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The Landscape of Pricing and Algorithmic Pricing

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Abstract

Algorithmic pricing is the practice of setting prices using computer programs. Understanding the foundations of pricing practices is fundamental to an assessment of the nature and potential of algorithmic pricing. Prices can be set in a number of ways and the practice of price setting has been examined from different and sometimes overlapping disciplinary perspectives – economics, marketing and operations research. The three key activities in price setting are data collection, demand analysis and optimization. Computer algorithms are used in these activities but they may not be fully integrated in practice. The organizational adoption of algorithmic pricing may assume different forms depending on the cost-benefit calculus across different components of price-setting activities.

Keywords: Pricing, Algorithmic Pricing, Market Competition

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1. Introduction

E-commerce has become increasingly important in many countries since the mid-1990s. E-commerce's share of total retail sales has grown rapidly in recent years, reaching 12 percent in the United States, 34 percent in China and 16 percent globally.[2] A key feature of e-commerce markets is the use of algorithmic pricing where prices are set using computer algorithms (program). The use of algorithmic pricing has impacted the different stake holders in society in various ways. For companies, algorithmic pricing offers opportunities to maintain their market competitiveness. The spectre of collusive practice via algorithmic pricing has become a key concern among competition regulators (Auer and Petit, 2015). Whichever perspective is taken, it is important to understand the nature of algorithmic pricing within the larger context of pricing as a business activity.

The understanding of algorithmic pricing begins with the nature of price and pricing. Price – which represents the term of an exchange - is a key feature of markets. For sellers and buyers in markets, the setting of prices is a key decision that determines gains from their transactions. It is thus not surprising that the study of pricing and pricing strategies has been undertaken in a number of fields within economic and business studies. Even though most of the approaches taken have an economics-oriented element and foundation, they can differ from each other in a number of ways depending on the goals and methodologies used. Thus, if one were to study the applications of new technologies to pricing – such as algorithmic pricing - it would be useful to examine the nature of the diversity in pricing strategies (and methodologies) and their implications in a new pricing-technology environment.

The goal of this paper is to review and synthesize the literature of pricing and algorithms. The outline for this paper is as follows: Section 2 will review the concept of price and pricing. The various approaches to the study of pricing is reviewed in Section 3. The process of price setting

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[2] Sources: US: https://fred.stlouisfed.org/series/ECOMPCTSA ; China: https://www.campaignasia.com/article/pandemic-may-help-chinas-big-3-ecommerce-giants-keep-lions-share-of-market/461628; Global: Statistica

is discussed in Section 4. The application of algorithms in pricing is the subject of Section 5. Finally, Section 6 will conclude.

2. Price and Pricing

2.1 What is a Price?

A **price** is essentially the term at which a good and/or service is exchanged. An exchange is not confined to goods and services that are traded using money as a medium of exchange. The term of exchange (term of trade) for a barter trade is implicitly a price. Thus, a "price" exists for a barter trade even though no money is used in the exchange. The use of money as a medium of exchange of course greatly facilitates exchange activities as it reduces the double coincidence of wants i.e. each party in an exchange does not need to want exactly what the other party is offering to exchange in terms of both type of goods/services and quantities.

Goods and services need not be confined to goods and services that are consumed directly. Exchanges can involve factors of production – rent for land, wage for labour and interest for capital. Exchange can also involve the buying and selling of goods and services that have a time dimension. An example of this is the futures market where goods and services that will be delivered in the future are traded.

2.2 The Structure of Exchange

The simplest structure of an exchange activity involves a **direct transaction** between a buyer and a seller (**Figure 1**). The buyer buys directly from a seller without any intermediary.

In an **indirect transaction** (or mediated transaction), the buyer and seller exchange through an **intermediary** (**Figure 2**). An intermediary can be a wholesaler or re-seller – an agent that buys from the seller and sells to the ultimate buyer.

Another type of intermediary involves an agent that provides a service in the form of matching buyers and sellers (Evans and Schmalensee, 2016). The **platform transaction** is a model used in a variety of industries such as accommodation (AirBnB) and transport (Uber).

Market intermediaries provide useful services and functions in a number of ways:

- It makes it possible for the transaction to take place (i.e. the exchange would not take place in the absence of the intermediary).

- It improves the efficiency of the transaction (i.e. the cost of transaction is reduced and/or revenues/profits are increased).

Information plays an important role in the use of market intermediaries. Platforms, for example, matches buyers and sellers by aggregating information about both sides of the markets.

Figure 1: Direct Transaction

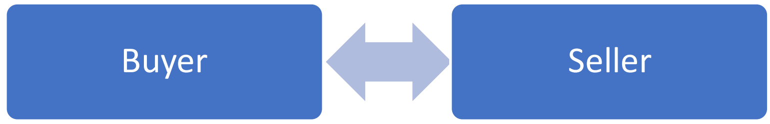


Figure 2: Indirect Transaction

Figure 3: Platform Transaction

2.3 Price Setting

How are prices set in economic transactions? There are a number of approaches or mechanisms to set prices. Phillips (2012, p.13) uses the term "pricing modality" to describe the approach to price setting:

> "The **pricing modality** is the way that buyers, sellers, and intermediaries interact in a market to determine the price for a particular transaction."

The main types of pricing modalities include the following:[3]

- **Haggling / Negotiation / Bargaining** – in which the price is negotiated between the seller and buyer.
- **Posted / List / Fixed Price** – in which a seller chooses a price and posts it in a market. In the case of procurement, a buyer can also set a price at which he/she will buy a product.
- **Auction** – in which buyers compete against each other for a product or service by offering the most attractive price to the seller. In the case of procurement, sellers compete to sell to a buyer by offering the most attractive price.
- **Beauty Contest** – in which buyers select sellers that meet a number of criteria aside from pricing. This process begins with buyers providing a list of specifications and criteria to sellers.

There could be other variations of pricing modalities that fall into any of the above categories.

How is a specific pricing modality selected in a market? Factors that affect the choice of modality include:

- Number of buyer and sellers in a market – static and dynamic (entry-exit)
- Nature of goods – homogeneity, characteristics, complexity
- Technology
- Norms
- State regulation

[3] See Phillips (2012), p.14 and Vohra and Krishnamurthi (2012), p.3.

Pricing modality could also change over time due to changes in the above factors. For example, a market could initially depend on bargaining but later adopt fixed pricing (Phillips, 2012, p.28-39).

