

# The general theory of behavioral pricing: Applying complexity theory to explicate heterogeneity and achieve high-predictive validity

Author: Arch Woodside

Persistent link: <http://hdl.handle.net/2345/bc-ir:103953>

This work is posted on [eScholarship@BC](#),  
Boston College University Libraries.

---

Post-print version of an article published in Industrial Marketing Management (2015)  
doi:10.1016/j.indmarman.2015.02.004.

These materials are made available for use in research, teaching and private study, pursuant to U.S. Copyright Law. The user must assume full responsibility for any use of the materials, including but not limited to, infringement of copyright and publication rights of reproduced materials. Any materials used for academic research or otherwise should be fully credited with the source. The publisher or original authors may retain copyright to the materials.

**The General Theory of Behavioral Pricing: Applying Complexity Theory  
to Explicate Heterogeneity and Achieve High-Predictive Validity**

Arch G. Woodside, Boston College

Submission: August 2013

Revision: January 2014

Accepted: February 2014

The author appreciates the insightful comments of the IMM guest editors, Andreas Hinterhuber and Stephan Liozu, and the three anonymous reviewers to earlier versions of this paper. Send correspondence to Arch G. Woodside, Boston College, Carroll School of Management, Department of Marketing, 140 Commonwealth Avenue, Chestnut Hill, MA 02467 USA; telephone/fax: +1 617 552 3069 / 6677; [arch.woodside@bc.edu](mailto:arch.woodside@bc.edu).

Woodside, Arch. "The general theory of behavioral pricing: Applying complexity theory to explicate heterogeneity and achieve high-predictive validity." *Industrial Marketing Management* (2015). doi:10.1016/j.indmarman.2015.02.004.

## Highlights

- A low price alone is insufficient but sometimes is a necessary condition for a sale.
- Not all the variability in prices is equally impactful—price effects occur beyond tipping points but not before.
- A price point is one ingredient only in a tentative seller-customer contract.
- We can build useful algorithmic models that include price in complex antecedent configurations that indicate a successful versus unsuccessful contract negotiation.
- The impact of a low price point is not the mirror opposite of the impact of a high price point.
- Equifinality occurs—both low and high price points in combinations with different antecedent conditions can result in the same outcome--a profitable sale for example. .

# **The General Theory of Behavioral Pricing: Applying Complexity Theory to Explicate Heterogeneity and Achieve High-Predictive Validity**

## **Abstract**

Building behavioral-pricing models-in-contexts enriches one or more goals of science and practice: description, understanding, prediction, and influence/control. The general theory of behavioral strategy includes a set of tenets that describes alternative configurations of decision processes and objectives, contextual features, and beliefs/assessments associating with different outcomes involving specific price-points. This article explicates these tenets and discusses empirical studies which support the general theory. The empirical studies include the use of alternative data collection and analytical tools including true field experiments, think aloud methods, long interviews, ethnographic decision-tree-modeling, and building and testing algorithms (e.g., fuzzy-set qualitative comparative analysis). The general theory of behavioral pricing involves the blending of cognitive science, complexity theory, economics, marketing, psychology, and implemented practices. Consequently, behavioral pricing theory is distinct from context-free microeconomics, market-driven, and competitor-only price-setting. Capturing and reporting contextually-driven alternative routines to price setting by a compelling set of tenets represents what is particularly new and valuable about the general theory. The general theory serves as a useful foundation for advances in pricing theory and improving pricing practice.

**Keywords:** behavioral; business-to-business; configuration; empiricism; pricing; theory

## 1. Introduction

Strategy theory has converged on a view that the crucial problem in strategic management is firm heterogeneity—why firms adopt different strategies and structures, why heterogeneity persists, and why competitors perform differently.

(Powell, Lovallo, & Fox, 2011, p. 1370)

Powell et al. (2011, p. 1371) go on to define “behavioral strategy” as follows: “Behavioral strategy merges cognitive and social psychology with strategic management theory and practice. Behavioral strategy aims to bring realistic assumptions about human cognition, emotions, and social behavior to the strategic management of organizations and, thereby, to enrich strategy theory, empirical research, and real-world practice.” “Merges” is the operative word for describing, understanding, predicting, and influencing behavioral strategy and its sub-fields including behavioral pricing.

The focus on capturing heterogeneity, realism, and the centrality of the merging tenet builds from the behavioral theory of the firm’s perspective that organizations comprise differentiated subunits with conflicting goals, resources, and time horizons (Cyert and March, 1963). Marketing, pricing, and organizational buying strategies are largely political processes within specific contexts; these contexts involve coalition building, bargaining, and conflict resolution among representatives of differentiated subunits with conflicting goals, resources, and time horizons (Cyert and March, 1963; Pettigrew, 1974). However, while including strategy as a political process, behavioral pricing theory goes beyond this perspective to include cognitive science theory and findings especially on how executives transform information into knowledge and how they create and apply useful algorithms (i.e., rules on how-to-decide that usually lead to desirable outcomes) in selecting choices outcomes (e.g., acceptable specific price-points and increases/decreases in prices). Examples of such cognitive science advances in behavioral pricing in business-to-business contexts include the studies by Morgenroth (1964), Howard and

Morgenroth (1968), Joskow (1973), Woodside and Wilson (2000), and Woodside (2003). These B2B studies and additional studies in business-to-consumer contexts (e.g., Woodside, Schpektor, and Xia, 2013) support the conclusion that the general theory of behavioral pricing is an insightful and useful blending of cognitive science, complexity theory, economics, marketing, psychology, and implemented practices in explicit contexts.

The core contributions of the present study and the general theory of behavioral pricing include explicating and solving the principal dilemma for advancing theory and research on behavioral pricing—that is, the need to generalize beyond the individual case and the need for specificity (reporting the nitty-gritty details necessary for deep understanding that captures the requisite complexity/heterogeneity within the individual case). Solving the dilemma includes embracing several steps possible but rarely taken-in-combination in pricing research; these steps include going into the field to perform “direct research” (Mintzberg, 1979) and embracing the major tenets of complexity theory (Byrne, 1998, 2005; Manson, 2001; Simon, 1962; Urry, 2005). The major tenets of complexity theory include the proposition that multiple paths lead to the same outcome/price, that is, “equifinality” occurs—alternative asymmetric combinations of indicators (i.e., algorithms) are sufficient but no one combination is necessary for predicting the occurrence of a specific pricing decision. A second tenet: causal asymmetry occurs, that is, indicator configural models that accurately predict a high price-point are not the mirror opposites of the indicator configural models that accurately predict a low price-point. A third tenet: both low and high price-points are antecedents to purchase in different sets of complex antecedent configurations. A corollary to the third tenet: both low and high price-points are antecedents to non-purchase in different sets of complex antecedent configurations. A fourth tenet: no one necessary antecedent condition is sufficient for purchase (e.g., low price alone is insufficient for purchase). A fifth tenet: theorists and

practitioners never explicate all necessary conditions; thus, mistakes occur and learning is a continuing process forevermore.

Another complexity theory tenet is that, “Relationships between variables can be non-linear with abrupt switches occurring, so the same “cause” can, in specific circumstances, produce different effects.” (“The Complexity Turn,” Urry, 2005, p. 4). Thus, an increase in customer demand may be an outcome of a price increase “in specific circumstances [contexts]” and an increase in demand may be an outcome of a price decrease in other specific contexts. The same point is relevant for demand decreases and price increases and decreases. The general theory of behavioral pricing includes explicating the specific configural contexts for the occurrences of all four price-demand relationships: demand increases associating with price increases and decreases and demand decreases associating with price increases and decreases.

The complexity turn to behavioral pricing practice and theory includes the tipping-point tenet as Urry (2005) and Gladwell (2002) describe. “Moreover, if a system passes particular thresholds with minor changes in the controlling variables, switches occur such that a liquid turns into a gas, a large number of apathetic people suddenly tip into a forceful movement for change (Gladwell, 2002). Such tipping points give rise to unexpected structures and events whose properties can be different from the underlying elementary laws” (Urry, 2005, p. 5). In behavioral pricing models such tipping points frequently involve replacing a negative with a positive response to one issue in a string (i.e., path or recipe) of questions and answers for a given complex configuration of antecedent conditions. Examples of such “causal complexity” (Ragin, 2000) appear in empirical examples later in the present study.

Following this introduction, section two presents the general theory of behavior pricing in the form of the theory’s major tenets and by illustrating applications of these tenets in industrial marketing and B2B-service contexts. Section three describes complementary research methods useful for examining the

tenets of the general theory and advancing new tenets. Section four discusses limitations in the study. Section five offers practical implications for planning and implementing pricing strategies in B2B contexts. Section six concludes with comparisons between the microeconomic and rational view of pricing decisions/outcomes and the general theory of behavioral pricing. Section six includes implications for further theory development and new research in behavioral pricing.

## **2. The General Theory of Behavior Pricing**

The three major objectives of the general theory include capturing heterogeneity of pricing decisions by marketers and responses to pricing decisions by customers; building isomorphic models of information-in-use within real-life contexts—of marketing and customer organizations participating in price-setting and price-responding (customer price-responses include evaluating, negotiating, and accepting/rejecting proposal and specific price-points of a vendor); and achieving high predictive validity (accuracy) that includes highly accurate predictions via heuristics-in-use by the vendors and the customers in deciding issues relating to setting and accepting/rejecting products/services for different price-points. Not all pricing researchers value these objectives highly; Joskow (1973) points out that some researchers criticize attempts to construct models of actual decision-making processes. Friedman (1966) argues that it is not a function of economic theory to recreate the real world, but to construct theoretical paradigms that predict well. Joskow (1973) responds to Friedman's perspective with evidence that current (i.e., symmetric-based) models of regulated firms do not predict pricing behavior very well. "In addition, the value of 'as if' models declines as we not only become interested in predicting how firms behave given current structural interrelationships, but begin to ask questions about structural changes aimed at changing the nature of firm responses. For those interested in public policy analysis regarding regulated [utility] industries, a more detailed [nuanced] understanding of firm decision processes, decision processes of regulatory agencies, and their interrelationship appears to be in order" (Joskow 1973, pp. 119-120). This

behavioral theory perspective is relevant for less regulated industries as well—a more detailed understanding is necessary (that is now lacking) of firm pricing-decision processes, customers' decision processes in evaluating and responding to marketers' responses to RFQs (request for quotation), and the subsequent process-dynamics—and final price points offered and accepted/rejected.

In his data collection during 1970-1971 on advancing a behavioral theory of pricing in highly regulated firms, Joskow (1972, 1973) did manage to take the necessary step of doing direct research but his data analysis is limited to symmetric testing via regression modeling. The idea of testing for sufficient but not necessary outcomes via algorithm modeling was advocated more than two decades later by McClelland (1998) and advanced substantially by Charles Ragin in several publications including his masterwork, *Redesigning Social Inquiry* (2008). Asymmetric theory and analysis of Joskow's (1972) behavioral pricing data awaits doing. However, unfortunately Joskow (2015) reports that his Ph.D. dissertation (Joskow 1972) does not include the data and the data are no longer available.

