# Participative pricing in B2B markets

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## *1. Introduction*

In this chapter, we discuss participative pricing in business-to-business (hereafter B2B) markets, with a focus on auctions and bargaining, and with some analysis of empirical findings in these two areas.

***Participative pricing*** is a term that refers to pricing mechanisms in which the buyer and the seller both have a say (i.e., inputs) in determining the price of each transaction. This type of pricing stands in contrast to a ***posted price format***. In a posted price format, the seller posts a price (known as posted price or list price) and the consumer buys the item if the price is lower than the consumer's reservation value.

The term ***participative pricing*** applies to auctions, buyer-seller bargaining, and other innovative pricing methods (Spann et al., 2018; Zhang et al. 2021). Following the advent of the Internet, it is relatively costless in terms of transaction costs for sellers to implement such pricing formats. That said, inertia and preferences for traditional retail shopping formats have made such advanced pricing methods slow to spread in consumer markets and confined to niche consumer markets. More typically, in business-to-consumer transactions, sellers primarily sell through posted price, or posted price in a dual channel with auctions (Caldentey & Vulcano 2007). This is despite evidence that both auctions and bargaining can produce higher revenues for sellers (Cason et al. 2003).

In sharp contrast to consumer markets, in B2B (business-to-business) markets, participative pricing—bargaining (Grewal et al. 2015) and auctions—have long been the norm. Advances in technology did not make such methods more prevalent (as they have always been prevalent) but they most certainly made them more structured. Specifically, ***B2B auctions***-- more commonly known as ***procurement auctions***-- can now incorporate and automate a sophisticated scoring system which evaluates numerous critical dimensions (in the case of Google Ad Words, hundreds of factors). Likewise, **bargaining** can now be automated to deal individually with each of tens of thousands of consumers.

The current chapter will deal with recent findings on the automated processes for both auctions and bargaining on mass scale. It then explains how to estimate key parameters using commonly available data on such transaction formats.

## 2. B2B (Procurement) Auctions.

Auctions refer to pricing formats where buyers (sellers) submit multiple bids for a contract and the bidder with the highest (lowest) bid wins. Auctions are a ubiquitous format in consumer retail. eBay is the dominant force in consumer auctions. eBay offers consumer a wide range of products at bargain prices, while offering small sellers a market for used products and collector items that they might otherwise dispose of. Many formats have been proposed for consumer auctions. While these formats are outside the scope of this chapter, but they can generally be divided along two dimensions. First, open-bid vs. sealed. In open-bid auctions, bidders can revise their bids continually and observe something about other bidders' actions in the course of the auction. In a sealed bid auctions, bidders submit a single bid and observe nothing about others until all bids have been received. The second dimension is first vs. second price, where in first

price auctions, the winning bidder pays its own bid and in second price auctions, the winning bidder pays the bid of the next highest bidder.

While eBay and other consumer auctions have been researched extensively and documented thoroughly in the literature (Haruvy & Popkowski Leszczyc, 2010a, 2010b; Haruvy et al. 2004; Haruvy et al. 2008), they may not resemble much B2B auctions. For once, the contracts under B2B auctions tend to be multi-unit and/or multi-attribute (Xu and Huang, 2017). In the case of multi-unit, that means that auction format needs to account for a market clearing price that involves multiple winners at different quantity amounts. In the case of a multi-attribute auction, it means that the winner-selection rule needs to accommodate for non-price quality-related features (Jap and Haruvy, 2008; Haruvy and Jap 2013; Engelbrecht-Wiggans et al. 2007).

