Price Estimation of PersianCAT Market Equilibrium

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Abstract

Market design is becoming more and more demanding, especially in terms of fulfilling human needs in day to day's activities. Recently, a new tendency towards designing agent-based multi-market systems, which can be robust, autonomous and do not require human expertise, has been emerged. In this paper, we introduce PersianCAT market that have been used in CAT 2008 final competition. We provide a new estimation of the market equilibrium price and show the robustness of this equilibrium estimation when used in accepting and pricing policies. We also demonstrate how fluctuation in charging fees leads to lower market performance when comparing markets with the same average fees throughout the game.

Introduction

Market is a group of interacting entities through platforms like stock-exchanges: a decentralized system with interacting self-interested agents whose activities are buying and selling goods and services. In this context, a mechanism (Parkes 2001) is a Combination of strategies available to participant agents in the system and the outcome rules, which provides solutions to resource allocation problem. MacKie-Mason and Wellman (MacKie-Mason & Wellman 2006) define market mechanism as "a mechanism where the possible ultimate outcomes comprise market-based exchange transactions" and in their definition, the marketplace system is a combination of agents that participate in the system and the market mechanism that provides the rules of the market.

Although there are many proposals about markets, few works study the effects of several concurrent markets and the global effects of this type of environment. CAT competition has provided a platform to promote new market designs and encourage research about multiple markets.

Related Work

During the last two years of CAT competition, several research works have been accomplished. Particularly, published papers have addressed: 1) issues related to mechanism design inside a market; and 2) the investigation of multiple markets. In the first approach, Niu et al. (Niu et al. 2008) have demonstrated a market with history based accepting policy, which is based on GD (Gjerstad and Dickhaut 1998) trading strategy. They have showed that their market would outperform specialists that participated in CAT 2007 final. In another work (Niu et al. 2006), the authors have estimated a running equilibrium of the market by introducing a new accepting and pricing policy in the auction. In terms of investigating the policies inside a market, some papers were focused on CAT 2007 final. IAMwildCAT, The winner of 2007 CAT competition, introduced its market strategies (Vytelingum et al. 2008) and described the conflicting factors that must be resolved for designing each market rule. CAT organizers have evaluated 2007 final participants (Niu et al. 2008) and demonstrated the outcome of different policies of participants. Authors have also speculated the market strategies that would be more effective.

In the second approach, researches have focused more on the multiple markets experiments rather than designing and evaluating policies inside a single market. Comparing charging policies, the authors in (Niu et al. 2007) have showed the result of different charging policies in multiple market experiments. Niu et al. have suggested that traders in general are attracted towards lower charging markets and these markets generate more profit. In another work (Niu et al. 2008), the authors have showed that the global market in multiple market setting takes much longer to reach the equilibrium point compared to a single market.

Moreover, on comparing single and multiple markets (Cai et al. 2008), the efficiency of a single market working alone is greater than the global efficiency of multiple markets. However, when considering multiple markets, trader mobility and charging fees lead to higher global efficiency. In (Phelps et al. 2007), an evolutionary approach is proposed where traders and markets are evolved to the equilibrium using evolutionary and genetic algorithms. Gruman and Narayana (Gruman and Narayana 2008) have had a different approach to CAT and tried to identify the traders' bidding strategies by unmasking some information in CAT platform. Hidden Markov model that have achieved the best results had only 62% accuracy in recognizing traders' bidding strategies. Consequently, it is very difficult to identify trader's bidding strategy and have a specific approach to each trader's policy.

In this paper, we describe PersianCAT specialist that have been used in CAT 2008 final. This paper has an approach similar to the first group of works, which introduces a new accepting and pricing policies. Our main contribution is introducing a new estimation value for the equilibrium price of the market, which can be used in both accepting and pricing policies. We demonstrate how a market that is based on an estimated equilibrium would achieve high market metrics. We also cover the second group of works mentioned above by evaluating the PersianCAT performance in both heterogeneous and homogeneous settings. Then we show how policies that involve more fluctuating charges lead to lower market performance, when comparing markets with almost equal average fees throughout the game. Finally, we give a brief overview of CAT 2008 final.