### ***2.1 The Most In-Depth Behavioral Pricing Study***

Unfortunately, the most in-depth, available, behavioral study of firms engaging (i.e., colluding illegally in this case) in setting prices in a business-to-business industry (Eichenwald, 2001) does not provide details with respect to conversations and decisions regarding specific price-points in the price-fixing meetings. Eichenwald (2001) does not report on customers' responses to the pricing decisions made by the colluding industrial (agricultural chemicals) marketers. The development of ethnographic pricing models using the price-collusion original data set awaits the researcher willing to wade into the court records and the FBI (U.S. Federal Bureau of Investigation) files—the multiple decision processes and outcomes in these processes that are available over a five-year period. Such research on decision processes of price setting and changes in B2B contexts rarely is available but the literature does include example studies (e.g., Morgenroth, 1965; Howard and Morgenroth, 1968; Woodside and Wilson, 2000).

## ***2.2 Capturing Heterogeneity***

To capture heterogeneity, the general theory of behavioral pricing does not rely alone on the use of written surveys with fixed-point scales and symmetric statistical tests of observable choices by vendors and customers but includes “direct research” (Mintzberg, 1979) ethnographic methods to record tacit knowledge and cognitive processes preceding the observable outcomes. These ethnographic methods include participant observation, applications of the think aloud method, historical analysis of documents, and the long interview method (Gladwin, 1980, 1982, 1983; McCracken, 1988; Woodside, 2010)—and the use of asymmetric analytics such as reporting on the use/value of fast and frugal heuristics (Gigerenzer et al., 1999) as well as fuzzy-set qualitative comparative analysis (Ragin, 2008). Direct research is going physically into the context of the study to observe, interview, record, and examine rather than rely principally on data from an internet, mail, or telephone survey. The later studies typically involve one executive responding per firm and less than 25 in 100 firms providing useable responses to the fixed-point scales items. Direct research seeks confirmatory evidence from multiple sources having direct knowledge of processes and the outcomes of thinking and actions of participants enacting behaviors related to a given context or issue.

While the core tenets of the general theory apply across B2B contexts and firms in different industries, presenting the tenets here make use of findings from a specific industrial marketing-buying pricing study (e.g., Woodside and Wilson, 2000). Taking a meso-step toward generalization, the study here describes how the tenets apply to a second study—a study on pricing petroleum at the wholesale level. The first study (Woodside and Wilson 2000) included multiple-rounds of meetings of executives by the researchers at the marketing headquarters of a solvents manufacturer in Houston and long interviews, face-to-face, with four of the manufacturer’s customers and 250 file-drawer customers; the four customers interviewed were located in Cleveland, north-central Pennsylvania, and western South Carolina. Each

customer interview was ninety minutes; customers were selected that filled certain profiles of interest in the study—configurations of customers with large versus small purchasing requirements for solvents and both aggressive versus non-aggressive customers. Figure 1 is an “ethnographic decision tree model (EDTM)” (Gladwin, 1989) of the marketer's framing and price-point selection processes for four customers in the study and more than 250 additional customers. EDTMs are suitable for linear programming and for use in testing the predictive accuracy of the algorithms appearing in subroutines in the model via fuzzy-set qualitative comparative analysis (Ragin, 2008; Woodside, 2010). EDTMs are isomorphic representations of reality in the thinking and doing processes of pricing and responding to specific price-points. While being a complex, heterogeneous model, the thoughts and actions of the product managers and sales representatives in this firm center on asking a brief series of questions. The questions cover the following issues. How much business does the customer represent (box 2)? How does the customer frame key aspects of his/her firm's relationship with us and our competitors (boxes 3-7)? Which objectives should dominate our response to the customer's response to our proposal (boxes 15 and 16)? For example, if the customer firm is a key account (i.e. large business for the marketer) and the customer insists on achieving a price reduction, the marketer is likely to respond with a “creative proposal” that includes: first, a low price; second, funding for storage equipment or related facilities at the customer's sites; and third, “price protection” against price increases during the contract period. Whether or not such an outcome occurs depends on the marketer's belief that “preferred supplier participation” status was given to the marketer's firm by the customer—a euphemism for being awarded the largest share or 100 percent of the customer requirements for solvents.

### ***2.3 The Core Tenets in the General Theory of Behavioral Pricing***

The following discussion covers the core tenets (T<sub>i</sub>s) of the general theory of behavior pricing. While the discussion of each tenant refers to findings in the study by Woodside and Wilson (2000), these

tenets are applicable and prevalent for nearly all pricing contexts in business and industrial marketing/purchasing contexts. “High score” in the following discussion refers to a calibrated score in fuzzy or crisp set qualitative comparative analysis (fsQCA, see Ragin, 2008). All QCA calibrated scores range from 0.00 to 1.00. Such calibrated scores indicate the degree of membership in a condition. For example, the score may indicate membership in “high price” with a score of 0.30 being a relatively low score in high price and a score of 0.95 equal to a score of “full membership” in high price. Calibrated scores do not indicate probabilities. From a practical as well as theoretical perspective, small-to-medium changes in fuzzy-set calibrated reference-points rarely change the substantive impact of findings in studies using QCA (for additional details, see Ragin 2008; Woodside 2013).

**T<sub>1</sub>: A case (e.g., one specific price decision among 100+ decisions) with a high score in one antecedent condition is insufficient in associating with a high or low outcome score (e.g., a high price-point).** A few specific combinations of two-plus antecedent conditions are sufficient in identifying with an outcome condition of particular interest (e.g., a high or low price-point) but a single antecedent condition is not. Consciously and/or unconsciously decision-makers (DMs) process two-plus antecedent conditions to reach a conclusion, decision, and action. For example, in Figure 1 the shortest path to an outcome involves asking and answering three questions. In Figure 1 “cost reduction” is a B2B purchasing term that refers to seeking price decreases in purchasing requirements from a supplier; “cost avoidance” refers to seeking price increases less than the industry price inflation rate. Cost reduction is a more aggressive stance some buyers assume than cost avoidance. A “market price” stance is less aggressive than cost avoidance; willing to accept “list price” is the least aggressive purchasing stance.

Figure 1 here.

Related to Figure 1, not all key account customers adopt a highly aggressive stance with respect to price. Consequently, a key account may or may not receive a low price quote or the lowest price quote. A

specific price-point in a response to an RFQ depends on the combination of two-plus antecedent conditions. From the perspectives of data analysis and sense-making, a discussion of net effects and relative sizes of net effects of independent variables provide limited usefulness in comparison to adopting a configural (i.e., recipe or combination) perspective.

**T<sub>2</sub>: Decision-makers rarely use all available information in all real-life cognitive processes.**

From a “property-space” (Lazarsfeld, 1937) or “truth table” (Ragin, 2008) perspective (i.e., identifying every theoretically possible combination of antecedent conditions) all configurations possible theoretically do not occur in practice or in behavioral pricing models. For example, the marketer considers the aggressiveness of customers’ responses to price-points only for key account customers. The marketer rarely considers how aggressive the customer stands for non-key account customers (e.g., Figure 1 does not include such a path). Customer price-lowering aggressiveness is a necessary but not sufficient condition for the customer to achieve the lowest price that the marketer is willing to offer. See Figure 2. Such a necessary but not sufficient condition for lowering price provides valuable information for customers—being a large-requirements (volume) customer who is willing to single-source a purchase requirement with a supplier is insufficient for achieving a high membership score in the outcome condition (i.e., a very low price). In addition, such a customer needs to aggressively pursue a lower price.

Figures 2 and 3 here.

Using Boolean algebra, the following configuration identifies a “causal recipe” that is sufficient for the marketer to include a very-low price-point in the response to the RFQ:  $K \cdot S \cdot A \geq 0.70$ , where K = key (large volume) customer account); S = willing to single-source; A = aggressively pursuing a price-lowering strategy. The mid-level dot (“•”) represents the logical “and” condition in Boolean algebra. A sideways tilde (“~”) represents negation or one minus the membership score, for example,  $\sim S = 1 - S$ , and represents a membership score in not being willing to single-source. The score equal to or greater than

0.80 indicates for this configuration that such customers have a high membership scores for all three of these antecedent conditions.

For a complex antecedent statement (i.e., the combination of two plus simple antecedent conditions), the total score for the statement is equal to the lowest score among the scores in the configural statement. Thus, a customer having the following scores,  $K = 1.00$ ;  $S = 1.00$ ; and  $A = 0.60$  would have a membership score equal to 0.60 for  $K \bullet S \bullet A$ . See Figure 3 for an XY plot that shows a pattern indicating high consistency—scores high on X associate with scores high on Y with the exception of one case—customer number 11.

Woodside and Baxter (2013) describes contexts where a very limited number of customers do not fit the general pattern of findings in a study and how to create and test alternative models to explain such instances as case 11. The note at the bottom of Figure 3 describes additional information on case 11 and how to refine the model to account for similar cases. A configuration of high membership scores for the combination of the first three antecedent conditions was sufficient for a very low price in the Woodside and Wilson (2000) study except for one customer firm. This one customer firm (case 11 in Figure 3) is a “contrarian case.” A contrarian case is an individual (e.g., decision or firm) that has an outcome score opposite to a substantial majority of the cases with similar high scores on the antecedent condition. The presence of contrarian cases means that a researcher needs to conduct “an elaborate dialogue of ideas and evidence that leads to a progressive refinement of understanding of the relevant cases and to a more nuanced elaboration of the relevant causal conditions” (Ragin, 2000, p. 317).

Case 11 in Figure 3 was a super-aggressive customer in demanding additional add-on concessions that the industrial marketer labelled, “an asshole” (cf. van Maanen, 1978). Adding the condition, “not an asshole” (i.e.,  $\sim H$ , where the sideways tilde indicates taking the negation and “H” stands for “asshole”) into the configural statement results in a shift to the far left of the XY plot for case 11 in Figure 11 and is a

useful explanation as to why case 11 did not have a high outcome associated with the three-term configural statement, K•S•A.

**T<sub>3</sub>: Decision-makers do not trade off high accuracy for low effort but create and use algorithms that are fast, frugal, and accurate/useful in achieving their objectives.** The suggestion Powell, Lovallo, and Fox (2011) imply that individuals fail to do as well as they can do in deciding and the proposition that DMs tradeoff high accuracy to achieve low effort (Payne, Bettman, and Johnson, 1982) are inaccurate (see Gigerenzer and Brighton, 2009, for evidence and a thorough discussion of these points). Professional B2B marketers and buyers are able to create and use relatively simple heuristics to achieve high accuracy and enable these DMs to achieve their objectives more than is possible by using all the available information and statistical multivariate procedures. While individuals are limited in their conscious cognitive capacity, the available evidence does not support a conclusion of lower competence by decision makers from not using all the information available as symmetric tests as the following perspective implies:

Research in behavioral decision theory (BDT) shows that individuals lack the cognitive capacity to make fully informed and unbiased decisions in complex environments (Kahneman, Slovic, and Tversky, 1982; Payne, Bettman, and Johnson, 1988). To cope with complex judgments and decisions, people use simplifying heuristics that are prone to systematic biases. Decision makers do not maximize the subjective expected utility of total wealth, but focus on deviations from cognitive reference points. BDT has found many applications in the social sciences, including strategic management (Bazerman and Moore, 2008). (Powell, Lovallo, and Fox, 2011)

Gigerenzer and Brighton (2009) provide an extensive review of compelling evidence that simple heuristics (i.e., simple algorithms) using limited amounts of information outperform the symmetric-based

statistical models using all information available—when using holdout samples to test for predictive validity. They conclude, “Heuristics are efficient cognitive processes that ignore information. In contrast to the widely held view that less processing reduces accuracy, the study of heuristics shows that less information, computation, and time can in fact improve accuracy” (Gigerenzer and Brighton, 2009, p. 107). Morgenroth (1964) and Howard and Morgenroth (1968) describe the use of holdout samples for testing for predictive validity and the achievement of high predictive validity for parsimonious algorithms in B2B pricing decisions.