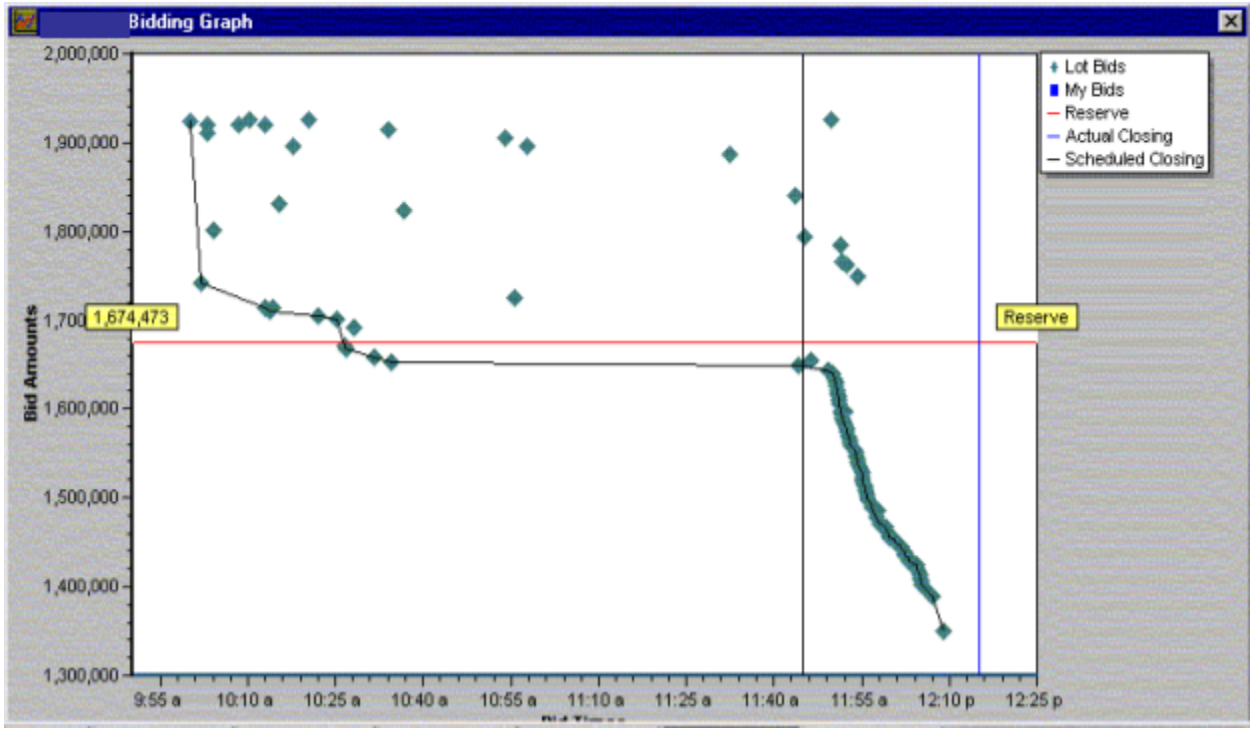
When it comes to B2B auctions, the purpose of the auction is critical to understand. Consumer auctions' purpose is generally understood to maximize seller revenues (Wolfstetter, 1996). In contrast, it has been eloquently argued (Bimpikis et al. 2020) that the purpose of B2B markets is to maximize thickness—i.e., to bring in lots of buyers and sellers.

Auctions in procurement settings offer a natural automated process for price discovery (Tunca et al. 2014; Beil, 2014). In fact, it could be argued that a price discovery tool is the primary purpose of B2B auctions (Anand and Aron, 2003; Chetan et al. 2018; Alcalde and Dahm, 2019). Whereas in consumer auctions, an auction can be regarded as a one-time event, B2B auctions are often followed by a more complicated relationship that involves repeated future transactions and relationships with buyers. Thus, the auction is not the final event, and can be regarded as a preceding event, or at least an intermediate event in the path to maximize profits—i.e., a price discovery tool.

B2B auctions can be forward auctions, where a seller receives offers from multiple buyers and the highest bidder wins, or they can be reverse auctions, where a buyer receives offers from multiple sellers and the lowest bidder wins. At least in theory, forward auctions and reverse auctions are isomorphic (Engelbrecht-Wiggans et al 2007). That is, in a structured formal setting, to transform a forward auction to a reverse auction, one needs to substitute sellers for buyers and buyers for sellers and then reverse the direction of bids, such that bids go down instead of up, and the winner is the lowest bid. Theoretically, this allows a forward auction format to be translated to an isomorphic reverse auction format without loss of generality.

In reality, because bidders are differentiated in B2B auctions, the flexibility for buyers to choose the winning bidders is of great importance in B2B auctions, making this a primary distinction between B2B auctions and other auctions. One consequence of differentiated bidders is that bidders adjust their bids to account for their non-price qualities. Thus, in many B2B reverse auctions we observe many bids above the lowest bid over the course of the auction (see Figure 1). Hence, buyers need a way to assess whether a supplier has bid aggressively or cautiously held back. To this end, Jap and Naik (2008) developed *BidAnalyzer*, an optimization algorithm using state-space models and a Kalman filtering technique not only to predict the ending bids of an auction (based on initial bid activity), but also to give insight into whether the supplier has held back in its bidding (implying that there is still money to be gained from post-auction negotiations), or has bid too aggressively (and perhaps in danger of a winner's curse).