Price setting is not a one-off activity. A host of follow-up activities are usually undertaken such as evaluating, updating, and managing prices. How these pricing activities are undertaken depends very much on the goals and approach to pricing which are explored next.

3. Approaches to the Study of Pricing

Pricing has been a subject of interest since ancient times. Greek philosophers such as Xenophon (427-355 BC) and Aristotle (384-322 BC) dwelt upon what determines the value of a good. Adam Smith (1723-1790), often regarded as the founding father of economics, examined the same question in the context of the Water-Diamond Paradox in which the value of a good is determined by its relative scarcity. Though the study of pricing today continues to be strongly grounded primarily in economics, the approaches to pricing taken in the business literature differ from the economic theory of pricing to some extent. Such similarities and differences are explored in this section.

3.1 Economics: Theories of Pricing

In economic theory, market price is determined by both buyers and sellers. When buyers take the form of individual consumers, individual demand can be constructed via utility optimization based on a set of preferences and a budget constraint (**Figure 4**). Price determination involves market or aggregate demand. This is a complex topic as there are a number of different approaches that can be used to aggregate a set of individual demands into market demand (Blundell and Stoker, 2005, 2007; Chiappori and Ekeland, 2011).

On the supply side, a seller's decision involves deciding the amount of a good to produce via profit maximization given its production function and factor prices. Price setting depends on market structure i.e. perfect competition, monopoly and oligopoly.

The equilibrium price in a **perfectly competitive market** is one in which demand equals supply (price clearing). The seller in such a market is a price taker and can only choose the quantity to produce. In contrast, a seller in a **monopoly market** sets a price (or a quantity) in which its marginal revenue equals marginal cost. Pricing in **oligopoly markets** – defined as those having two (duopoly) or more sellers – have a strategic element in that the actions of a seller depend on the actions of other sellers.

Figure 4: Consumer Choice Theory

This strategic interdependence in an oligopoly market is modelled using game-theoretic models. The three basic models of oligopoly pricing are the Cournot model (quantity setting), Bertrand model (simultaneous price setting) and Stackelberg model (sequential pricing). The equilibrium price in a Cournot model is somewhere between the equilibrium prices in monopoly (obtained in a collusive setting) and perfectly competitive markets. In the Bertrand model, firms compete by setting prices resulting in the equilibrium price equals marginal cost. In the Stackelberg model, a dominant seller sets its quantity first followed by other firms. The equilibrium price in the model is lower than the equilibrium price in the Cournot model.

Another important topic in pricing is **price discrimination**. In the case where a monopolist seller is able to sort heterogenous consumers and prevent price arbitrage, it can practice price discrimination. The goal of price discrimination is to extract as much of **consumer's surplus** as possible by charging a price closest to the consumer's willingness to pay. This is of course constrained by the seller's knowledge (information) of consumer's willingness to pay. The different degrees of information about willingness to pay leads to three types of price discrimination, namely:[4]

[4] These descriptions are based Oren (2012). For a technical exposition, see Varian (1992).

- **First-degree price discrimination** – in which a seller sets the price equal to the buyer's maximum willingness to pay.
- **Second-degree price discrimination** (**nonlinear pricing**) – in which prices are based on observable characteristics of purchases. In this case, the seller sets different prices for different amounts of goods purchased for each buyer.
- **Third-degree price discrimination** – in which pricing is based on observable characteristics. The different types of buyers based on these characteristics will self-select to pay for different prices (e.g. students, retirees etc.).

With regards to second-degree price discrimination, the economics literature on **nonlinear pricing** discusses the different schemes of nonlinear pricing. These include the following:

- **Bundling** - in which different combinations (bundles) of goods and services are sold at different prices to maximize profits.
- **Quantity discount** – in which goods and services sold are priced based on different units of purchase. This can take the form of a two-part tariff comprising a fixed charge and a constant price per unit purchased.
- **Ramsey pricing** – in which different prices are set for different groups of buyers based on their demand elasticity.

Pricing is also affected by **product differentiation**.[5] There are essentially two types of product differentiation – horizontal and vertical. **Horizontal product differentiation** takes place when there is no consensus amongst buyers about which differentiated good (e.g. by a characteristic such as location) is preferred when prices are equal. In such cases, buyers compare between the product characteristics and price in their purchase decision. In **vertical product differentiation**, buyers have consensus on which product is preferred based on a characteristic (quality). Price in such cases will depend on the differences in the characteristics. Thus, second-degree price discrimination or nonlinear pricing can also be undertaken when there is product differentiation. In so far as buyers can sort themselves in purchasing goods and services with different quality (e.g. tolled versus un-tolled roads), product differentiation can also lead to third-degree price discrimination.

[5] For more detailed discussions, see Belleflamme and Peitz (2015).

One significant development in the economic theory of pricing is the incorporation of ideas and findings from **behavioural economics**. Though the pioneering works were mostly experimental in nature, the theoretical models in industrial organization have been extended through making changes in the assumptions made for buyers' preferences (inconsistency), reasoning (sampling-based choice and coarse representation of data), and reference dependence (loss aversion and inertia).[6] In terms of pricing, naïve consumers could end up paying what is termed as "hidden price" - a component of the price that is ignored ex-ante but is paid ex-post. The type of price discrimination (e.g. second or third degree) employed by sellers also depends on the naivete/sophistication of consumers.

3.2 Marketing I: Pricing Management

In business studies on pricing, the implicit framework adopted is broadly consistent with that of economics - prices are determined by demand and supply factors in markets. However, in business studies, there is greater interest in what and how business decisions as well as actions can be taken to proactively manage market conditions with the goal of enhancing profitability. In economics, such market conditions are often assumed to be given in basic models. Often, the demand curve is assumed to be known and stable (or preferences are stable). Non-price actions, however, can be undertaken to change specific market conditions – for example, through advertising, innovation, collusion and mergers.

Nagel (2017) makes the distinction between conventional and strategic pricing. In **conventional pricing**, pricing is constrained by "functional areas" (finance, marketing and sales). Each has its own goal(s). These can be profit margins, increasing sales and enhancing market share. One conventional pricing approach is the **cost-plus pricing** in which prices are set based on the production cost (e.g. fixed cost). This is akin to cost-recovery approach to pricing which requires an accurate forecast of demand. Another conventional approach discussed in the literature is **share-driven pricing** in which prices are set to obtain a given market share goal.

