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M.Sc. IN FINANCIAL ANALYSIS FOR EXECUTIVES

BARGAINING MODELS IN E-MARKETPLACES

by

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ABSTRACT

The scope of this thesis is to examine the different bargaining models that can be used in the continuously-growing sector of e-marketplaces. Based on Faratin scoring functions which used in multi-agents systems, the Rubinstein bargaining model example of multiple games, which adding the discount factor in the bargain process, and the axiomatic approach of Nash, we create a two dimensional function that can be incorporate in e-marketplaces and support the counterparts of the bargain to decide the better solution for both sides and reach to an agreement as soon as possible. Afterwards by changing the parts of the function we export some useful results about the strategy that each player should follow to obtain the most of the bargain.

Keywords:

E-marketplaces

Multi-agents systems

Multiple games theory

Scoring functions

Discount factor in game theory

Strategies in a Bargain

2-Dimensional Bargain model

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1. Introduction

An **E-marketplace** is an internet place owned by a company or consortium which allows other companies or individuals to acquire new suppliers or buyers for their products as well as advance trading networks which perform negotiating, settlement and delivery easier and more efficient.

A site is called as an e-marketplace when it is delivered to many buyers and sellers by providing commerce related functionalities like auctioning (forward or reverse), catalogues, ordering, wanted advertisement, trading exchange functionality and capabilities like RFQ (**Request For Quotation)**, RFI (**Request For Invitation)** or RFP (**Request For Proposal)**.

These 3 functionalities refer to options that the buyer has in order to start the bargain with the seller. More specific a RFP (Request for Proposal) is a document that an organization posts to bring out bids from potential vendors for a product or service. An RFP is part of an organization's procurement process, which begins with an assessment of needs and ends with delivery and/or support of the finished product or service.

Other than RFP we have the RFQ that stands for Request for Quotation. An organization issues a RFQ when it is merely checking into the possibility of acquiring a product or service. A response to an RFQ by a prospective contractor is not considered an offer, and consequently, cannot be accepted by the organization to form a binding contract.

Finally RFI is Request for Information. It is a kind of request made typically during the project planning phase where a buyer cannot clearly identify product requirements, specifications, and purchase options. RFIs clearly indicate that award of a contract will not automatically follow.

1.1 Examples of E-marketplaces

E-marketplaces are everywhere around in our life and grow with rapid speed especially the latest years. Some of the most important and well-known E-marketplaces are EBay, NASDAQ, Covisint.

To start with E-Bay, the world largest in online auction and shopping site in which people and businesses buy and sell a broad variety of goods and services worldwide. Founded in 1995, eBay is one of the notable success stories of the dot-com bubble; it is now a multi-billion dollar business with operations localized in over thirty countries. Bidding on eBay's auction-style listings is called proxy bidding and is essentially equivalent to a Vickrey auction, with the following exceptions.

- The winning bidder pays the second-highest bid plus one bid increment amount (that is, some small predefined amount relative to the bid size), instead of simply the second-highest bid. However, since the bid increment amounts are relatively insignificant compared to the bid size, they are not considered from a strategic standpoint.
- The highest bidder's bid is sealed, as in a Vickrey auction, but the current winning bid (second highest plus one increment) is displayed throughout the auction to allow price discovery.

Following EBay in the list of the largest online sites **NASDAQ** is the second-largest stock exchange by market capitalization in the world, after the New York Stock Exchange . When the NASDAQ stock exchange began trading on February 8, 1971, it was the world's first electronic stock market. NASDAQ quotes are available at three levels:

- Level 1 shows the highest bid and lowest offer—the inside quote.
- Level 2 shows all public quotes of market makers together with information of market dealers wishing to sell or buy stock and recently executed orders.
- Level 3 is used by the market makers and allows them to enter their quotes and execute orders.

Last in our list of well-known sites is the **Covisint**, an American information technology company that was established in 2000 by a consortium of organizations(General Motors, Ford, and DaimlerChrysler) In February, 2004, Compuware Corporation acquired Covisint. Initially focused in the automotive industry, Covisint has expanded into the healthcare, oil and gas, and other industries.

In 2010 Covisint acquired DocSite, an award-winning clinical decision support and quality performance management Company based in Raleigh, N.C.

The ExchangeLink Platform offers industry specific services including: identity management, collaborative portals and data exchange, as well as third-party application marketplace.

Since becoming part of Compuware, Covisint continues to provide and expand EDI, portals, and identity management services to the automotive community, including significant ongoing business with the original stakeholders. The company has also moved beyond its automotive roots and into additional verticals such as health care, government, and financial services.

1.2 E-marketplaces categorization

E-Marketplaces can be distilled into six primary flavors of online marketplaces, serving both the B2B and B2C markets [Kaplan and Sawhney 2000; Bakos1991] :

Online Buying Services

These facilities offer support for the duration of the awareness and request generation phases of the selling process. In detail, they offer price and product transparency (e.g., through shopping agents and comparison websites), buyer and seller discovery (e.g., shopping agents, price aggregators and industry catalogs), and quality recommendation and selection aides (e.g., market analyst and evaluation websites).

Online buying services are directed primarily to B2C markets, as well as small business/SOHO markets.

The specific services that make up online buying services will be absorbed into more mature exchanges and net markets over time.Main examples for this category are mySimon, CarPrices.com, and CNET.

Auctions

Auctions are online markets that search for demand and match buyers and sellers for a wide range of B2B and B2C products. They service a variability of market-making tools (e.g., reverse, Dutch, English, and sealed-bid auctions) to meet particular commercial aims such as demand collection and price maximization.

Auctions serve B2C, C2C, and B2B markets, as well as retail, repair and operations (MRO) purchases, spot acquisitions of supplies and raw materials, and previously owned capital equipment. In the B2B space, auctions are generally targeted to small business/SOHO customers that absence both buying power and erudite buying operations.In this category we have some famous examples include Amazon.com (auction) and Mercata (demand aggregator).

Vertical Exchanges

Vertical exchanges are reliable mediators that enable B2B e-commerce with vertical market and product-specific know-how. They propose real-time pricing and complete product info. In time, they are to suggest a range of value-added services across an array of vertical markets .Examples of vertical exchanges include PaperExchange.com and FreeMarkets.

Functional Exchanges

Functional exchanges are trustworthy intermediaries that facilitate mostly B2B e-commerce involving process, functional, or channel-specific expertise. These exchanges market an array of primary services or solutions that automate or support specific business functions or processes Functional exchanges offer real-time pricing, complete product information, and value-added services. Examples here include trade hub and Celarix.com.

Industry-Sponsored Exchanges

Mainly in B2B commerce, these exchanges have equity participation or sponsorship from chief industry buyers and technology partners as well. They act as intermediaries to facilitate B2B e-commerce in industries with high concentrations of buying power. Industry-sponsored exchanges offer the same variety of services as other exchanges, as well as real-time pricing, complete product information, and value-added services and information. Over time, these exchanges will accommodate more highly engineered products and direct materials.In this category we find COVISINT and Global net.

Net Markets

The main online marketplaces will be Net markets. These markets are classy networks and mixtures of online marketplaces that will arise over the next three years. Net markets will develop from the quilting of functional and vertical exchange capabilities and expertise, and the gathering of value-added services across the supply chain (e.g., logistics, inventory, demand forecasting). This style of market will distribute more value-added services and will need high levels of buyer collaboration to conduct complex transactions. Because Net markets will demand the integration of many industry supply chains and the coordination of multiple large and small markets, they will not mature for quite a few years.

In the short term, each of these online marketplaces generates value by enabling the sharing of data about products and pricing, matching many buyers and sellers and improving the ease and speed of transactions. Longer term, value will arise from greater levels of purchase-process integration and through the delivery of value-added information and services.

1.3 SMEs follow

Some researchers are demonstrating that big constructors have adopted B2B e-commerce leaving their suppliers, mostly Small and Medium Enterprises (SMEs), in the manufacturing sector, with little choice but to follow. A recent survey of the Aberdeen Group (2006) appraised the following benefits for companies that adopt B2B strategies:

Reduction of their requisition-to-order cycles by 75%;

Reduction of their requisition-to-order costs by 48%;

Reduction of their maverick spends by36%.

The following table reports the trend of the e-procurement applications upon 2001 and 2006 (Table 1).

E-Procurement performance.

Performance area	2001	2004	2006
Total suppliers enabled	30	253	361
Total end-users	1000	2309	1381
Users: current vs. planned (%)	12%	43.5%	68%
Transactions per month	1340	5244	2977
Percentage of indirect spend managed by system	18%	37.6%	55%
Percentage of services spend managed by system	–	32.7%	29.3%

It is, therefore, very important for SMEs' managers to understand the impact of these activities on their organizations' performance and competitiveness. The literature one-commerce (Favier etal.,2000) reveals a number of associated benefits. First of all the SMEs can access international markets at minimal cost: it can represent one crucial competitive advantage for SMEs. Second, it can be obtained at a reduction in transaction costs, especially fore-procurement and economies of scale such as consolidation of sales or group buying. Taking a broader perspective, it can be summarized that e-commerce generates positive impacts on operations management and improves efficiency and effectiveness.

Third, in a manufacturing context, e-commerce creates potential opportunities such as faster product design, speedier ordering of parts and components, reduced lead times and lower inventory costs.

Moreover, according to Barrat and Rosdahl (2002) it is fundamental to reduce waste and inefficiency in highly fragmented industries, by increasing visibility and a neutral knowledge base for both buyers and sellers. Buyers or sellers usually do not establish such marketplaces, which are frequently set up by an independent company such as an ICT provider or a bank. This is because the external ''third part'' aims to put together isolated group of buyers and sellers in order to inaugurate a sort of ''procurement virtual district''. The seller benefits normally come from getting access to more buyers growing its market, while the buyer benefits come from the possibility to get lower procurement costs, wider choice of products and better quality.