Gigerenzer and Brighton (2009) describe how, “In the 1970s, the term “heuristic” acquired a different connotation, undergoing a shift from being regarded as a method that makes computers smart to one that explains why people are not smart. Daniel Kahneman, Amos Tversky, and their collaborators published a series of experiments in which people’s reasoning was interpreted as exhibiting fallacies. ‘Heuristics and biases’ became one phrase. It was repeatedly emphasized that heuristics are sometimes good and sometimes bad, but virtually every experiment was designed to show that people violate a law of logic, probability, or some other standard of rationality... Another negative and substantial consequence was that computational models of heuristics, such as lexicographic rules (Fishburn, 1974) and elimination-by-aspects (Tversky, 1972), became replaced by one-word labels: availability, representativeness, and anchoring. These were seen as the mind’s substitutes for rational cognitive procedures. By the end of the 20<sup>th</sup> century, the use of heuristics became associated with shoddy mental software, generating three widespread misconceptions: (1) heuristics are always second-best; (2) we use heuristics only because of our cognitive limitations; (3) more information, more computation, and more time would always be better” (Gigerenzer and Brighton, 2009, p. 109).

Gigerenzer and Brighton (2009) show how multiple regression analysis (MRA) and additional symmetric statistical tests outperform simple algorithms for fit validity but the opposite holds for

predictive validity (via cross-validation with holdout samples). In cross-validation a model is fitted to one half of the data and tested on the other half and vice versa. Test of sufficiency models in industrial pricing contexts support the conclusion that simple heuristics provide high validity in predicting decision choices. Given that the proof of a model's worth lies in predictive validity, algorithm models such as the model appearing in Figure 1 need to be tested on fresh data—data not used in creating the model.

In a behavioral-pricing research example, in a study creating and using simple heuristics in a B2B pricing context, Morgenroth (1964, p. 21) reports, “To determine its predictive accuracy [of the behavioral pricing model] fresh data were introduced into the [whole pricing algorithm] model. From a series of cabinets in the office of the division one file drawer in each cabinet was haphazardly chosen. The cabinets contained pricing data and decisions of the division over a six-year period. A systematic sample of every tenth filing was taken. The filings were arranged internally in chronological order, with the date that a competitor's move was initially made (the triggering) serving as the specific criterion of order. This sample yielded 32 decisions which were compared with the decisions predicted by the model... Agreement existed in all cases tried. Hence the hypothesis that the model can predict the executive's decision was not disconfirmed by the tests.”

Unfortunately, neither Morgenroth (1964) nor Woodside and Wilson (2000) provide a side-by-side comparison of MRA and QCA tests for predictive validity in B2B contexts—QCA as a tool was unavailable at the time these two studies were done. Woodside and Wilson (2000) also do not report testing for predictive validity using a holdout (fresh) sample of customer cases. Thus, the evidence supporting higher predictive validity for algorithms versus MRA models is not conclusive in the context of pricing in B2B contexts—but the studies by Gigerenzer and colleagues (Gigerenzer & Selten, 2001; Gigerenzer, Todd, & the ABC Research Group, 1999) offer consistent findings that algorithms created by biased minds provide more accurate models in predicting outcomes than the use of MRA and models that

maximize subjective expected utility. Additional field studies using both symmetric (e.g., MRA) and asymmetric tests (e.g., QCA) are necessary to confirm this claim.

**T<sub>4</sub>: Necessary but insufficient conditions (NBICs) are always present in behavioral pricing but often are unreported.** Both marketers and buyers do not think to report on NBICs that researchers may find of great interest for advancing theory and practice. NBICs include antecedents that appear in a limited number of branches in an ethnographic decision tree model such as the one appearing in Figure 1 as well as antecedents that pricing decision participants fail to mention and researchers fail to ask about. “You can’t think of everything” and “we learn from our mistakes” might come to mind here; both sellers and buyers learn to include additional necessary conditions into their configural process models as mistakes surface.

Information on both types of NBICs in-use can be learned by asking participants to use “the think aloud method” (van Someren, Barnard, & Sandberg, 1994) in responding to different highly-relevant pricing scenario-problems. Such scenario-problems can be presented to participants in the form of paragraphs and/or choice and conjoint experiments. In one instance of doing so, a buyer announced, “I would never buy from a supplier I never heard of.” “Buyer awareness of the supplier” is a seemingly obvious NBIC that did not occur in the study before hearing this oral remark by a purchasing agent.

NBICs are often put forth explicitly in marketers’ and buyers’ documents and face-to-face statements as well as appearing without warning in long interviews. The second category of NBICs represents a form of “tacit knowledge” (Nonaka, 1994; Polanyi 1958/2002). Tacit knowledge is unconscious and semi-conscious beliefs—“the type of knowledge that you gain through personal experience of working in an organization, but that is not written down and is difficult to share” (FT Lexicon, 2013).

**T<sub>5</sub>: Participants in setting price and responding to a price-point use neither equally weighted nor unequally weighted conditions in compensatory rules when crafting a price-point or responding to a price-point—marketers and buyers make use of conditional configural statements.**

Examples of the conditional statements with respect to price-points that marketers use appear in Figure 4 and below in Figure 7. These conditional statements refer to specific contexts and require asymmetric, rather than symmetric, tests of their efficacy, that is, for high sufficiency—whereby low outcome scores associate with both low and high outcome scores. Only high scores on the path in the statement associates with a high score for the outcome condition. A simple antecedent condition may have a statistically significant positive relationship with price for all cases while at the same time have a highly negative association with price for several individual cases. Consequently, studies on how participants weight the importance of simple antecedent conditions and whether or not a series of simple antecedent conditions each have a significant positive or negative influence on price are not very useful. For example, the positive impact of customer aggressiveness on lowering price changes to an apparent negative impact if the customer scores high on being an asshole. Useful, accurate, interpretation of what is happening depends on focusing on multiple configurations (paths) of complex antecedent conditions.

Figure 4 here.

Figure 4 includes the main paths (i.e., configurations or recipes) that appear in Figure 1. The findings in both Figures 1 and 4 illustrate the tenet that a marketer may apply price-increasing and price-decreasing strategies for the same B2B product/service for different customers, strategies that do not depend exclusively on the buyers' purchase quantities—the implementation of quantity discount sizes depends on the presence and absence of additional antecedents in the configurations.

**T<sub>6</sub>: The average price increase or decrease across all customers provides insufficient information for advancing theory because specific price points are contingent on several complex**

**antecedent conditions—monthly or annual prices may increase on average for most customers but decrease for a substantial minority, while some customers receive the same price quote as one given last year.** Figure 5 illustrates this sixth tenet from data in the Woodside and Wilson (2000) study. Figure 5 shows most customers receive price increases of varying amounts contingent on the membership score for a combination of three antecedent conditions. However, customers with high scores on all three antecedent conditions (location B in Figure 5) receive substantial price decreases.

Figure 5 here.

Customers knowing their configural location within such three- to five-sided dimensions are more likely to more able to create effective strategies to reduce price increases or even gain price decreases than customers without such knowledge. One strategy planning take-away is that an average price increase rarely applies to all customers.

**T<sub>7</sub>: Equifinality occurs: more than one configuration leads to the same solution (outcome), that is, a specific price-point.** For example, several routes lead to outcomes 11 and 12 in Figure 1. Behavioral pricing theory and research includes observations of usually two-to-five combinations of complex antecedent conditions that lead to the same outcome. The findings from the wholesale pricing study by Morgenroth (1964) and Howard and Morgenroth (1968) illustrate tenet 7 vividly. Figure 6 summarizes these authors behavioral pricing model in an ethnographic decision tree diagram. The model includes three outcomes: an increase in price (top-third of Figure 6), a price decrease (bottom two-thirds of Figure 6) and no change in price (box 1) in Figure 6.

Figure 6 here.

Figure 6 looks complex at first blush but examining a few paths in the model show that such isomorphic models are easy-to-grasp. The shortest path in Figure 6 appears at the top of Figure 7—makes

no change in our (X) price if the competitor's (O) price remains the same as our price. Price increases are less complex than price decreases in this model because the market has few competitors and demand is inelastic. Consequently, if O increases its price, then X can increase price and profits for both will increase. Thus, the second path in Figure 7, as appearing in Figure 6, includes boxes 1-2-3-4-5 for such a price increase by O and then by X.

Price decreases in Figure 6 and 7 are more complex than price increases because firm X wants to limit the possibility of a price war between X and Y. Additional antecedent conditions are activated for price decreases that do not appear for price increases—such as information on the market shares for O and X in the local and nearby markets (boxes 9 and 10 in Figure 6). This point illustrates the eighth tenet.

Figure 7 here.

**T<sub>8</sub>: Causal asymmetry occurs: the explanations for price increases are not the mirror opposites of the explanations for price decreases—different complex configurations sometimes having different simple antecedent conditions occur for different outcomes in behavioral pricing.**

Fiss (2011), Ragin (2008), and Woodside (2013) all stress the reality of causal asymmetry. “While a correlational understanding of causality implies causal symmetry because correlations tend to be symmetric [i.e., correlations test for symmetry]. For instance, if one were to model the inverse of high performance, then the results of a correlational analysis would be unchanged, except for the sign of the coefficients. However, a causal understanding of necessary and sufficient conditions is causally asymmetric—that is, the set of causal conditions leading to the presence of the outcome may frequently be different from the set of conditions leading to the absence of the outcome” (Fiss 2011, p. 394).

Such findings in behavioral pricing as in Figure 1 by Woodside and Wilson (2000 and Figure 6 by Morgenroth (1964) and Howard and Morgenroth (1968) support the causal asymmetry stance for theory

development and theory testing. Relying solely on symmetric testing tools such as MRA and structural equation modeling does not reflect the reality of asymmetric relationships in behavioral pricing. As Gigerenzer (1991) stresses, tools shape theory as well as how a researcher goes about analyzing data. Tools and theory are necessary to use that support consistent findings of causal asymmetry as well as equifinality and configural complexity (i.e., heterogeneity) in relationships among antecedent conditions and outcomes of interest—such as specific price-points and price increases/decreases.

**T<sub>9</sub>: From a behavioral pricing perspective, two or more participants engage in interactions involving setting a specific price-point resulting in a sale/purchase.** Behavioral pricing theory recognizes that B2B price setting usually involves multiple participants influencing the selection and calibration of antecedents in the pricing process. In the Morgenroth (1964) study for example, Figure 6 shows three persons are involved in setting price: the pricing manager, the district sales officer, and the pricing analyst. A set price is frequently negotiated between the marketer and customer. The customer frequently includes multiple-parties in B2B contexts as well (Woodside and Samuel, 1981).

**T<sub>10</sub>: Price setting frequently involves a series of feedback loops in real-life contexts. Formal meetings often occur in negotiating annual contracts among manufacturers buying component parts and informal meetings both precede and follow these formal meetings.** Woodside and Samuel (1981) provide a marketing-purchasing participant observation study that confirms this tenth tenet. Their study includes a decision systems analysis (DSA) showing several feedback loops in negotiation processes involving centralized purchasing offices and various plant-level purchasing officers and well as company-wide purchasing committees negotiating with global suppliers. The use of DSA is a useful precursor tool for the creation of more formal ethnographic decision tree models and the use of fuzzy set qualitative comparative analysis.