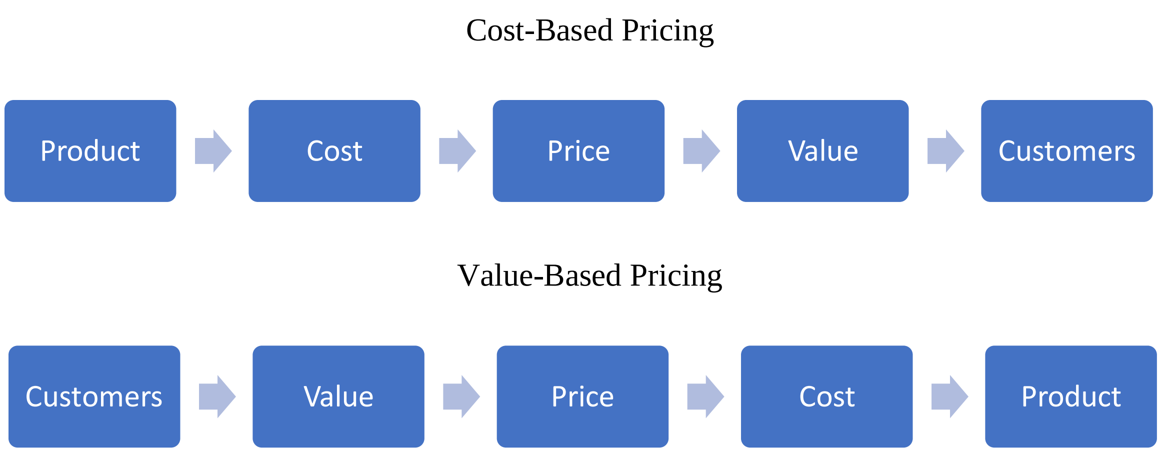
The term "strategic" is often used differently in business studies compared to the way economists use the term. For economists, strategic refers to a situation of interdependence between players e.g. in oligopoly models. In management and marketing, the term strategic is used in a broader sense to mean coordination of actions that lead to more profitable outcomes.

[6] For detailed treatment of the subject of behavioral industrial organization, see Spiegler (2011) and Heidhues and Koszegi (2018).

In **strategic pricing**, demand is not assumed to be given but can be changed by the seller's actions. Such actions include communicating the value of a product value and changing the expectations of buyers (Nagle, 2017). These actions can change buyers' willingness to pay by changing the context of the purchasing decision and/or the perception of the buyers. The impact of behavioral economics has been substantial in this area (and much earlier compared to industrial organization). This literature has examined how willingness to pay is influenced by framing effect (presentation of choice as gain or loss), endowment effect (dependence of the value of a product on establishment of ownership), present bias (immediate gain/loss is weighted more), and aversion to inequality (preference for fair distribution) (Ozer and Zheng, 2012).

Clearly, buyers' willingness to pay depends on how much they value the goods or services. This emphasis in pricing has lead to **value-based pricing** – an approach which focuses on "value creation" at the early stage of the pricing process. The pricing process in value-based pricing is completely the reverse of that of cost-based pricing (**Figure 5**). In the former, the focus is on the buyer at the early stage whilst the latter focuses on the product.

Figure 5: Cost-Based vs. Value-Based Pricing



3.3 Marketing II: Demand Models

Analytical and applied models of consumer demand are also used in marketing. These analytical demand models which are derived from economic theory can be categorized into two classes – aggregated demand model (product, firm, market, industry and national) and microeconometric demand model (disaggregated at individual consumer level).

Aggregate Demand Models

Aggregated demand models are based on specific and often parsimonious functional forms that make it convenient to apply in theoretical and empirical models (Van Ryzin, 2012). Functional forms that are often used include:

- Linear demand: $q(p) = a – bp$ (1)
- Exponential demand: $q(p) = e^{a-bp}$ (2)
- Constant-elasticity demand models: $q(p) = ap^{-b}$ (3)

where q is the quantity of demand, and p is the price.

One main use of estimating demand models is the derivation of the demand elasticity of a product which measures the percentage change in quantity of demand given a percentage in price. Demand elasticity is a key consideration in setting prices.

Microeconometric Demand Models

For microeconometric demand models, the focus is on the modelling and estimation of the individual buyer's demand. The buyer's decision is often modelled not in terms of the amount of goods purchased, but in the form of a binary (1/0) yes-no decision to purchase. The latter is a discrete choice that can be modelled using a random utility model in which the total utility U_i that a consumer gains from choosing a product i is given by:

$$U_i = u_i + \varepsilon_i \qquad (4)$$

where u_i is a representative component utility and ε_i is the random component utility.

The probability of choosing a product can be modelled in a number of ways depending on what assumption is made about the distribution for ε_i. The three most common models are:

- Probit model - 2 choices with ε_i having a normal distribution;
- Logit model – 2 choices with ε_i has a logistic distribution; and

- Multinomial model – more than 2 choices with ε_i having a double exponential distribution.[7]

Microeconometric demand models require individual-level data which has become more easily available today. With the availability of transaction-level data at the point of sale that can be linked to individual consumers, it is now possible to estimate microeconometric demand models for the purpose of personalized pricing.

3.4 Operations Research: Revenue Management

Revenue management (RM) is a form of demand-management decision-making. Some of the key characteristics of industries where RM is extensively used include the following (Talluri, 2012, p.655):[8]

- a capacity that is fixed and cannot be changed in the short-run;
- high fixed cost and low marginal cost;
- resource usage is sold in advance;
- perishable inventories;
- fluctuating demand over time; and
- incomplete information about heterogenous buyers.

RM is now extensively in services industries such as airlines, hotels, rental cars, freight transportation, and cruise lines. Talluri and van Ryzin (2004, pp.2-3) categorized decisions in RM into three types:

- **Structural decisions** – product design and pricing e.g. selling format, segmentation mechanisms, terms of trade and bundling.
- **Quantity decisions** – acceptance of buyer's offer, allocation of capacity (across segments, products and channels) and timing of product sale.
- **Price decisions** – price setting across different pricing mechanisms (posted individual-offer and reserve), product categories, over time and over product lifetime (markdown).

[7] Other extensions of the multinomial logit models include finite mixture logit measures and random-coefficients logit models (see Van Ryzin, 2012, pp.349-350). For a more advanced treatment of the subject including more recent extensions, see Dube (2019).
[8] See Phillips (2005) and Talluri (2012) for more detailed discussions. Talluri and van Ryzin (2004) provides a comprehensive and technical treatment of revenue management.

Structural decisions are fundamental decisions that are usually taken at the initial stage and revisited at subsequent stages (often infrequently). These decisions are also known as **strategic decisions** in the RM literature (Talluri, 2012).

