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Pricing and data science: The tale of two accidentally parallel transitions

Jacek Wallusch[1]

Abstract

Accidentally parallel at the beginning, the transition to value-based pricing and transition to pricing data science have blended harmoniously, changing the pricing landscape. Using the marketing capability approach, I show that the introduction of pricing data science is costly and requires higher management support. Despite its cost, algorithmic price optimisation allows one to react swiftly to changes in demand. The optimisation process is applied to inherently non-linear, multimodal, and right-skewed pricing data. Presenting the interactions between new computational techniques and value-data pricing, I concentrate on altered perceptions of price elasticity, value-driver estimations, and contract opportunity analysis.

Keywords

- pricing
- value-based pricing
- machine learning
- data science

JEL codes: L11, C81, M31

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Introduction

In the ever-changing world of business, some managerial habits can be remarkably persistent. A great deal of strategic thinking, and no small amount of upper management support, is needed to change the old habits. Sometimes random events accelerate the change. When the transition to value-based pricing started gathering steam, another transition began. More and more companies started investing in collecting, analysing, and modelling data. Accidentally parallel at first, soon enough the transitions entwined. Slowly yet decisively, the pricing landscape has changed.

Already in the mid-1990s, visionary academics like Woodruff (1997) advocated for a shift towards customer value in managerial practice. Two value-based pricing champions, Hinterhuber and Liozu, in a series of papers have addressed the superior effects of the value-oriented pricing and raised awareness amongst pricing managers. Despite the efforts, cost-based and competition-based price-setting strategies dominated pricing policy. What is even more symptomatic is that a decade ago, the term *value-based pricing* was not fully understood amongst pricing practitioners (Füreder et al., 2014). Today, value-based pricing is not just an academic concept taught at business schools, but it is successfully implemented by companies of various sizes and in various business sectors, from Major League Baseball[2] to heavy industry. It also successfully contributes to company performance (Liozu & Hinterhuber, 2013).

How did the unprecedented increase of data usage and computational power affect the transition to value-based pricing? I hazard an opinion that data science played an important role in the widespread application of value-based pricing. Hinterhuber (2008) identified five major impediments jeopardising the successful application of value-based pricing. Besides management and communication issues, the author identified value assessment and market segmentation as the main roadblocks.[3] Raja et al. (2020) named customer data analytics as essential to the pricing and selling process. Big data and artificial intelligence have been identified as one of four major supplementary trends to value-based pricing (Steinbrenner, 2020). Another aspect related to the introduction of pricing data science to the value-based transition is connected to the managerial aversion to ambiguity (Kienzler, 2023).[4] This follows closely Lord Kelvin's remark on meagre and unsatisfactory knowledge

[2] See the concept of value-based salaries in the MLB introduced by Winston et al. (2022).

[3] The importance of segmentation goes far beyond pricing. Mora-Cortez and Hidalgo (2022) mentioned segmentation as one of three universal marketing capabilities.

[4] Even though I agree with the notion that managers display a considerable concern regarding ambiguity, I would argue that unit cost *is often readily available and may appear precise and unambiguous*.

of things one cannot measure and express in numbers. Incidentally, this is exactly what data scientists do.

Segmentation and customer analytics are standard exercises run by data scientists, thus reducing ambiguity. But how data science domain should be analysed? Is it a new marketing capability? I tend to position data science within the market research capability, whilst pricing data science at the interception of two major marketing capabilities: market research and pricing. Even though data science is not a distinct capability, it should be analysed within the capability framework. Similarly to what Dutta et al. (2003) wrote about pricing capability, to utilise data science potential, companies must invest in resources and routines. The necessary spending on pricing departments, data science support, and computational resources determines that the price-setting process is costly. In sharp contrast to the small menu cost literature, the costs are borne to promptly react to market changes and optimise prices, not to make prices sticky.

The transition to data science resulted in considerable changes in the quantitative toolbox. Statistical models have been replaced with machine learning algorithms. Pricing has not remained immune to these changes. A prerequisite for successful application of value-based pricing is to understand and influence price elasticity (Liozu & Hinterhuber, 2013). Predictive analytics, however, has altered its perception. The elasticity is no longer a continuous, twice-differentiable, strictly convex function. Rather, it is discontinuous with unspecified curvature. So are the machine learning predictions based on structured yet unfiltered vast amount of pricing data. And so is the perception of price elasticity amongst managers setting prices. The magnitude of response to price changes is in the centre of their attention. Focus on sales characteristics like channel or region decide, however, that a smooth, convex elasticity curve is of very little help.