A Brief Overview of CAT

CAT (Gerding et al. 2007) is abbreviation for CATallactics, the science of exchanges[1]. CAT is part of Trading Agent Competition [2] since 2007 and is part of Market Based Control (MBC) project. CAT software is based on JCAT (Niu et al. 2008) platform. CAT Competition consists of traders, which are supplied by game organizers and specialists, which are provided by game entrants. Each trader comprises of a bidding strategy and a market selection strategy. Bidding strategy determines the shout prices and includes ZI-C (Gode and Sunder 1993), ZIP (Cliff and Bruten 1997), GD and RE (Roth and Erev 1995). Market selection strategy determines the selected market of a trader and includes softmax (Sutton and Barto 1998) and ε-greedy (Sutton and Barto 1998). Each specialist designs and sets a set of policies inside its market, which are accepting, pricing, charging, clearing, matching and quoting policies.

Estimation Methods of Market Equilibrium Price in JCAT

CAT competition is composed of several virtual markets. Each market has an equilibrium point where the supply equals demand if all agents bid their private values. Establishing the policies of a market based on the equilibrium strengthens the outcomes of the market. The problem is that the underlying equilibrium price cannot be calculate as traders are self interested and do not reveal their private values. So an estimation based on reported supply and demand would be a suitable alternative. Considering the previous works, there are two estimation methods already introduced in JCAT platform. These estimations are either an approximation of current trend of the market or an estimation of the market equilibrium price.

[1] http://www.marketbasedcontrol.com

[2] http://www.sics.se/tac

Equilibrium Beating

For estimating a running equilibrium of the market, Niu et al. (Niu et al. 2006) use a sliding window to calculate an average of the recently matched ask-bid pairs. They introduce n-pricing policy and equilibrium beating accepting policy as pricing and accepting policies in their market. These policies do not aim to calculate the equilibrium of the market, however they try to be an approximation of the current trend of the market. Consequently, the accepting policy could justify the suitability of the forthcoming shouts based on previous shouts in the market and therefore decide either to accept or reject them. N-pricing rule also tries to find a reasonable transaction price based on the previous transactions of the market so that the transaction price is justified towards the current trends of the market. This is the intuition behind describing this estimation method as a "running equilibrium of the market". By using this estimation value, the authors reduce the fluctuation of transaction prices and achieve a high overall efficiency in their market. We refer to the market than contains these two policies, equilibrium beating accepting policy and n-pricing policy, as EQ-beating in our paper.

Equilibrium Calculator

Equilibrium Calculator (EQ-Calculator) estimates the price and quantity of the market equilibrium based on 4-Heap Algorithm (Wurman, Walsh, and Wellman 1998). The equilibrium price is the average of the ask-Quote and bid-Quote of the auction and the equilibrium quantity is the number of goods that would be exchanged when the market is cleared at the equilibrium. The ask quote and bid quote are given by:

$$BidQuote = Max(HMA, HUB) \tag{1}$$

where HMA represents Highest Matched Ask and HUB represents Highest Unmatched Bid.

$$AskQuote = Min(LUA, LMB) \tag{2}$$

where LUA represents Lowest Unmatched Ask and LMB represents Lowest Matched Bid.

This algorithm is used to estimate the equilibrium price of the market. If traders are truthful the calculated value is theoretical equilibrium, however since in CAT platform traders are not truthful this value would be just an estimation of the market equilibrium price. Based on this equilibrium price, allocative efficiency and convergence coefficient are calculated and also intra and extra-marginal traders are differentiated in CAT environment. We use this approximation of the equilibrium price in the accepting and pricing policies of a market, which we call EQ-calculator in our paper. We aim to measure to what extent a market based on this equilibrium price is robust when working as a single market and also to what extent this estimation value improves market performance when competing with other markets that also

Table 1: Results of experiment 1, summarization of competing equilibrium markets in a heterogeneous setup using ZIC, GD, RE and ZIP traders.