In contrast, both quantity and price decisions are **tactical decisions** that relate day-to-day operational decisions. The choice between quality and quantity decisions depends on industry characteristics such as the relative flexibility of quantity versus pricing decisions. The distinction between price and quantity decisions have led to two approaches to RM, namely:[9]

- **Quantity-based RM** – in which prices are fixed and optimization involves allocation of resources (inventory/quantity to be sold).
- **Price-based RM** – in which the quantity to be sold is fixed and prices are changed in response to variations in demand.

The study of quantity-based RM has traditionally been structured into three types of problems, namely, (i) capacity allocation of single resources, (ii) network management of multiple resources, and (iii) overbooking. Price-based RM has focused on two areas, namely: (i) dynamic pricing and (ii) auctions. Comparing between quantity and price-based RM, Talluri and van Ryzin (2004, pp.176-177) argues that the latter is usually preferred over the former as it is usually easier and more profitable to change price than quantity.

3.5 Dynamic Pricing

Dynamic pricing refers to the practice of varying the prices of products and services in response to changing market conditions and/or to greater access to market information (about demand and supply). As a subject matter, the study of dynamic pricing cuts across a number of overlapping areas discussed earlier – economics, marketing and revenue management. The common forms of dynamic pricing that have been studied extensively include sales promotion, markdown, and personalized pricing. **Sales promotions** involve price discounts that are temporary price reductions within a specified timeframe (Blattberg and Briesch, 2013). **Markdown pricing** involves reduction in the prices of goods that are either perishable (e.g. food items) or have lower values after a given season (e.g. fashion items) (Ramakrishnan, 2013). In **personalized pricing** (also known as customized pricing), different prices are charged for different buyers based on their characteristics.

[9] See Talluri (2012), pp.658.

Another mechanism for dynamic pricing that is widely used is auction (Ockenfels et al., 2006). In an **auction**, buyers reveal their valuation of a product that is being sold by declaring the price they would pay for it (bidding). There are many ways to auction goods. They vary in terms of heterogeneity of goods (homogenous, heterogenous), units of goods sold (single, multiple), pricing direction (ascending, descending), timing of bids (simultaneous, sequential), duration of auction (fixed, flexible), and bid increment (fixed, jump). There are four basic types of auctions that are commonly discussed, namely: (i) English auction an ascending auction in which the winner is the highest bidder; (ii) Dutch auction an ascending auction in which the first bidder wins; (iii) first-price sealed-bid auction in which bidders simultaneously submit sealed bids with the highest(lowest) bid wins; and (iv) Vickrey Auction is a second-price sealed-bid in which bidders simultaneously submit sealed bids but with the highest winning bid paying the second-highest price bid. As sealed-bid auctions involve simultaneous and one-off bids, only the English and Dutch auctions are dynamic auctions.

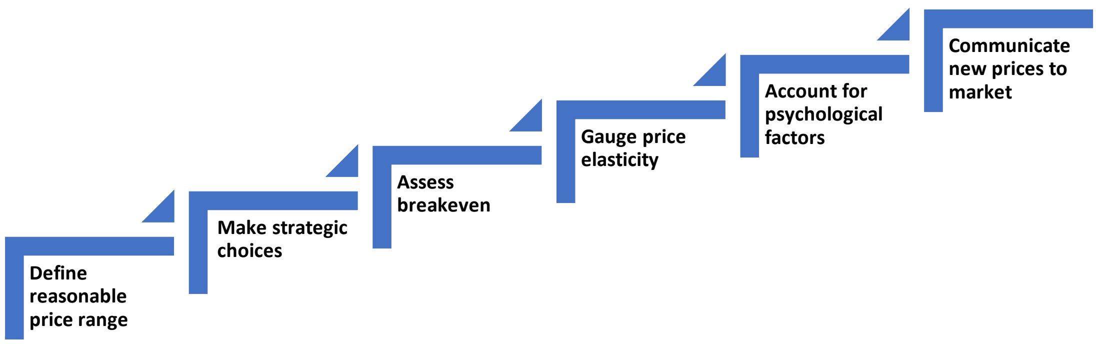
4. The Processes of Price Setting

The setting of prices is a fairly eclectic activity. Various elements from the different and often overlapping theories of pricing are incorporated in the practice of setting prices. The various ways in which these elements can be combined and the different goals of pricing imply that there is no single best approach to set prices. This is reflected in the following examples of the process of setting prices discussed in the literature.

Nagel and Muller (2017) provides a broad description of the practice of price setting within a strategic framework. The price of a product is determined through a series of steps (activities). The six steps in this process of price setting are depicted in **Figure 6**.

In the first step, the price ceiling is determined by willingness to pay of buyers whilst the price floor is the next-best competing alternative. The second step is "strategic" in nature, in that it involves narrowing down the price range to one that will yield profits that can be sustained in the long-term. Nagel and Muller (2017, pp.138-142) identifies three alternative strategic choices – skim pricing (to match buyer's willingness to pay), penetration pricing (to gain market share) and neutral pricing (to minimize the role of pricing by using other marketing tools e.g. branding). In the third step, the price range is further narrowed down by simulating the potential effects of different price levels on the profit margin based on estimates of the product's price elasticity. The fifth and sixth steps are more qualitative in nature. The fifth step draws insights on factors that can affect buyers' price sensitivity. These factors include buyer's reference value, switching costs, ability to make comparison, cost of the product in comparison with total benefit, price as a proxy of quality, cost of the product in comparison to buyer's budget, extent of the cost of the product which is shared with others, and perceived fairness (Nagel and Muller, 2017, pp.147-148). At this step, it may not entirely be about the price level as there may be complementary marketing strategies that affect price sensitivity. The price of the product is more or less set by the end of step five. The sixth (final) step involves convincing the buyers the price level is an appropriate one. This marketing approach draws upon some of the factors identified as influencing buyer's willingness to pay.

