Rising to the challenge of today's volatile supply and demand conditions

A serious look at pricing capabilities

Sourced Economics

Summarizing the current state of pricing research

Unsurprisingly, the topic of pricing is among the first that crops up in discussions with strategy, finance, and even supply chain leaders alike. For those operating in mature industries, pricing has historically required relatively limited effort as simple rules, such as account-based markups, have proven effective.

Enter COVID-19, large expansions of the money supply, and whole bunch of other stuff. Pricing has become a different ballgame.

Adding to the complication is the reality that inflation, though in every headline everywhere, is by no means the only disruption to existing pricing processes and systems. Among others, radically different buying environments brought on by the pandemic led to unprecedented volatility in many companies' price elasticities of demand, and in many other demand elasticity measures. Consumers compare prices, qualities, and features differently online than they do in-store or for that matter, at a restaurant or an event.

Despite the surge in importance, the capabilities, technologies, and processes supporting pricing decisions have yet to catch up. Specifically, we've identified five major issues in this function:

1. Many teams are under-utilizing external market data in pricing decisions.

2. Many teams are examining too few demand variables in pricing decisions.

3. Many teams are not incorporating supply variables into pricing decisions appropriately.

4. Many teams lack strong methods to analyze pricing where good data is not available.

5. Many teams view quantitative pricing research as relevant only for consumer industries.

Note that the six issues do not apply to all companies. In particular, the strongest capabilities we recognize are often from dedicated revenue management teams at large consumer products or retail companies. As such, we view the most significant opportunities for improvement to be in business-to-business markets, especially industrials and manufacturing.

To answer your question... yes... we are really going to take these one-by-one. Bear with us.

Quick refresher...

$$Demand\ quantity = \beta_1 Price + \ ...$$

- Demand quantity: Dependent variable
- Price: Independent variable
- β_1: Impact of price on a demand. Referred to most often as a "coefficient" or "elasticity."

Altogether, "Demand is a function of the price of a product to the beta-1 extent"

1. The accessibility and usefulness of market data

No rocket science here. Our tool of choice is the FRED, the St. Louis Federal Reserve database, which tracks over 100,000 indices relating to prices and volumes.

100,000+

price and volume indices available through the FRED database

This includes sub-industries ranging from “fiber box manufacturing” to “accounting and bookkeeping services.” Dig further into the Bureau of Economic Analysis data sets, and you will find products as detailed as “integrated circuits” or “aircraft parts” and with additional research, evetn specific brands. Subscriptions like IBISWorld go a step further in consolidating production data on end customer markets. What’s more, the data from all of these sources can all be extracted, brought together and imported into a statistical software.

Modeling deep-dive

The foundational economic analysis technique for pricing research is then a series of standard linear regression models to estimate price elasticities of demand for a pre-determined set of markets.

A typical model for demand analysis may look like this...

$$Demand\ quantity = \beta_1\ Price + \beta_2\ Income + \beta_3\ Substitute\ price + \beta_4\ Controls$$

or more precisely, programmed as follows

$$\log Q = \beta_1 \log rP + \beta_2 \log I + \beta_3 \log rP_o + \beta_4 \log X + \epsilon$$

where, for illustration, β_1 is each market’s own real price elasticity of demand, β_2 is the median income elasticity of demand, β_3 is the real cross-price elasticity of demand, and X represents a series of control variables, such as seasonality.

The output of these models, which we often run via Stata software, is a set of tables with quantitative estimates for each demand coefficient, or beta. Some may be statistically significant enough to rely on, and others may not be.

2. The importance of *"blowing up"* demand functions

Whereas some view the above model simply as an input for statistics purposes, we view it as a platform. This platform's applications extend well across three dimensions: across variables, across markets, and across time.

"Across variables" relates most immediately to the need of many departments to investigate, not just own price elasticities of demand, but also cross-price and income elasticities. The latter, for example, provides crucial information into the resilience of demand to business cycle volatility. The structure of this model can be found above.

However, this dimension also relates to the quantitative and qualitative methods that can be used to understand the priorities of customers beyond financial variables. We employ this method of research most frequently in analyzing the features of a product, and the findings may be based on direct insights from data and analysis or indirect insights. A project may involve determining the impact of a change in lead time preferences on price elasticities of demand or vice versa. These cases tend to extend well beyond pricing research or the revenue management function.

"Across markets," simply put, involves comparing demand coefficients, or the above betas, between products, geographies, or business units. One might find, as we have, surprisingly large differences between even similar products, and might find these to change over time also.