Specialist	Allocative Efficiency	Convergence Coefficient	CAT Game Scores			Transaction Price	Number of Intra Marginal Traders	Number of Entra Marginal Traders
			Mean					
	Mean	Mean	TSR	MS	Profit	Stdev	Mean	Mean
EQ-Beating	57.36 %	10.76	0.74	0.21	0.13	5.02	3.44	39.41
EQ-Calculator	79.12 %	8.35	0.81	0.24	0.23	6.20	4.83	43.91
PersianCAT	95.34 %	4.66	0.96	0.55	0.63	3.38	23.26	85.16

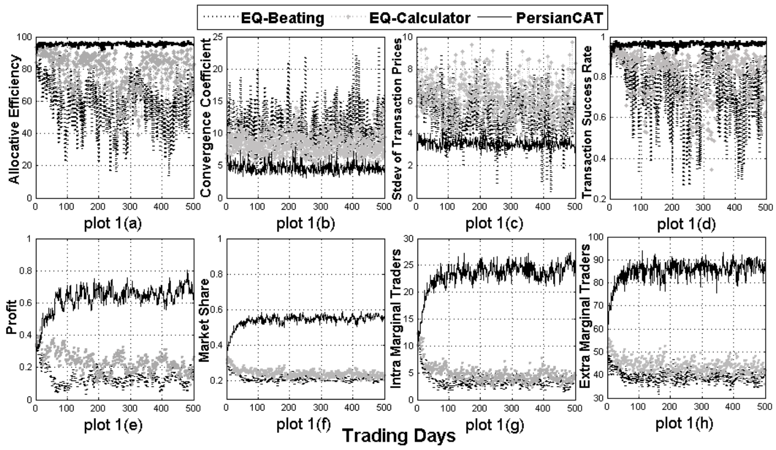

Figure 1: Results of experiment 1, average daily values of 50 runs of competing equilibrium markets over 500 trading days.10-ZIC, 10-GD, 90-RE and 90-ZIP traders (equally split between buyers and sellers) are used.

establish their market on an estimation of the equilibrium price.

PersianCAT Equilibrium Price Estimation

To measure an estimation of the current trend of the past few trading days and use it as a basis for accepting and pricing policies in the following day, we measure an estimation of the equilibrium price of the market by running a sliding window over the last few trading days. If $MaxTAj$ and $minTBj$ are the maximum transacted ask and the minimum transacted bid at day j and n is the length of sliding window, then Eq_{day_i} represents estimated equilibrium of PersianCAT market for the day i:

$$Eq_{day_i} = \frac{1}{2n} \sum_{j=day_{(i-1)}}^{day_{(i-n)}} (MaxTA_j + MinTB_j) \quad (3)$$

Note that the sliding window covers a series of n days from day $i - n$ to day $i - 1$. We use a sliding window of length 4 in our experiments to be accurate and reactive to the changes in the market. One feature of PersianCAT equilibrium(EQ) price estimation is its usage of values over several trading days, which makes its estimation values more robust compared to the other two EQ estimations. Since EQ-beating uses only the values of past few transactions, it may not have a good estimation if traders with the same bidding policy bid and deviate their running EQ price from the real EQ of the market. EQ-calculator also has a shortcoming in terms of the values it uses for its EQ price estimation. Every time the market gets cleared, the matched heaps get empty and the EQ-calculator is left with only unmatched heaps. This causes an increase in the gap between unmatched heaps and consequently the estimated equilibrium price becomes less accurate. Considering PersianCAT's equilibrium estimation, we continue this section by describing PersianCAT policies and their features on different market metrics.

Accepting policy

We accept incoming shouts to PersianCAT market by using PersianCAT EQ price estimation. We also use a slack variable (α) to moderate the restriction on our accepting policy. We set Eq-α as the minimum price for a bid and correspondingly Eq+α as the maximum ask price that can be placed in PersianCAT market. We set the slack value (α) to 10% of the EQ price.

A powerful accepting policy should find a trade-off between several contradictory features in CAT platform. Having a too-open accepting policy would reduces the TSR due to lots of unmatchable shouts (Vytelingum et al. 2008). Furthermore, this shortcoming puts a heavy burden on matching policy(Niu et al. 2008) since matching intra and extra marginal shouts leads to migration of intra-marginal traders. Similarly, having a too-closed accepting policy would contribute with less profit to both traders inside the market and the specialist (Vytelingum et al. 2008). This would lead to migration of intra-marginal traders since they do not make sufficient profit. Consequently, trader migration causes less

Table 2: Results of experiment 2, summarization of competing equilibrium markets in a heterogeneous setup using only ZIC traders.