*The Informant* (Eichenwald, 2001) is viewable correctly as a report on a marketing anthropological study of behavioral pricing by the United States Federal Bureau of Investigation (FBI). The study includes in-depth reporting on several (in this case, illegal) meetings of competing manufacturers jointly setting prices globally for agricultural-related products with several feedback loops in discussions of the same issues. The FBI study employed a mixed-methods design. Along with unobtrusively (secretly) filming these price-setting meetings and recording verbal exchanges occurring during the meetings, the FBI analyzed thousands of price-fixing documents from several years, and completed multiple rounds of interviews with a participant observer (the informant). The result is a treasure trove that appears to support the tenth tenet—and all tenets of the general theory of behavioral pricing. T<sub>10</sub> needs formal testing via separate studies comparing data from the FBI case with the behavioral pricing and classic microeconomic pricing theory.

### **3. Discussion with a Worked Example of Examining Complex Antecedent Configurations**

Behavioral pricing modeling and testing has been around a while now but still such modeling is a mouse next to the dominating elephant of symmetrical theory and testing approaches in pricing research. The availability of behavioral pricing studies reporting complex configural antecedents, equifinality, and causal asymmetry is spotty in comparison to the plethora of studies by authors adopting a combination of net effects, finality, and causal symmetry stance. The principle objective of this paper is to generate the start-up of continuing behavioral pricing research that provides an annual stream of useful studies capturing heterogeneity, realism, and accurate predictive—not just fit—validity. The intention is to present a set of tenets that together offers a new reality-based behavioral pricing theory that has much promise in describing, explaining, and predicting price-related decisions and actions by marketers and buyers. The set of tenets itself includes a configuration of theory and tools.

Table 1 here.

Table 1 is a summary of comparisons of the assumptions and perspectives of microeconomics and the dominant logic theory toward pricing and decision-making (e.g., Kahneman, Slovic, & Tversky, 1982; Nicholson, 2011; Perloff, 2004) versus the behavioral theory of pricing for B2B products and services. The central point in considering the comparisons in Table 1 is that while microeconomic theory and the dominant logic of research on decision-making are elegant and frequently inaccurate, the perspectives and assumptions of behavioral pricing theory are messy and frequently accurate. The general theory of behavioral pricing may offer unique advantages for attaining the objectives of heterogeneity, realism, and high-predictive accuracy.

Gladwin (1989), Morgenroth (1964), Howard and Morgenroth (1968), van Maanen (1978), Van Someren, Barnard, and Sandberg (1994), Vyas and Woodside (1984), Woodside and Samuel (1989), Woodside (2010), and Woodside, Pattinson, and Montgomery (2012) offer details and examples for collecting data from decision participants on their perceiving information, sense-making, assessing issues, and choice-making processes in natural contexts; these sources also discuss the collection of documents and data from direct observations of participants' actions in natural contexts. The blessings from such data collection and handling include the combination of verbal and written data and process information relevant to specific contexts that the use of fixed-point (e.g., 1 to 5 or 1 to 7 valuations) surveys cannot provide; also, invariably, participants blurt out information during moments in think aloud data collection procedures that they would never report in written survey responses—especially when the participants are interviewed on two or more occasions.

The bane of management ethnographic research is the great amount of effort and time necessary for implementing field data collection in behavioral pricing research. However, the data collection of 5 to 100+ such case studies enables useful construction of isomorphic models—models that support Kotler's (1967) perspective of the features of real-life decision processes in ways that symmetric models (structural

equation models) using fixed-point responses cannot do. The data collection of an additional 5 to 100+ management ethnographic cases enables the testing for predictive validity of algorithms (i.e., complex configurations consisting of two or more simple antecedent conditions) within the isomorphic models created from the first set of data. McClelland (1998), Morgenroth (1964), and Howard and Morgenroth (1968) illustrate such tests for predictive validity; their findings include high predictive validities (e.g.,  $r$ 's  $> 0.90$ ) between predictions and observed outcomes.

The blessings of collecting fixed-point survey data include the relative ease of data collection and ease of testing models using symmetric methods (MRA and SEM). The banes include requiring participants to convert what they think they know into scaled responses (the failure to collect real-life, naturally-occurring, data), the absence of contextual information, usually the absence of confirmations of facts and procedures learned by going into the field and comparing documents and observations with verbal and/or fixed-point scaled responses, and the circumspect nature of any open-ended written responses by respondents to survey questions. While surveys using fixed-point scales followed by symmetric model-building and testing may provide useful information on participants' evaluations of the quality of procedures and outcomes, such studies offer inadequate information in describing and understanding the nitty-gritty steps in the processes and provide models with low fit validity—and low predictive validity (on the rare occasions when these studies include predictive validities). The implicit suggestion by Kotler (1967) and the explicit suggestions by Mintzberg (1979) and Woodside (2013) to move beyond fixed-point surveys coupled with symmetric testing to ethnographic studies coupled with asymmetric testing has merit for model building in behavioral pricing.

### *3.1 Embracing Complexity Theory*

Marketing scholars would benefit from heeding Urry's (2005) and others' (Davis, Eisenhardt, & Bingham, 2009; Popper, 1961; Simon, 2009) call to embrace many tenets of complexity theory. As Simon

(2009, p. 32) states aptly, “Science seeks parsimony, not simplicity searching for pattern in phenomena.” Simon (2009) refers to this perspective as one of Popper’s (1961) major dictums. Both theory and Ragin’s (2000, p. 317) recommendations for “elaborate dialogue of ideas and evidence” should guide searching for patterns in the data. Complex (i.e., recipes of a few to many specific levels of simple antecedent conditions) resulting in outcomes of interest is the focus of pattern search in the general theory of behavioral pricing. Given the relevancy of complexity theory and Gigerenzer’s (1991) wisdom that “Scientists tools are not neutral” in behavioral pricing, fuzzy-set qualitative comparative analysis (fsQCA) is a particularly useful theory-method for explicating parsimonious patterns in pricing-related data. At the minimum, the focus and use of fsQCA in testing theory and searching for asymmetric parsimonious patterns complement the theoretical stance and use of MRA for testing for the net effects of individual variables in symmetric models (cf. Ragin, 2006).

### ***3.2 A Worked Example of Relevant Analytics for Testing the General Theory***

The website fsQCA.com provides a software program for testing theory and elaborate dialogues with data for identifying parsimonious patterns. The data in Table 2 and the output in Table 3 serve to illustrate the use of the fsQCA software in testing core tenets of the general theory of behavioral pricing. The data in Table 2 are based in part on data collected for the Woodside and Wilson (2000) study but the data in Table 2 are presented as a thought experiment (Gendler, 1998). All conditions (columns) in Table 2 represent calibrated data. Assume for the thought experiment that the measures have high nomological validity (our purposes here does not include a full accounting on how the measures were developed). Table 2 includes 11 conditions (8 antecedents and 3 outcomes). Applying McClelland’s approach of using quintiles for each of the 8 antecedent conditions (McClelland, 1998, focuses on building algorithms of cases in the highest and lowest quintiles of variables to describe and predict highly competent individuals), a property space analysis (i.e., “truth table”) indicates 32,768 possible combinations or

patterns. Considering terciles (low, medium, and high) results in 512 combinations; it is best not to consider dichotomizing the conditions into high and low only due to the normal distribution for many of the simple conditions (Fitzsimons, 2008).

The data in Table 2 are fuzzy-set membership scores for each condition; fuzzy-set scores range from 0.00 to 1.00. Consider fuzzy set scores as taking steps beyond the use of quintiles whereby membership scores represent a logarithmic function of original scores. Calibration conceptually refers to a kind of membership, for example, “high price point” and not price points in general. The fsQCA software program computes all membership scores given the researcher provides the original values associating with the full membership threshold score equal to 0.95; the original value indicating “maximum ambiguity score equal to 0.50; and the value indicating the threshold for non-membership equal to 0.05. The median value of an original scale is usefully calibrated to be equal to 0.50. For a variable that is normally distributed, the original score having a z-score equal to +1.65 is a useful first estimate for a calibrated membership score equal to 0.95; an original score having a score of -1.65 is a useful first estimate for a calibrated membership score equal to 0.05. However, Ragin (2008) emphasis that theory and prior experience should be the guiding forces in calibration. Consider the following data of price points in a set of 12 cases (values are U.S. dollars): 1.25; 1.30; 1.33; 1.40; 3.80; 4.50; 8.60; 11.10; 14.20; 15.10; 18.10; 25.50. The pricing manager decides to calibrate these original values; the pricing manager identifies values below a breakpoint of 1.50 as clearly indicating non-membership in a high-price scale; she selects the median price equal to 6.46 as the cross-over membership score equal to 0.50, and the score of 13.0 (the upper 90<sup>th</sup> percentile limit for the mean original value equal to 9.84 as equal to full membership in high-price membership. Using the fsQCA software subroutine, here are the resulting calibrated membership scores for the 12 original prices \$1.25→0.04; \$1.30→0.04; \$1.33→0.04; \$1.40→0.04; \$3.80→0.17; \$4.50→0.23; \$8.60→0.73; \$11.1→0.89; \$14.1→0.97; \$15.1→0.98;

\$18.1→1.00; \$25.50→1.00, where the numbers following the arrows indicating the calibrated scores.

Note that the variability in the original values is not equally important in the calibrated membership scores; once the full membership threshold is reached, all higher values receive nearly identical membership scores—including in this instance the very high price \$25.50 even though the z-score for \$25.50 for a mean equal to 8.848 and a standard deviation equal to 2.314 equals 7.196. Using terciles for clarity purposes, the eight antecedent conditions provide for a truth table with 512 cells (i.e., complex configurations) that include big/medium/small, high/medium/low profit focused, high/medium/low expert seller; big/medium/small, high/medium/low profit focused, high/medium/low expert customer very/somewhat/not willing to single-source, for a high/medium/low price-point. Complexity theory, empirical findings from applying fsQCA, and elementary logic indicate that most of the 512 cells will be empty if a given study has a few or even 1,000 plus cases. The outcomes include the seller only, the customer only, and both seller and customer agreeing on a contract that the particular combination represents.

Table 2 here.

The tenets of complexity theory provide several expectations to follow from examining the data in Table 2. These expectations support the following perspectives. A few (not many) of the patterns will provide highly consistent outcomes (e.g., seller-customer joint agreements). Both low and high price points within different complex antecedent configurations will associate with seller-customer joint agreements. Not all eight antecedent conditions will occur necessarily in the configurations indicating high consistency with seller-customer joint agreements. The valences for most-to-all antecedents will not be consistent for the configurations providing the highly consistent outcome of seller-customer joint agreements. A few of the combinations will provide highly consistent seller agree outcomes; a few of the combinations will provide highly consistent customer agree outcomes; such models of agreement will be

distinct from the combinations indicating that both the seller and buyer agree—thus, model testing for high consistency of outcomes can and should be done for all three possible outcomes. The testing for the negation of outcomes provides for distinct models of high consistency which are not mirror opposites of the positive outcome models (the causal asymmetry tenet).

Table 3 here.

Empirically examining all the tenets of the general theory of behavioral pricing is beyond the scope of the present study. However, the configural findings for testing for seller-customer agreement using the data in Table 2 appear in Table 3. These findings include six complex antecedent conditions that associate consistently with high scores in the outcome condition, that is, high scores in each of the six models indicates high score in the outcome condition of seller-customer agreement. Positive price-points appear in four of the six complex configurations and negative price-points appear in two of them.