Therefore, on to "across time." Much like prices and volumes themselves, demand coefficients, such as price elasticities, have histories. A simple application of this insight is to examine changes in price elasticity of demand through the

COVID-19 period. A more complicated application is to, with sufficient data, measure price elasticity of demand for each year. This level of detail enables companies to also forecast price elasticities and other demand coefficients with reasonable accuracy, an exercise that may prove feasible for high transaction volume, commoditized product markets especially.

Underpinning all three dimensions above is a common theme: the need to supplement data and analytics with market research and logic. Knowledge of a widening discrepancy in demand conditions for two products has little-to-no use without the “why?” As demand functions are “blown up” into smaller and smaller pieces, the data becomes less and less available and relevant. Therefore, knowing the “why?” becomes increasingly necessary.

Modeling deep-dive

Here, we represented these three dimensions with a few simple additions to our demand model

$$\log Q_{it} = \beta_1 \log rP_{it} + \beta_2 \log I_t + \beta_3 \log rP_{ot} + \beta_4 \log X_t + \beta_5 \log F_{it} + \epsilon$$

where t represents time periods, i represents products, and F is a product feature. For illustration, the β_5 represents the contribution to quantity demanded of feature, F, at time, t, for product, i.

3. The importance of "*blowing up*" demand functions

One of the most common misconceptions among finance and strategy leaders is that there are only two pricing models available in their markets: a "cost-plus" model or a "price-taker" model. At the heart of this view is another view: that supply and demand functions do not interact. The reality is much more complicated.

Case in point, nearly every price elasticity model regresses quantity on price and uses the result to represent price elasticity of demand. However, price is also a significant determinant of supply. An estimated price coefficient or β_1 of, for example, -0.8 may be composed of counteracting demand elasticity of -1.2 and supply elasticity of 0.4. The latter will tend to be smaller in absolute value terms as, in short, upstream production often requires larger fixed assets and are therefore more difficult to substitute in the event of a decrease in consumer product prices. An increase in price deters customers but also attracts suppliers.

The result is a complex and constantly evolving relationship between supply variables, such as the prices of commodities, and demand variables, such as a product's own price.

Modeling super-duper deep-dive

Strap in. Methodically, a model which connects supply and demand functions may look like this

$$Demand\ Q_D = \beta_1 P + \beta_2 I$$

$$Supply\ Q_S = \alpha_1 P + \alpha_2 A + \alpha_3 M$$

$$Q_D = Q_S$$

$$P = \frac{\alpha_2 A + \alpha_3 M - \beta_2 I}{\beta_1 - \alpha_1}$$

$$\log P = \frac{\alpha_2}{\beta_1 - \alpha_1} \log A + \frac{\alpha_3}{\beta_1 - \alpha_1} \log M - \frac{\beta_2}{\beta_1 - \alpha_1} \log I$$

where for simplicity the demand function is limited to current state Price and Income variables for a single product, and a new supply function is composed of Price, Aluminum, and other Materials. α_1 therefore is the price elasticity of supply like this.

The outputs of these models are generally two-fold. On the one hand, each involves a series of regressions to again estimate supply and demand elasticity metrics. New and insightful quantitative results, like the impact on cost of goods sold of a 1% increase in the global price of stainless steel, turn up. These can additionally be... again... extended across variables, markets, and time.

The second and perhaps more relevant output is a system of analysis producing clear and explicit price change calculations and more generally, producing a platform for sensitivity analyses, trend analyses, market research and more. More clearly, it is a system for analyzing "cost pass-through rates."

As mentioned, with statistically significant coefficients, optimal pricing can be determined directly. First, a few example coefficients, which we believe to be reasonable based on previous projects

Price elasticity of demand (β_1)	-0.7
Income elasticity of demand (β_2)	0.2
Price elasticity of supply (α_1)	0.3
Aluminum price change supply impact (α_2)	-0.2
Other price change supply impact (α_3)	-0.3

Next, a few sample variable values, which were pulled from actual index data and, in the case of the price of the other material, generated randomly

$70,000

Current median income (I)

$170

Current aluminum price index (A)

$100

Current other material price (M)

The values now specified can be effectively plugged into the model we previously developed

$$\log P = \frac{-0.2}{-0.7 \;\; -0.3} \log \$170 + \frac{-0.3}{-0.7 \;\; -0.3} \log \$100 - \frac{0.2}{-0.7 \;\; -0.3} \log \$70{,}000$$

$$\log P = 4.64$$

$$P = e^{4.64} = 103.54$$

Our price therefore, according to the highly simplified supply and demand characteristics, we laid out, should be $103.54 for markets to clear, inventory planning and forecasting considerations aside.

The model serves different purposes for different teams. As a mechanism for estimating a price point which can be copied and pasted into a report, this model is often not very useful. As a mechanism for understanding cost pass-through rates under varying conditions of price elasticity of demand, for example, this model can be extremely useful.