***FIGURE 1***
***BIDDING ACTIVITY IN ONLINE REVERSE AUCTION***



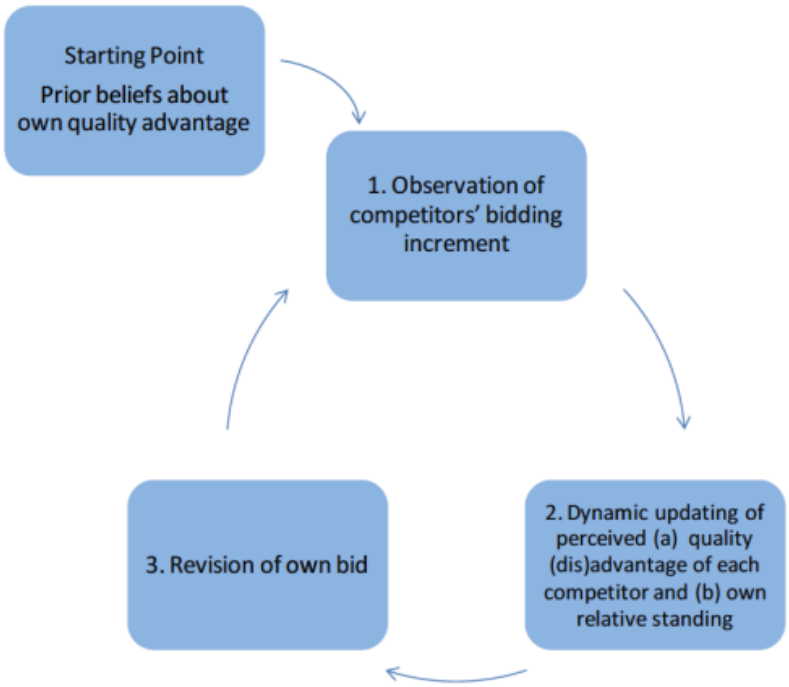

The horizontal axis denotes time over the course of the auction. Diamonds represent bids received over the course of the auction. The black line traces the lowest bid at any point in time. Reproduced from Jap (2002)

While bid data from procurement auctions, along the lines of the format in Figure 1 is available, analyzing it empirically is far from trivial. This is because unlike consumer auctions, prices are not the primary variable of interest. In many cases, relationship variables matter greatly as well). Combining point-by-point bid data of online buyer-determined reverse auction lots from an industrial buyer with pre- and post-surveys of bidder relationship states (i.e., propensity for a relationship with the buyer, willingness to make investments, relationship satisfaction, etc.) in online reverse auctions, Jap and Haruvy (2008) find that bidders with higher relationship propensity (both past and future) and a greater willingness to make specific investments with the buyer prior to the auction bid less aggressively during the course of the

auction, while bidders who bid aggressively during the auction reduce their propensity for a relationship and sour incumbent satisfaction with the buyer post-auction (cf., Carter and Stevens 2006). This research was the first to use field data to examine bidding behavior during the auction with factors *outside* of the auction mechanism (both before and after), but more importantly, it suggests that bidders systematically intertwine and trade-off bid prices and non-price attributes against each other as part of their strategic bidding behavior.

Haruvy and Jap (2013) propose that quality differentiated bidders would systematically impact bidding behavior. They propose a model in which a bidder's beliefs and observations of competitive bids jointly feed into a dynamic loop with updating to result in bid revisions (see Figure 2). Using bid-by-bid data from an industrial buyer, they find that differentiated, anonymous bidders appear to be making inferences about their own implied quality differentials and adjust their bidding strategies and bidding aggression accordingly. Specifically, high quality bidders tend to be more aggressive in bidding against potentially higher-quality competition and less aggressive when bidding against potentially lower-quality competition. In contrast, low-quality bidders compete fiercely regardless of their relative quality compared to the competition.

***FIGURE 2: DYNAMIC UPDATING PROCESS FOR DIFFERENTIATED BIDDERS***




Reproduced with permission from Haruvy and Jap (2013)

In summary, empirical auction research on B2B auctions should first identify the primary purpose of the auction, rather than assume it to be revenue maximization, as the purpose is likely to be more evolved than in consumer auctions. Second, the relationship variables need to be mapped out and incorporated into the equilibrium solution. Third, dynamic adjustment methods need to account for bidders respond to each other.

## 3. B2B Bargaining

As demonstrated in the previous section, auctions can prove productive to arriving a price point as long as they are sensitive to relationships and allow a participatory role to both buyer s and sellers. To this end, there has been literature exploring how the bidding process typical in

auctions might be married with, sequenced with, or replace negotiation efforts in order to provide increased flexibility and viable options for procurement efforts.

Bargaining is obviously a time-consuming process, and it is particularly cumbersome for suppliers that deal with thousands of customers and tens of thousands of negotiation occasions, as is the case in the data we study. That is, whereas an effective autonomous salesforce dealing with customers works well in many procurement settings (Elmaghraby et al. 2015), the autonomous salesforce model is not expected to extend to settings with a large number of transactions with smaller buyers, especially if salesforce pricing decisions must be automated (Karlinsky-Shichor and Netzer, 2019).

## 4. Combining Auctions and Bargaining

Research has explored mechanisms that combine auction elements with negotiation processes. Haruvy et al. (2020) compares a bargaining protocol that allows sellers to make concessions dynamically to one where the seller receives a take-it-or-leave it offer. The dynamic concession protocol is like a dynamic auction, except the buyer can accept the offer and end the process at any time, and bargaining is done bilaterally with no competition. Laboratory experiments allow a test the interaction of the bargaining form with contract formats (i.e., a wholesale price and two-part tariff contracts), each using two different bargaining protocols. Their main finding is that contracts are more efficient when sellers can make concessions dynamically. We use this insight in the present design, where three consecutive alternating offers, where the last one is a take-it-or-leave it ultimatum offer. Because concessions matter, it is not optimal for the seller to begin with its final ultimatum offer. That is, we allow for the possibility that three consecutive alternating offers can improve over a single ultimatum offer.