These findings are from the “intermediate solutions” from using the fsQCA software; these intermediate solutions include all eight antecedents—such a finding does not always occur when testing using intermediate solutions. The fsQCA output includes parsimonious solutions and complex solutions—in this example application the intermediate and complex solutions are the same. Coverage in Table 3 indicates the share of cases whereby high scores for the complex antecedent condition associates with high scores for the outcome solution—coverage is analogous to the “coefficient of determination” ( $R^2$ ) in MRA (Woodside, 2013).

#### **4. Limitations**

The intention here does not include a complete exposition of the general theory of behavioral pricing. While Woodside, Schpektor, and Xia (2013) provide direct comparisons of theory and findings using symmetric versus asymmetric tools (e.g., MRA versus QCA), they do so for a field experiment

focusing on pricing in a consumer goods context and not a B2B context. Certainly, direct comparisons of using both theory-method approaches in B2B contexts warrant researchers' attention. The paper's title may appear to claim too much given that the evidence is limited in support of the general theory.

However, the presentation here focuses on developing the theory and to call for the use of marketing and consumer anthropological studies focusing on the tenets of behavioral pricing to test the general theory. One objective for the study here is to encourage additional research and literature reviews on behavioral pricing topics to both confirm and extend the core tenets of the theory.

The general theory of behavioral pricing as explicated here fit well in Cyert and March's (1963) four objectives for starting the quest for a behavioral theory of the firm. Here are the four objectives as Cyert and March expressed in 1962:

1. Focus on a small number of key economic decisions made by the firm. In the first instance, these were price and output decisions; subsequently they included internal allocation and market strategy decisions.
2. Develop process-oriented models of the firm. That is, we viewed decisions of the firm as the result of a well defined sequence of behaviors in that firm; we wished to study the decisions by studying the process.
3. Link models of the firm as closely as possible to empirical observations of both the decision output and the process structure of actual business organizations. The models were to be both explicitly based on observations of firms and subject to empirical test against the actual behavior of identifiable firms.
4. Develop a theory with generality beyond the specific firms studied. We wanted a set of summary concepts and relations that could be used to understand the behavior of a variety of organizations in a variety of decision situations. (Cyert and March 1963, p. 2, italics in original)

Yet, the present study is limited in its scope and depth in contributing to these four objectives. The present paper provides an approach to constructing and testing complex antecedent conditions that builds upon the objectives of the behavioral theory of the firm and complexity theory but does not provide a full empirical examination that matches the four commitments as Cyert and March (1962) describe. Clearly the tenets of the general theory of behavioral pricing need examination by field studies involving more than one marketer and only a limited number of cases of customers. However, the advances of joining complexity theory, complex configural modeling, and the tenets of the basic behavioral theory of the firm provide insight for a useful way forward.

## **5. Practical Implications**

Famously, Kotler (1967, p. 1) pronounced, “Marketing decisions must be made in the context of insufficient information about processes that are dynamic, nonlinear, lagged, stochastic, interactive, and downright difficult.” Kotler’s perspective is relevant to pricing decisions and customers’ responses to specific price points as well as to advancing knowledge in behavioral pricing.

Consequently, research on issues involving pricing decision processes and outcomes in industrial marketing contexts requires the use of methods that go beyond arms-length surveys using fixed-point scales. The Morgenroth (1964), Howard and Morgenroth (1968) and the Woodside and Wilson (2000) studies included multiple face-to-face interviews with multiple participants in the pricing decision processes, document analysis of several cases (decisions), and in the study by Woodside and Wilson (2000) interviews with customers as well as members of the industrial marketing firm. The data analysis benefitted by the use of asymmetric analytical tools as McClelland (1998) and Ragin propose (2008). The findings support the tenets of the general theory of behavioral pricing as described in the present article.

### ***5.1 One Antecedent Condition is Rarely Sufficient as an Indicator for a High or Low Outcome Score***

Reviewing the tenets of the theory and empirical findings offers strategic insights for both marketers (M) and customers (C). An insight for both M and C that follows from the first tenet: very large customer size alone is insufficient for offering or receiving price-points lower than the average price point for all customers. B2B customers need to call attention to their size when aggressively pursuing a low price-point.

### ***5.2 Decision-Makers Rarely Use All Available Information in Real-Life Contexts***

An insight for M from the second tenet: different information streams relevant for different customer segments results in modifications to marketing strategy designs for these different customer segments. Customers can be segmented by a combination of size and the decision processes that they enact. For C: what works for big customers in the industry in gaining favored price treatment with suppliers is unlikely to work with small customers. Small customers will need to enact decision processes relevant for their size to gain favored treatment from suppliers.

### ***5.3 Decision-Makers Do Not Tradeoff High Accuracy for Low Effort but Create and Use Algorithms***

Woodside and Wilson (2000) describe purchasing executives reporting the use of compensatory decision rules for information gathering purposes but not when making actual choices among suppliers and their responses to RFQs—buyers use algorithms. Their conscious explication of these algorithms is likely to be a valuable exercise in learning how well the algorithms serve to reach their buying objectives. For M, learning buyers' algorithms-in-use will likely impact how M designs RFQ responses and the effectiveness of these responses in gaining share-of-business from the customers.

### ***5.4 Learning Necessary but Insufficient Conditions (NBICs)***

M and C are likely not to be consciously aware of all relevant necessary but insufficient conditions affecting the setting of price and responses to price-points. The in-depth study of multiple cases using the

long interview method is likely a necessary requirement for uncovering such information—such was the case in learning the seemingly trivial information that not all customers were aware of all three national manufacturers of the chemical purchasing requirements in the study by Woodside and Wilson (2000).

***5.5 Prices Vary Considerably for Different Customers in the Same Industry but the Variance Occurs in Different Complex Configurations-in-Use by their Industrial Suppliers***

The wide variation in prices for the same company manufacturing commodities in the chemical industry in Woodside and Wilson's (2000) study might surprise many industrial buyers. The low price among all customers was one-tenth of the highest prices that some customers were paying for the same products. Part, but not all, of this price variance would relate to costs in servicing large versus small customer accounts. Small-order customers are at a considerable disadvantage in attempting to negotiate price reductions with manufacturers of their purchase requirements. However, a share of large customers would likely benefit from an increase in their aggressiveness in negotiating price reductions. The cases were rare whereby large customers were too aggressive for the manufacturer to comply with requests for additional price reductions and additional add-on benefits (shipments with very low transportation charges)—compliance to such requests was usually granted.

## References

- Bazerman M.H., Moore D. 2008. Judgment in managerial decision making. Hoboken, NJ: Wiley & Sons: Hoboken.
- Byrne, D. (1998). Complexity theory and the social sciences. London: Routledge.
- Byrne, D. (2005). Complexity, configurations and cases. *Theory, Culture and Society*. 22 (5), 95-111.
- Cyert R.M., & March J.G. 1963. A Behavioral Theory of the Firm. Englewood Cliffs, NJ: Prentice-Hall: Englewood Cliffs.
- Davis, J.P., Eisenhardt, K.M., & Bingham, C. B. (2009), Optimal structure, market dynamism, and the strategy of simple rules. *Administrative Science Quarterly*, 54, 413-452.
- Eichenwald, K. (2001). The informant. New York: Broadway Books.
- Fitzsimons, Gavan J. (2008), Death to dichotomizing. *Journal of Consumer Research*, 35(1), 5-8.
- Fishburn, P. C. (1974). Lexicographic orders, utilities and decision rules: A survey. *Management Science*, 20, 1442–1471.
- Fiss, P. (2011). Building better causal theories: A fuzzy set approach to typologies in organization research. *Academy of Management Journal*, 54, 393–420.
- Friedman, M. (1966). The methodology of positive economics. *Essays in Positive Economics*, Chicago: University of Chicago Press, 3-16 & 30-43.
- FT (Financial Times) Lexicon (2013). Tacit knowledge. <http://lexicon.ft.com/Term?term=tacit-knowledge>.

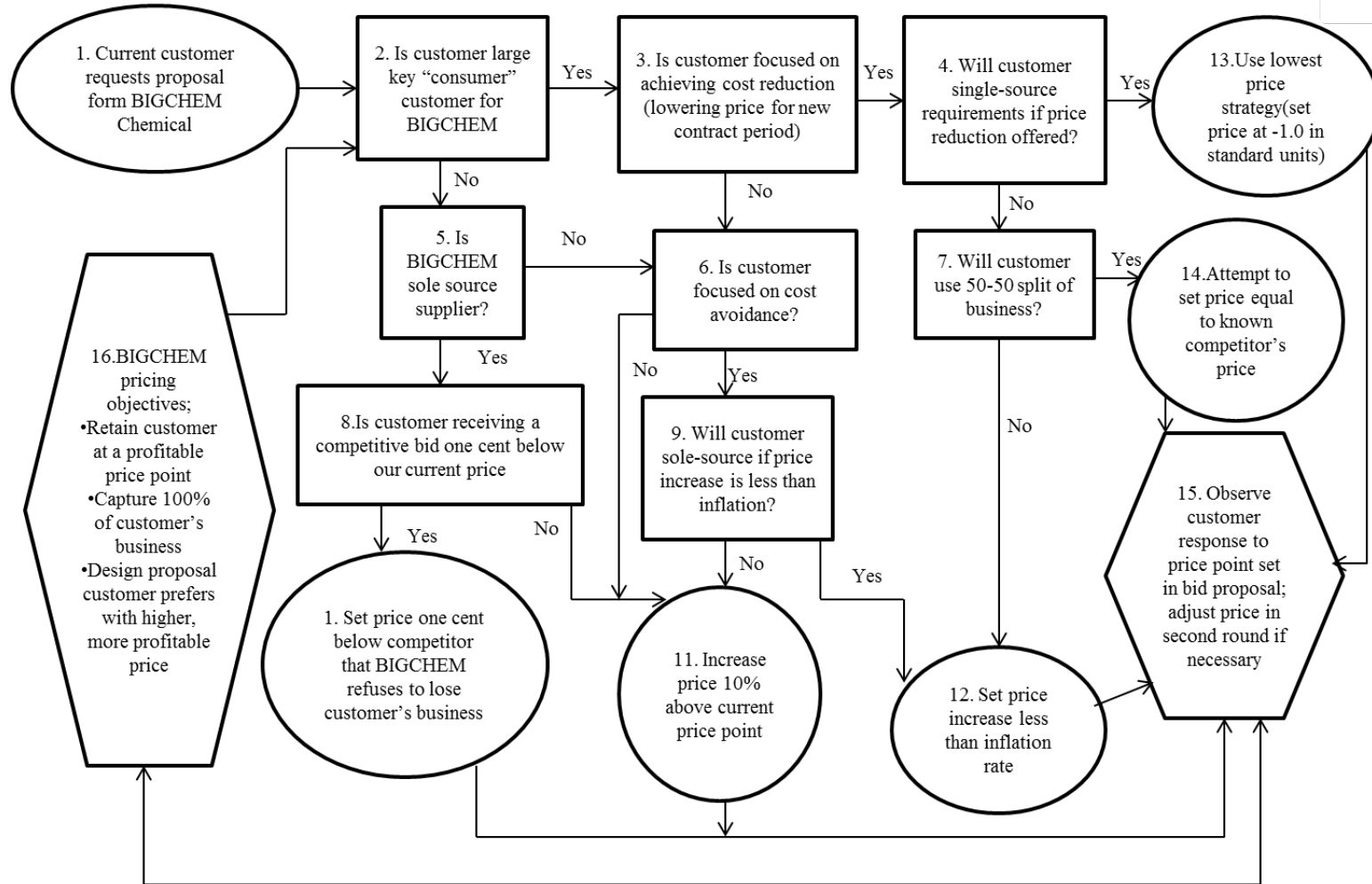
- Gendler, T. S. (1998). Galileo and the indispensability of scientific thought Experiment. *The British Journal for the Philosophy of Science*, 49, pp. 397-42.
- Gigerenzer, G. (1991). From tools to theories: A heuristic of discovery in cognitive psychology. *Psychological Review*, 98, 254-267.
- Gigerenzer, G., & Brighton, H. (2009). Homo heuristicus: Why biased minds make better inferences. *Topics in Cognitive Science*, 1, 107–143.
- Gigerenzer, G., & Selten, R. (Eds.) (2001). *Bounded rationality: The adaptive toolbox*. Cambridge, MA: MIT Press.
- Gigerenzer, G., Todd, P. M., & the ABC Research Group (1999). *Simple heuristics that make us smart*. New York: Oxford University Press.
- Gladwin, Christina. 1980. A theory of real-life choice: Applications to agricultural decisions. In P. Barlett (ed.), *Agricultural Decision Making: Anthropology Contributions to Rural Development*. NY, USA: Academic Press.
- Gladwin, C. H. 1982. The role of a cognitive anthropologist in a farming systems program which has everything. *The Role of Anthropologists and Other Social Scientists in Interdisciplinary Teams Developing Improved Food Production Technology*, Los Banos, the Philippines: IRRI.
- Gladwin, C. H. 1983. Contributions of decision tree methodology to a farming systems program. *Human Organization* 42(2): 146-157.
- Gladwin, C. H. (1989). *Ethnographic decision tree modeling*. Thousand Oaks, CA: Sage.
- Howard, J. A., & Morgenroth, W. M. (1968). Information processing model of executive decision. *Management Science*, 14, 416–428.