Bargain is one of the main and most important components of e-marketplaces and this paper will try to mirror and describe the bargaining models in e-marketplaces and the negotiations between the counterparts.

2. Literature review

2.1 Negotiations and preferences

To create an integrative solution in a bargaining problem, negotiators need to have information about each other's preferences.

Negotiations are an important way of solving conflicts in many fields. In contrast to other approaches of conflict resolution, negotiations provide the opportunity to reach a win–win, or integrative solution, which improves the position of both sides beyond the status quo (Sebenius, 1992).

According to the widely used Dual Concern model of negotiations (Blake and Mouton, 1964; Pruitt, 1983; Thomas, 1992; Carnevale and Pruitt, 1992), negotiators need to have both a high concern for their own outcomes in the negotiations as well as for their opponent's outcomes to reach a win–win situation. Consequently, the success of negotiations be determined by the ability of negotiators to develop an understanding of the goals and preferences of their opponents (Keeney and Raiffa, 1991; Sebenius, 1992; Kersten, 2001).

The significance of knowing preferences of other negotiators can best be illustrated by the well-known ‘‘Orange” example (Kersten, 2001): two chefs negotiate how to share the last orange that is left in the kitchen, and lastly they split the fruit in half. One chef then proceeds to put the peel of his half into a cake and throws away the inner portion, while the other squeezes his half, uses the juice for a sauce and throws away the covering. Knowing the preferences of each other would have led to a superior division.

Awareness about the opponent's preferences is therefore an important element in negotiations. Its impact on the accomplishment of negotiations has been studied in the literature since the early 1990s. Thompson and Hastie (1990) studied the different types of decision errors negotiators might make about the preferences of their adversaries, and the learning processes that take place during negotiations to reduce these faults.

They identified two types of errors: the ‘‘Fixed Sum Error” and the ‘‘Incompatibility Error”. In the fixed sum error, negotiators incorrectly view the negotiation as a zero-sum game. This incorrect assumption is caused by the failure to recognize differences in the importance of issues to the parties, which would make it conceivable to perform connections advantageous for both sides. In the incompatibility error, the parties believe to have opposite preferences about an issue, while in fact their preferences are identical, and there is no conflict at all the empirical research of Thompson and Hastie (1990) led to several important results. Many negotiators indeed start negotiations under the fixed sum error, but it could also be shown that during negotiations, learning takes places and the extent of this error are reduced over time.

Furthermore, several later studies (Thompson, 1991; Thompson and DeHarpport, 1994; Arunachalam and Dilla, 1995; Mumpower et al., 2004) showed that in negotiations where the parties learn more about each other’s preferences, the joint outcome at the end of the negotiation is higher.

All these studies used very similar approaches to measure awareness about the competitor’s preferences. Preferences were prescribed to experimental subjects in the form of a multi-attribute payoff table, which enclosed partial values for all potential outcomes in each issue being negotiated. After finishing point of the negotiation experiment, a blank table was given to negotiators and they were requested to complete with the values they believed were enclosed in their opponent’s table. The variance between this table and the real table given to the opponent was used as an indicator of the negotiators’ considerate of their opponents’ preferences.

Later studies prolonged the work of Thompson and Hastie (1990) mainly to analyze different aspects which influence the amount of learning taking place during negotiations.

For example, Thompson (1991) studied whether it makes a variance if preference info is directly made accessible to negotiators by a third party, or if negotiators appeal their opponents about their preferences. Thompson and DeHarpport (1994) studied how negotiators change their learning behavior about preferences when they receive different types of feedback from earlier negotiations.

In a similar study, Nadler et al. (2003) compared four training methods for negotiators. One of the outcome measures they used to evaluate the training methods was a ‘‘trade-off score” indicating how well negotiators understood differences in each other’s preferences and exploited them to achieve a win–win situation.

In an altered, but connected line of research, Arunachalam and Dilla (1995) found that negotiators learn less about their opponent’s preferences when they use a computer-based negotiation support system, than when they negotiate face-to-face. The technique used in these studies to measure awareness about preferences was put into question by Mumpower et al. (2004), who distinguished between the ‘‘Payoff schedule estimation method” used in the earlier studies, and another method called ‘‘Holistic estimation method”. In the second technique, subjects are straight asked to guess the holistic evaluations of alternatives for their rivals, rather than the different components of their opponents’ value functions.

Both approaches rely on information about the opponent’s true value function, which is used as a benchmark for the model which a negotiator forms about his or her opponent’s preferences. This requirement can easily be fulfilled in experiments in which preferences are given to subjects in the form of a known payoff table. But this is not the condition which negotiators face in real life. Furthermore, the extent to which subjects actually follow such prearranged partialities in their negotiation behavior cannot be strong-minded; this might affect empirical results acquired with this method.

From experimental research in decision investigation (Shoemaker and Waid, 1982), it is well known that different approaches to provoke a multi-attribute value function can lead to different results. Guessing the preferences of revelry is even tougher than describing one’s personal preferences and the direct requirement of preference information used in these experiments is less reliable than other, more elaborate techniques which use redundant information. It is therefore very likely that this method presents a considerable measurement error, and that the use of different methods to specify the presumed payoff table of the opponent could clue to other results.

Our main ally in negotiation analysis is game theory.

Game theory is a subdivision of mathematics that is concerned with the actions of Individuals who are conscious that their actions affect each other''. As such, game theory deals with collaborating optimization problems. While many economists in the past have worked on what can be described as game-theoretical replicas, John von Neumann and Oskar Morgenstern are formally credited as the ancestors of modern game theory. Their book Theory of Games and Economic Behavior (von Neumann and Morgenstern 1944) recaps the rudimentary ideas existing at that time.

Game Theory has since enjoyed an detonation of expansions, including the idea of equilibrium (Nash 1950), games with deficient information (Kuhn 1953), cooperative games (Aumann 1959; Shubik 1962) and auctions (Vickrey 1961), to name just few of them.

The models of game theory are highly abstract depictions of classes of real-life situations. Their abstractness permits them to be used to study a wide range of phenomena. For example, the theory of Nash equilibrium has been used to study oligopolistic and political competition. The theory of mixed strategy equilibrium has been used to explain the distributions of tongue length in bees. The theory of repeated games has been used to illuminate social phenomena like threats and promises. The theory of the core reveals a sense in which the outcome of trading under a price system is stable in an economy that contains many agents. The boundary between pure and applied game theory is vague; some developments in the pure theory were motivated by issues that arose in applications. Citing Shubik (2002), ''In the 50s game theory was looked upon as a curiosum not to be taken seriously by any behavioral scientist. By the late 1980s, game theory in the new industrial organization has taken over: game theory has proved its success in many disciplines.''

Game theory is separated into two subdivisions, called the non-cooperative and cooperative subdivision. The two subdivisions of Game theory differ in how they formalize interdependence among the players.

In the non-cooperative theory, a game is a detailed model of all the movements available to the players. In the opposite, the cooperative theory abstracts away from this level of detail, and describes only the outcomes that result when the players come together in different combinations. Though standard, the terms no cooperative and cooperative game theory is perhaps unfortunate. They might suggest that there is no place for cooperation in the former and no place for conflict, competition etc. in the latter. In fact, neither is the case.

One parts of the no cooperative theory (the theory of repeated games) exams the possibility of cooperation in ongoing relationships. And the cooperative theory embodies not just cooperation among players, but also rivalry in a mainly strong, unconstrained form.

The non-cooperative theory might be better called procedural game theory and the cooperative theory combinatorial game theory. This would specify the real distinction between the two subdivisions of the subject, namely that the first specifies various movements that are accessible to the players while the second describes the results that result when the players come together in different combinations

A game is a description of strategic interaction that includes the constraints on the actions that the players can take and the players' interests, but does not specify the actions that the players do take.

A solution is a systematic description of the outcomes that may emerge in a family of games. Game theory suggests reasonable solutions for classes of games and observes their properties. To break the ground for next section on non-cooperative games, basic Game theory notation will be introduced:

The reader can refer to Friedman (1986) and Fudenberg and Tirole (1991) if a more deep knowledge is required.

A game in the normal form consists of:

Players (indexed by i . 1; 2; . . .; n)

a set of strategies (denoted by xi; i . 1; 2; . . .; n) available to each player and payoffs (pi.x1; x2; . . .; xn.; i . 1; 2; . . .; n) received by each player.

Each strategy is defined on a set Xi, xi ∈ Xi; so we call the Cartesian product X1 x X2 x . . . x Xn the strategy space (typically the strategy space is Rn)

Each player may have a one-dimensional strategy or a multi-dimensional strategy. Though, in simultaneous-move games each player's set of feasible strategies are autonomous from the strategies chosen by the other players, i.e., the strategy choice of one player does not limit the feasible strategies of another player.

A player's strategy can be thought of as the complete instruction for which actions have to be taken in a game. For example, a player can give his or her strategy to a person who has absolutely no knowledge of the player's payoff or preferences and that person should be able to use the directions delimited in the strategy to select the movements the player desires.

Because each player's strategy is a complete guide to the actions that are to be taken, in the normal form the players choose their strategies simultaneously. Actions, which are adopted after strategies, are thus chosen and those actions correspond to the given strategies.

The normal form can also be described as a static game, in contrast to the extensive form which is a dynamic game. If the strategy has no randomly determined choices, it is called a pure strategy; otherwise it is called a mixed strategy. There are situations in economics and marketing in which mixed strategies have been applied: e.g., search models (Varian 1980) and promotion models (Lal 1990). In a non-cooperative game the players are unable to make binding commitments regarding which strategy they will choose before they actually choose their strategies. In cooperative game players are able to make these binding commitments. Hence, in a cooperative game, players can make side-payments and form coalitions. After the clarification of what in Game theory is considered to be the rationality, the overview reported here starts with non-cooperative static games.