Equally important for the application of value-based pricing are machine learning-powered attempts to quantify value. Value quantification customarily appears amongst the road-blocks most difficult to remove on the way to value-based pricing (Hinterhuber, 2008; Hinterhuber & Liozu, 2018). Even though the prevailing focus on product attributes considers the "lowest level of the customer value hierarchy" (Woodruff, 1997), the attribute analytics is undeniably beneficial for manufacturers, adding precision to list and net price positioning.

The capability optics allows to focus on organisational issues that diminish the efficacy of data science, rather than algorithmic issues. I illustrate this problem with the contract opportunity analytics and the limited information on opportunities closed or lost. The issue resonates well with the synergistic information distribution defined by Day (1994). One of its pillars is a systematic, thoughtful, and anticipatory gathering of data. In terms of the limited data, a company's system of data gathering requires fundamental changes, which in turn calls for upper management support and successful change management.

The remainder of this paper is as follows. In Section 1 show how data science is positioned within the market research capability. Section 2 presents a set of specific pricing data features. Although I focus mostly on B2B pricing, I employ the prices of used cars to illustrate the inherently multi-modal distribution of pricing data. I argue that the strong impact of product characteristics on price results in probabilistic specificities. In Section 3, I place data science within the marketing capability framework, locating it in market research. Then, I show how machine learning alters the perception of price elasticity, how data science helps quantifying value, and how win-loss probability estimations go beyond the project opportunity management, calling for change management. The last section summarises.

As pricing data science is still in its adolescence, this paper is a medley of academic rigour and practitioner's remarks. The framework in which pricing data science is analysed requires the former. The illustration of how pricing data science affects the price setting process requires the latter. For seven years, I had been a part of two major transitions at Schneider Electric. I offer two penn'orth of an insider, who performed pricing data science on-site projects in Sweden, Russia, Australia, Indonesia, the United States, and in three commercial zones in Europe.

1. Data science and marketing capabilities

Long before data science became a standard tool in marketing practice, Day had prophesied that information technology would enable organisations to do things they could not do before (Day, 1994). But is data science a distinct marketing capability? Marketing capability combines human resources, market assets, and organisational assets (Möller & Anttila, 1987). Although data science can contribute to both external (e.g., macroeconomic and sectoral analysis) and internal (e.g., application of marketing concepts and tools like segmentation) capabilities,[5] I tend to include data science to a broad range of market research capabilities. Market research capabilities have been concisely defined by Vorhies et al. (1999) as the set of processes needed to discover information about customer needs and broad market information. The discoveries embody the very essence of data science application in marketing, hence

[5] The external-internal classification of capabilities was introduced by Möller and Anttila (1987). Since the late 1990s, market research is listed as one of major marketing capabilities (see, e.g., Vorhies et al., 1999).

making a separate capability for data science superfluous. Nonetheless, pricing data science should be analysed within the marketing capability approach.

Since pricing has also gained the status of marketing capability (Dutta et al., 2003), pricing data science is an intersection of two capabilities. Consequently, wearing two hats creates enormous opportunities for revenue and pricing management. Where there are considerable upsides, however, difficulties multiply. The capability optics is very helpful to understand why pricing data science has not yet become standard routine in many companies.

Without calling them as such, Day (1994) listed the requirements for a successful application of data science: shared databases, high-speed communication networks, decision-support system, automatic product identification and tracking, and large-scale computing. Price optimisation, as noted by Dutta et al. (2003), requires investment in resources and routines as well as in effective pricing process. Similarly to other processes, setting prices is costly. Even though this statement might ring a not-so-distant macroeconomic bell, the small menu costs a la Mankiw are the least of a problem for companies; costly pricing results in price optimisation, not nominal rigidities. The necessary expenses are twofold. Data scientists, data analysts, and data engineers are amongst the highest-paid professionals in the job market. Data stewards and ERP specialists are less celebrated but equally important for data processing. The other position on the cost sheet is related to the resources the data professionals use. Through data connectors, the data from local ERP systems are stored in the enterprise data lake. A pricing data warehouse contains well-structured data ready to use. As we live in a predominantly visual learning society, dashboards are extremely important means of storytelling and communicating pricing KPIs. Contrary to popular belief, the data lake, the data warehouse, and the set of dashboards need to be physically stored. Therefore, a company chooses between cloud solutions and internal servers. Whether it is a world tech leader or a smaller provider, the services are costly. And so are physical servers. High-performance laptops, licenced software, and vendors providing external time series contribute to the expenses as well. An often-omitted aspects of successful analytics are repeatability, replicability, and maintenance. Data collection in not a one-off table extraction. Data science is not a one-off project. This is why price optimisation is an investment, and this is why the investment is costly.

