these markets, the difference between  $P_{Max}$  and  $P_{Min}$  is very small if not effectively zero.

Most markets however have a wide range of prices and products within the category. Just consider the price difference between Relic and Philippe Patek watches, Kia and Mercedes cars, or Nokia and Apple smartphones. Alternatively, consider the variation in prices captured for your own products and services in the market. Differentiated offering markets can see price ranges

with a difference greater than 1,000 times between the lowest- and highest-priced product within a category. These price differences directly reflect the non-commodity nature of these markets. Even if the highest-priced transaction in the market is only 50% higher than the lowest-priced transaction in the market, it remains difficult to call that a commoditized market. There is still room for price differentiation.

Let's here take Vulcan Materials as an example—even they can charge different prices to different customers for something as common as dirt and rocks.

### Number Three: Mental Models Matter

Many people like the idea of using economic price optimization to set prices, but it isn't as simple as identifying a number and plugging it into the model. That is the wrong mental model.

The key to pricing lies in understanding market demand, understanding what customers want and what they will pay for it, understanding that no two customers are alike and that each may have a different willingness to pay. And for that, there are many methods and no one approach solves all pricing problems. Not data analysis, not surveys, not interviews, but all of them and each for their own pricing challenge.

Firms don't confront a linear demand function. They don't even confront a demand function where the elasticity is relatively constant at different prices. They confront a demand function bounded at the top and at the bottom by some range within which prices should lie.

### Part 4: A/B Tests and Economic Price Optimization

Which is a better price: \$15.99 or \$16.49? From the customer's perspective, the lower of the two is normally preferred, but that doesn't mean it is the best price. Customer relationships need to be mutually beneficial. From the firm's perspective, the higher of the two may be preferred. To balance these two perspectives, we have the profit equation of the firm and the demand function of customers. Sometimes, the demand function can be adequately identified locally through a sample A/B experimental market test, and in these rare cases, firms may actually be able to economically optimize prices.

### Step 1: A/B Price Experiment

In a simple design of an A/B experimental price test, the exact same product, promotional material, and distribution outlet is presented to two sample sets of customers drawn from a representative population of prospective customers. The price varies in a controlled manner between specific high and low points. One sample only sees the high price. The other sample only sees the low price. After the samples have been shown the offers, the firm measures how often each sample does and does not purchase.

If the sample shown the high price purchases more often than that shown the low price, executives can safely conclude that the higher price is more profitable. Otherwise, two key analyses need to be conducted: 1) The Chi-Squared Test to determine if difference in purchase frequencies between the two samples is real or just a result of the inherent randomness of life. 2) A profit analysis to determine if the volume gains outweigh the margin losses at the lower price to identify the optimal price.

### Step 2: Chi-Squared Test for Significance of Difference

The first analysis, the Chi-Squared test, is a statistical test of significance. The Chi-Squared test identifies the probability that the difference in sales volumes between the two prices is the result in random variations between the samples, also known as random sample error. If the probability (the p-value) that the differences are due to random sample error is greater than 5%, a commonly used significance level, then executives generally conclude that the differences are meaningless. Else, they generally conclude the difference is statistically significant.

People don't have need to program a calculator nor be an expert in statistics to conduct a Chi-Squared test. They can do it easily in something as simple as Microsoft Excel, or they can turn to any of a number of statistical software packages.

### Step 3: Profit Analysis

The profit analysis enables executives to identify which price delivers the greater profit.

Let us call the high price PH and the low price PL. Similarly, let us call the frequency of purchases by the sample shown the high price %QH and the frequency of purchases by the sample shown the low price %QL. Finally, let V be the variable costs associated with the product. Since the product, promotion, and distribution is the same for both samples, V doesn't change.

Mathematically, if  $\%QL (PL - V) > \%QH (PH - V)$ , then the lower

price is more profitable. Otherwise, the higher price is superior.

Importantly, the profit analysis is contingent upon the Chi-Squared test. If the p-value of the Chi-Squared is greater than 5%, then any variation between the %QL and %QH may be meaningless and the firm should choose the higher price. Only when the statistical analysis has ruled out random sample error as the culprit behind observed purchase frequency differences can the profit analysis be conducted with any level of decision reliability.



### Simple, But Limited in Application

This approach is relatively simple to execute, analyze, and formulate recommendations, but it is also highly limited in its applicability. This approach often requires well over a thousand experimental runs before any reliable pricing decision can be made. Moreover, each of these experimental runs must be run in a relatively short time period to enable executives to exclude exogenous factors interfering with the experimental control.

For example, let us consider a relatively typical scenario. Executives are considering a 10% price reduction on an item. Based on experience, these executives know that only 5% of the people who see their offer purchase. The other 95% don't, perhaps because they were just curious about the market, checking availability, collecting a budgetary estimate, or, in a minority of situations, conducting comparison shopping. And even the comparison shoppers aren't necessarily all price sensitive, some were comparing differences in the whole customer experience (utility).

They may expect lower prices to be associated with higher sales volumes, but even assuming a slightly high market elasticity of 2 the 10% price reduction can only be expected to drive a 20% sales volume increase. Doing that math, we see that is equivalent to suspecting that a 10% price cut increases the purchase frequency from 5% to 6%. Detecting a 1% ( $10\% \times 2 \times 5\%$ ) difference in purchase rates isn't easy.

If each sample had only 100 customers in it, that would mean a difference of 6 purchases versus 5. That evidence alone would not suffice in convincing most rational business executives that the lower price is more profitable.

To satisfy the Chi-Squared at the 5% significance level, the experiment would have to run about 1,000 times, and even then



the difference would only be between 30 purchases at the low price versus 25 at the high price.