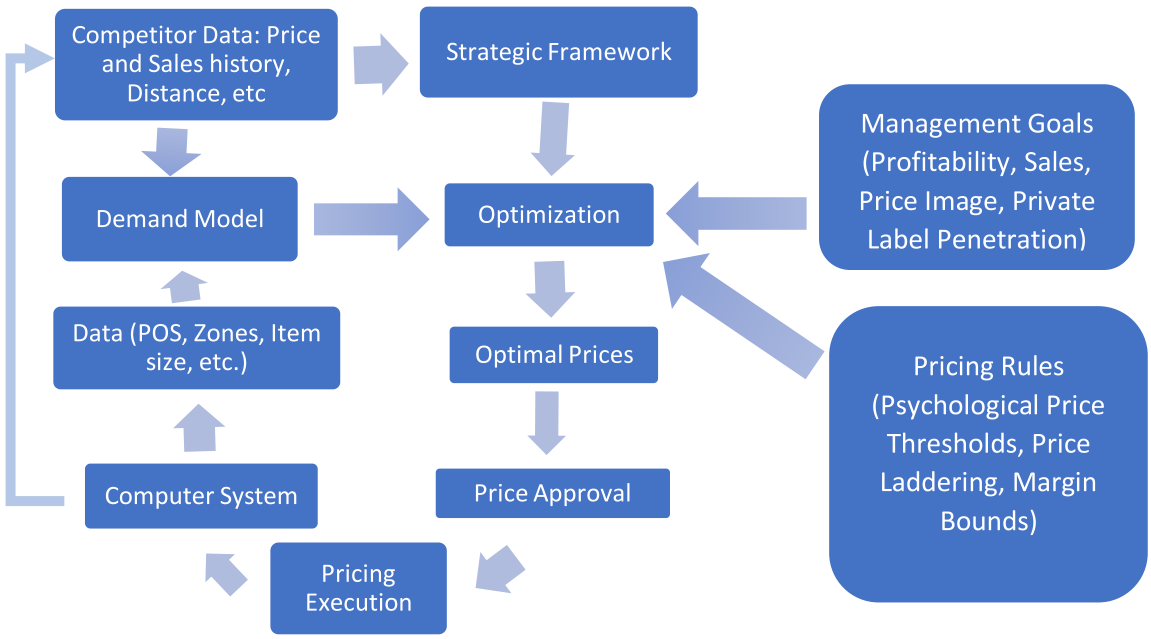
Figure 6: Six Stages of Price Setting



Source: Nagel and Muller (2017), p.135

Many of the above elements are also present in the pricing process discussed by Kopalle and Shumsky (2012) (see **Figure 7**). Human judgment and intervention take place in three areas: (i) strategic framework (ii) management goals and (iii) pricing rules. Once decisions in these areas are made, it is possible to automate the price execution partially (via the use of computer algorithms), especially in areas utilising data (own and competitors) to estimate the demand model.

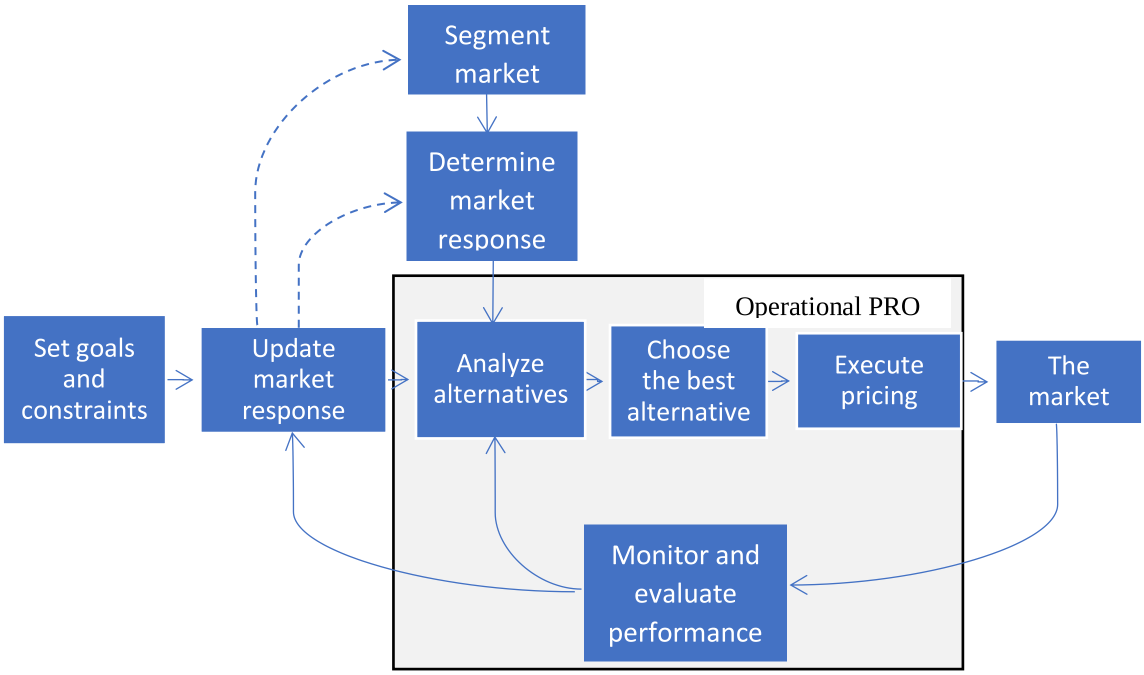
Figure 7: Pricing Process



Source: Kopalle and Shumsky (2012), p.409.

Phillips (2005) organizes the activities involved in the pricing and revenue optimization (PRO) process into two major areas – (i) four activities in the operational PRO (in shaded box), and (ii) four activities in supporting activities (**Figure 8**). It is the set of activities under the operational PRO that can be operationalised algorithmically in such a way that prices are set and dynamically updated using computer software (Phillips, 2005, pp.30-31). In contrast, the supporting activities are updated more infrequently – (i) goals and constraints – quarterly (ii) market segmentation (annually); (iii) market response estimations – weekly or monthly.