- Joskow, P. L. (1972). A behavioral theory of public utility regulation. Unpublished Ph.D. dissertation. New Haven, CT: Yale University.
- Joskow, P.L. (1973). Pricing decisions of regulated firms: A behavioral approach. *The Bell Journal of Economics and Management Science*, 4 (1) 118-140.
- Joskow, P. L. (2015). Email correspondence with Arch G. Woodside, January 15.
- Kahneman, D., Slovic P., & Tversky A. 1982. *Judgment under uncertainty: Heuristics and biases*. Cambridge University Press: New York.
- Kotler, P. (1967). *Marketing management: Analysis, planning and control*. Englewood Cliffs, NJ: Prentice-Hall.
- Lazarsfeld, P. F. (1937). Some remarks on the typological procedures in social research. *Festschrift fur Sozialforschung*, 6(1), 119–139.
- Manson, S. (2001). Simplifying complexity: A review of complexity theory. *Geoforum*, 32, 404-414.
- McClelland, D.C. (1998). Identifying competencies with behavioral-event interviews. *Psychological Science*, 9, 331-3339.
- McCracken, G. (1988). *The long interview*. Thousand Oaks, CA: Sage.
- Mintzberg, H. (1979). An emerging strategy of “direct” research. *Administrative Science Quarterly*, 24, 582–589.
- Morgenroth, W. M. (1964). Method for understanding price determinants. *Journal of Marketing Research*, 1, 17-26.

- Nicholson, Walter (2011). *Microeconomic Theory: Basic Principles and Extensions*. Independence, KY: Cengage Learning.
- Nonaka, I. (1994): A dynamic theory of organizational knowledge creation. *Organization Science*, 5(1), 14-37.
- Payne J.W., Bettman J.R., & Johnson, E.J. 1988. Adaptive strategy selection in decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 14, 534–552.
- Perloff, Jeffrey M. (2007). *Microeconomics*. Boston: Pearson-Addison Wesley, 4th Edition.
- Pettigrew, A. (1975). The industrial purchasing decision as a political process. *European Journal of Marketing*, 9, 4–19.
- Polanyi, Michael (1958/2002). *Personal Knowledge: Towards a Post-Critical Philosophy*. London: Routledge.
- Popper, K. (1961). *The Logic of Scientific Discovery*. New York, NY: Science Editions.
- Powell, T. C., Lovallo, D., & Fox, C.R. (2011). Behavioral strategy. *Strategic Management Journal*, 32, 1369-1386.
- Ragin, C.C. (2000). *Fuzzy Set Social Science*. Chicago: Chicago University Press.
- Ragin, C.C. (2006). Turning the tables: How case-oriented research challenges variable-oriented research. *Comparative Social Research*, 16, 27-42.
- Ragin, C. C. (2008). *Redesigning social inquiry: Fuzzy sets and beyond*. Chicago: Chicago University Press.

- Simon, H.A. (1962). The architecture of complexity. *Proceedings of the American Philosophical Society*, 106, 467-482.
- Simon, H.A. Science seeks parsimony, not simplicity searching for pattern in phenomena. In Zellner, A., Keuzenkamp, H.A., & McAleer, M. (2009). *Simplicity, inference and modelling: Keeping it sophisticatedly simple*, (pp. 32-72). Cambridge, UK: Cambridge University Press, working paper available at <http://digitalcollections.library.cmu.edu/awweb/awarchive?type=file&item=47027>.
- Tversky, A. (1972). Elimination by aspects: A theory of choice. *Psychological Review*, 79, 281–299.
- Urry, J. (2005). The complexity turn. *Theory, Culture & Society*. 22 (5), 1-14.
- Van Maanen, J. (1978). The asshole. In: P. K. Manning & J. Van Maanen (Eds.), *Policing: A view from the street* (221-238). Santa Monica, CA: Goodyear Publishing (available at [http://petermoskos.com/readings/Van\\_Maanen\\_1978.pdf](http://petermoskos.com/readings/Van_Maanen_1978.pdf)).
- Van Someren, M. W., Barnard, Y. F., & Sandberg, J. A. C. (1994). *The think aloud method*. London: Academic Press.
- Vyas, N. & Woodside, A. G. (1984). An inductive model of industrial supplier choice processes. *Journal of Marketing*, 47, 30-44.
- Woodside, A.G. (2003). Middle-range theory construction of the dynamics of organizational marketing-buying behavior. *Journal of Business & Industrial Marketing*, 18, 305-335.
- Woodside, A.G. (2013). Moving beyond multiple regression analysis to algorithms: Calling for adoption of a paradigm shift from symmetric to asymmetric thinking in data analysis and crafting theory. *Journal of Business Research*, 66, 463-472.

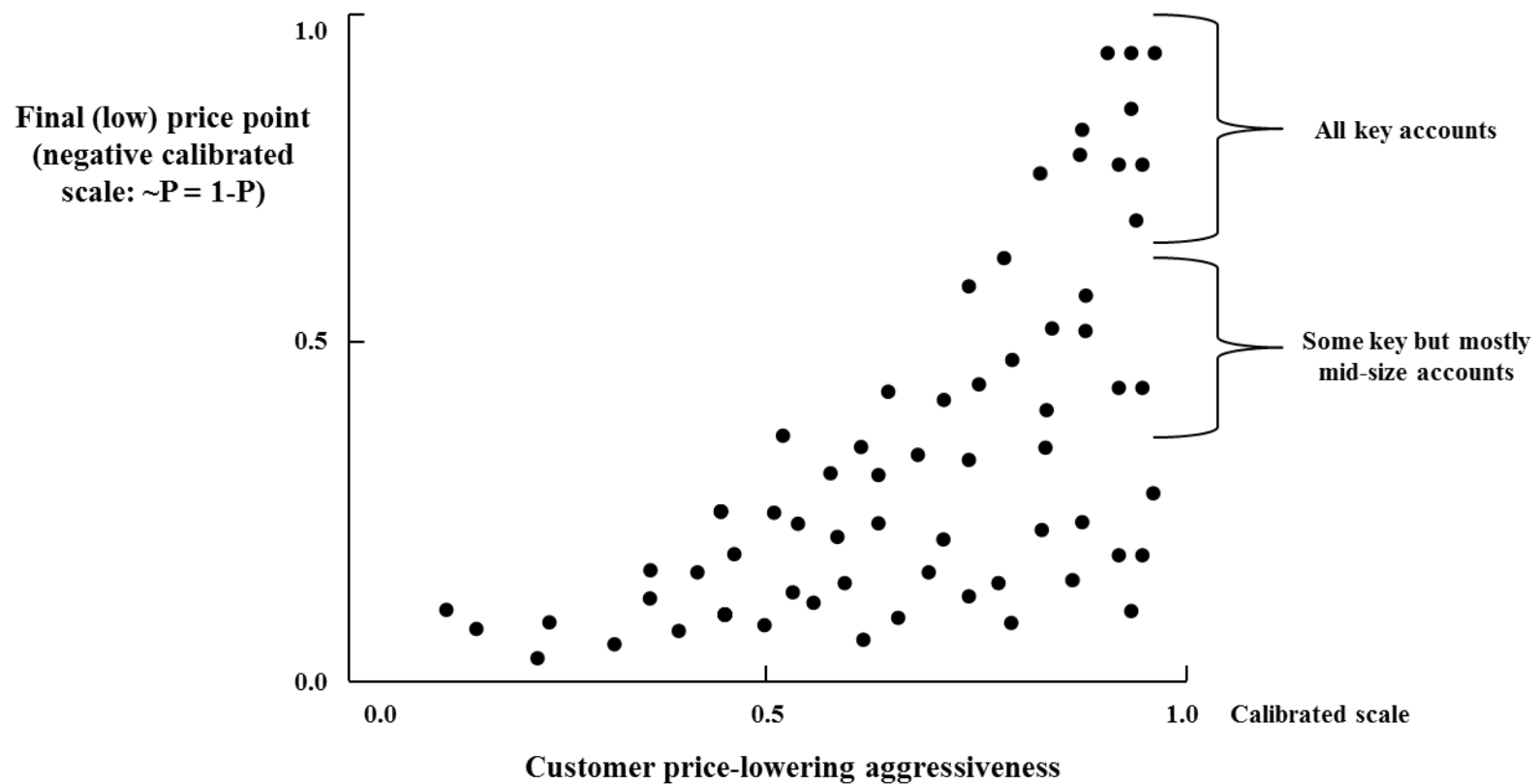
- Woodside, A.G., & Baxter, R. (2013). Achieving accuracy, generalization-to-contexts, and complexity in theories of business-to-business decision process. *Industrial Marketing Management*, 42, 382-393.
- Woodside, A.G., Pattinson, H., & Montgomery, D.B. (2012). Implemented strategies in business-to-business contexts. In M. S. Glynn and A.G. Woodside (Eds.), *Business-to-Business Marketing Management: Strategies, Cases and Solutions* (323-354). London: Emerald.
- Woodside, A.G., & Samuel, D. (1979). Observations of centralized corporate procurement. *Industrial Marketing Management*, 10, 191-205.
- Woodside, A.G., Schpektor, A. & Xia, X (2013). Triple sense-making of findings from marketing experiments using the dominant variable based-logic, case-based Logic, and isomorphic modeling. *International Journal of Business and Economics*, 12 (2), 131-153.
- Woodside, A. G., & Wilson, E. J. (2000). Constructing thick descriptions of marketers' and buyers' decision processes in business to business relationships. *Journal of Business and Industrial Marketing*, 15, 354–369.



**Figure 1**

**Summary pricing, and sales negotiations, decision model for BIGCHEM chemical based on customer decision profiles**

Source: Adapted from Figure 6 in Woodside and Wilson (2000, p. 363).