A recent study performed by Mora Cortez and Hidalgo (2022) offers an insight into the importance of market research for a company's performance. Interestingly, the authors discovered that market research capability in developing and emerging countries might have an insignificant impact on performance. The finding is even more intriguing when juxtaposed with the positive effect of pricing capability on performance. Mora Cortez and Hidalgo offer a possible explanation, mentioning the lack of strong data management, technological infrastructure, managing skills, as well as statistical skills. Because of the operational costs of modern market research, companies facing limited resources prioritise pricing over data science. This is perhaps even more visible amongst smaller manufacturers. Emerging and developing countries, however, may, in fact, be amongst the leaders of the data-driven transition. More recently, global leaders have moved data science centres to emerging and developing countries. India, Romania, and Poland are particularly popular destinations for relocating data science centres of excellence.

Perhaps it is more than just a coincidence that the transition to value-based pricing in B2B and the widespread use of data science techniques in pricing started nearly simultaneously. The resemblance between both transitions is remarkable. Obstacles impairing the implementation of value-based pricing are strangely familiar to all pricing data scientists.

The 'If-Ain't-Broke' attitude as well as the organisational inertia are serious challenges for value-based pricing implementation (Töytäri et al., 2015), but without doubt, they are also the major pain points of every transition in manufacturing. Therefore, as stated by Raja et al. (2020), pricing and selling based on value require a break from the traditional paths. The same applies to the introduction of data science to pricing practice. Old habits die hard, and without support from senior management,[6] neither new pricing strategy nor new pricing analytics tool can be applied. Two reasons decide that for the latter, the top management support is even more important than for the former.

Pricing data scientists are often mistaken for pricing auditors. After all, data reveal irregularities and overwritten rules, thus burdening the auditors with a sinister reputation. Without help coming from upper management, the unmerited reputation prevails, diminishing the potential for price optimisation. The second reason why senior management is essential for a successful transition to data-driven pricing is data availability. Crucial information on the marketplace is hoarded in the obscure collection of Excel files. Offer managers gather an extensive information regarding competitor pricing and value management. Regional front offices collect vital data outside the usual ERP software. Upper management alleviates the reluctant attitude towards sharing information and enables a sustainable usage of data in company. In the words of Baer (2019), "don't assume that your data scientist is evil".

2. The complexity of pricing data

In the words of Henry Skinner, the secret to riches is the same as the secret to comedy—timing. Due to the complexity and atypical properties of pricing data, timing is precisely why data science is used for price optimisation practice. Pricing data are inherently multimodal, asymmetric, and possibly het-

[6] This is one of five major obstacles listed by Hinterhuber (2008).

eroskedastic. As depicted in Figure 1, even publicly available data from used car retailers[7] exhibit multimodality and skewness.

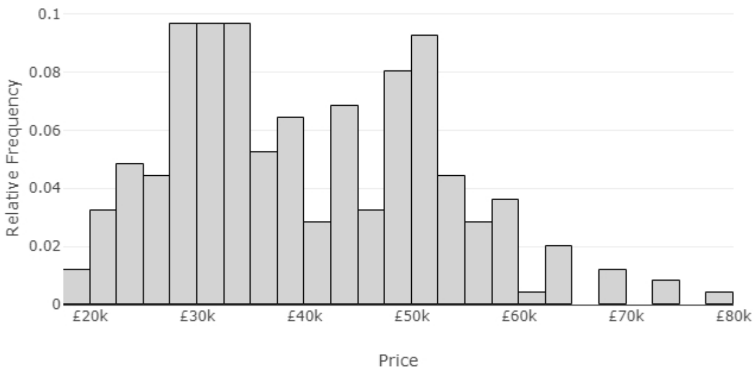

Figure 1. Price distribution of used Jaguar F-Pace cars

Source: Own estimations based on www.autotrader.co.uk data.

The price distribution is at least bimodal. The kernel distribution suggests that the first mode is located around £30,000 whilst the second one is around £50,000. The right tail of the distribution is longer, suggesting a positive skew. Indeed, testing for positive skewness, the D'Agostino test returned the p-value of 0.998.