Teisch et al. (2001) proposed a hybrid procedure that has both auctions and negotiations running side-by-side. This mechanism also includes an auto mode wherein the system suggests prices to the bidders based on the reserve price or previous bids, NBI discounts[1], Bid Premiums, and the bid increment, subject to constraints. We use that insight to propose automated adjustments in our sequential alternating-offer setting.

Zhang et al. (2014) point out that customized offers should take into account relationships--i.e., relationships have value. In the next section we use that insight to demonstrate a relationship-driven adjustment (based on relationship tiers) in an industrial buying setting.

## 5. A demonstration of empirical analysis of B2B Bargaining

In this section we demonstrate the empirical analysis of bargaining data with attention to differentiating relationship variables. The focus here is on the balance between bargaining and power of both buyer and seller related to these relationship variables.

### 5.1.Data Description

A dataset was obtained from a large international manufacturer. The company sells various components and parts used in manufacturing. The items can be bought at the price indicated for each item on the company's website, but buyers can and do often engage in rounds of negotiations for a lower price. Each observation in the data records how a price of a product changed from the list price down to the final negotiated price through a bargaining process between a buyer and the seller. The data also include whether the negotiated price was approved after a delay, whether the negotiated price was converted to revenue as well as buyer information

[1] Negotiable Bid Issues are issues besides price and quantity that bidders will include in the actual bid, such as warranty and delivery. Discounts may be applied to different levels of such issues by the auction owner, resulting in a higher price paid for preferred terms

– customer loyalty level, geographical location, and industry represented – and product information – type of product, product uniqueness, product volume.

For the purpose of the present demonstration, we look only at the data where the buyer negotiate directly with the seller, without an intermediary such as a distributor. A summary of the data cleaning process is in Table 1.

Table 1. Summary of Data Cleaning Process

| Excluded | Rationale for Exclusion |
|---|---|
| Distributor Channel | We are interested in a bargaining process between an end customer and the seller. |
| Auto-Approved Quotes | We only investigate deals that entered a bargaining process. |
| Seller Loss Leaders | Sometimes sellers sell below cost as a loss-leader technique and this is cannot be considered to be the outcome of negotiation. |
| Buyer Loss Leaders | Buyers should not buy at a price higher than the list price. That's a loss-leader proposition on the part of the buyer. |
| Incorrect Quote Approval | A quote should be approved without delay if a buyer did not ask for a concession. |

Also excluded were transactions in which the buyer's requests were automatically approved by the computer algorithm. These transactions were automatically approved because these are likely renewals of the price approved from the previous bargaining process. Such transactions are outside of the scope of the current chapter since no current bargaining took place.

In our data, there were two lowball threshold prices – Level 1 Threshold ($L_1$) and Level 2 Threshold ($L_2$) – that determined whether the company approved a price quote immediately or after a delay. $L_1$ was strictly higher than $L_2$. The company approved the final negotiated price immediately if the price was higher than $L_1$. However, if the price fell between $L_1$ and $L_2$, the price quote was transferred from sales agents to regional pricing managers for further evaluation, resulting in a delay. The same was true if the price fell below $L_2$.

After all the exclusion criteria were applied to the dataset, data on 82,345 negotiations were entered into further analyses.

### 5.2.Relationship Tiers

In the dynamic concession protocol, the company applies different discount rates to each buyer. The data shows that some buyers were given a considerable amount of discount while others were not. Furthermore, we found that the discount rates varied across the bargaining process. The company gave some buyers their discounts early in the bargaining process while it gave other buyers discounts late in the process. We theorize that the buyer-seller relationship is a crucial factor in predicting how much discounts were given to each buyer.

The company classified each buyer into one of several relationship tiers. For the purpose of this analysis, we classify prospective buyers into one two broad relationship tiers (each encompassing some of the original company-assigned tiers). We call these two broad classes preferred and regular customers. 30% of the buyers in the data were preferred customers either because they have repeatedly bought from the company in the past or because they are buying products in very large quantity. Presumably, the company would give more generous concession

to preferred customers than to regular customers since they are more likely to continue a long-term partnership with the company in the future.

### 5.3.Seller Power: Product Differentiation

The central tenet of Economics is that supply and demand are negatively related. If a product is short in supply while holding the customer demand constant, sellers would have more say in the bargaining process. In our data, 25% of the products were unique in that they were manufactured and sold only by the company. It is assumed that the company would be less likely to offer a generous concession to buyers who wish to buy such products, since there is no competition.

On the other hand, 75% of the products in the data were non-exclusive goods. Since the buyers could obtain these products elsewhere, the company is more likely to offer a generous discount to maximize the chance of procuring a deal.

As we will discuss later, customer relationship tiers and product differentiation were two consistently significant predictors of the discount amount given as well as the probability of agreement. We will also show the relative contribution of the two predictors, while controlling for other factors, which we describe below.

### 5.4.Three-Stage Bargaining Framework

Businesses are more efficient when sellers can make concessions dynamically. The context in which our data was extracted captures that notion. In the current section, we describe a version of the dynamic concession protocol with which the company uses to procure deals from multiple buyers.