Leveraging the above functions, assume a 10% increase in the price of aluminum from the current $170 level, to $187. Running through the operations above with the new $187 “A” value yields an end price calculation of $105.53, a 1.92% increase from the original price.

In practice, when the price of one global commodity moves, all others might be correlated. Therefore, it would not be surprising to observe price increases closer to 10% in these cases. Here, we are only analyzing aluminum.

What about for a products or business unit with slightly more price elastic customers? Or one where aluminum makes up a more significant proportion of its direct materials? Per the below sensitivity table, it's clear that even small differences, or perhaps growing differences, in coefficients matter.

A 10% increase in the price of aluminum should lead to the following increases in price

Aluminum price change impact on supply available		**-0.05**	**-0.10**	**-0.15**	**-0.20**	**-0.25**	**-0.30**
Price elasticity of demand	-0.4	0.68%	1.37%	2.06%	2.76%	3.46%	4.17%
	-0.6	0.53%	1.06%	1.60%	2.14%	2.68%	3.23%
	-0.8	0.43%	0.87%	1.31%	1.75%	2.19%	2.63%
	-1.0	0.37%	0.74%	1.11%	1.48%	1.85%	2.22%
	-1.2	0.32%	0.64%	0.96%	1.28%	1.60%	1.92%
	-1.4	0.28%	0.56%	0.84%	1.13%	1.41%	1.70%

The key takeaway is hopefully easy to spot: Even small changes in coefficients result in significant differences in pricing implications, especially considering the narrow scope of our objective. That is, when looking at a larger basket of raw materials, across aluminum, plastics, fibers, lumber and others, these values and differences will of course be amplified.

The cost pass-through rate increases nearly 30% between price elasticity measures of -0.6 and -0.4, and increasingly so when aluminum represents a larger proportion of supply, to the right side of the table.

For reference, in our most recent econometric research engagement, the largest range in price elasticities of demand between products we estimated to be -1.027 to -0.409. This discrepancy, 618 basis points, had increased ~25% through COVID-19, mostly unbeknownst to the finance management team. As such, the cost pass-through rates being used were overly generalized.

4. Developing good analytics even without good data

An inevitable challenge, surprisingly even in many mature industries and developed geographies, is that good data is difficult to come by. There are several solutions to this problem

Firstly, teams may not be looking in the right place for the data, or can be more resourceful about which data sets to analyze. External industry price and production data is often overlooked, as discussed in #1 above. Further, though the immediate market in question may be lacking data, data sets reporting on adjacent supplier or customer markets can be weighted and combined to effectively "construct" an approximate model of supply or demand. If for example, a customer base is split between life science and energy, data sets for each can be combined and demand metrics weighted accordingly.

Secondly, for those with the incentive and background to access them, there are incredibly creative methods for empirical testing that can be found in academic literature across nearly all industries. Testing the price elasticity of demand for insurance customers, for example, sometimes involves a process to build data sets and models around the effects of new regulations. Though complicated, these studies churn out both statistically significant findings and modeling techniques that can be leveraged in the appropriate situations.

For reference, the three types of empirical testing are categorized as: experimental, quasi-experimental, and observational. The above insurance example falls under the quasi-experimental flavor.

Finally though, where data is truly unavailable or alternatively, where building advanced data science processes is not economical, there are simpler tactics available. A further review of academic literature, in this case of management literature, will yield many interesting frameworks for theory-based or inference-based tests of current demand coefficients. Specifically, we have in the past delivered the below simple but effective framework for judging price elasticities of demand using only a series of questions and a heat mapping exercise.

Price elasticities of demand for a production input are especially high where...

Criteria	Geography A	Geography B
There are readily available and direct substitutes.	**Very high** (Trend: decreasing)	**Medium** (Trend: increasing)
The input makes up a large share of the total costs of its consumer products.	**Medium** (Trend: N/A)	**Low** (Trend: decreasing)
Demand is highly elastic for its consumer products.	**High** (Trend: decreasing)	**Medium** (Trend: increasing)

where the product being evaluated is used in the production of a consumer product, as is most often the case where data availability is a challenge. It should be clear from the above that Geography A is likely to face more elastic demand, but that the two are converging which may result in more and global and centralized pricing processes and systems.

We've described our philosophy on this problem in the past as follows:

> **“ Anyone can do econometrics with good data. Bringing together a cohesive story even without it is a particular niche**

5. Implementing pricing research across all markets and situations

The above should demonstrate an extensive inventory of research techniques that can be leveraged to add more rigor to pricing decisions. Yet, some are without doubt uneconomical for many. Our team has managed to develop a bit of a niche, not only in building and communicating these research techniques, but also in determining which truly drive strong return on investment.