Figure 2 plots the prices against 4 attributes: fuel type, engine capacity, year of build, and brake horsepower. A high dependence on specific product attributes results in grouping prices around multiple local maxima in the probability density function. A multifaceted relationship between price and attributes also contributes to the non-linearity. After inspecting thousands of disaggregate, invoice-line level transactions, however, I have a strong suspicion that the significant deviation from linearity is an intrinsic characteristic of pricing data. Figure 3 illustrates the non-linear relationship between price and two car attributes.

The B2B pricing data is even more complex. Commercial policy that differentiates between channels, regions, product lifecycle, and product types introduces another source of multimodality. Skewness and kurtosis may also be affected by commercial policy. If a company targets a specific distribution channel or region, heteroskedasticity might be present in price distribution.

Let us return to timing. The ability to perform pricing action quickly at the right time calls for methods that can deal with pricing data specificities. Time is the essence, which is why the modellers face two trade-offs. Firstly, there

[7] Due to confidentiality reasons, I could not employ the B2B transactional data. To depict the standard properties, I used the prices and selected attributes of 249 used Jaguar F-Pace cars listed by Auto Trader Group plc. on their website.

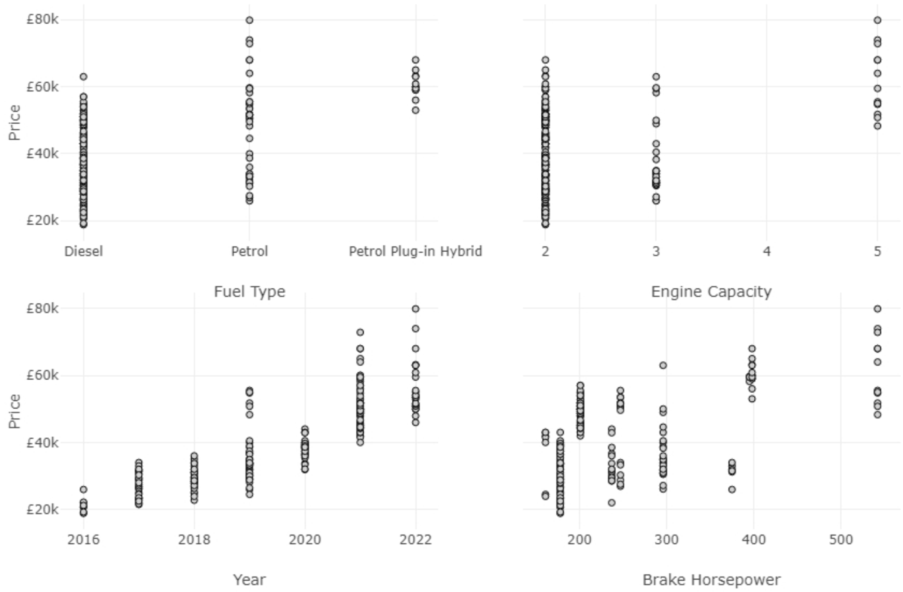

Figure 2. Price and selected attributes of used Jaguar F-Pace cars

Source: Own estimations based on www.autotrader.co.uk data.

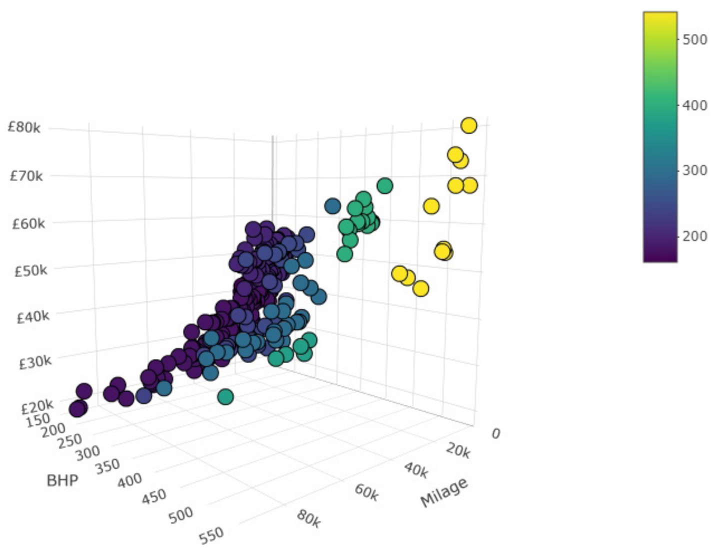

Figure 3. Non-linear relationship between price, milage, and brake horsepower

Source: Own estimations based on www.autotrader.co.uk data.

is the standard interpretability versus forecast precision dilemma. Secondly, there is the time needed to prepare the data for estimations. Standard econometric methods offer perfect interpretability but often lack the forecast precision. They also need a thorough understanding of the dataset. Unfortunately, data quality is not perfect, and databases frequently miss the detailed description of specific events. In other words, big data mostly refers to the number of rows, but not necessarily to the number of columns. Global pricing data science teams are deployed for projects around the world and learn about local market specificities from highly knowledgeable sales and product experts. If the said global team optimises prices in multiple countries and zones simultaneously, however, expert knowledge becomes impossible to gather. Machine learning algorithms, despite their imperfect interpretability, offer a solution to act quickly with high precision. Impeccable timing is worth much more than perfect interpretability.