Worse, if the executives were considering a smaller difference, such as \$15.99 vs. \$16.49, they may need 10,000 experimental runs to come to a reliable decision.

While running thousands of experiments in a day may be reasonable for fast-moving consumer goods, it presents an insurmountable challenge for most products sold in most markets. For a wide host of long-tail (infrequently purchased) products, any hope that such an undertaking might be feasible may be dismissed out of hand. Purchase decisions about locomotive engines, manufacturing equipment, fiberglass roving, apartment units at a specific address, obscure textbooks, and many other products just aren't made that frequently.

## Part 5: A Broader Framework for Price Determination Methodologies

Economic price optimization through A/B tests is probably the simplest applied approach to using economic price optimization reliable. In comparison, the heuristic-based approaches for optimization through globally linear and locally measured demand models are overly simplistic and suffer from unrealistic assumptions about the market's response function. The mental modeling techniques we explored above more accurately describe the market's response function but generally rely on market research data, not historical sales data.

But although A/B testing has proved the most reliably option thus far, this approach can't be used very often. So what should an executive do?

First, let's reframe the question. Let us ask instead what data should be used to inform pricing decisions. Is historical transactional data both predictive of the future and rich enough to clarify relationships? If not, can market research techniques be used to develop a more predictive and rich vision of the relationships for pricing decisions? Which source of data should be used to optimize pricing?

In some cases, pricing decisions based on historical data is the right approach. In other cases, market research approaches prove superior. Specifically, in cases where the company is making the product or delivering the service itself, when the offering is differentiated, or when the product is new, market research approaches are usually more appropriate and accurate than economic price optimization approaches. These market research approaches usually take the form of either Voice of Customer (VOC) executive interviews informing the development of models of the Exchange Value to Customer (EVC), or Market Surveys using Conjoint Analysis. As an added bonus, market research can uncover actions which executives can take to improve their pricing power.

Second, if managers really believe pricing based on historical data is appropriate for their market, then more sophisticated econo-

metric approaches can be used. Numerous consulting firms and software vendors have developed algorithms and data-collection solutions to serve this need, and many executives have reported positive results. These methodologies can be collectively named Data Mining Pricing.

## Data Mining Pricing

Data Mining Pricing does involve econometrics in improving pricing decisions, but it does not usually involve the quantification of the demand curve nor the taking of the derivative of the firm's profit equation to identify the price associated with maximal profits. As such, it is distinct from economic price optimization though it does fit within the larger category of price optimization methodologies.

In a common application of Data Mining Pricing, executives accept that they can't optimize each individual price across their thousands of goods, or across each of their thousands of customers. But even unable to optimize each individual price, they can segment their customers and group their products, and at least "optimize" the price within those segments and groupings. From this process, some of the individual prices therein may be too low while others may be too high, but overall, they are better prices than would have arrived at otherwise—"better" here meaning that the customers find the prices to be reasonable and purchase, and that the firm finds that these prices improve

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its profits overall.

Data Mining Pricing doesn't necessarily require big data or large IT investments. For some challenges, executives should keep it simple with off-the-shelf statistical software and a good data analyst. For others, dedicated software from a pricing software firm may be more appropriate.

## Better is Better

Moreover, it should not be understated that a price optimized at one point in time may not be the right price for another point in time. Data Mining Pricing takes this reality into account. They depend on human beings reviewing the individual prices coming out of a pricing data mining exercise to ensure the output is reasonable. This process also depends on human beings checking after the fact to ensure that the goods that were re-priced higher are still being sold, and that the goods that were re-priced lower aren't leading the company into an unintended price war. It requires iterative improvements.

Data Mining Pricing also accepts that the issue in pricing isn't

to find the perfect price every time but rather to identify a better price than it would have identified otherwise. By better, here we mean one that enables the firm to outperform its competitors. To outperform, you don't have to be perfect, you just have to beat the competition more often than it beats you.

By analogy, the best stock picker doesn't have to pick the right stock 100% of the time, she needs only to pick it 51% of the time, and she will beat the market. Similarly, some leading executives of pricing have said that the best Data Mining Pricing process doesn't have to identify a better price 100% of the time, only 51% of the time, for it to be worth the effort.

Data Mining Pricing is a compromise and requires tradeoffs. Many executives and pricing practitioners don't like compromises and tradeoffs, but the reality is that a compromise in the right direction can often do more good than a lengthy and in-depth analysis that leads only to small points of clear agreement. In truth, economics isn't about pricing, it is about how people achieve their goals with scarce resources through compromises and tradeoffs. At the end of the day, measurable improvement now beats out an intangible and fleeting 'ideal price' achieved in the rearview mirror.

## **Choosing a Price Determination Methodology**

Executives are tasked with managing complex systems under varying degrees of certainty with limited resources and time towards goals which enable firms to thrive and customers to reach satisfaction. We know there are many tools we can throw at a challenge in the aim of reaching our goals. We also know that simply throwing tools at a problem on an ad hoc and arbitrary basis to see if they work is a waste of time and resources.

By the same logic, we know that proper pricing isn't simply a matter of applying the enticing-sounding economic price optimization tool to our pricing questions perforce, however attractive such a proposal may be to certain executives. Rather, we seek to identify the optimal prices for our offerings. In terms of choosing the technique for reaching that goal, select the one which provides the best tradeoff in accuracy and efficiency. In some situations, price decisions deserve economic price optimization, but in most situations, data mining or market research will prove superior in predicting relationships between cause and effect and identifying the best price to charge.