The models studied assume that each decision-maker is rational in the sense that he is aware of his alternatives, forms expectations about any unknowns, has clear preferences and chooses his action deliberately after some process of optimization. In the absence of uncertainty the following elements constitute a model of rational choice:

- A set A of actions from which the decision-maker makes a choice;
- A set C of possible consequences of these actions;
- A consequence function that associates a consequence with each action;
- A preference relation on the set C.

Generally the decision-maker's partialities are specified by giving a utility function, which defines a preference relation. An assumption upon which the usefulness of this model of decision-making depends is that the individual uses the same preference relation when choosing from different set B. It could also be that individuals have to make decisions under conditions of uncertainty.

The players may be

- Uncertain about the objective parameters of the environment;
- Imperfectly informed about events that happens in the game;
- Uncertain about actions of the other players that are not deterministic;
- Uncertain about the reasoning of the other players.

To model decision-making under uncertainty, almost all game theory uses the theories of von Neumann and Morgenstern, that is, if the consequence function is stochastic and known to the decision maker then the decision-maker is assumed to behave as if he maximizes the expected value of a function that attaches a number to each consequence. If the stochastic connection between actions and consequences is not given, the decision-maker is assumed to behave as if he has in mind a (subjective) probability distribution that determines the consequence of any action.

In real-life context there is an asymmetry between individuals in their abilities. For example, some players may have a clearer perception of a situation or have a greater ability to analyze it.

These differences, which are so critical in life, are missing from game theory in its current form. To illustrate the consequences of this fact, the game of chess could be a valid example. In an actual play of chess the players may differ in their knowledge of the legal moves and in their analytical abilities. In contrast, when chess is modeled using current game theory it is assumed that the players' knowledge of the rules of the game is perfect and their ability to analyze it is ideal. It has been demonstrated that chess is a trivial game for rational players: an algorithm exists that can be used to solve the game. This algorithm defines a pair of strategies, one for each player that leads to an equilibrium outcome with the property that a player who follows his strategy can be sure that the outcome will be at least as good as the equilibrium outcome no matter what strategy the other player uses. The existence of such strategies suggests that chess is uninteresting because it has only one possible outcome. Nevertheless, chess remains a very popular and interesting game. Its equilibrium outcome is yet to be calculated; currently it is impossible to do so using the algorithm.

Modeling asymmetries in abilities and in perceptions of a situation by different players is a fascinating challenge for future research, which models of bounded rationality have begun to tackle.

In non-cooperative stationary games the players choose strategies at the same time and are afterward committed to their chosen tactics. The solution concept for these games was formally introduced by John Nash (1950) although some instances of using similar concepts date back to a couple of centuries. The concept is best described through best response functions.

2.2 Nash axiomatic approach

Nash axiomatic approach is one of the well-known in game theory. Consider a group of two or more agents facing with a set of feasible outcomes, any one of which will be the result if it is accepted by unanimous agreement of all participants. In the event that no unanimous agreement is reached, a given disagreement outcome is the result. If the feasible outcomes are such that each participant can do better than the disagreement outcome, then there is an incentive to reach an agreement; however, so long as at least two of the participants differ over which outcome is most preferable, there is a need for bargaining and negotiation over which outcome should be agreed upon. Note that since unanimity is required, each participant has the ability to veto any outcome different from the disagreement outcome. To model this atomic negotiation process, we use the cooperative bargaining process initiated by Nash (1951). It is pertinent to mention that experimental bargaining theory indicates stronger empirical evidence of this bargaining theory than any others. Nash engaged in an axiomatic derivation of the bargaining solution.

The solution refers to the resulting payoff allocation that each of the participants unanimously agrees upon. The axiomatic approach requires that the resulting solution should possess a list of properties. The axioms do not reflect the rationale of the agents or the process in which an agreement is reached but only attempts to put restrictions on the resulting solution. Further, the axioms do not influence the properties of the feasible set.

Before listing the axioms, we will now describe the construction of the feasible set of outcomes. Formally, Nash defined a two-person bargaining problem (which can be extended easily to more than two players) as consisting of a pair (F, d) where F is a closed convex subset of R^2, and d =(d1, d2) is a vector in R^2. F is convex, closed, non-empty and bounded. Here, F, the feasible set, represents the set of all feasible utility allocations and d represents the disagreement payoff allocation or the disagreement point. The disagreement point may capture the utility of the opportunity profit. Nash watched for a bargaining solution, i.e., an outcome in the feasible set that satisfied a set of axioms.

The axioms ensure that the solution is:

- symmetric (same players have same utility distributions)
- feasible (the sum of the distributions does not exceed the total pie)
- Pareto optimal (it is impossible for both players to improve their utilities over the bargaining solutions),
- Preserved under linear transformations and be independent of ''irrelevant'' alternatives.

The notable result due to Nash is that there is a bargaining solution that satisfies the above axioms and it is unique.

Theorem 4 (Nash 1951) There is a unique solution that satisfies all the ''axioms''. This solution, for every two-person bargaining game (F, d) is obtained by solving:

$\text{Arg}_{x=(x1,\, x2) \in F,\, x \geq d} \max (x_1 - d_1)(x_2 - d_2)$.

The axiomatic approach, though simple, can be used as a building block for much more complex bargaining problems. Even though the axiomatic approach is prescriptive, descriptive non-cooperative models of negotiation such as the Nash demand game (Roth 1995) and the alternating offer game (Rubinstein 1982), reach similar conclusions as Nash bargaining. This somehow justifies the Nash bargaining approach to model negotiations. In our discussion, we have only provided a description of the bargaining problem and its solution between two players. However, this result can easily be generalized to any number of players simultaneously negotiating for allocations in a feasible set.

2.3 Rubinstein model

The Nash demand game demonstrates that a sensible bargaining protocol might have much equilibrium. A remarkable paper by Rubinstein (1982), however, showed that there was a fairly reasonable dynamic specification of bargaining that yielded a unique sub game perfect equilibrium. It is this model of sequential bargaining that we now consider.

Imagine two players, one and two, who takes turns making offers about how to divide a pie of size one. Time runs from t = 0, 1, 2, ...n

At time 0, player one can propose a split (x0, 1 − x0) (with x0 ∈ [0, 1]), which player 2 can accept or reject. If player 2 accepts, the game ends and the pie is consumed.

If player two rejects, the game continues to time t = 1, when she gets to propose a split (y1, 1 − y1). Once player two makes a proposal, player one can accept or reject, and so on at infinitum

We assume that both players want a larger slice, and also that they both dislike delay. Thus, if agreement to split the pie (x, 1−x) is reached at time t, the payoff for player one is $\delta_1 x$ and the payoff for player two is $\delta_2 (1 - x)$, for some δ1, δ2 ∈ (0, 1).

To get a flavor for this sort of sequential-offer bargaining, consider a variant where there is some finite number of offers N that can be made.

To solve for the subgame perfect equilibrium, we can use backward induction, starting from the final offer.

For concreteness, assume N = 2. At date 1, player two will be able to make a final take-it-or-leave-it offer. Given that the game is about to end, player one will accept any split, so player two can offer y = 0.

What does this imply for date zero? Player two anticipates that if she rejects player one's offer, she can get the whole pie in the next period, for a total payoff of δ_2.

Thus, to get her offer accepted, player one must offer player two at least δ_2. It follows that player one will offer a split $(1-\delta_2, \delta_2)$, and player two will accept.

In the N = 2offer sequential bargaining game, the unique SPE involves an immediate $(1 - \delta_2, \delta_2)$ split.

It is fairly easy to see how a general N-offer bargaining game can be solved by backward induction to yield a unique SPE. But the infinite-horizon version is not so obvious.

Suppose player one makes an offer at a given date t. Player two's decision about whether to accept will depend on her belief about what he will get if he rejects. This in turn depends on what sort of offer player one will accept in the next period, and so on. Nevertheless, we will show:

In other way there is a unique sub game perfect equilibrium in the sequential bargaining game described as follows.

Whenever player one proposes, she suggests a split $(x, 1 - x)$ with

$x = (1 - \delta_2) / (1 - \delta_1\delta_2)$.

Player two accepts any division giving her at least $1 - x$.

Whenever player two proposes, he suggests a split $(y, 1 - y)$ with

$y = \delta_1 (1 - \delta_2) / (1 - \delta_1\delta_2)$. Player one accepts any division giving her at least y. Thus, bargaining ends immediately with a split $(x, 1 - x)$.

Proof: We first show that the proposed equilibrium is actually an SPE.

By a classic dynamic programming argument, it suffices to check that no player can make a profitable deviation from her equilibrium strategy in one single period. (This is known as the one-step deviation principle)

Consider a period when player one offers. Player one has no profitable deviation. She cannot make an acceptable offer that will get her more than x. And if makes an offer that will be rejected, he will get $y = \delta_1 x$ the next period, or $\delta_1^2 x$ in present terms, which is worse than x. Player two also has no profitable deviation. If she accepts, she gets $1 - x$. If she rejects, she will get $1 - y$ the next period, or in present terms $\delta_2 (1 - x) = \delta_2(1 - \delta_1 x)$.

It is easy to check that $1 - x = \delta_2 - \delta_1\delta_2 x$.

A similar argument applies to periods when player two offers.

We now show that the equilibrium is unique. To do this, let v_1, v_2 denote the lowest and highest payoffs that player one could conceivably get in any subgame perfect equilibrium starting at a date where he gets to make an offer.

To begin, consider a date where player two makes an offer. Player one will certainly accept any offer greater than $\delta_1 v_1$ and reject any offer less than $\delta_1 v_2$. Thus, starting from a period in which she offers, player two can secure at least $1 - \delta_1 v_1$ by proposing a split $(\delta_1 v_1, 1 - \delta_1 v_1)$.

On the other hand, she can secure at most $1 - \delta_1 v_2$.

Now, consider a period when player one makes an offer. To get player two to accept, he must offer her at least $\delta_2 (1 - \delta_1 v_1)$ to get agreement.