3. Price elasticity: A new approach to an old concept

Interpretability, however, is still a desirable property. Without fitting a function to the data and estimated coefficients, it is difficult to grasp two basic concepts for pricing decision-making—willingness-to-pay and price elasticity.[8] Despite the changing world of economics and marketing, both concepts are still utilised. As highlighted by Liozu and Hinterhuber (2013), value-based pricing implies understanding, increasing, and influencing willingness-to-pay and price elasticity.

Although the concepts are still in use, the evolution of data modelling has altered their perception. The switch from procedures focusing on coefficient estimation to predictive analytics has particularly affected price elasticity. In econometric practice, price elasticity is calculated in two steps. Firstly, a model of a general form $y = F(p, \boldsymbol{X})$ is fitted to the data, where vector $\boldsymbol{X}$ contains the explanatory variables other than price p. The functional form of $F(p, \boldsymbol{X})$, as well as its properties, are known. Secondly, the estimates are used to obtain the expected value of output y, possibly at mean values of price and $\boldsymbol{X}$, which leads to the elasticity ε_A:

$$\varepsilon_A = \left.\frac{\partial F(p, \boldsymbol{X})}{\partial p}\right|_{p=\bar{p}, \boldsymbol{X}=\bar{\boldsymbol{X}}} \times \frac{\bar{p}}{F(p=\bar{p}, \boldsymbol{X}=\bar{\boldsymbol{X}})} \tag{1}$$

[8] It is somehow symptomatic for the modern pricing literature that willingness-to-pay is explicitly described as “central to any pricing decision” (Jedidi & Jagpal, 2009), whilst price elasticity is virtually omitted.

Machine learning techniques do not focus on estimating coefficients. In some cases, the functional form is extremely difficult to specify. Price elasticity ε_{AB} is approximated by employing the expected values of output $E(y \mid p_1, \bar{\boldsymbol{X}})$ and $E(y \mid p_2, \bar{\boldsymbol{X}})$ obtained for two pre-specified price points p_1 and p_2:

$$\varepsilon_B = \frac{\left(E(y \mid p_1, \bar{\boldsymbol{X}}) - E(y \mid p_2, \bar{\boldsymbol{X}})\right)\left(E(y \mid p_1, \bar{\boldsymbol{X}})\right)^{-}}{(p_1 - p_2)p_1^{-1}} \tag{2}$$

When estimating the response, continuity and curvature differ sharply from the example presented in Figure 4. To illustrate the differences, I have applied an extreme gradient boosting algorithm, using similar features as plotted in Figure 2—milage, one-hot encoded fuel type, brake horsepower, and engine capacity. Figure 5 plots the simulated 'trend' obtained for the milage sequence, which is similar to Friedman (2001) partial dependence function.

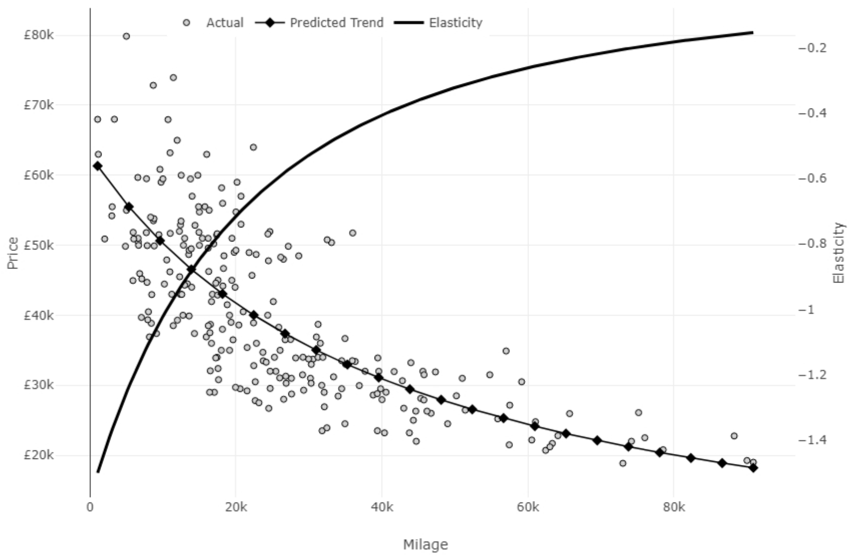

Figure 4. Simulation results and elasticity: Standard approach

Source: Own estimations based on www.autotrader.co.uk data.