The company deals primarily with buyers who buy products in large volumes. These buyers have the bargaining power to request a concession, which can come in many different forms. Here, we focus on monetary discounts.

When buyers decline to pay the list price[2] and rather request a concession, the company can entice a deal by engaging in a bargaining process that consists of three stages of alternating offers between the company and a buyer. The first stage of the process in our framework (see Stage 1 in Figure 3) begins with the seller (aka, the company) determining a list price for every product. At this point, buyers can take one of three actions: they can pay that list price to obtain the target product, exit the bargaining with the company, or request a concession. If a buyer either agrees to pay the list price or exits entirely, the buyer is considered to have exited the bargaining process and does not advance to the next stage.

Buyers who request a concession in the first stage enter the second stage of the bargaining process (see Stage 2 in Figure 3). The stage begins with the seller conceding and suggesting a new price for each buyer. With the new price in hand, buyers can then take one of four actions: accept the suggested price, quit bargaining, ask for another concession, or make a counteroffer by stating how much they would like to pay. Note that none of these actions guarantees that buyers purchase the product. In other words, buyers can exit the bargaining process even after the company incorporates additional concessions to the price. Also, in the case of buyers making a counteroffer, they can exit later, but we consider them to enter the next and final bargaining stage before they can do so. Buyers at this stage do not advance to the next stage only if they either agrees to pay the suggested price or exit the bargaining.

[2] In the current chapter, the terms “posted price,” “list price,” “MSRP,” and “Internet price” are interchangeable.

Lastly, the third stage in our framework begins with buyers making a counteroffer to the seller (see Stage 3 in Figure 2). After a counteroffer is made, the seller can either accept it or counter-suggest a "take-it-or-leave-it" ultimatum. The seller's ultimatum offer determines the final price which buyers must decide to pay or forego the purchase. The ultimatum offer is often made with a delay for buyers who made a particularly low counteroffer in the previous stage.

In the rest of this section, we explain each stage of the bargaining process in more detail.

*<INSERT FIGURE 2 HERE>*

**Stage 1: Seller Determines List Price and Buyers Can Either Buy or Quit**

Even though no alternating offers have yet been exchanged between buying and selling parties, we consider all buyers to have entered the bargaining process at this stage. Here, the company (i.e., seller) determine the list price and buyers determined the convergence (i.e., agreement to pay) to revenue. The data showed that 33% of the buyers concluded the bargaining process at Stage 1 and did not request a concession of any sort. Of these buyers, 25% bought the target product while 75% quit without seeking a better deal from the company (see Stage 1 in Figure 3).

**Stage 2: Seller Concedes with a Suggested Price and Buyers Can Either Buy or Quit**

In our data, 67% of buyers requested a concession and they advanced to Stage 2 of our bargaining framework. At this stage, the company conceded to buyers' requests and dynamically determined a new price for each buyer (see Stage 2 in Figure 3). It is important to note that 16% of the buyers at this stage appeared to receive a suggested price that was higher than the list price

– possibly because they asked for ancillary services in addition to their target product. However, the price was ultimately lowered after the company incorporated multiple concessions requested by the buyers. Therefore, a new, suggested price was always lower than a list price after incorporating buyers' request for concession.

After a suggested price was first determined, the data showed that 33% of the buyers accepted the new price while 50% asked for another concession to obtain a better deal. The data also showed that more than twice the buyers ended up paying for a product when they asked for another concession than when they did not.

**Stage 3: Seller Determines the Final Price and Buyers Determines Convergence**

Unwilling to accept the company's offer at Stage 2, 17% of the buyers advanced to the next and final stage of the bargaining process. Buyers at Stage 3 made a counteroffer to the company by stating the price that they wished to pay. Of all the counteroffers made by the buyers, 48% were accepted by the company and the rest, 52%, were countered with a "take-it-or-leave-it" ultimatum offer.

Central to the bargaining process is strategic delay. In fact, 36% of all the accepted counteroffers were accepted with delay while 35% of all the unaccepted counteroffers were countered (with the ultimatum offer) with delay. It seems unnecessary and wasteful to introduce a delay in the bargaining process, but as a strategic device it may be effective.

The delay affected the proportion of buyers who ended up paying for the product. When the company accepted buyers' counteroffers, 26% of the buyers whose counteroffers were accepted without delay ended up purchasing while 35% of the buyers whose counteroffers were

accepted with a delay ended up purchasing. On the other hand, when the company made an ultimatum in response to buyers' counteroffers, 20% of the buyers who received the ultimatum without delay ended up purchasing while 16% of the buyers who received an ultimatum with a delay ended up purchasing (see the bottom of Stage 3 in Figure 2).

### 5.5.Different Prices at Different Stages

We now turn our attention to different types of prices and other relevant variables that enabled our conceptualization of the three-stage bargaining process. There were four types of prices in the data: (1) list price, (2) suggested price, (3) negotiated price, and (4) requested price (see Table 2 for description).