**Figure 2**

**XY Plot of Pricing Antecedent Condition for a Necessary but Not Sufficient Condition**

Note. Each dot is a case, that is, a customer firm, plotted on the customer's price-lowering aggressiveness and the final price quoted to the customer by the marketer's firm. Data ( $n = 80$ ) and plot are from additional analysis of marketer's responses to customers' requests for proposals (RFQs) and follow-up documents of customers' responses to marketer's proposals from the study by Woodside and Wilson (2000).

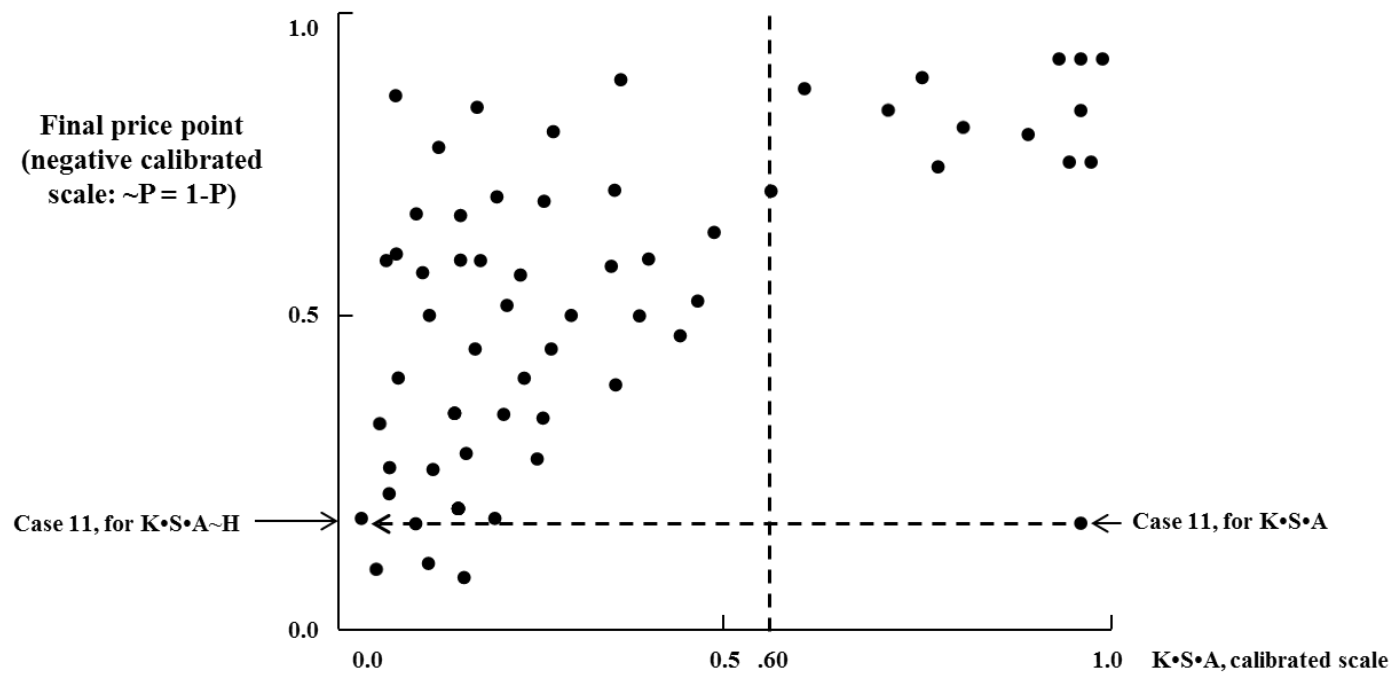


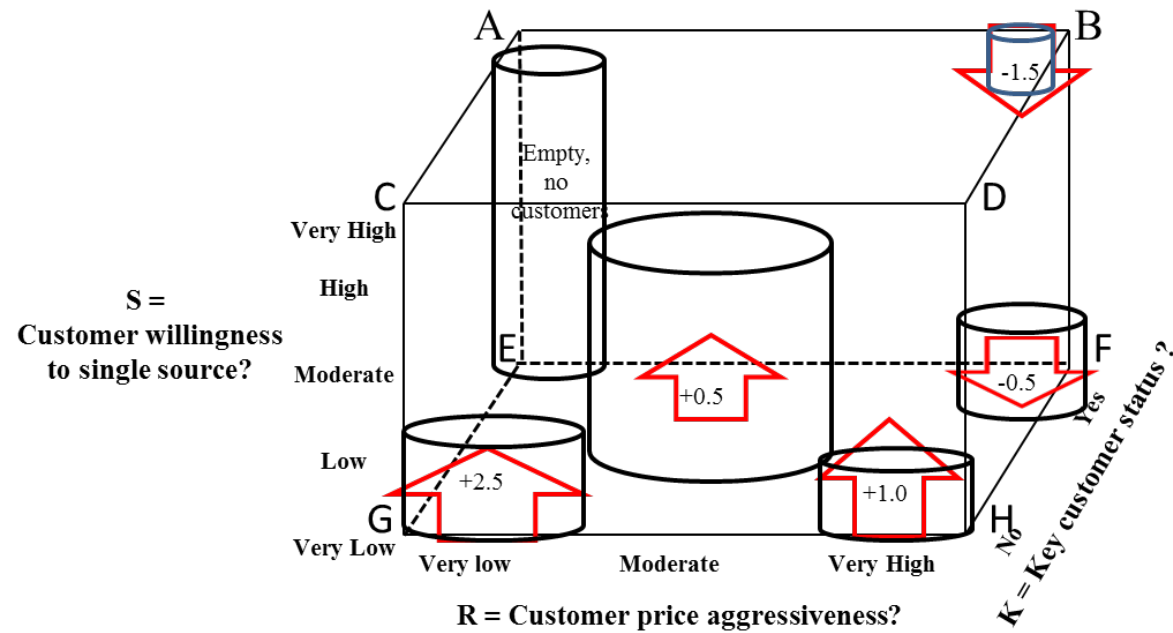
Figure 3

**Complex antecedent condition the is sufficient but not necessary:**  
 **$K \cdot S \cdot A$  where  $K$ = key account;  $S$  = willingness to singe-source;**  
 **$A$  = customer aggressiveness in seeking to lower price**

Note. Customers with high membership scores ( $\geq 0.60$ ) on  $K \cdot S \cdot A$  receive very low final price quotes with the exception of case 11. The explanation for case 11 relates to the title of Van Maanen (1978), "The Asshole." Case 11 is super-aggressive in attempting to lower price. Assuming that case 11 to be the only asshole ( $H$ ), the membership scores on not an asshole ( $\sim H$ ) for case 11 equals 0.0. Creating a configuration that incudes  $K \cdot S \cdot A \cdot \sim H$  serves to shift the position of case 11 on the X axis to the far left. Thus, a very complex antecedent condition is necessary to include case 11 to result in very high consistency.

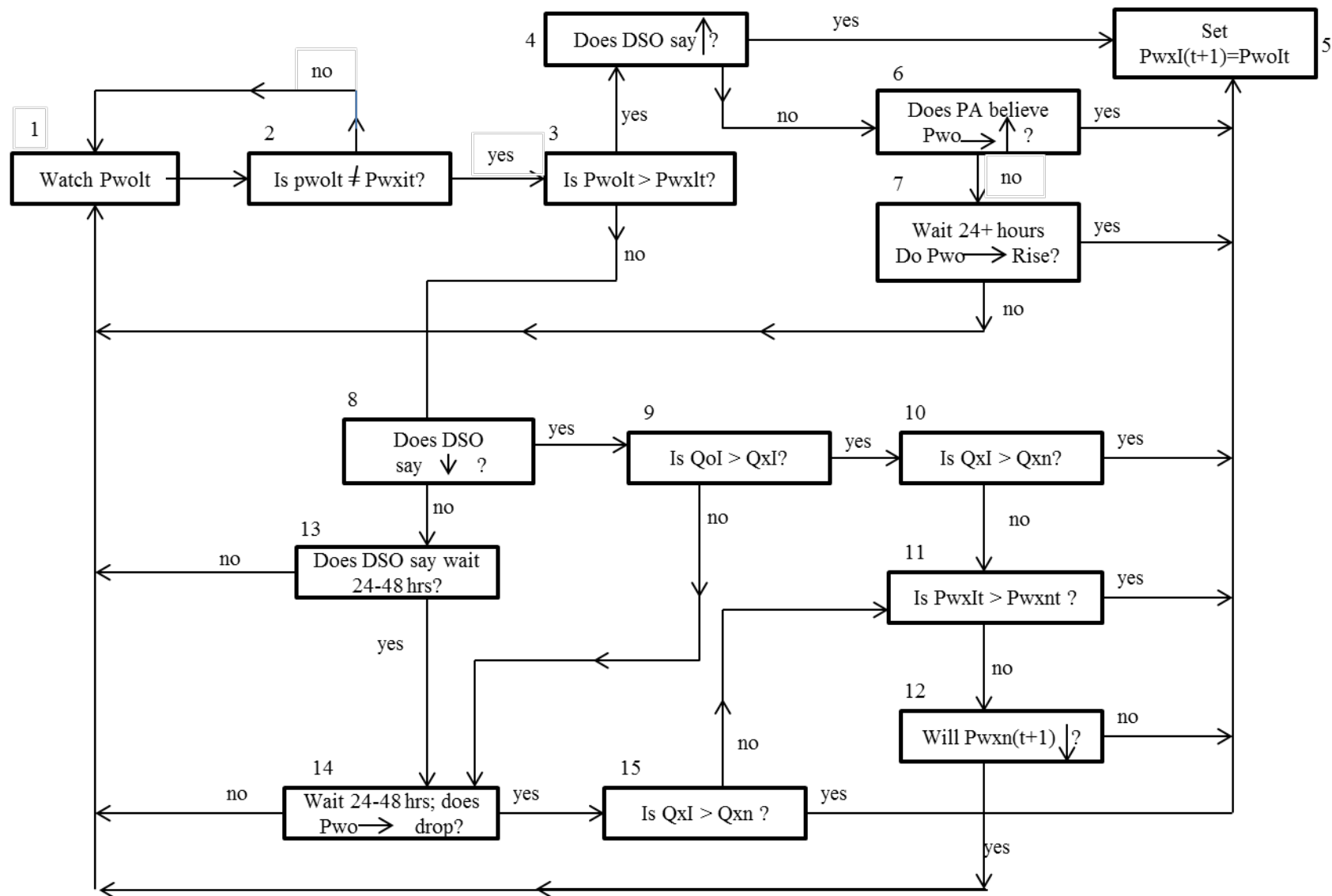
Configuration (Alternative path/Boolean expression)	Conditional Statement
<p><b>A</b></p> <p>Path: <math>1 \rightarrow 2 \rightarrow 3 \rightarrow 4 = 13</math></p> <p>reductions Boolean: <math>K \cdot R \cdot S \leq (\text{Price} \leq -1.0)</math></p>	<p><b>Lowering-price-strategy:</b> If a key (K) account customer who is focused on cost aggressively on lowering-price (A) and is willing to single-source (S), then price more than 35% below the annual average price.</p>
<p><b>B</b></p> <p>Path: <math>1 \rightarrow 3 \rightarrow 6 \rightarrow 9 = 11</math></p> <p>Boolean: <math>K \cdot \sim A \cdot \sim V \leq 11</math></p>	<p><b>High-price-increase strategy:</b> If key (K) account customer who is <b>not</b> focused on aggressively (<math>\sim A</math>) on price reductions and <b>not</b> focused on cost avoidance (<math>\sim V</math>), then increase price 10% above the current price that K is now paying. (A rare context.)</p>
<p><b>C</b></p> <p>Path: <math>(1 \rightarrow 2 \rightarrow 5 \rightarrow 8 = 10) \rightarrow 15</math></p> <p>Boolean: <math>(\sim K \cdot S \cdot C \leq 10) \cdot 15</math></p>	<p><b>Signaling competitor pricing for small but important customer:</b> If customer is not a key account (<math>\sim K</math>) but does single source (S), but has received an RFQ response from a competitor (C), then price 1¢ below competitor's bid; observe customer's response.</p>
<p><b>D</b></p> <p>Path: <math>1 \rightarrow 2 \rightarrow 5 \rightarrow 8 = 11</math></p> <p>Boolean: <math>\sim K \cdot S \cdot \sim C \leq 11</math></p>	<p><b>Highest-price-increase strategy:</b> If customer is not a key account (<math>\sim</math>) but does single source (S) and has not received a competitor's response (<math>\sim C</math>) to an RFQ, then increase the price above the already high price by 10% that this customer is now paying.</p>
<p><b>E</b></p> <p>Path: <math>(1 \rightarrow 2 \rightarrow 3 \rightarrow 4 \rightarrow 7 = 14) \rightarrow 15</math></p> <p>Boolean: <math>(K \cdot R \cdot \sim S \cdot L = 14) \cdot 15</math></p>	<p><b>Competitor-pairing pricing:</b> If customer is a key account (K) and is focused on cost reductions (R) but is unwilling to single-source (<math>\sim S</math>) but will split business 50-50 (L), then set new price equal to competitor's price and watch competitor's response.</p>