Thus:

$v_1 \leq 1 - \delta_2 (1 - \delta_1 v_1)$

At the same time, player two will certainly accept if offered more than

$\delta_2(1 - \delta_1 v_1)$. Thus:

$v_1 \geq 1 - \delta_2 (1 - \delta_1 v_1)$

It follows that:

$v_1 \geq (1 - \delta_2) / (1 - \delta_1\delta_2) \geq v_2$

Since $v_1 \geq v_2$ by definition, we know that in any subgame perfect equilibrium, player one receives $v_1 = (1 - \delta_2) / (1 - \delta_1\delta_2)$.

Making the same argument for player two completes the proof.

A few comments on the Rubinstein model of bargaining.

1. It helps to be patient. Note that player one's payoff, $(1 - \delta_2) / (1 - \delta_1\delta_2)$, is increasing in δ_1 and decreasing in δ_2. The reason is that if you are more patient, you can afford to wait until you have the bargaining power (i.e. get to make the offer).

2. The first player to make an offer has an advantage. With identical discount factors δ , the model predicts a split .

$1/(1+\delta)$, $\delta/(1+\delta)$

which is better for player one. However, as $\delta \rightarrow 1$, this first mover advantage goes away. The limiting split is (1/2, 1/2).

3. There is no delay. Player two accepts player one's first offer.

4. The details of the model depend a lot on there being no immediate counter-offers. With immediate counter-offers, it turns out that there is much equilibrium.

2.4 Roth behavioral analysis

Roth (1979) and (1995) has tried to examine the behavioral implication and empirical testability of the game theoretic models of bargaining that follow in the tradition begun by Nash. He present a new game theoretic model based on the assumptions that more closely correspond to the conditions under these many of the experiments have been conducted.

An experiment manipulate the proper kind of info supported the theory that Nash's bargaining model has prognostic value in situations that follow its assumptions about information, but the results also propose that only a relatively narrow range of situations may fit in completely to these norms.

Further that Roth said that no one can look at experimental data without observing that experience matters.

Specifically for the first few times a game is played, observed behaviors are expected to change as players obtain experience, in a way that suggests that learning is important- -learning both for the structure of the game being played, but also about the behavior of others players that take part into the model.

So it is normal to consider how well we can explain observed behavior in terms of adaptation.

And, while adaptive behavior may theoretically be quite multifaceted, it is useful to check how much of what we perceive can be described with very simple models of adaptation.

Roth in his paper of 1995 considers the behavior observed in experiments with three different games of 2 stages each, a public goods provision game, a market game, and an "ultimatum" game, which all will be defined below.

The three games have in common not only a 2-stage, alternating move structure, but also that the perfect equilibriums prediction for each game is that all or sometimes almost all of the gains will be seized by one player.

Though, the observed behavior for the three games is altered. For the public goods and the market games, under a variety of conditions involving different subject pools and different information about payoffs, behavior is observed to converge quickly to the perfect equilibrium prediction.

But as we see in the ultimatum game, behaviors are observed to be far from the perfect equilibrium prediction even after the players have gained a reasonable amount of experience. Furthermore, the behavior observed in the ultimatum game is different in different subject pools, and seems to become more different as players gain experience.

We consider adaptive models from a family of dynamics models, in which each player increase the probability of playing pure strategies that have met with success in former periods.

These simple dynamics do an amazingly job of replicating the major features of the experimental data. Each dynamic we consider from the family meets quickly to the perfect equilibrium of the public goods and market games, from a wide range of initial conditions. However these same dynamics do not converge quickly, if at all, to the perfect equilibrium of the ultimatum game, and their behavior in the ultimatum game is sensitive to the initial conditions.

One lesson we will seek to magnet, therefore, concerns variances among the games, taken by the fact that the same dynamic models make different forecasts for different games. Both the experimental and computational results we report support the perception that we can assume to find classes of games in which certain kinds of equilibrium are rapidly observed, and others in which they are not. And some games are relatively unresponsive to original conditions, while in other games original conditions are important.

A second lesson concerns which aspects of dynamic models offer testable predictions.

Although almost all of the academic literature on adaptive dynamics has focused on the very long term, via theorems about convergence as time goes to infinity, we will claim that intermediate term results may be even more important.

To make this argument, we will consider specific dynamic models with fairly different long term properties models whose asymptotic forecasts approach perfect equilibrium, imperfect equilibrium, and no equilibrium and observe that these models however make similar intermediate term predictions for the above games.

We will argue that, because it would be difficult to differentiate among these different dynamics on the data, and because dynamic models are more likely to be informative when the learning curve is steep than when it is flat, there is a strong reason to pay attention to their intermediate term forecasts. (Even though we will not try to exactly define what constitutes the "intermediate " term, our active definition will be to take the intermediate term forecasts of a model to be those it makes as the learning curve begins to be very flat.)

To use an analogy, even if we believe that time and the tide eventually turn all coastlines into sandy beaches, knowing the difference between granite and sandstone is a great help in understanding why, in the intermediate term, some coastlines have rocky cliffs.

2.5 Roth 3 simplified models

Roth study based on 3 simplified models as described above and help us understanding deeper the learning process that Roth describe in his experiments.

The **Ultimatum game** in which players 1 and 2 have nine pure strategies. Player 1 chooses a demand d~, which is an integer between 1 and 9, and is the amount player 1 demands for himself. Player 2 chooses a maximal acceptable demand m2, which is also an integer between 1 and 9.

The **Best shot game** in which Player I chooses one of three possible contributions q = 0, 2 or 4. Player 2 chooses one of 27 response rules where the first number in each response rule is the amount q2 that player 2 will provide in response to a contribution of q = 0, the second a response to q = 2 and the third a response to q = 4.

And last the **Market game** in which each buyer n chooses one of 11 prices from the set {.25, 1, 2, 3, 4, 5, 6, 7, 8, 9, 9.75}. If the price Pn chosen by buyer n is strictly higher than the price chosen by any other buyer, then buyer n earns 10 - p and all the other buyers earn 0.

If the maximum price p, is chosen by k buyers, then each one of them earns (I0 - p,)/k, while all the other buyers earn 0.

The conclusion of Roth (1995) paper is easily to summarize and provide us the big picture of his experiments on behavioral approach.

Individualistically of the experimental data, the simulation results starting from random primary tendencies reveal a structural difference between the ultimatum game and the other games. And in contrast with the experimental data, the intermediate term forecasts of both the limit model and the local experimentation models track the major experimental observations well.

In spite of the changed long term behavior of these dynamic models, their intermediate term predictions agree with the experimental data in that:

1. In the Market and Best shot games, both forecasted and observed behavior rapidly approach perfect equilibrium, but in the ultimatum game neither forecasted nor observed behavior approaches perfect equilibrium.

2. Both forecasted and observed behavior approach perfect equilibrium play more fast in the best shot game with full information (in which the experimental subjects knew one other's payoffs) rather than in the best shot game with limited information (in which the experimental subjects knew only their own payoffs).

3. Both predicted and observed behavior in the ultimatum games but which not observed in the market or best shot games are different in the different countries sampled, and the forecasted intermediate term differences track the observed differences (within the restrictions of the simplified games).

These results point to that even very simple adaptive models may be relatively useful both for distinguishing which games are likely to be sensitive to original conditions and for predicting how original conditions matter in time.

And while it looks clear that much of the growth to be made in understanding learning in games will come on the border of economics and psychology, the fact that there are some games which exhibit both forecasted and observed behavior that seems not to be sensitive either to original conditions or subject pools suggests that there is also substantial growth to be made by understanding which classes of games fall into which category.

There appear to be sessions of games for which it will turn out that the observed learning behavior is mainly a property of the games, rather than of the exact learning processes used by the players. (This is the traditional economists' viewpoint, but similar views have inaugurated to arise among cognitive psychologists. i.e somebody can check Anderson (1990), who argues that in many cases the best available predictions about mental processes come from an understanding of the structure of the environment.) Anderson in his important 1990 study examines the phenomena of cognition from an adaptive perspective. Rather than adhering to the typical practice in cognitive psychology of trying to predict behavior from a model of cognitive mechanisms, he develops a number of models that successfully predict behavior from the structure of the environment to which cognition is adapted. The methodology -- called rational analysis -- involves specifying the information-processing goals of the system, the structure of the environment, and the computational constraints on the system, allowing predictions about behavior to be made by determining what behavior would be optimal under these assumptions

Back to Roth and recall that the adaptive models studied here do not model in any way what players know about the game, or believe about the future behavior of other players.

That such simple dynamic models, when initiated with first period observed behavior, however do a decent job of forecasting how observed behavior will evolve, recommends that a significant part of how players knowledge and principles influence the game may have been reflected as of the first round data.

For instance, the data from the two information conditions of the best shot game suggest that players' behavior in that game approaches perfect equilibrium quicker when they know other's payoffs.

But the simulation results recommend that the consequence of this knowledge may be mainly to adjust the first period behavior, and that the ways in which players adapt in following periods to their experience may be similar in both information conditions.

The similar can be believed about the between the countries differences in the ultimatum game data. It could be that these different results from different perceptions held by players in different countries.

That the same dynamic model can track the between-country differences when initiated from the first round data lends support to the former hypothesis.

Of course the comments of the earlier paragraph are still somewhat hypothetical, based as they are on a relatively small data set arising from only three kinds of games.

Initial indications are that the correspondence between predicted and observed behavior may survive the transition to larger data sets and different kinds of games.

To speculate a little on theoretical matters, there are motives to think that these outcomes will also be robust to the choice of dynamics, so that very different dynamic models might produce similar results. The families of models we have well thought-out are determined in the early rounds by the payoff differences among strategies, based on the early propensities to play each strategy.