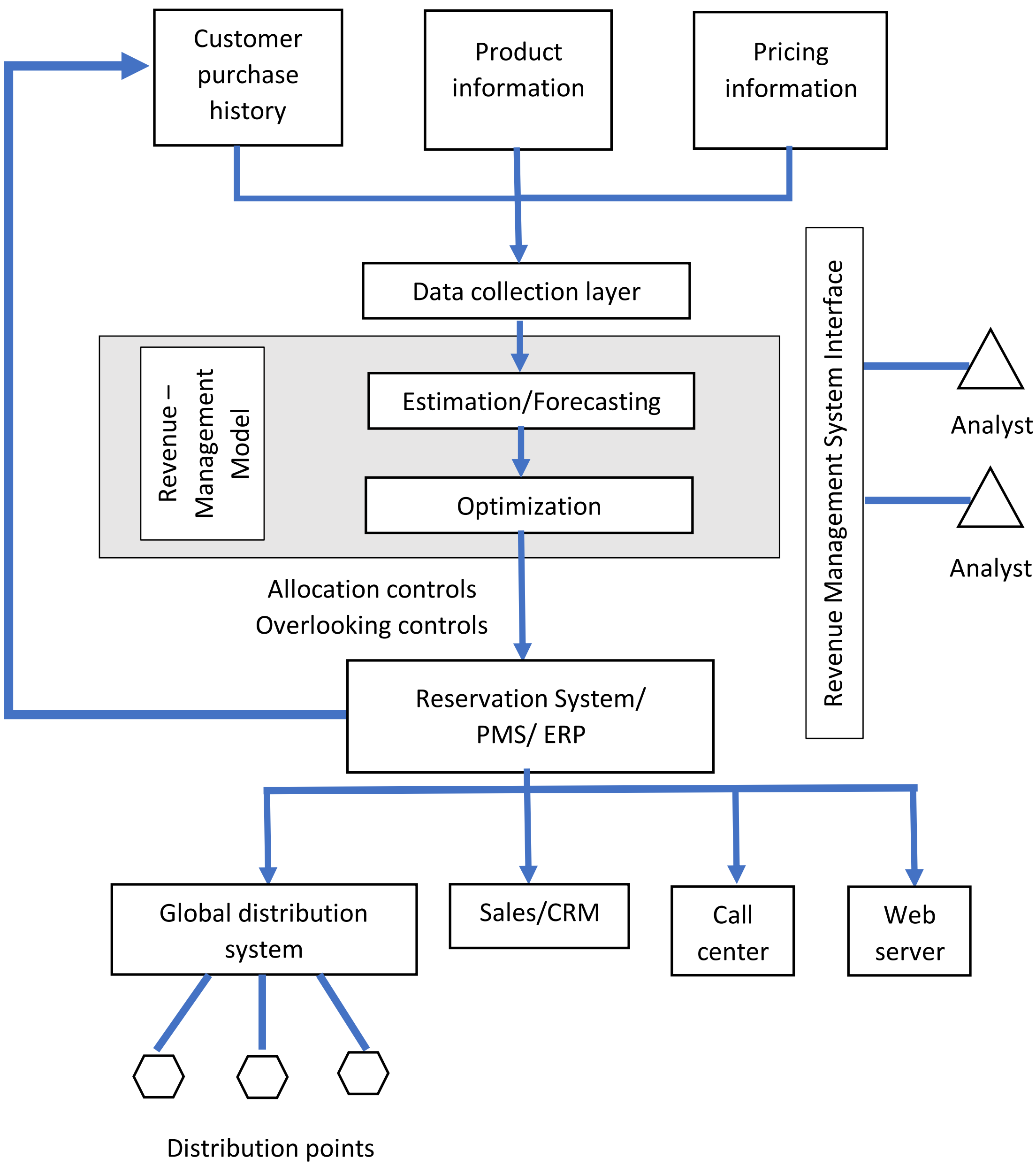
Figure 8: Pricing and Revenue Optimization (PRO) Process



Source: Phillips (2005), p.30.

A more fine-grain depiction of the operational PRO can be seen from **Figure 9**. The data collected is used to estimate and forecast demand, and these in turn, are used to find the optimal set of controls in terms of capacity allocation, prices, markdowns, discounts and overbooking limits (Talluri and van Ryzin, 2004, p.18). Today, the capabilities of human analysts can be complemented by using revenue optimization software packages (Phillips, 2005, p.30). The allocation and overbooking controls play the important role of managing inventory by linking these to global distribution systems.

Figure 9: Pricing in Revenue Management Process Flow



Source: Talluri and van Ryzin (2004, p.19)

5. The Application of Algorithmic Pricing

Advances in information and communications technology (ICT) have accelerated the application of computer programs and/or software in setting prices. In the early 1960s, the airline industry was an early adopter of computer programs to manage inventories and bookings (Barnes, 2012). Revenue management emerged in the airlines industry in the early 1980s after the industry was deregulated following the passage of the Airline Deregulation Act in 1978. Two key inventions further accelerated the application of ICT in dynamic pricing – the internet in the early 1970s and the World Wide Web in the early 1990s. These technologies spurred the development of e-commerce from the mid-1990s onwards.

Today, computer programs are used extensively to set prices in many industries. Some of the industries where this has been a standard practice for a long time are airlines and hotels as well as in the online retail industry. The transformation brought about by computer programs can be seen in the way in which the field of revenue management is defined:

> "Revenue management can be defined as a *data-driven*, *computerize system* to support the tactical pricing of perishable assets at the micro-market level to maximize expected revenues from sunk investments in capacity." Gallego and Topaloglu (2019, p.ix), italics added.

This section explores the areas within which computer programs (algorithms) are used to set prices. From the above discussions on the sequence of activities in the process of price setting, the key components of price setting are data, demand estimation, demand forecasting, and optimization. This follows up with a discussion on the various ways to organize algorithmic pricing.

5.1 The Role of Algorithms in Price Setting

Price in a theoretical model is determined by mathematically solving an optimization problem. The resulting optimal price is one associated with maximum profits (or revenues, depending on the goal set). The same problem can also be solved numerically by framing the optimization problem as a computational process that involves the application of a sequence of procedures (i.e. algorithms) on a set of data inputs. The output is a set of values (prices, quantity) associated with the optimal outcome (i.e. maximum profit and revenue). Shy (2008) provides many examples of how algorithms can be used to obtain optimal prices numerically. The algorithmic approach brings the analysis of pricing closer to the process of pricing as practised in industry.

There is no standard single set of algorithms for price setting. The coverage of a pricing setting algorithm depends on the extent to which various activities are integrated in the seller business processes. From the earlier review, the three major processes in price setting are: data collection, estimation of demand models and price optimization. Each of these processes involves the use of algorithms to some extent.

Data Collection

Data has no value in itself. It is only valuable as an input for (pricing) decision-making. The data for price setting comes from a number of sources:

- Buyer - quantity purchased, price paid, personal characteristics (age, income, etc.) and context of purchase (time, etc.),
- Seller (price, cost, product characteristics, marketing activities. sales promotion, inventory/stock, etc.)
- Competing sellers (price, product availability/stock, etc.)
- Market conditions (macroeconomic growth, inflation, unemployment, weather, etc.)

Computer programs are useful for automating data collection. This is particularly the case for a large number of observations due to one or more of these factors - number of buyers, number of sellers, number of products and frequency of transactions. The largest e-commerce platforms today have millions of users and products (**Table 1**). For these platforms, the computer programs record transactions that are used as data for modelling and price optimization. The purchasing behaviour of each buyer provides a cumulative database for this process.