Table 2. Types of prices and other relevant variables

| Types of Prices* | Description |
|---|---|
| List Price | List price is the price that is listed on the company's website. It is determined by the seller at the beginning of Stage 1. |
| Suggested Price | Suggested price is the price that the seller suggests after it incorporates concessions. It is determined by the seller at Stage 2. |

| | |
|---|---|
| Negotiated Price | Negotiated price is the final price offered by the seller before buyers either pay for a product or quit the bargaining process. It is determined at every stage unless buyers make an exit from the deal. |
| Requested Price (i.e., counteroffer) | Requested price is the price that a buyer requests to pay for a product. It is determined by the buyer at the beginning of Stage 3. |

| Other Variables | Description |
|---|---|
| Level 1 Threshold ($L_1$) | Level 1 threshold is the lowest price that can be approved without a delay. If a negotiated price falls below this threshold, the bargaining is delayed but there is a strong chance that the price is accepted. |
| Level 2 Threshold ($L_2$) | Level 2 threshold functions much like a Level 1 threshold but an offer that falls below it is further delayed and is likely to be countered. |
| Cost | Cost is the seller's cost of production. |

* Types of Prices are presented in decreasing order of the average values.

List price was the price that the company stated on its website. In our data, it had the highest mean normalized by cost ($M$ = 10.67, $SE$ = .26)[3] compared to other types of prices. List

[3] For the sake of meaningful comparisons, the means for list price, suggested price, negotiated price, and requested price reported in this section were calculated from the observations that contained no missing data in any of the prices (n = 9387). In other words, buyers who concluded the bargaining process before Stage 3 were excluded from the calculation. Also, instead of the standard deviations, +/- 1 standard errors are reported.

price was determined prior to Stage 1 by the company, and buyers are assumed to never pay a price higher than the list price.

After the company incorporated concessions that buyers requested at Stage 2, suggested price was determined. It had the second highest mean ($M$ = 7.71, $SE$ = .33) compared to other prices after normalizing it by the cost of production.

Negotiated price was the final price the company offered to its buyers. The price was determined at every stage of the bargaining process unless buyers made an irreversible exit from the negotiation. In the data, a suggested price was entered as a negotiated price if a buyer accepted the company's offer determined at Stage 2. If a buyer requested additional concessions, the two prices were different. On average, negotiated price had the third highest normalized mean ($M$ = 6.10, $SE$ = .13) compared to other prices.

Requested price was the price that buyers determined – as a counteroffer – at the beginning of Stage 3. The data showed that requested price had the lowest normalized mean ($M$ = 4.91, $SE$ = .13) compared to other prices since buyers would ideally want to pay just above the cost of production, which is the lowest acceptable price by the seller.

Figure 54displays the relationship between different types of prices for preferred customers and regular customers, separately. Note that, for both customer groups, the normalized mean of negotiated price is smaller than the normalized means of list price and suggested price but is bigger than requested price and cost. That is, more generous concessions were given to preferred customers than regular customers which is visually recognizable by looking at the second and third highest bars – suggested price and negotiated price, respectively – in each

customer group: the difference between the two bars is bigger in the preferred customer group, indicating more generous concession.

*<INSERT FIGURE 4 HERE>*

## 6. Conclusions

We began by covering the literature extolling the virtues of participative pricing. While such a strong pitch may be called for to convince retailers to adopt participative pricing more widely with consumer pricing, in the B2B space, participative pricing has long been a widely accepted mode of transaction, either through auctions[4] or through bargaining and negotiations. Our review of the literature as well as review of our data reveals several regularities present in both auctions and bargaining in the B2B sphere.

1. Differentiated sellers and differentiated buyers. The auctions we reported on were reverse auctions, where multiple sellers bidding over each contract. In these auctions, we noted that buyers strongly differentiate between sellers and that sellers differentiate among themselves in the manner they bid relative to one another. While a sizable literature has emerged to try to formalize this process, especially via scoring auctions which quantify each possible dimension (Asket and Cantillon 2008; Pham et al. 2015), it is our experience and observation that such formal quantification of consideration attributes is either not workable or not practiced. Instead, we find a seemingly more informal yet strong differentiation.

[4] To be clear, here we classify the standard RFP process as a degenerate form of auction. An RFP, or request for proposal, is generally mandated by most organizations for substantial contracts. That is, even if the organization has a preferred supplier, it should solicit competitive offers for sizable contracts. Whether formal, informal, structured or unstructured, such a process of soliciting competing offers is within the definition of auctions.

2. A more informal and bargaining-oriented auction structure. The differentiation between bidders in B2B auctions allows for bargaining power before and after the auctions, whether in a pre-qualification phase, or in a post-auction subsequent negotiation phase. Thus, everything we see in practice and in trends going forward is a movement to make auctions more flexible and in doing so to move auctions away from the rigid market structure and more towards a bargaining-like structure, albeit bargaining between one and many (as in one buyer and many sellers).