Specialist	Allocative Efficiency	Convergence Coefficient	CAT Game Scores			Transaction Price	Number of Intra Marginal Traders	Number of Entra Marginal Traders
			Mean					
	Mean	Mean	TSR	MS	Profit	Mean	Mean	Mean
EQ-Beating	65.37 %	9.89	0.76	0.21	0.08	6.21	2.28	39.67
EQ-Calculator	78.69 %	8.51	0.78	0.23	0.11	7.02	3.03	43.60
PersianCAT	97.59 %	5.03	0.97	0.56	0.81	3.89	23.23	88.20

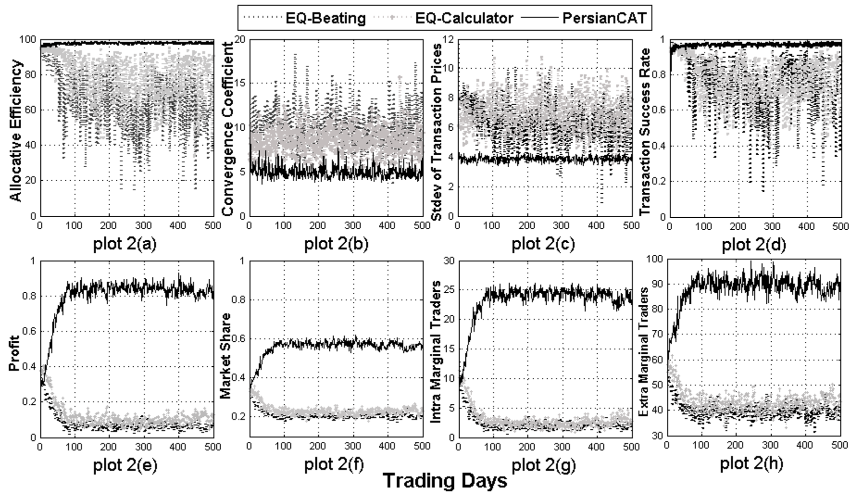

Figure 2: Results of experiment 2, average daily values of 50 runs of competing equilibrium markets over 500 trading days. 200-ZIC traders (equally split between buyers and sellers) are used.

profit for the specialist.

Our accepting policy is similar to transaction-based-accepting-policy (Niu et al. 2008), which accepts asks smaller than maximum-transacted-ask and accepts bids higher than minimum-transacted-bid of the previous trading day. However, PersianCAT's adopted policy differs in the way it calculates its acceptance range. PersianCAT uses an average value of these two prices and employs a sliding window over the past trading days so that it would not be vulnerable to sudden changes in the market as it relies on several trading days. Then PersianCAT moderates its estimated price by an alpha value to be flexible with changes in the market.

PersianCAT's adopted policy is also different from the EQ-calculator policy in the following features: 1) unlike EQ-calculator that changes the values of each one of its 4 heaps several times throughout a day and consequently, has a fluctuating equilibrium, PersianCAT equilibrium is constant throughout an entire trading day; 2) EQ-calculator uses the values of current trading day while PersianCAT equilibrium is based on the values of the previous trading days. Consequently, max-matched-ask in EQ-calculator policy means the maximum ask price since the last market clearance of current day but max-transacted-ask in PersianCAT policy means the maximum ask price that is obtained from an entire trading day in its sliding window; and 3) PersianCAT uses a sliding window of the past trading days while EQ-calculator does not keep a history of its previous values.

Pricing policy

PersianCAT sets the transaction price to its estimated equilibrium price. If equilibrium price is outside the range of $[ask, bid]$, PersianCAT sets the transaction price to the nearest price of ask and bid pair. This pricing policy, based on equilibrium, affects the distribution of profit between traders in the sense that higher profit is given to more competitive shouts. In other words, the more the intra-marginal shout is placed from the equilibrium, the more profit is gained by the trader. This is due to the fact that the transaction price is based on the equilibrium price and not the shout prices. Moreover, the shouts that are matched are intra-marginal shouts since they have to beat the estimated equilibrium price to be accepted and transacted together. Another feature of PersianCAT pricing policy is reduction in the fluctuation of transaction prices due to the usage of the same equilibrium price throughout an entire trading day.