In example, the goal that behavior in the ultimatum game remains detached from the perfect equilibrium is that the propensity to make very high demands falls more quickly than the propensity to accept very high demands rises. This is because the difference between accepting and rejecting a very high demand is small and thus has only modest impact on the propensities of players 2, while the difference for players 1 between having a very high demand rejected, and earning zero, or having a moderately high demand accepted, and consequently earning more than half the pie, is much larger, and more quickly increases the propensity to make only moderately high demands.

Once player 1 rarely makes very high demands, there is even less pressure on players 2 to learn not to discard them, and so on.

A associated conclusion about ultimatum games is reached by Gale et al. (1995), using a model of evolutionary dynamics.

Note also that there are good motives to consider that the actual learning rules (or even the strategies) used by the subjects in the experiments diverge in important ways from our simple models, supports the assumed robustness of the results.

That the simple simulated learning rules may be very altered from those used by the experimental subjects, but both sets of rules produce similar intermediate term effects, suggests that very different learning rules will quickly approach perfect equilibrium in the best shot and market games, but not in the ultimatum game.

Procedurally, an important difference between Roth paper and most of the academic literature on game dynamics is his concern with intermediate term results.

Even though we have not tried to define the intermediate term any more precisely than to say that it starts when the learning curve flattens out, this has not demonstrated to be a difficulty in looking at the replicated behavior we report, precisely because the learning curves soon become very flat.

For the dynamics reflected here, the intermediate term starts in the tens of iterations, and, at least in the ultimatum game, does not give way to the sometimes very different long term forecasts for thousands or even hundreds of thousands.

Of course these figures will be different for altered dynamics. To the extent that intermediate term behavior of dynamic models is crucial, it may be valuable for theorists to pay more attention to the entire vector field generated by a dynamic, and not just to its limit points and basins of attraction.

Above all in repeated games, the set of strategies offered to the players may be enormous. The traditional position of game theory has been to regard all potential strategies as available, but as long as players may not be hyper rational in other respects, their capacity to consider a huge number of strategies may also be inadequate. (One attempt to deal with this has been to symbolize the strategies available to a player in a repeated game as those which can be applied by limited state automata of restricted size.

An example of this approach can be found in Tsetlin, 1973. Before his untimely death in 1966, he developed interesting models of learning in repeated games, with players modeled as automata.) .

As Tsetlin explain in his study a learning automation is an adaptive decision-making unit situated in a random environment that learns the optimal action through repeated interactions with its environment.

The actions are chosen according to a specific probability distribution which is updated based on the environment response the automation obtains by performing a particular action.

With respect to the field of reinforcement learning, learning automata are characterized as policy iterators. In contrast to other reinforcement learners, policy iterators directly manipulate the policy.

Study in psychology has often identified specific strategies which may occur with high original inclinations. In example, in continual experiments with T mazes, rats have an initial inclination to follow an alternation strategy (i.e., not to select the same leg of the maze twice in sequence); see, e.g., Dember and Fowler (1958).

Dember and Fowler (1958) research concerned with spontaneous alternation behavior in rats is examined and related to learning theory. It is concluded that alternation behavior can no longer be adequately interpreted in terms of concept of reactive inhibition. The view of stimulus satiation as an explanation of alternation behavior has received general support from the research literature, but some data seem to require a more general theoretical explanation and include in the research some motivational concepts such as curiosity are suggested.

We anticipate that the precision of forecasts of models like those considered from Roth may be improved by assessing the repeated game strategies the subjects employ.

For our present purposes, the very slow convergence of the models without forgetting only serves to emphasize the difference between the ultimatum game and the other two games (in which all three models nevertheless converge quickly).

For more extended study of games with very slow convergence properties it will likely be desirable to consider faster converging dynamics, e.g., by having a positive forgetting parameter, or some other way of keeping the strengths of the inclinations from increasing without limit.

This has the consequence of giving more importance to recent events, instead of weighting all payoffs in the same way whenever they happen, as in our models without forgetting. (The flat learning curves come about because after a while there are so many more past events than recent ones.)

In general, new tools may be required, since for stochastic learning rules understanding the intermediate term means examining the transient phase of a stochastic process.

2.6 Experimental results of Roth Games

To bring together the conclusions of Roth about games and about models, recall once again that the three games considered here have similar equilibriums:

In the ultimatum and market games all prices can be supported by some Nash equilibrium, but only extreme results, in which all the wealth accumulates to one side, can be supported by a perfect equilibrium.

Similarly, the perfect equilibrium of the best shot game yields extreme payoff differences.

The experimental results of Roth et al. (1991) and Prasnikar and Roth (1992) show that this similarity of equilibrium does not produce similarity of behavior:

Only in two of the games did detected behavior approach the perfect equilibrium. To the extent that equilibrium is reached, if at all, through a dynamic modification process that begins out of equilibrium, the opportunity of different behavior seems normal, since games with similar equilibriums may be quite unrelated of equilibrium.

Roth in his 1995 paper further shows that the path of the dynamic process may also be inadequate to foresee behavior if its velocity is not also taken into account.

This is clearest in our model with experimentation and forgetting, whose predictions approach perfect equilibrium eventually (e.g., by t = 1,000,000) for all three games, but whose rates of change become very low much earlier (e.g. by t = 100). It is the real (t = 10) or intermediate term (e.g. t = 100) predictions which correspond to the observed behavior, both when these predictions are close to the perfect equilibrium and when they are not (and both in the models whose intermediate term predictions are close to their long term predictions and those in which they are not).

That being the case, the reasons for our concern with real time and intermediate term predictions (in contrast to asymptotic predictions) for both field and experimental data are worth restating.

First, we believe that much of the economic phenomena we observe in the world is intermediate term in nature. Although we have concentrated here on demonstrating this for a body of experimental data, it is not only in experiments that long term behavior may be difficult to observe.

For example, none of the annual labor markets and matching processes whose historical evolution is studied in Roth (1984, 1990, 1991), Mongell and Roth (1991), and Roth and Xing (1994) have gone for more than fifty years--i.e. 50 iterations, without a change of environment substantial enough to mean that the same game was no longer being played.

After such a change the behavior of participants typically goes through a period of readjustments as they adapt both to the new environment and to the new strategies of other agents.

Second, even when we identify economic phenomena with sufficient longevity and stationary so that it is reasonable to believe they are yielding long term behavior, there is reason to be cautious about the long term behavior of any models we create.

This is because every model includes some elements of the situation being modeled while ignoring others. And when the learning curve becomes flat, there is room for unmodeled factors to become important--factors that may be present at every stage of the learning process, but are unimportant when the learning curve is steep.

To extend the geological analogy used before, erosion is not the only force that acts on coastlines. If we can expect volcanic eruptions every millenium or two, then, if erosion is slow, this will change our predictions about whether all coastlines will be sandy beaches.

And there are also gentle but steady forces such as sedimentation, that work in the opposite direction from erosion, so that when erosion is fast we may be able to neglect them, but when it is slow, they may cause coastlines to rise rather than fall.

So the reasons for devoting more attention to intermediate term results are not only that we live and die in the intermediate term and that changes in the environment (including the players) make data for the very long term hard to gather, but also that we have less reason to be confident in a particular model of learning when the learning curve is fiat than when it is steep.

Our results here suggest, however, that such models may have considerable predictive power when the learning curve is steep.

In conclusion, Roth 1995 and 1974 papers report an exercise in "low" (rationality) game theory.

Low game theory differs from traditional, "high" game theory in how the players are modeled:

Where high game theory models the players as hyper-rational, we have modeled them as simple adaptive learners.

What low game theory has in common with high game theory, which distinguishes both approaches from nongame-theoretic models, is the central place given to modeling the strategic environment, i.e., to the game itself. But here too, there is room to consider the cognitive capacities of the players, since the full strategy sets in a repeated or multi-period game quickly become large.

Although the players in the experiments discussed here were engaged in multi-period games, we have modeled their strategies by (discretized subsets of) their stage game strategies.

This has proved to be sufficient, perhaps because they are not engaged in repeated games (i.e., against the same opponent). However, it is likely that future research in low game theory will have to, at least sometimes, pay close attention to what subsets of very large strategy sets are accessible to and employed by the players.

Of course we have chosen one of very many possible ways to model less-than-complete rationality, and the question of what are the best ways will be empirical. (The equilibrium refinement literature shows that there are also multitudes of ways to model hyper-rationality.)

Most of the theoretical research on adaptive models has focused on finding conditions under which the adaptive models converge to equilibrium as time goes to infinity. (Thus high game theory can sometimes arise from low game theory.)

In contrast, we have argued that, when the object is to develop low game theory in directions useful for empirical economics, infinite time horizons deserve to be treated with the same skepticism as other idealizations.

Nevertheless, we have seen (in the best shot and market games) that for some games the intermediate term predictions of low game theory correspond with those of high game theory.

We conjecture that, when they coincide, the common forecasts of both kinds of game theory will quite generally demonstrate to be robustly evocative of observed behavior, as they were here. For other games, like the ultimatum game, the predictions of low and high game theory diverge. We have shown that even in such cases, the forecasts of low game theory may be of independent interest, because they are descriptive of observed behavior.

3. B2B Bargaining model in E-marketplaces

3.1 The bilateral negotiation model of Faratin

Faratin in his 1998 paper provide a model that describes the bargaining model in B2B environment. It proved to be a very useful tool in our analysis since the scoring function that he use is essential in an automated system where the best solution for counterpart must calculated by a server negotiation agent.

Let i (i ∈ {a, b}) symbolize the negotiating agents and j (j ∈ {1 . . . . . n}) the topics under negotiation. The set of topics in actual world negotiations is always limited. Let x_j ∈ [min~, max,.] stand for a value for topic j acceptable by agent i. Here we limit ourselves to considering topics for which negotiation quantities to defining a value between an agent's distinct delimited ranges. Each agent has a scoring function V_j : [min_j, max_j] ~ [0, 1] that provides the score agent i assigns to a value of issue j in the range of its acceptable prices. For convenience, scores are kept in the intermission [0, 1].