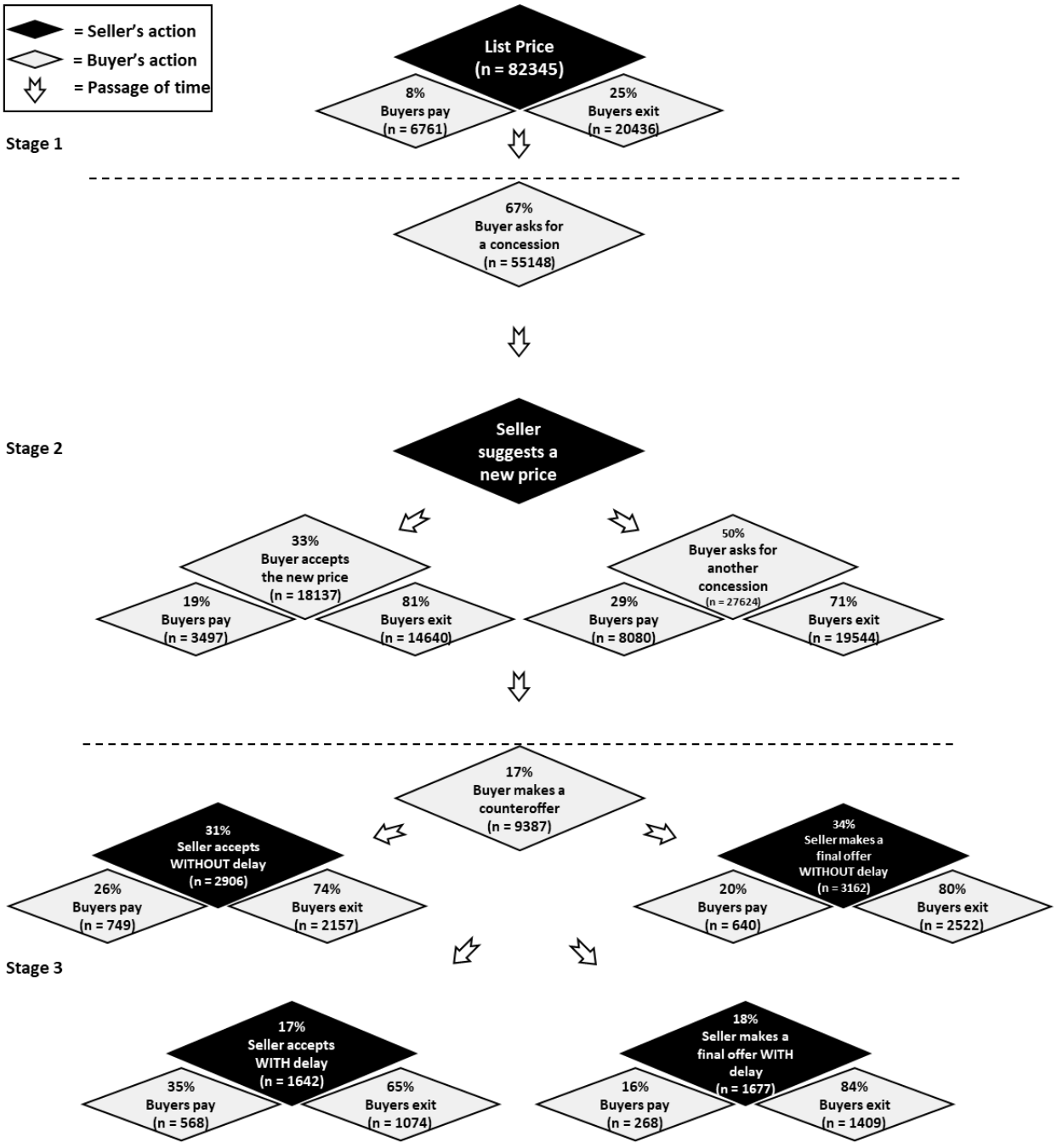
3. A more formal and auction-like bargaining structure. Just as auctions gravitate towards a more bargaining-like structure, bargaining practices appear to gravitate towards a more formal auction-like structure. That is, the entire description of the bargaining process in the previous section revolved around the organization replacing its autonomous pricing decision makers with automated pricing rules that have strict thresholds and preset response functions for every eventuality. In essence, these rules constitute a single-bidder auction against an internal privately known (to the seller) set of reservation prices. This movement towards a more rigid set of bargaining responses is enabled with advances in computation powers and AI tools. It constitutes a potential for greatly increased efficiencies. It also means that in the near future, we may see a convergence of auctions and bargaining formats to a common space of hybrid formats.

4. Relationship tiers. Both our auction data and our bargaining data suggest that relationships matter, and so buyers and sellers move towards quantifying and formalizing these relationships as their key attributes. That is, while we dismissed the possibility of quantifying every possible dimension that matters, that dismissal does not extend to relationship tiers. They appear to be one of the primary considerations in both auctions and bargaining, and the movement appears to be towards formalizing that measure.

5. Successive concessions. In both auctions and bargaining, it seems that it was not solely the attributes of the contact that mattered, but the incidence and magnitude of concession relative to the last price considered. This is consistent with findings by Haruvy et al. (2020) that show that concessions in supply-chain bargaining are the driving force in the agreement ultimately reached. The Kalman filter proposed by Jap and Naik (2008) suggested exactly that notion, as did the data reported on in the bargaining analysis we presented.