Charging Policy

For designing an effective charging policy, a trade-off between market share and profit must be found to maximize the overall outcome. As described in (Niu et al. 2008), charging high fees would increase profit temporarily but would gradually decrease market share. In contrast, low fees maintain market share but reduce the profit. In addi-

Table 3: Results of homogeneous equilibrium markets using ZIC, GD, RE and ZIP traders in Multiple and Single Market setups

Homogenous Runs	Specialist	Global Allocative Efficiency		Global Convergence Coefficient	
		Mean	Stdev	Mean	Stdev
Multiple Markets	5 PersianCATS	90.16 %	3.41	4.25	0.88
	5 EQ-Calculators	86.85 %	5.04	9.00	1.74
	5 EQ-Beatings	76.62 %	6.06	7.78	1.04
Single Market	1 PersianCAT	94.70 %	0.95	3.66	0.78
	1 EQ-Calculator	93.04 %	3.05	6.64	2.01
	1 EQ-Beating	83.63 %	6.06	7.26	1.15

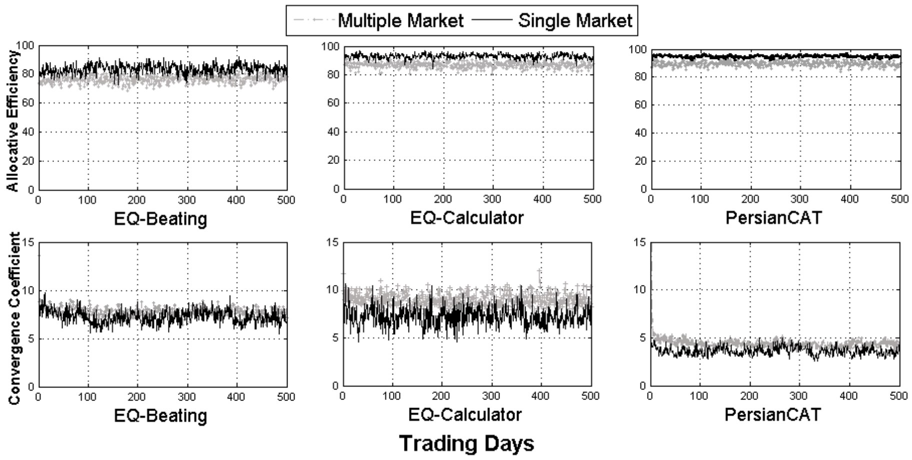

Figure 3: Results of experiment 3, comparing average daily values of 50 runs of homogeneous multiple and single equilibrium markets over 500 trading days. 10-ZIC, 10-GD, 90-RE and 90-ZIP traders (equally split between buyers and sellers) are used. Each equilibrium market is separately run in both multiple and single market setups.

tion, charging registration, information and shout fees could flee extra-marginal traders(Niu et al. 2008).

PersianCAT has a fixed charging policy, which only charges profit fee. By charging no information, registration and shout fees, we keep extra-marginal traders in our market, which usually do not make sufficient profit. Keeping extra-marginal traders would increase the market share (Niu et al. 2008) but comes with a heavy burden of lots of extra-marginal shouts inside the market that could reduce the TSR. By using a powerful accepting policy, we have both maintained a high TSR (more than 90% in the CAT final as shown in our experimental runs discussed later) and increased PersianCAT market share. On the other side, intra-marginal traders are susceptible to high charges of profit fee. By charging only a small portion of profit fee and having successful transactions, PersianCAT keeps intra-marginal traders, which lead to high profit. Keeping intra-marginal traders due to their potential intra-marginal shouts also increases the market efficiency.

Clearing Policy

We use Continuous Double Auction (CDA) in PersianCAT market. This policy compared to round clearing makes less profit(Vytelingum et al. 2008). However, we utilize this policy considering two reasons. First, as each trader only has an active shout in the market, CDA allows more possible transactions without considering the number of rounds in a trading day and the number of goods that a trader can deal. Second, as the transactions are made as soon as two shouts are matchable, this policy helps adaptive traders like GD and ZIP, adjust themselves more quickly to the market and produce more transactable shouts.