The next component of the model is the absolute importance that an agent assigns to each issue under negotiation, w_{ji} is the importance of issue, j for agent i. We accept that the weights of both agents are normalized, i.e. ∑ 1 ≤ j ≤ n w_{ji} = 1 for all i in {a, b}. With these elements in place, it is now likely to describe an agent's scoring function for a agreement that is, for a value x = (Xl . . . . . Xn) in the multi-dimensional space defined by the subjects value ranges:

$$V^i(x) = \sum_{1 \le j \le n} \mathrm{w}_j^i \mathrm{V}_j^i(\mathrm{x}_j)$$

If both negotiators use such a preservative scoring function, Raiffa(1982) indicated that it is likely to compute the optimal value of x as an element on the efficient border of negotiation.

For example, the set of negotiation issues for a server agent a may contain of {price, volume} - the price required to provide the service and the number of service instances attainable by a.

In addition to this, let a have the next registration values

$$[min^a_{price}, max^a_{price}] = [10,20] \; and \; [min^a_{volume}, max^a_{volume}] = [1,5]$$

Also shoulder that a understandings the price as more significant than the volume by assigning a higher weight to it, where $[w^a_{price}, w^a_{volume}]$= [0,8, 0,2].

To finish, let the value of an offer x, for a topic j, $v^a_j(x_j)$, be displayed as a linear function:

$$V^a_{price}(X_{price}) = \frac{x_{price} - min^a_{price}}{max^a_{price} - min^a_{price}}$$

$$V^a_{volume}(X_{volume}) = \frac{x_{volume} - min^a_{volume}}{max^a_{volume} - min^a_{volume}}$$

Now think through two contracts, [12, 6] and [15, 2], offered by a client b to the server a. Given the above parameters for a, the value for the first offered price by b is (12 – 10 / 20 - 10) = 0.2, while the value for the first requested volume is (1 - (6 - 1/6 - 1) = 0. The total value for the offered contract is the sum of the weighted values for each individual issue (namely, 0.8 * 0.2 + 0.2 * 0 = 0.16). By the same cognitive, the value of the next contract from b, on the other hand, is 0.55. Since rational action is to maximize its utility, a therefore selects the second contract offered by b and discards the first.

3.2 Service-oriented negotiation requirements

The above bilateral negotiation model may be valid for some service-oriented settings but it has several assumptions.

Needs:

(i) Privacy of information. To discover the optimal value, the scoring functions have to be unveiled. This is, in general, unfitting for competitive negotiation.

(ii) Privacy of models. Both negotiators have to use the same scoring model. Although, the models used to evaluate offers and produce counter offers are one of the things that negotiators try to hide from the other side.

(iii) Value restrictions. There are pre-defined value areas for debate (they are necessary to define the bounds of the scoring function). Nevertheless, it is difficult to find these mutual areas and in many cases negotiation actually includes determining whether such areas even be present.

(iv) Time restrictions. There is no notion of timing issues in the negotiation. Although, time is a major restriction on agents' behavior. This is mostly true on the customer side; agents frequently have strict deadlines by when the negotiation must be finished. For example, a video link has to be provided at 06:00 because at that time a conference should begin; negotiation about set up cannot last after that time.

(v) Resource restrictions. There is no notion of resource issues in the negotiation. Although, the amount of a particular resource has a solid and direct impact on the behavior of agents, and, furthermore, the correct appreciation of the remaining resources is an vital characteristic of a good negotiators.

Resources from the customer's point of view relay straight to the number of servers engaged in the ongoing negotiation; similarly from the server's point of view. Consequently, the quantity of resource has a related effect on the agents' behavior as time.

Even just taking the first thought alone, it is clear that optimum results cannot be found in our fields: it is not likely to enhance an unidentified function. Hence, we shall suggest a model for separate agent negotiation that pursues to find deals suitable to its associates but which, nevertheless, maximizes the agent's own scoring function.

3.3 Service-oriented negotiation model

In service-oriented negotiations, agents can accept two possible roles that are, theoretically, in conflict. From now we shall differentiate (for our convenience) two subsets of agents.

Agents = Clients U Servers. We use letters to characterize agents; c, c_1, c_2, stands for clients, s, s_1, s_2 . . . . for servers and a, a_1, b, d, e , for non-specific agents.

Generally, clients and servers have opposing comforts, e.g. a client needs a low price for a service, while the potential servers try to achieve the highest price. High quality is preferred by clients, but not by servers, and so on.

As a result, in the space of negotiation values, negotiators represent opposing forces in each one of the dimensions.

In consequence, the scoring functions verify that given a client c and a server s negotiating values for issue j, then if

X_j, V_j ∈ [min_j, max_j] and $x_j > y_j$ then $V_j^c(x_j) \geq V_j^c(y_j)$ However, in a minor amount of cases the clients and service providers may have a joint interest for a negotiation issue.

In example, Raiffa in 1982 describe a case in which the Police Officers Union and the City Hall realize, in the course of their negotiations, that they both want the police commissioner fired. Having recognized this mutual interest, they quickly agree that this course of action should be selected. Thus, in general, where there is a mutual interest, the variable will be assigned one of its extreme values. Hence these variables can be removed from the negotiation set.

For example, the act of firing the police commissioner can be removed from the set of issues under negotiation and assigned the extreme value "done".

Once the agents have determined the set of variables over which they will negotiate, the negotiation process between two agents (a, b ∈ Agents) consists of an different sequence of offers and counter offers of values for these variables. This lasts up to an offer or counter offer is accepted by the other side or one of the partners ends the negotiation (e.g. because the time limit is reached without an agreement being in position).Negotiation can be started by clients or servers.

We symbolize by $x^t_{a \to b}$ the vector of values suggested by agent a to agent b at time t, and by $x^t_{a \to b}[j]$ the value for issue j suggested from a to b at time t.

The variety of values acceptable to agent a for issue j will be symbolized as the intermission $[min^a_j, max^a_j,]$. For convenience, we accept a common global time (for example the calendar time) represented by a linearly ordered set of times, namely Time, and a consistent communication medium introducing no postponements in note transmission (so we can accept that transmission and response times are indistinguishable). The joint time hypothesis is not too solid for our application fields, because in time granularity and offer and counter offers occurrences are not high.

Negotiation thread among agents a, b ∈ Agents, at time t_n ∈ Time, noted $x^t_{a \leftrightarrow b}$, is any limited sequence of length n of the form ($x^{t1}_{a \to b}, x^{t2}_{a \to b}, x^{t3}_{a \to b}$, with t_1 , $t_2 \ldots . \leq$ $t_{n)}$ where :

(i) $t_{i+1} > t_i$, the sequence is ordered over period,

(ii) For each topic

j, $x^i_{a \to b}[j] \in [min^a_j, max^a_j,], x^{i+1}_{b \to a}[j] \in [min^b_j, max^b_j,]$ with i = 1,3,5, ..., and optionally the latest component of the sequence is one of the elements {accept, reject}.

We say a negotiation thread is on the go if last ($x^{t}_{a\leftrightarrow b}[j]$ $\in$ {accept, reject}, where last is a function returning the last component in a sequence.

For straightforwardness reasons, we assume that t_1 agrees to the opening time value, that is $t_1 = 0$. In other words, there is a local time for each negotiation thread, which starts with the statement of the first offer. When agent a receives an offer from agent b at time t, $x^{t}_{b\rightarrow a}$, it has to rate the offer using its scoring function. If the value of V^{a} $x^{t}_{b\rightarrow a}$ is greater than the value' of the counter offer agent a is ready to send at the time t' when the evaluation is performed, that is $x^{t'}_{b\rightarrow a}$ with t' > t then agent a accepts. Else, the counter offer is acquiesced. Stating this idea in a mathematic way:

Assume an agent a and its related scoring function V^a , a's explanation at time $x^{t}_{b\rightarrow a}$ sent at time t < t', is defined as

$$I^a(t', x^{t}_{b\rightarrow a}) = \begin{cases} reject & if\ t' > t^{a}_{max} \\ accept & if\ V^{a}(x^{t}_{b\rightarrow a}) \geq x^{t'}_{b\rightarrow a} \\ x^{t'}_{b\rightarrow a}\ otherwise & \end{cases}$$

where $x^{t'}_{b\rightarrow a}$is the agreement that agent a would offer to b at the time of the interpretation, and t^{a}_{max} is a constant that represents the time by which a must have finalized the negotiation.

The outcome of I^a (t', $x^{t}_{b\rightarrow a}$) is used to prolong the current negotiation thread between the agents. This interpretation formulation also permits us to model the point that a contract improper today can be accepted tomorrow simply by the point that time has passed.

In order to prepare a counter offer, $x^{t'}_{b\rightarrow a}$, agent a uses a set of strategies that produce new values for each of the variables in the negotiation set. Based on the needs of our business process applications, we established the below families of strategies:

(i) Time dependent. If an agent has a time boundary by which an agreement must be in position, these strategies model the fact that the agent is possible to accept more quickly as the time limit approaches. The form of the curve of concession, a purpose reliant on time, is what distinguishes strategies in this set.

(ii) Resource dependent. These strategies model the pressure in reaching an agreement that the limited resources - e.g. left over bandwidth to be assigned, money, or any other - and the situation - e.g. amount of clients, amount of servers or financial parameters - execute upon the agent's behavior. The functions in this set are similar to the time dependent functions except that the arena of the function is the amount of resources available instead of the left over time.

(iii) Behavior reliant on or Imitative. In situations in which the agent is not under an excessive deal of pressure to reach an agreement, it may choice to use imitative strategies to defend itself from being demoralized by other agents. In this situation, the counter offer hinge on the behavior of the negotiation rival. The strategies in this family fluctuate in which feature of their opponent's behavior they duplicate, and to what degree the opponent's behavior is imitative.