Table 1: Comparison Between Selected E-Commerce Platforms

	Amazon	e-Bay	Alibaba
Number of Products (2018/2019)	1.5 billion	1.3 billion	1 billion (Taobao)
Total Revenues (US$, 2019)	280 billion	10.8 billion	56 billion
Number of Users (2018/2019)	200 million	182 million	654 million

Sources: https://www.scrapehero.com, https://www.macrotrends.net, https://fortune.com, https://www.ebayinc.com, https://www.ebayinc.com, https://www.macrotrends.net, https://www.alibabagroup.com, https://www.alizila.com

Given the large number of products sold, it would be difficult to manually change the prices of products on the largest e-commerce platforms. For example, Amazon.com is reported to change its prices 2.5 million times a day (or 29 times per second).[10]

Estimation of Demand Models

Demand models can be used to provide a quantitative measurement of how buyers' purchasing decision (propensity and intensity) are affected by price level and other non-price factors such as personal characteristics (income, age, gender etc.), past purchasing patterns/behaviour and marketing activities. The estimation of a demand model begins with an econometric specification of the model with purchasing decision as the dependent variable. For a discrete **choice demand model** using transaction-level data, the dependent variable y_i can take the form of a binary "propensity" variable (yes/no purchasing decision). In a **volumetric demand model** (or a continuous "intensity" model), the dependent variable y_i is the amount of goods purchased.

The independent (explanatory) variables in demand models include the price of the product (p_i), price(s) of competing product (p_{i-1}) and a vector of variables (M) representing various non-price factors such as sales promotion, branding, holiday season and weather. The model specification can be expressed formally as:[11]

$$y_{it} = \beta_0 + \beta_1 p_{it} + \beta_2 p_{i-1,t} + M_t'\beta_3 + \varepsilon_i \qquad (5)$$

More sophisticated dynamic demand models can also be constructed to take into account buyers' purchasing decisions that are affected by sales (delayed purchase), stock-piling and product life cycle (Seetharam, 2009; Dube, 2019; Nair, 2019).

Products in markets are often differentiated (heterogenous) in terms of attributes (characteristics, features). This has led to two approaches in estimating demand for differentiated goods. Economists have introduced the **hedonic pricing analysis** which involves regressing price (dependent variable) against product attributes (independent variables) using real data. This approach yields the willingness to pay for the different product attributes.

Marketing scientists use the **conjoint analysis** to estimate the expected demand (discrete choice or volumetric) by using product attributes as independent variables (Allenby et al,

[10] Source: https://qz.com/157828/amazon-changes-its-prices-more-than-2-5-million-times-a-day/, accessed 4 June 2020.
[11] See Leeflang et al (2000) and Katsov (2018).

2019). This approach involves using survey data to capture the potential demand for new products. Conjoint analysis can contribute to product design via the identification of product attributes that maximizes the expected demand for the product.

The econometric estimation of demand models is mostly implemented using computer programs. However, the extent to which both data collection and estimation of demand models are automated with their outputs fed into pricing depends on the extent to which demand models are used in the price optimization process. The estimated coefficients from the demand model can be used to construct a **price response function** that can be used to forecast the demand for a product given the price level. Even though hedonic pricing and conjoint analyses are carried out using computer programs, these methods may not be used in price optimization in an automated fashion (e.g. real-time automated price adjustments). Instead, they may be used for product design and at the initial stages of pricing process (narrowing down price range). The automation of price optimization can be driven by greater use of machine learning and big data. This can extend the number of variables used for predictions including uncovering important psychological factors that feature in behavioural economics (Camerer, 2019).

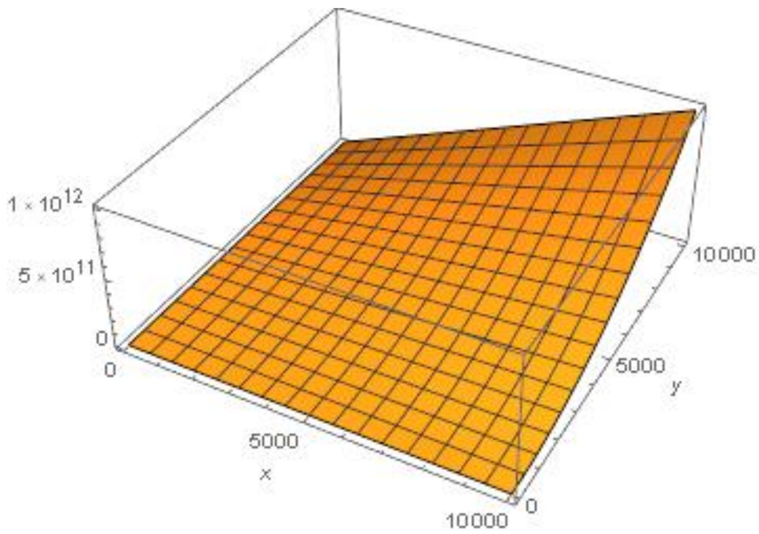
Optimization

The price of a product is a decision variable in an optimization process aimed at achieving goal(s) set by the seller. It may not be the only variable as other non-price variables such as product placement and advertising are likely to be important as well. The extent to which the optimization process involves the use of algorithms range from 0 to 100 percent. At the one end, computer programs can be used to generate demand forecasts, but the actual execution of pricing is done entirely by human judgment. At the other extreme, prices are set dynamically by using purely computer algorithms. This form of dynamic optimization is known as embedded optimization where real-time pricing decisions are automated (Hwang and Kim, 2006 and Chen et al, 2-16). It should be noted even though dynamic pricing is driven extensively by algorithms, the constraints for the optimization processes are to some extent determined (coded) by humans based on a number of factors, e.g. cost structure. Thus, a hybrid approach involving a mix of human decision-making and algorithms is another possibility.

There are a number of factors determining the extent and how algorithms are used in the optimization process. One factor is the nature of business in terms of the size of the product portfolio, heterogeneity of products portfolio and the frequency of product sales (see earlier discussions comparing Amazon.com, E-Bay and Alibaba). It is likely to be too difficult to adjust prices frequently without the use of algorithms when sellers have a large portfolio of products and high product turnover. In such cases inventory management can also be integrated and automated.