Experimental Setup

For comparing the 3 mentioned equilibrium estimation markets, we experimented 50 runs of each game composing these 3 markets. We used the EQ price estimation of each market for pricing and accepting policies of that market. Each market sets the transaction price to its EQ price estimation and accepts bids higher or equal to Eq and asks less or equal to Eq. However, PersianCAT uses an α value to moderate its EQ estimation as mentioned in PersianCAT's accepting policy section. We set the charging policy of all of them to fixed charging policy (0.2) for profit fee and (0) for other fees. In addition, we set the clearing of equilibrium-beating market to CDA, as it is used in (Niu et al. 2006). We set the clearing of EQ-calculator market to round clearing. This is because if we set the clearing policy to CDA, it would disregard max-matched-ask and min-matched-bid heaps as soon as a transaction is made. Consequently, this policy would only use highest-unmatched-bid and lowest-unmatched-ask heaps, making its accepting policy work like quote-beating accepting policy. The pricing policy would also be less accurate, if it is based on the two unmatched heaps with a noticeable gap.

Each run is composed of 200 traders, 10 GD - 10 ZIC

Table 4: Results of homogeneous equilibrium markets using ZIC traders in Multiple and Single Market setups

Homogenous Runs	Specialist	Global Allocative Efficiency		Global Convergence Coefficient	
		Mean	Stdev	Mean	Stdev
Multiple Markets	5 PersianCATS	92.48 %	2.94	4.46	0.83
	5 EQ-Calculators	89.30 %	3.80	9.95	1.63
	5 EQ-Beatings	86.01 %	3.15	9.14	0.78
Single Market	1 PersianCAT	97.29 %	0.65	4.44	0.58
	1 EQ-Calculator	94.64 %	0.93	4.15	1.16
	1 EQ-Beating	89.83 %	1.53	8.86	0.63

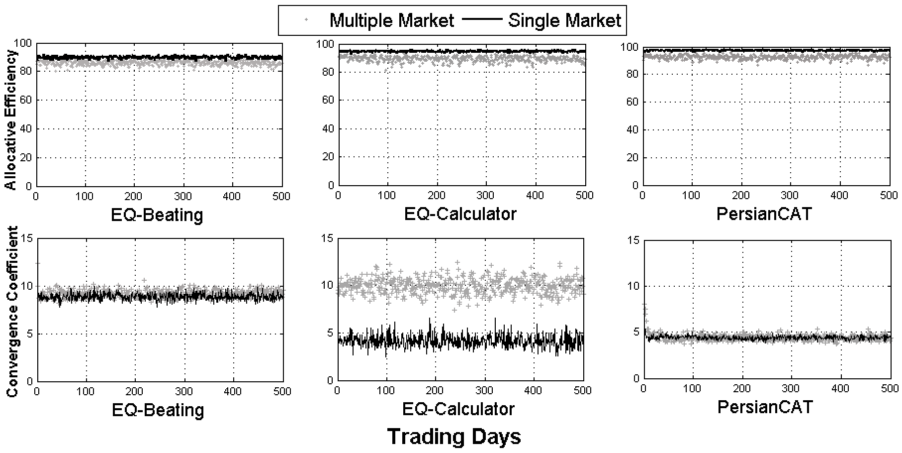

Figure 4: Results of experiment 4, comparing average daily values of 50 runs of homogeneous multiple and single equilibrium markets over 500 trading days. 200-ZIC traders (equally split between buyers and sellers) are used. Each equilibrium market is separately run in both multiple and single market setups.

- 90 RE - 90 ZIP split evenly between buyers and sellers. Traders' private values are allocated from a uniform distribution between 50 and 150. Each game is run over 500 trading days, split into 10 rounds of 500 milliseconds. Table 1 shows the result of the average values of this experiment over 50 runs. Figure 1 also gives the average daily values of these runs.

As it is clear in figure 1, plots 1(d) and 1(h), PersianCAT obtains higher TSR compared to the other two markets despite having more number of extra-marginal traders. Moreover, the TSR value remains more than 90% throughout the entire game, which is an indication of its reliable EQ estimation values in accepting policy. As plots 1(g) and 1(h) in figure 1 show, our market attracts higher number of intra-marginal and extra-marginal traders compared to the other two markets due to its better established equilibrium estimation that affects the performance of the policies in our market. Unlike PersianCAT market, EQ-beating and EQ-calculator markets have produced more volatile values throughout each day and also from one day to another due to high fluctuation in their equilibrium price estimations. Since convergence coefficient shows to what extent the transaction price in a market is placed away from the equilibrium point, lower convergence coefficient in PersianCAT market (figure 1, plot 1(b)) shows that it has a better estimation of EQ price compared to the other two EQ price estimations. Allocative efficiency shows to what extend the actual profit in a market is close to the equilibrium profit. Lower convergence coefficient in PersianCAT market has made its actual profit a more accurate approximation of theoretical profit (figure 1, plot 1(a)). In addition, better estimation of EQ price has attracted higher number of intra-marginal traders to PersianCAT market since it would give them more profit and accepts better their shouts. Consequently, PersianCAT has produced higher profit (figure 1, plot 1(e)). This experiment shows that if a market is based on an accurate estimation of the EQ price, several positive outcomes are achieved.