Fig. 4. Examples of industrial solvent conditional pricing in alternative contexts.



**Figure 5**  
**Price Increase and Decrease Points in Standard Units (Z-scores) with**  
**Cylinders Indicating Number of Customers (not Volume of Business)**

Notes. Most customers accept price increases. High scores in all three antecedent conditions ( $K \cdot R \cdot S$ ) sufficient for lowest price point. Focusing on the overall average price change ( $Z = +0.2$ ) is misleading because specific configurations of antecedent conditions associate with a specific price point.



**Figure 6**  
**Wholesale Pricing of Petroleum**  
 (Source: Morgenroth, 1964, p. 19)

Key. P = price; t – time, at present; PA=price analyst; r = retail; (t+1) = time, subsequent to considering price change; w = Wholesale; Q = Quantity; ≠ - is not equal to; or is different from; x – our company; l = local market, wherein price change is being considered is greater than; o-> is other major competitors in local market; n= nearby market with funnel influences; ↑= raise price o = other major competitor initiator; DSO = district sales office; ↓ - drop price

<b>Alternate Route</b>	<b>English Equivalent</b>
A. 1 – 2 – No – 1	Watch Others' Wholesale Local price. Is it different from the Company's price? If "No", watch.
B. 1 – 2 Yes – 3 Yes – 4 Yes – 5	Another raises his Local Wholesale Price. District Sales office (DSO) says to raise price so the Company meets the price
C. 1 – 2 – Yes – 3- Yes – 4 – Yes – 5	Another raises his Local Wholesale price. DSO says not to raise price, but Price Analyst (PA) believes others may follow, so Company meets the price.
D. 1 – 2 – Yes – 4 – No – 6 – No – 7 No – 1	Another raises his price. DSO says not to raise price. PA is dubious. The company waits 24-48 hours. The other competitors follow up, so the Company meets the price.
E. 1 – 2 – Yes – 3 – Yes – 4 – No – 6 - No – 7 - 1	Same as D, but others do not follow, so Company watches market.
F. 1 – 2- Yes – 3 – Yes – 9 – 10 – Yes – 5	Another drops his Local Wholesale Price. DSO says to follow down. The other's local market share is larger than the Company's local market share. The company's local market volume is larger than its nearby market volume. The Company meets the price.
G. 1 – 2 – Yes – 3- No – 8 – Yes – 9 - Yes- 10 – 11 – Yes 5	Same as F, except that the Company's nearby market volume is larger than its local market local market volume. The nearby market wholesale price is below the local wholesale price, so the Company meets the price.
H. 1 – 2 Yes – No – 8 – Yes – 9 – Yes 10 – No – 11 – No – 12 – 1	Same as G, except that the Company's Local Wholesale Price is below its nearby market wholesale price. This will funnel the larger market, so the Company does not change price.

**Figure 7**  
**Example Heuristics in the Wholesale Petroleum Pricing Model**  
Source: Morgenroth (1964, p. 23)

<u>Alternate Route</u>	<u>English Equivalent</u>
A. 1 - 2 - No - 1	Watch Others' Wholesale Local price. Is it different from the Company's price? If "No", watch.
B. 1 - 2 Yes - 3 Yes - 4 Yes - 5	Another raises his Local Wholesale Price. District Sales office (DSO) says to raise price so the Company meets the price
C. 1 - 2 - Yes - 3- Yes - 4 - Yes - 5	Another raises his Local Wholesale price. DSO says not to raise price, but Price Analyst (PA) believes others may follow, so Company meets the price.
D. 1 - 2 - Yes - 4 - No - 6 - No - 7 No - 1	Another raises his price. DSO says not to raise price. PA is dubious. The company waits 24-48 hours. The other competitors follow up, so the Company meets the price.
E. 1 - 2 - Yes - 3 - Yes - 4 - No - 6 - No - 7 - 1	Same as D, but others do not follow, so Company watches market.
F. 1 - 2- Yes - 3 - Yes - 9 - 10 - Yes - 5	Another drops his Local Wholesale Price. DSO says to follow down. The other's local market share is larger than the Company's local market share. The company's local market volume is larger than its nearby market volume. The Company meets the price.
G. 1 - 2 - Yes - 3- No - 8 - Yes - 9 - Yes- 10 - 11 - Yes 5	Same as F, except that the Company's nearby market volume is larger than its local market local market volume. The nearby market wholesale price is below the local wholesale price, so the Company meets the price.
H. 1 - 2 Yes - No - 8 - Yes - 9 - Yes 10 - No - 11 - No - 12 - 1	Same as G, except that the Company's Local Wholesale Price is below its nearby market wholesale price. This will funnel the larger market, so the Company does not change price.

Fig. 7. Example heuristics in the wholesale petroleum pricing model.  
Source: Morgenroth (1964, p. 23).

**Table 1**

Comparison of perspectives of microeconomics/dominant logic and the general theory of behavioral pricing.

	Concept	Microeconomics/dominant logic	General theory of behavioral pricing
1.	Context?	Ignore	Embrace
2.	XY relationship assumption?	Symmetric	Asymmetric
3.	Stance toward complexity?	Dismiss ("all else equal")	Capture, report
4.	Research focus?	Variables; statistical models	Cases; isomorphic algorithms
5.	Focus of findings?	Net effects; fit validity only	Configurations; fit and predictive validity
6.	Theoretical stance?	Rationality	Bounded rationality
7.	View of decision-maker?	Biased; mistake prone	Biased; prone toward high accuracy
8.	Decision-maker?	Individual	Group (e.g., "buying center")
9.	Directionality	Ignore	Feedback loops
10.	Stance toward information?	Use all information available	Use all information necessary
11.	Foundation for analysis?	Matrix algebra	Boolean algebra
12.	Stance toward markets?	Many buyers and sellers	Few buyers and sellers
13.	Weighting attributes?	Yes	No
14.	Firm's principal objective?	Maximize profits	Context-bound satisficing profits

**Table 2**

Simple antecedent conditions and compound outcome of seller-offer•customer-acceptance: calibrated scales with S•O = union of S-offer and C-accept.

Case	ss: S-Size	so: S-Objective	se: S-Expertise	cs: C-Size	co: C-Objective	ce: C-Expertise	cw: C-Willing	pp: Price-Point	sof: S-Offer	ca: C-Accept	sof_ca: S•O
1	.96	.85	.97	.86	.92	.98	.74	.18	1	1	1
Case 1 description: Big, high-profit focused, expert seller; big, high-profit focused, expert customer willing to single-source, for a low price-point, both seller and customer agree on this price-point; thus, S•O = 1.											
2	.96	.95	.65	.34	.12	.77	.07	.94	1	1	1
3	.22	.99	.32	.92	.96	.40	.93	.04	1	0	0
4	.05	.91	.05	.96	.92	.99	.30	.06	0	0	0
5	.50	.20	.65	.15	.22	.05	.96	.95	1	1	1
6	.05	.05	.25	.95	.60	.88	.05	.77	1	0	0
7	.61	.99	.23	.81	.19	.21	.91	.91	1	1	1
8	.96	.44	.72	.91	.60	.99	.90	.07	1	1	1
9	.31	.09	.14	.23	.08	.11	.35	.88	0	1	1
10	.91	.22	.13	.88	.99	.88	.43	.21	0	1	0
11	.56	.88	.78	.23	.86	.07	.89	.14	1	1	1
12	.96	.85	.97	.12	.30	.18	.91	.81	1	1	1

Key: S-Size = seller size for this product category; S-Objective = seller profit aggressive; S-Expertise = seller knowledge•experience•capability; C-Size = customer size for this product category; C-Objective = customer aggressiveness for price reduction; C-expertise = customer knowledge•experience•capability; C-Willing = customer's willingness to single source requirements; Price-Point = price point now on table; S-Offer = does seller offer this price point? C-Accept = does buyer accept this price point?

**Table 3**  
Findings for high consistency that both parties accept.

	Models with high consistency in predicting	Raw	Unique	
	Both seller offer and buyer accepts	Coverage	Coverage	Consistency
1	pp* ~ cw* ~ ce* ~ co* ~ cs* ~ so* ~ ss	0.11	0.07	0.92
2	pp*cw* ~ ce* ~ co*cs* ~ se*so*ss	0.14	0.05	0.91
3	pp*cw* ~ ce* ~ co* ~ cs*se*so*ss	0.18	0.07	0.93
4	pp* ~ cw*ce* ~ co* ~ cs*se*so*ss	0.15	0.07	0.89
5	~pp* ~ cw* ~ ce*co*cs*se*so*ss	0.13	0.05	0.80
6	~pp*cw*ce*co*cs*se ~ so*ss	0.14	0.07	0.82
Solution coverage: 0.51				
Solution consistency: 0.93				

Example: Model 1, description: high price point, not customer willing to single source, customer low in expertise, customer's objective is not aggressive, seller low in expertise; seller size is small, seller not high profit objective, seller is not large in size.

Notes. The price point in a seller's offer that the buyer accepts is high in models 1–4 and low in models 5 and 6. The customer is willing to single source in models 2, 3, 5, and 6 but not willing to do so in models 1 and 2. The six configurations do not include one valence consistently for any of the simple antecedent conditions. Thus, the direction of the impact on price (and other simple antecedent conditions are contingent on the recipe for the complex configuration in which (and the other simple conditions) it appears.

Key: S-Size = seller size for this product category; S-Objective = seller profit aggressive; S-Expertise = seller knowledge\*experience\*capability; C-Size = customer size for this product category; C-Objective = customer aggressiveness for price reduction; C-expertise = customer knowledge\*experience\*capability; C-Willing = customer's willingness to single source requirements; Price-Point = price point now on table; S-Offer = does seller offer this price point? C-Accept = does buyer accept this price point?