TLDR; we would never advocate forcing complicated models into processes where simple ones will do.

There is however a misconception among even finance leaders that companies selling “inputs,” or business-to-business transactions especially those further upstream, can not be subject to the same pricing analysis as those downstream. For reference, an upstream company might be in metals processing, whereas its downstream counterpart might be a retailer of home appliances.

This misconception is driven by two assumptions. First, that good data is not available on highly specific business-to-business markets. We’ve mostly covered this above with a discussion on crafting techniques where good data is not available, though also in discussing external market data. Most are surprised when they discover the amount of useful and highly relevant market data that exists on even niche industrial markets.

Secondly, and more importantly, teams struggle to apply pricing research to transactions which are governed by contracts. Longer contract durations certainly require more customized analytics due to, among other factors, the need to forecast market conditions through contract scope periods. The result is that few of these companies leverage these analytics appropriately and therefore, there is a stronger opportunity in these markets to build unique capabilities. Further, though price or contract changes may take place periodically, they do not take place at once and there is generally a series of price changes being evaluated by revenue management, legal, and project teams at any given time. Additionally, similar demand analytics can be used for ongoing promotions, contract amendments, and other related decisions.

Modeling qualitative deep-dive

For simplicity, let's take the case of a one-year contract which is renegotiated annually. Given that the new price level set will remain fixed for a full year, or in other cases into the future at all, a best-case scenario is one where teams also take forecasts into account.

There are many techniques used to forecast output, prices, and other variables. Examples include techniques based on extrapolating trends from historical data into the future, leveraging futures market prices, or perhaps judgment-based methods leveraging expert opinions and other indicators, among others. The selection of forecasting techniques is based on, in short, information. How much is available, who has the best handle on all of it, and where are there opportunities to contribute?

A set of techniques and processes to forecast supply and demand coefficients has clear applications across functions, well beyond pricing. For illustration though, we will use the specific case of attempting to forecast price elasticity of demand. The ways in which those forecasts are used will vary based on an organization's discount rate. The most precise approach would involve discounted cash flow models associated with various price changes, incorporating the fluctuations in quantities and market share that accompany them. However, this is unlikely to be a useful exercise. A better approach is to aim to simply develop a strong hypothesis on the direction of price elasticity of demand in the coming year, and use that hypothesis to inform pricing, at the margin.

In this narrow case, two of the forecasting techniques mentioned will likely be most useful, especially when they are combined: historical data-based forecasts and judgment-based forecasting. Where significant data exists, much like how demand planners predict volumes by analyzing historical transactions, revenue management teams can do the same for coefficients and here, price elasticities of demand. Statistically significant results across, for example, monthly or quarterly intervals, where trends can be identified and explained, can certainly be leveraged to make predictions for the future.

Forecasting large global markets in this fashion is unproductive for two reasons. Firstly, prices often incorporate future expectations more fully than forecasts.

Secondly, where prices do not fully reflect expectations, dedicated analysts, firms, or agencies specialized in forecasting those markets can do so more competitively than the revenue management team of a corporation.

Suffice to say, however, the number of analysts forecasting one company's demand coefficients specifically, and equipped with the data to do so well, are few-to-none. There is arbitrage in building these forecasts or at least, a clear set of hypotheses around them!

A review of historical records of price elasticities of demand, supported by internal and external market data, may yield a clear finding that the metric has spiked in recent years.

Upon further market research, the team concludes that this spike is due to a shift in buying environments to one where customers are more price sensitive. Combining this finding with a judgment-based approach, teams can leverage prevailing forecasts and informed hypotheses on the makeup of consumption habits in the coming year to directly inform a price elasticity forecast. If expectations are that foodservice will increase at a similar rate in the coming year, extrapolate the previous year's price elasticity of demand increase into next year, though of course with a bit of caution. There are limitless sources of market expectations that can be used to inform forecasts. The amount of research will depend on the materiality of the pricing decision being made.

A set of pricing capabilities built for 2023

Margin recovery, input cost inflation, optimal pricing and market share… thanks to persistent inflation, macroeconomic uncertainty, and continuing structural changes in labor markets, we are confident that these topics will continue to dominate the leadership agenda in 2023. We hope corresponding investments in analytics, software applications, and new talent around revenue management will follow suit, as it has in supply chain management over the past decade in response to greater globalization.

There are a few clear opportunities for immediate improvements in pricing research capabilities, and a few opportunities to also lay the groundwork for major long-term transformations. Altogether, after nine months of evaluating countless processes, systems, and teams on their pricing capabilities, we feel the #1 spot is up for grabs across nearly all markets… just need to reach out and grab it!

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