3.4 Scoring function in infinite bargain model

Faratin scoring functions model as introduced above has not any time restriction or discount factor in its calculation even if it is more than important in real life situations.

Hence, we can use Faratin scoring functions combined with Rubinstein discount factor we mention above in order to describe better a scenario of a technology company and how can a buyer create an automatic system that will decide the exact price that he should pay according to the technology level that he search for.

In this scenario the set of negotiation issues for a server agent a may consist of {price, volume, technology level}.

Because the volume is on mutual interest we will remove it from negotiation set and we will have price and technology level to negotiate.

The price that a reasonable buyer will ask would be as low as possible when the technology level would be as high as possible. On the other hand the seller would ask for higher price and lower technology level (since this mean lower cost for him).

In addition to this, let have the following a reservation values

$$[min^{a}_{price}, max^{a}_{price}] = [10,20] \ and \ [min^{a}_{technology}, max^{a}_{technology}] = [1,10]$$

Also assume the price as more important than the technology by assigning a higher weight to price, where $[w^{a}_{price}, w^{a}_{technology}]$= [0,6 , 0,4].

Furthermore, let the value of an offer x, be modeled as a linear function:

$$V^{buyer}_{price}(X_{price}) = 1 - \frac{x_{price} - min^{buyer}_{price}}{max^{buyer}_{price} - min^{buyer}_{price}}$$

$$V^{buyer}_{technology}(X_{technology}) = \frac{x_{technology} - min^{buyer}_{technology}}{max^{buyer}_{technology} - min^{buyer}_{technology}}$$

The above functions refer to the buyer profit for the bargain and since the seller profit is opposite (both price and technology have adverse interests as described above) we can assume that seller functions would be:

$$V^{seller}_{price} = 1 - V^{buyer}_{price}$$

$$V_{technology}^{seller} = 1 - V_{technology}^{buyer}$$

Following the above the buyer total scoring function will be:

$$V_{t=1}^{buyer} = w_{price} \times V_{price}^{buyer} + w_{technology} \times V_{technology}^{buyer}$$

And seller:

$$V_{t=1}^{seller} = w_{price} \times (1 - V_{price}^{buyer}) + w_{technology} \times (1 - V_{technology}^{buyer})$$

The price will give the above function is [0,1] since each of the part can take price between [0,1]

Further that based on Rubinstein discounting factor model we can suppose that both time and technology have a discount factor when δ=0,8.

Price discount factor refers to the value of money that decline through time when the technology discount factor refers to the aging of technology since new technology always invented making the old one losing its original value.

So on time t=2 the scoring function of buyer will be:

$$V_{t=2}^{buyer} = \delta(w_{price} \times V_{price}^{buyer} + w_{technology} \times V_{technology}^{buyer})$$

Without time limitation the solution of the above bargain can occur in time t=1 provides the best solution for buyer and seller following the Rubinstein 1982 paper.

The first who propose have the advantage since the split will be :

$$\left(\frac{1}{1+\delta}\right),\left(\frac{\delta}{1+\delta}\right)$$

So by assuming that both have the same (but opposite) scoring function we can understand that the player 1(i.e. the buyer) will have to propose a combination to the seller (choosing between price and level of technology) that will provide him a split of $\left(\frac{\delta}{1+\delta}\right)$:

$$\left(\frac{\delta}{1+\delta}\right) = w_{price} \times (1 - V_{price}^{buyer}) + w_{technology} \times (1 - V_{technology}^{buyer}) = V_{t=1}^{seller}$$

The buyer for him will have the following split

$$\left(\frac{1}{1+\delta}\right) = V_{t=1}^{buyer} = w_{price} \times V_{price}^{buyer} + w_{technology} \times V_{technology}^{buyer}$$

3.5 The solution of the Bargain

The below example will help us understand exactly how smoothly we can combine a scoring function with 2 variables with having a discount factor for both variables and this can give us a solid solution according to our needs.

In our example we will use the above numerical data for a buyer that wants to buy a mobile phone on an e-marketplace and we will have the range for both variables.

$$[min_{price}, max_{price}] = [10,20] \; and \; [min_{technology}, max_{technology}] = [1,10]$$

Further that we have suppose the following weights $[w_{price}, w_{technology}]$= [0,6 - 0,4] and the discount factor δ = 0,8 that is the same for both buyer and seller.

So using Rubinstein model the buyer knows that his function will be

$$\left(\frac{1}{1+\delta}\right) = V_{t=1}^{buyer} = w_{price} \times V_{price}^{buyer} + w_{technology} \times V_{technology}^{buyer} \xRightarrow{\delta=0,8\ ,Wprice=o,6\ ,Wtech=0,4}$$

0,55 =$0,6 \times V_{price}^{buyer} + 0,4 \times V_{technology}^{buyer}$ (1)

On top of that we will suppose that the buyer's need in technology is of level 10(max)

So using the buyer function for technology we have:

$$V_{technology}^{buyer}(X_{technology}) = \frac{x_{technology} - min_{technology}^{buyer}}{max_{technology}^{buyer} - min_{technology}^{buyer}} =$$

$$V_{technology}^{buyer}(X_{technology}) = \frac{10-1}{10-1} = 1 \ \ (2)$$

So from (1) , (2) we have

0,55 =$0,6 \times V_{price}^{buyer} + 0,4 \times 1 \quad \Rightarrow V_{price}^{buyer} = 0,25$

So using the buyer function for price we have :

$$V_{price}^{buyer}(X_{price}) = 1 - \frac{x_{price} - min_{price}^{buyer}}{max_{price}^{buyer} - min_{price}^{buyer}} \Rightarrow$$

$$x_{price} = 17,5$$

The conclusion of this calculation is that in an e-marketplace where we can negotiate price and technology if we have the above data we can propose from the t=1 the best solution. In our example the buyer who knows his need (technology level = 10) he knows that he should pay 17,5 in order to acquire the mobile phone and he knows that this is the best solution for both sides.

Generalizing the above case we can easily have the whole table and the buyer can easily choose according to his needs as provided in table 2.

Table 2 – Price according to level of technology

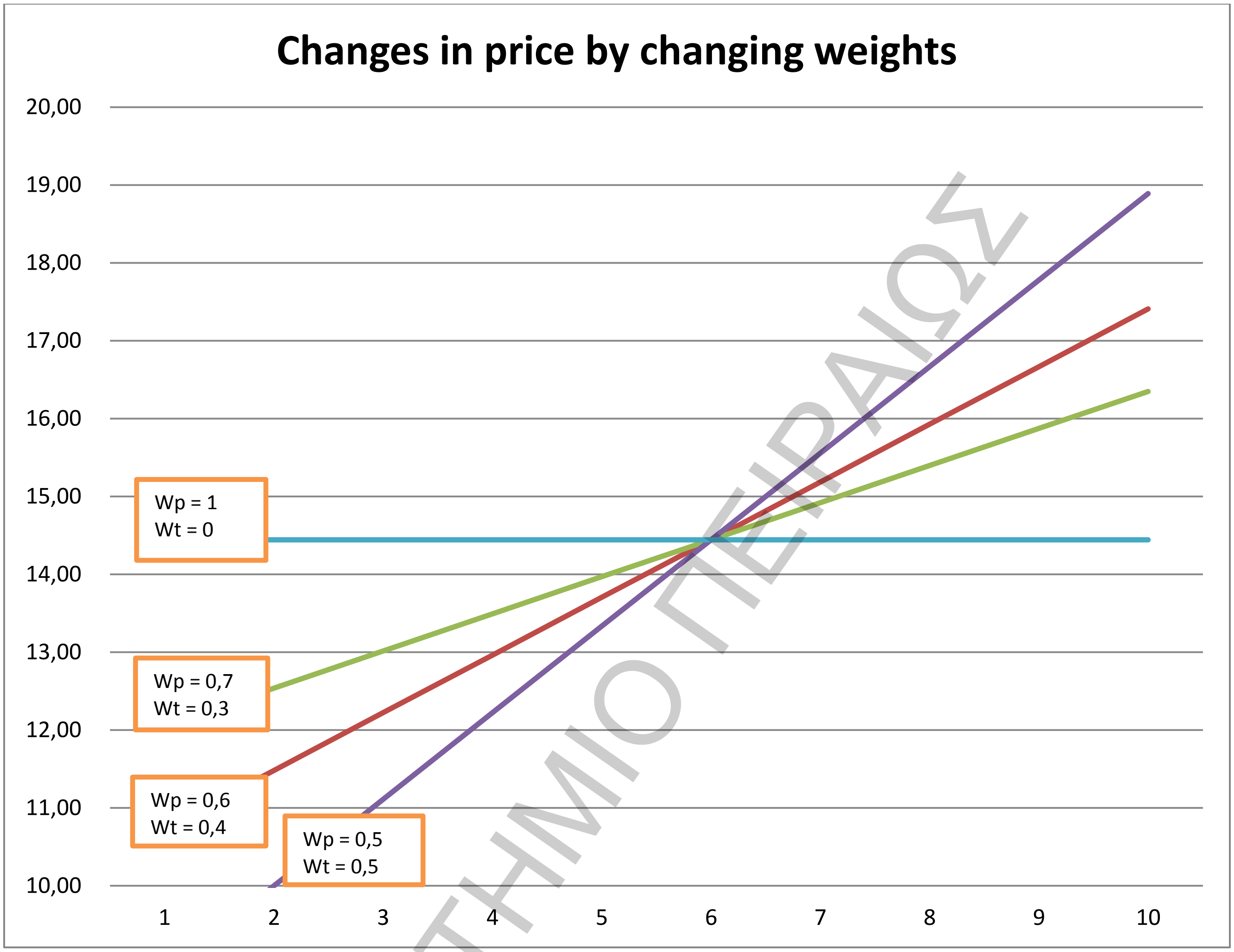
	Level of Technology	Price
δ : 0,8 for both sides	1	10,74
	2	11,48
	3	12,22
	4	12,96
	5	13,70
	6	14,44
	7	15,19
	8	15,93
	9	16,67
	10	17,41
		Wp = 0,6 / Wt = 0,4

3.6 Changing Weights

Going one step forward it is interest to observe the changes in prices when the weights change (table 3).