6. Strategic delay. The last major reveal in the data is the importance of delay. It has long been known that strategic delay can be advantageous to one or both parties in bargaining (Admati and Perry, 1987; Crampton, 1992; Gul and Sonnenschein 1988). However, our presentation here is the first demonstration that strategic delay can structured and formalized in the field in B2B settings, and that it is widely practiced for bargaining advantage.

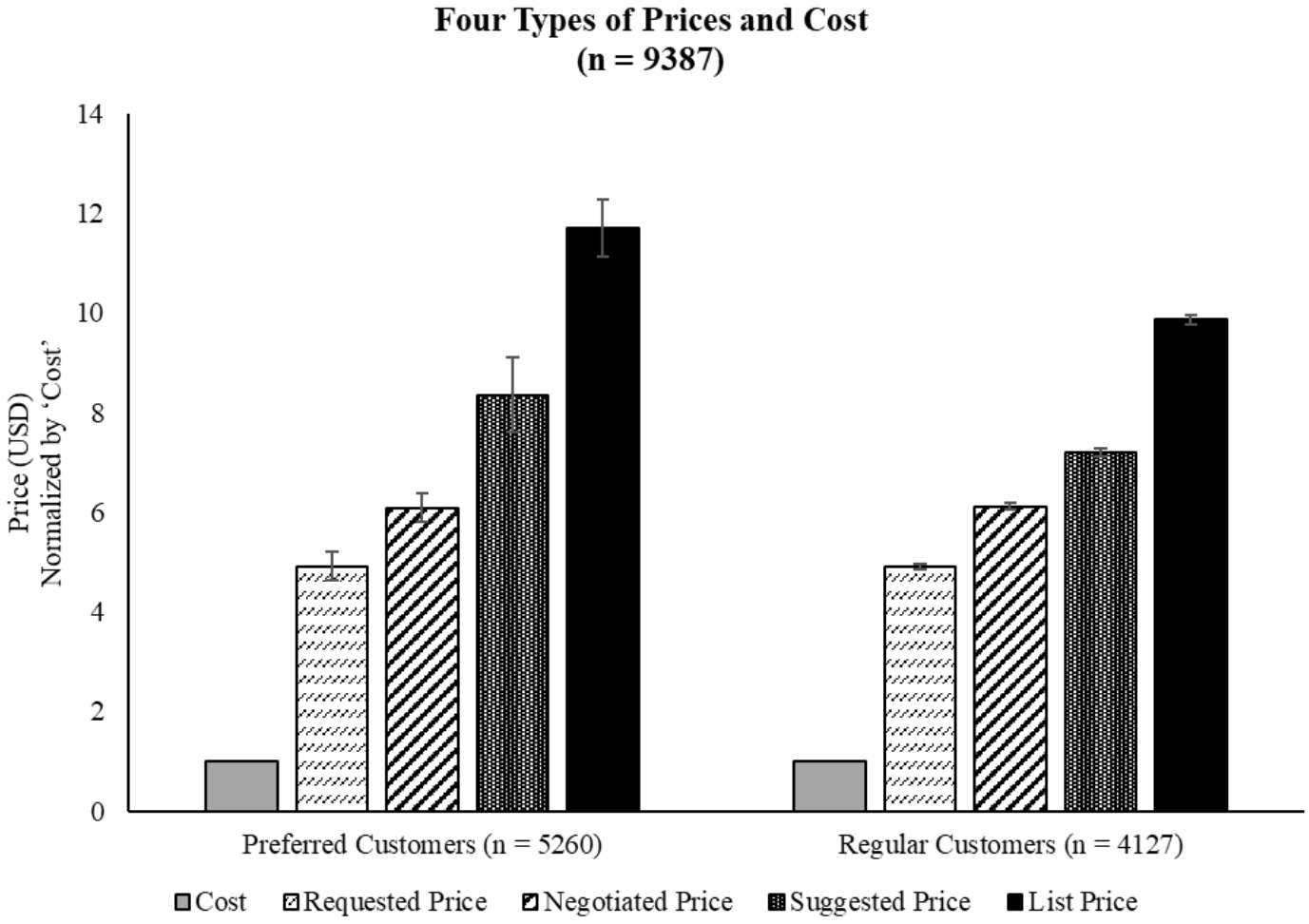
*Figure 3*. A flow chart of the bargaining context




**Summary of Results**

| Stage 1 Result | | Stage 2 Result | | Stage 3 Result | |
|---|---|---|---|---|---|
| 25% Buyers Pay (n = 6761) | 75% Buyers exit (n = 20436) | 25% Buyers Pay (n = 11577) | 75% Buyers exit (n = 34184) | 24% Buyers Pay (n = 2225) | 76% Buyers exit (n = 7162) |

*Figure 4.* Mean of four different types of prices normalized by cost for preferred and regular customer loyalty levels (n = 9387)




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