A second factor is technology in terms of the computational complexity of algorithms required for the optimization process.[12] The computational time required to solve a least-squares optimization problem (which can be the basis of demand estimation) is proportional to x^2y, where x is the number of optimizing variables and k is the scalar size (Boyd and Vandenberghe, 2004). This is depicted in Figure 10 where the vertical axis represents computational time.

Figure 10: Computational Time for a Least-Squares Optimization



Source: Author

Nonlinear optimization problems are even more complex. To ensure the optimization process is feasible, alternative approaches to brute force optimization such as local optimization and machine learning (supervised and unsupervised) can be used.[13] Unsupervised machine learning can lead to the type of pricing rules that emerges from the application of learning algorithms

[12] See Wigderson (2019) and MacCormick (2018) for a comprehensive treatment of computational complexity.
[13] For a useful general discussion on the use of machine learning in pricing, see: https://tryolabs.com/blog/price-optimization-machine-learning/ (accessed 16 June 2020)

on large data sets. Such pricing rules are essentially black boxes in that it is not possible to deconstruct or reverse engineer the algorithms to discover the basic structure of the program. Not completely understand how AI construct pricing rules could imply human judgment may still play a role. Agrawal et. al. (2018) argue that AI complements human judgment especially in complex decisions.

A third factor is the cost of implementing algorithmic pricing. A fully integrated and automated algorithmic pricing system can be expensive to implement. Such a system integrates the inventory system with an optimization program that draws data from the seller's own customers (past purchases and search behaviour) and the price-stock data from competitors. The cost of implementing such a system can become justifiable only when sellers reach and exceed a given operational threshold. To overcome the prohibitive cost of adopting algorithmic pricing, alternative modes of algorithmic ownership can be implemented especially with the business platform models. This leads to the discussion on the different vertical boundaries of algorithmic pricing.

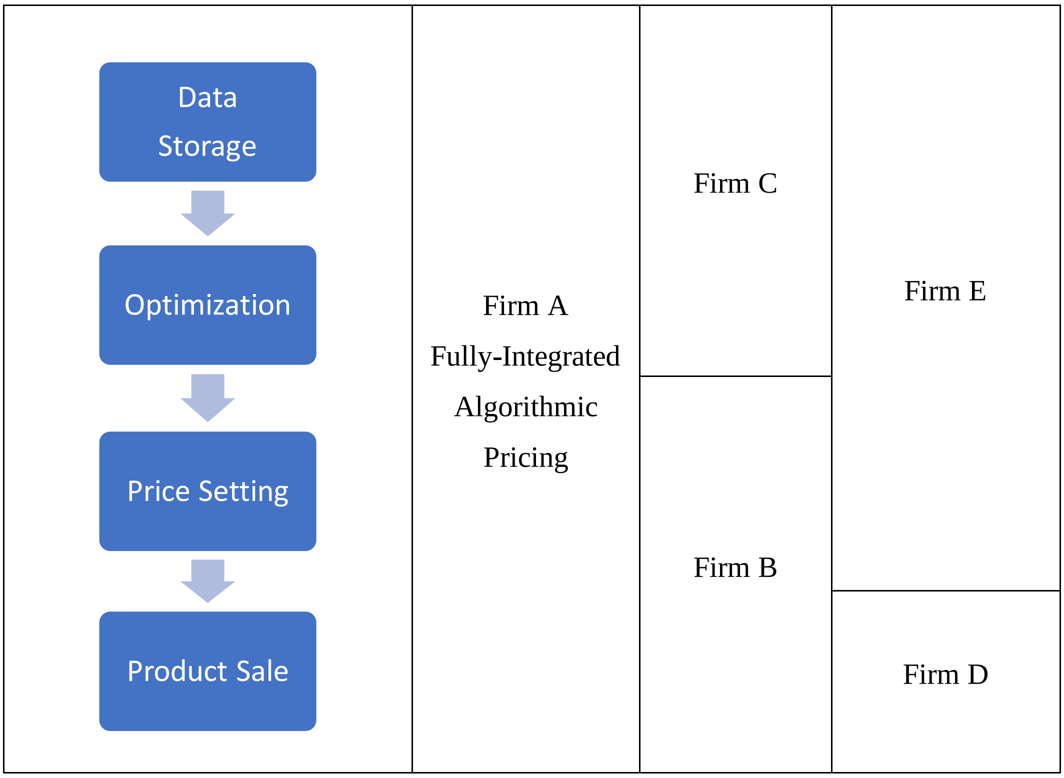
5.2 The Vertical Boundaries of Algorithmic Pricing

The implementation of algorithmic pricing is part of a broader set of a sequence of activities that begins with data collection and ends with the sale of a product. Such activities can be analysed with the framework of the vertical boundaries of a firm which refer to the range of activities that are undertaken internally by the firm vis-à-vis other activities that are bought from or outsourced to other firms. The idea of vertical boundaries originates from the literature on the theory of the firm pioneered by Coase (1937). What activities are performed internally by a firm depends on the net benefit (i.e. benefit minus cost) of doing so compared to outsourcing it to another firm. The incentive structure associated with the different vertical boundaries is an important dimension – if an activity involves investment in human capital (programming knowledge), ownership of the activity ensures an optimal investment in human capital (Hart, 1995).

This framework can be applied to understand the ownership aspect of algorithmic pricing activities. Firms might be able to undertake all the activities related to algorithmic pricing (Firm A in **Figure 11**). An example of this is Amazon's own retail business (not third-party sale). Smaller firms may find it too expensive to do everything.

An alternative arrangement is depicted in Figure 11 where firm B opts to set prices at an e-commerce portal (firm C) but uses the service of the portal to collect data and undertake optimization. Yet another possibility is for a firm (D) leave the price setting activities as well as other related activities to the e-commerce portal (E).

Figure 11: Vertical Boundaries of Algorithmic Pricing



Source: Author

6. Conclusions

Algorithmic pricing – the use of computer algorithms to set prices - has become an increasingly important business practice. Like in any new technology, it is a double-edged sword – it offers both opportunities and risks to society. Whilst businesses may welcome the benefits of using algorithmic pricing to increase their profits, regulators are concerned about collusive activities. To truly understand the nature of algorithmic pricing it is useful to begin with a broad review of the various forms of pricing – the nature, goals and modus-operandi. Various disciplines – economics, marketing and operations research – provide useful perspectives on the mechanics of pricing and its implementation. The implementation of algorithmic pricing is driven by a host of factors – scale of businesses, technology and cost. The locus of algorithmic pricing may differ across firms/sellers leading to a rich spectrum of vertical boundaries for algorithmic pricing.

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