The properties of the simulated 'trends' depicted by the dotted lines in Figures 4 and 5 differ considerably. The discontinued trend obtained for the gradient boosting procedure is globally decreasing, but for some milage ranges it increases. I summarise the differences[9] in Table 1.

[9] I am grateful to one of the referees for drawing my attention to the distinction between global and local differentiability. Even though the machine learning-based price elasticity

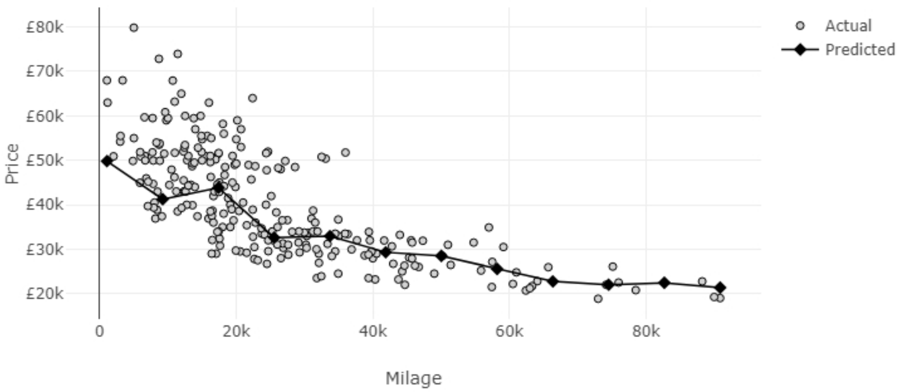

Figure 5. Simulation results: XGBoost

Source: Own estimations based on www.autotrader.co.uk data.

Table 1. Price elasticity features by estimation method

Elasticity function properties	Estimation procedure	
	Econometrics	**Machine learning**
Continuity	continuous	discontinuous
Differentiability	twice differentiable	globally unspecified
Curvature	strictly convex	globally unspecified

Source: Own work.

What managerial insights does the comparison offer? First and foremost, the elasticity obtained by applying machine learning procedures is a side effect of the predictive analysis. As its direct calculation is not possible, the elasticity is re-calculated by using expected values of output obtained for specific values of price. In terms of extreme gradient boost estimations showed in Figure 5, the milage elasticity between 30,000 and 40,000 miles is equal to –0.676.

Supporting offer managers on four continents, I have discovered that the term 'price elasticity' is rarely mentioned. Offer managers have requested help either with price optimisation or with simulating sales effects of price movements. Does it mean that price setters do not understand the concept of elasticity or do not use it? Quite the opposite. The magnitude of response

function is globally non-differentiable, it is twice-differentiable locally (i.e. between two price points).

By simulating the response of output to changes in price and controlling for other variables (setting them to their respective averages), the prediction for two neighbouring price points is approximated by a linear function. The local curvature is thus both convex and concave. This property of machine learning-based price elasticity requires further research.

to price changes remains their biggest concern. The focus, however, differs from the standard, continuous elasticity function. Simulations for various sales characteristics like channel or region are requested. How offer managers perceive the elasticity is much closer to what the characteristics presented in the right rather than in the middle column of Table 1.

As a final note on price elasticity, it is worth mentioning that pricing professionals operating in the electronic marketplace often lean towards A/B testing, employing it as a tool for capturing the magnitude of response to price changes. This approach exemplifies the relatively new experimental pricing, possibly adopted from user-experience projects. Despite trenchant criticism launched by some practitioners, I expect the A/B testing to enter the standard pricing analytics toolbox in the nearest future.

4. Value-driver estimation

The customer value determination process consists of 5 elements: identification of value drivers, identification of value driver hierarchy, value delivery assessment, root cause analysis for value delivery assessment, and identification of future trends in value drivers (Woodruff 1997). The process is tedious, costly, and requires full commitment from both suppliers and customers. It is not surprising that value assessment and value quantification are commonly named as key challenges for value-based pricing implementation (Hinterhuber, 2008; Hinterhuber & Liozu, 2018). The latter, defined by Hinterhuber et al. (2021) as the ability to translate a firm's "competitive advantages into (…) monetary value", is also a key aspect of sales practice in B2B.