In another experiment, we ran the same three markets using 200 ZI-C traders to see to what extend these markets are robust when dealing with almost irrational traders. As viewed in table 2, PersianCAT market has produced higher deviation in its transaction prices and higher convergence coefficient compared to the previous experiment. This result is predictable as PersianCAT market is dealing with random generated shouts. However, it has obtained both high TSR and high efficiency showing that it has still a good estimation of the equilibrium price of the market and thus has a balanced accepting approach, especially in unpredictable markets. The average daily values of this experiment are presented in Figure 2. PersianCAT market shows a stable performance throughout the entire game, the same as the previous experiment.

In both first and second experiments, EQ-calculator shows a better performance compared to EQ-beating, except for deviation in transaction prices (plots 1(c) of figure 1 and 2(c) of figure 2). This is probably due to lack of usage of sliding

Table 5: Results of experiment 5, summarization of 4 competing PersianCAT markets with different charging of profit fee.

Specialist	Changing Range	Changing Period	Changing Value	Market Share		Profit		TSR	
				Mean	Stdev	Mean	Stdev	Mean	Stdev
PersianCAT4	0.0-0.6	Every day	0.2	0.2338	0.0495	0.1945	0.1390	0.9059	0.0804
PersianCAT3	0.1-0.5	Every 5 days	0.1	0.2407	0.0488	0.2339	0.1192	0.913	0.0666
PersianCAT2	0.2-0.4	Every 20 days	0.05	0.2589	0.0467	0.2745	0.1101	0.9244	0.0570
PersianCAT	0.3 fixed	fixed	0	0.2667	0.0452	0.2973	0.1068	0.9282	0.0554

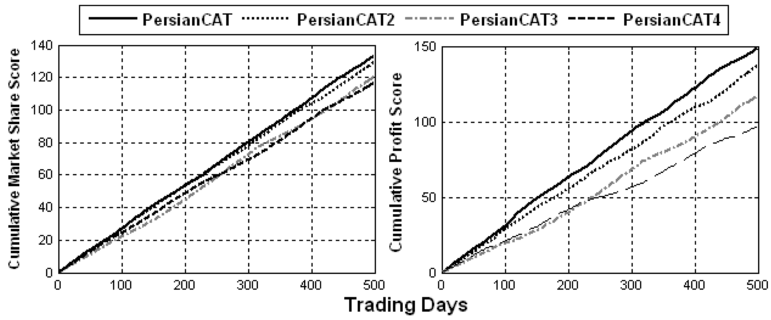

Figure 5: Results of experiment 5, comparing cumulative profit and market share of 4 PersianCAT markets with different charging of profit fee. The results represent average daily values of 50 runs using 10-ZIC, 10-GD, 90-RE and 90-ZIP traders, equally split between buyers and sellers.

window in EQ-calculator algorithm. Moreover, as shown in Figures 1 and 2, the global market in both experiments settles after almost 100 trading days, which shows the learning period of traders before they almost settle in a market. All of the features in the second experiment are the same as the first experiment except for the traders' bidding strategy.

We could gain almost the same results with other types of traders, but only ZIC traders are used due to the following reasons: 1) lack of space; and 2) The results achieved against almost irrational traders indicates better the robustness of a market compared to the other more intelligent traders like ZIP, GD and RE. ZIC traders indicate how the market strategies deal with uncertainties and irrationalities.

Homogeneous Markets

To evaluate the performance of each EQ market in a homogeneous setup, we run a multiple homogeneous market of 5 identical EQ markets and then we run a single EQ market. The game setting is the same as the first experiment. The results of this experiment is given in table 3. Considering both single and multiple markets, PersianCAT contributes better outcomes compared to EQ-beating and EQ-calculator.