Table 3 – Price according to level of technology using different weights

	Level of Technology	Price	Price2	Price3	Price4
δ : 0,8 for both sides	1	10,74	12,06	10,00	14,44
	2	11,48	12,54	10,00	14,44
	3	12,22	13,02	11,11	14,44
	4	12,96	13,49	12,22	14,44
	5	13,70	13,97	13,33	14,44
	6	14,44	14,44	14,44	14,44
	7	15,19	14,92	15,56	14,44
	8	15,93	15,40	16,67	14,44
	9	16,67	15,87	17,78	14,44
	10	17,41	16,35	18,89	14,44
		Wp = 0,6 / Wt = 0,4	Wp = 0,7 / Wt = 0,3	Wp = 0,5 / Wt = 0,5	Wp = 1 / Wt = 0



Few comments that we can export from the above diagram is:

- As far as the Wprice increase the range of the price decrease. This has to do with the price sensitivity that increases together with the Wp.
- In the extreme case when the Wp = 1(and Wt = 0) there is an ultimate solution for the bargain and this is at price : 14,44 same for all level of technologies
- The solution at Wp = 1 is not at the middle of the range that somebody will easily suppose but lower at price 14,44 something that approve that the first who make the offer(in our case the buyer) has the advantage in such type of bargains.

3.7 Changing discount factor

We have seen above the results of changing the weights and in this section we will examine the results of changing the discount factor (δ).

Discount factor mirror the patience of buyers and sellers. For example a buyer that needs the product soon and has little patience he will have a lower δ than the seller who has not need to sell the product and he can afford to stock it.

In this case with different δ the solution provided by the below split, as proved above from Rubinstein model:

$$\frac{1-\delta 2}{1-\delta 1\delta 2}, \frac{\delta 2-\delta 1\delta 2}{1-\delta 1\delta 2}$$

So for the buyer who make the first offer in the electronic system the split will be $\frac{1-\delta 2}{1-\delta 1*\delta 2}$

And the Scoring function that he will have:

$$\left(\frac{1-\delta 2}{1-\delta 1*\delta 2}\right) = V_{t=1}^{buyer} = w_{price} \times V_{price}^{buyer} + w_{technology} \times V_{technology}^{buyer}$$

So using the previous example and supposing that the seller is more patient, the δ_1 (of the buyer) will be lower than the δ_2 (of the seller), in our case we will have

δ_1 = 0,75

δ_2 = 0,85

$$\left(\frac{1-\delta 2}{1-\delta 1 * \delta 2}\right) = V_{t=1}^{buyer} w_{price} \times V_{price}^{buyer} + w_{technology} \times V_{technology}^{buyer}$$

$$\xRightarrow{\delta 1=0{,}75,\ \delta 2=0{,}85,\ Wprice=0{,}6,\ Wtech=0{,}4}$$

$$0{,}41 = 0{,}6 \times V_{price}^{buyer} + 0{,}4 \times V_{technology}^{buyer} \ (1)$$

By using the same numbers as the above example and given the case that buyer ask for level 10 of technology we will have the below solution.

$$V_{technology}^{buyer}(X_{technology}) = \frac{x_{technology} - min_{technology}^{buyer}}{max_{technology}^{buyer} - min_{technology}^{buyer}} =$$

$$V_{technology}^{buyer}(X_{technology}) = \frac{10-1}{10-1} = 1 \ (2)$$

So from (1), (2) we have

$$0{,}41 = 0{,}6 \times V_{price}^{buyer} + 0{,}4 \times 1 \ \Rightarrow V_{price}^{buyer} = 0{,}02$$

So using the buyer function for price we have :

$$V_{price}^{buyer}(X_{price}) = 1 - \frac{x_{price} - min_{price}^{buyer}}{max_{price}^{buyer} - min_{price}^{buyer}} \Rightarrow$$

$$x_{price} = 19{,}77$$

Now we can again generalize the data and we can create the below table (table 4) for all options.

Table 4 – Generalize the example

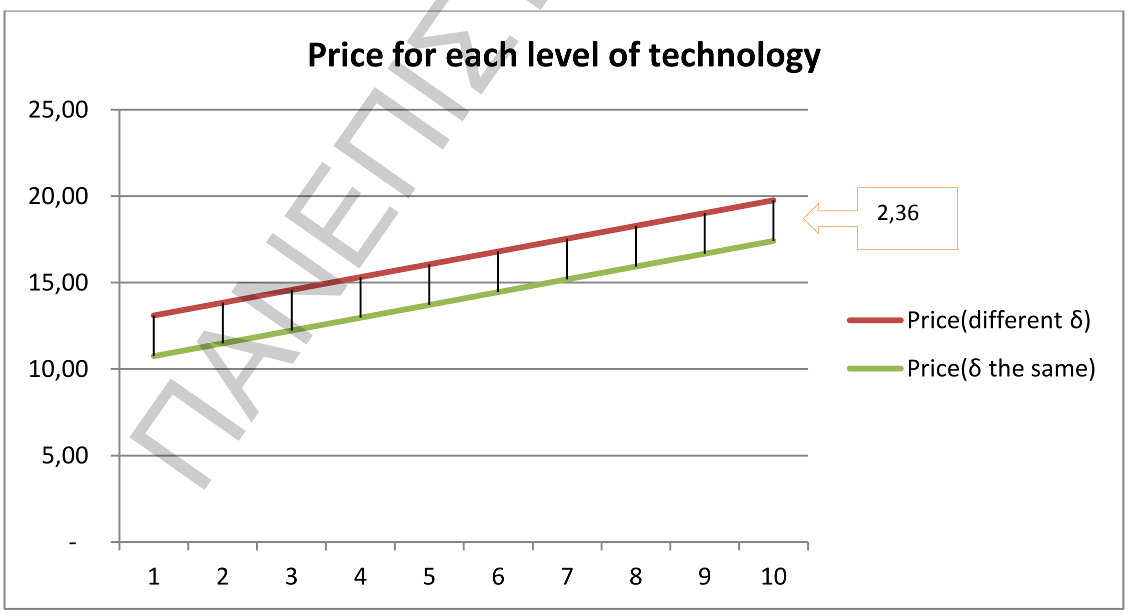
	Level of Technology	Price
δ : 0,75 for buyer 0,85 for seller	1	13,10
	2	13,84
	3	14,58
	4	15,33
	5	16,07
	6	16,81
	7	17,55
	8	18,29
	9	19,03
	10	19,77
Wp = 0,6 / Wt = 0,4		

The table above includes all the possible choices the buyer has in this case and we can export interesting results by comparing the above table with the previous one where both buyer and seller had the same patience (δ).In order to compare better the results we present them side by side in table 5 below

Table 5 – Difference results with different strategies for the players

	Level of Technology	Price(heterogeneity δ)	Price(homogeneity δ)	Dif
δ : 0,75 for buyer 0,85 for seller	1	13,10	10,74	- 2,36
	2	13,84	11,48	- 2,36
	3	14,58	12,22	- 2,36
	4	15,33	12,96	- 2,36
	5	16,07	13,70	- 2,36
	6	16,81	14,44	- 2,36
	7	17,55	15,19	- 2,36
	8	18,29	15,93	- 2,36
	9	19,03	16,67	- 2,36
	10	19,77	17,41	- 2,36
Wp = 0,6 / Wt = 0,4				

As we can easily understand the buyer payoff has been reduced since he pays more for the same level of technology and this happen due to his low patient for the deal which is mirrored in the lower δ.The results of this low patience is to pay more 2,26 whatever the choice of the technology would be.



4. Conclusion

E-marketplaces rapid growth in recent years has led to more and more needs for elevated bargaining models. These models should be able to be part of an automatic system which will be the server agent that will help counterparts to reach an agreement .Due to the fact that the time is valuable also one of the main responsibility of the agent should be to lead the negotiation to an agreement as soon as possible.

In order to have a model in an automatic system we need a function that will provide the solution by scoring the offers and the counter offers.

Faratin provides a model that based on a server and two buyers who make offers for a product, by setting the price and the volume (of the product) the buyer are intend to buy. The servers calculate the profit through a scoring function and based on the importance of the two parameters decide the best solution.

Even if Faratin model works smoothly in this case it has some serious gaps since it refers to time t=1 and it is not contain a discount factor in order to test the model in infinite time and in order to be more realistic in his results. We have tried to overcome this by combine the idea of scoring function with the Rubinstein multiple games model.

By testing this in a high technology company (in our example a mobile manufacturer) the results were really interesting since we create a function that can calculate the best solution in infinite time for both players. The buyer in our case has to choose the desirable level of technology and through the scoring function he can estimate the price that required in order to obtain the cell phone.

After having combine the scoring function with a discount factor and having test the results with success the next step was to change parts of the functions in order to exam the reaction of the model and to export some useful results over the strategies that the players should follow.

Thus, by changing the weights between the importance of the price and the technology level we noticed that as far as the importance of the price increase, the price range decrease. This was something that we are waiting for, since the price sensitivity led the counterparts focus on price and so the price range are collected more to middle-average prices.

Further that we observed that if only price was important the first who made the offer he will have the advantage and he will obtain the most from the bargain. More specific in our example when buyer made the first offer he achieved a price lower than the average price something that consist to the fact that he made the first move and so he take the advantage from that.

Finally it is interesting to spot the different results by testing the patience of buyers and sellers. So having an impatient buyer (lower discount factor) and a patient seller (higher discount factor) the results was the seller to obtain higher split from the bargain comparing to the case that both shares the same discount factor, so once again being patient helps.

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