Attempting to quantify the value, many manufacturers focus primarily on product attributes. In terms of the customer value determination process, attributes correspond to the "lowest level of the customer value hierarchy" (Woodruff, 1997). Indeed, the attribute optics is related to answering two first questions in customer value determination design—"what do target customer value and of all the value dimensions that target customers want, which are the most important" (Woodruff, 1997).[10] It does not necessarily mean the questions are less important than those located higher in the Woodruff and Gardiall system. Even pricing professionals often identify value-based pricing as a tool that leverages price increases (Steinbrenner & Turčínková, 2021). Brand image and benefit perception are undeniably factors enabling higher

[10] Notice, however, that the machine learning approach can also be employed to estimate value driven by non-core product attributes (Christen et al., 2022).

price, value-based pricing has a much wider application for list and net price positioning. This is where the attribute approach to value estimation is applied.

Product attributes are easily distinguishable. Access to product sheets and full product feature descriptions is usually not restricted. Thus, suppliers and customers use product attributes as value-drivers to define the price. Focus on product characteristics is not unique to value-based pricing. Sport apparel offers a good example—the difference in prices of pro and replica shirts of Rugby Union teams are driven by attributes, but the differences form two trends. Moreover, for the Home Nations, Italy, and Ireland both prices and the price differences between pro shirts and replica shirts are strikingly similar. Whether fans pay €150.00 to Fédération française de rugby or £105.00 to Rugby Football Union, price positioning reflects how much more value a pro shirt delivers in comparison to a replica shirt.

To illustrate how data scientists approach the value quantification, let us inspect again the used Jaguar F-Pace database. The list of attributes is not complete, but the features introduced in the previous section are essential to price setting. One way to capture the value offered by technical attributes is to estimate the relative importance of the features. Using again the extreme boosting algorithm, it turns out that mileage accounts for 76% of attributes' relative importance, brake horsepower for 23%, diesel engine type for nearly 1%, whilst petrol and petrol-plug-in hybrid for less than 0.5%.

What makes the relationship between mileage and price so unique is the nearly continuous nature of both variables. From 1,056 miles to 90,867 miles, from £18,850 to £79,850, the dots in Figures 4–5 do not form well-defined clusters. The vast majority of manufacturing product attributes does not share this characteristic. Let us take for instance current rating for miniature circuit breakers, seam height for mining feeder breakers, or outer diameter for diagnostic knee arthroscopy telescopes. These attributes are discrete and sometimes even ordinal. Pricing data scientists cross-examine the sales figures to quantify the value drivers. Ideally, algorithms define a set of parameters mapping the relationship between attributes. Using once more the used Jaguar F-Pace database and the extreme gradient boosting procedure, I simulated the price for two hypothetical cars sharing all attributes save the braking horsepower. For a car with a diesel engine, 19,000 miles, and a 2-litre engine, the relationship between 201 BHP and 178 BHP is equal to 1.24. Retailers can now employ the parameter to position a 201 BHP vehicle against a standard 178 BHP one.

Closely related to attributes and value-drivers, product grouping optimisation is another area of expertise for pricing data science. It is also a vital element for the implementation of value-based pricing, as strategically important value dimensions vary between customer segments (Woodruff, 1997). Focusing on product attributes, clustering and classification techniques assist in segmenting products and customers. For multi-channel manufacturing companies, product and customer grouping optimisation becomes a challenging aspect of commercial policy. This is also the area contributing to higher levels of the Woodruff and Gardiall customer value determination process. The diagnostic part of grouping optimisation consists of assessing and explaining the value delivery process. Lastly, companies able to construct multivariate time series can observe and anticipate the changes in value delivery for specific channels. The multivariate machine-learning-powered time series analysis seems to be the next breakthrough in pricing analytics.

5. Data science and change management: Contract opportunity analytics

Because of their size, contract opportunities are important contributions to turnover. Commissioning a nuclear-powered icebreaker, equipping a sports medicine department, or building a five-star hotel require package deals of considerable size. Price optimisation for contract opportunity follows slightly different rules, as special discounting policy becomes the main driver for winning the opportunity. From the analytics standpoint, the problem is equivalent to a binary-choice classification problem. In pricing literature, the estimations are called contingent valuation methods and are classified as willingness-to-pay measurement (Jedidi & Jagpal, 2009). Machine learning and econometrics offer a variety of classification procedures ranging from Bayesian neural networks to standard logit and probit models. The selection of computational procedure, however, is much less important than the data quality issue.

The problem faced by pricing data scientists modelling the contract opportunities is similar to the representation bias (van Giffen et al., 2022) or more generally to the sample bias (d'Allesandro et al., 2017). Whilst contract opportunities databases are commonly overloaded with successfully concluded negotiations, lost opportunities are underrepresented. The sample does not sufficiently represent the population, which consequently leads to overly optimistic predictions that no hyperparameter tuning can prevent. In terms of fairness-aware classifiers, it is the negative legacy issue defined by Kamishima et al. (2012) as unfair sampling or labelling in the training data. Not related to fairness, the sample bias is generated by standard reporting practices.

Representation bias first emerges during the business understanding phase and can be countered by establishing a diverse research team, as well as discussing the project objectives with domain experts (van Giffen et al., 2022). Insufficient communication between the data science team and business users may introduce additional bias (Baer, 2019). In the curious case of contract opportunity modelling, however, the sample bias is purely introduced during the data preparation phase. A contract opportunity negotiation is a long, multi-stage process. Legal and supply-chain aspects are debated first, then the preliminary price negotiations are underway. Every so often, this stage disappears from statistical reporting as it offers very little to no reward for the reporting staff. In all fairness to the sales managers, there was very little to no application for the information on the lost opportunities before data scientists began to utilise the data.

To effectively solve the issue, teams need to return to the business and data understanding phase and solve it as such. Fundamental changes to the opportunity data collection process can only be achieved when those in charge of reporting will co-operate with those in charge of modelling. Marketing researchers and practitioners emphasise the superior position of business understanding in quantitative analytics projects. Defining the business understanding phase, van Giffen et al. (2022) highlight the understanding of project objectives from a business perspective. The second stage of the data understanding phase is defined in a similar manner, determining the researcher as the party becoming familiar with the data. Conventional wisdom paints data scientists as detached from business reality, and in many cases rightly so. The understanding phases, however, require data and sales managers to be equally committed to data quality improvement. They also require sales managers to follow data scientist guidelines.

Conclusions

When asked about advances of AI possibly increasing inequality, ChatGPT pointed to AI-driven algorithms for price optimisation leading to increased costs for customers (Korinek, 2023). For pricing professionals, coupling price optimisation with a necessary price increase[11] is a travesty. By way of definition, price optimisation is beneficial for both suppliers and customers. By way of experience, price optimisation can also lead to price decrease.

ChatGPT merely reflects the widespread belief that price setting predominantly favours the supplier. Despite empirical evidence,[12] macroeconomic models still utilise the rigid price assumption. What might have been applied during the early years of the Great Moderation, however, is not necessarily

[11] Or for that matter monopolistic competition.

[12] Long before inflation re-emerged, microeconometric studies showed much more frequent price changes than customarily assumed in macroeconomic models. See, e.g., Baumgartner et al. (2005), Bils and Klenow (2004), Coenen et al. (2007), or Lünemann and Mathä (2005).

valid recently. During the last decade, two major transitions have changed the pricing landscape: value-based pricing and machine learning-powered price optimisation. These developments have allowed pricing professionals to monitor, predict, and response quickly to changes in demand. Contemporary pricing contradicts the small menu costs.

Without a highly skilled pricing team, no pricing strategy can ensure an optimum margin management. Nor can machine learning ensure an optimum margin without a highly skilled data science team. The introduction and maintenance of algorithmic value-based pricing is a dynamic process that carries risk and considerable costs. That is the reason why companies, especially of a smaller size, hesitate before committing to both transitions. Another reason is rooted in not-so-distant history. The dot-com bubble bears resemblance to the hype and razzmatazz of AI evangelism. The efficacy of machine learning algorithms, however, suffers greatly from trivial data quality issues. Furthermore, their efficiency also weakens when the non-technical staff does not support the transition. Strangely enough, the same applies to the transition to value-based pricing as stressed by Dutta et al. (2003) or Hinterhuber (2008).

Some managers who co-exist with data scientists often presume ignorance and corrupt intentions (Barocas & Boyd, 2017). Others are simply resilient to change. To turn machine learning into more than just a new wand in the pocket of the sorcerer's apprentice requires cross-functional co-operation. Managers who deny guidance and partnership are confronted with their self-fulfilling expectations of data scientists' business aliteracy. Oddly enough, it applies to algorithmic price optimisation as well as to value-based pricing. In the foreseeable future, value-based pricing powered by machine learning will probably become the dominant pricing strategy. Empirical evidence shows that companies introducing it lead the race to efficient revenue management.

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