Comparing single and multiple markets, as shown in figure 3, single markets have achieved better results considering all three EQ estimation markets. Cai et al. have already demonstrated that allocative efficiency in a single market is higher than the global efficiency of multiple markets (Cai et al. 2008), but with different individual markets. However, achieving lower convergence coefficient in a single market compared to multiple markets is not discussed there. Here our results show that convergence coefficient of a single market is lower than the global convergence coefficient of homogeneous multiple markets.

We also run the same homogenous experiment using only ZIC traders. Table 4 and figure 4 strengthen the outcomes discussed in experiment 3. Again, the performance of a single market outweighs the global measures of multiple homogeneous markets. Unlike the previous experiment, a single market of EQ-calculator has a better estimation of equilibrium price compared to a single PersianCAT market, thanks to its lower convergence coefficient(table 4). However, allocative efficiency of a single EQ-calculator market has a mean value of 94.64% in this experiment and 93.04% in the previous experiment, which are less than expected 100% value. This is due to the fact that the traders that are used in these experiments are not truthful and consequently the optimal 100% allocative efficiency is not achieved. The results of EQ-beating market are obtained by direct usage of this market from JCAT and without any modifications.

Stability in PersianCAT Market

PersianCAT market behaves stably thanks to three factors: 1) an equilibrium based pricing policy; 2) an equilibrium based accepting policy; and 3) a stable charging policy. To show the effect of fluctuation in fees when comparing markets that almost charge the same average fees throughout the entire game, we run an experiment using 4 different PersianCAT specialists.

As demonstrated in table 5, the forth market ("PersianCAT4") charges fixed fees throughout all 500 trading days and the other three markets have fluctuation in their profit fees. However, these three markets charge a profit fee of almost 0.3 throughout the 500 trading days. The difference between these three specialists is the way they change their profit fees and the fee they charge from one day to another. This difference makes the profit fee charged by PersianCAT4 more volatile than PersianCAT3 and PersianCAT3's fees are more unstable compared to PersianCAT2. As shown

Table 6: CAT 2008 final results, summarization of values over 1100 trading days of three CAT game finals (100-final1, 500-final2 and 500-final3). Values are obtained from CAT final log files.

Specialists	Allocative Efficiency		Convergence Coefficient		CAT Game Scores- Mean			Transaction Price
	Mean	Stdev	Mean	Stdev	TSR	MS	Profit	Stdev
BazarganZebel	88.10 %	9.05	8.22	3.49	0.612	0.07	0.08	8.54
CrocodileAgent	74.37 %	29.14	6.89	4.23	0.748	0.06	0.05	4.62
DOG	84.82 %	22.62	7.16	4.36	0.846	0.08	0.01	5.39
Hairball	81.65 %	25.30	9.05	7.2	0.633	0.02	0.1	4.56
IAMwildCAT	89.77 %	13.12	7.04	3.58	0.851	0.09	0.04	6.37
MANX	89.97 %	9.68	7.34	3.54	**0.922**	0.09	0.12	6.96
Mertacor	90.62 %	8.49	7.64	3.49	0.839	0.09	0.12	7.63
MyFuzzy	72.33 %	30.92	7.15	3.88	0.652	0.07	0.06	5.51
PSUCAT	93.24 %	4.3	6.56	3.31	0.896	0.12	0.10	6.31
PersianCAT	**94.27 %**	**3.97**	**5.51**	**3.16**	0.920	**0.13**	**0.2**	**4.10**
Jackaroo	93.45 %	4.27	6.63	3.29	0.900	0.12	0.09	6.24

in table 5, there are three different fee fluctuating factors: 1) changing range: the range of profit fee that the specialist charges traders throughout the entire game; 2) changing period: the period that the specialist charges the same fee before changing it; and 3) changing value: the amount that the specialist changes its profit fee when it wants to change. In the three markets that have fluctuating profit fee, the profit fee goes up and down repeatedly between the changing range throughout the game. Therefore, changing the number of trading days like doubling them would produce the same average profit fee(0.3) in each market. All specialists charge 0 for other fees and other policies in all the four markets are the same. The game setting is the same as the first experiment.

As table 5 shows, the markets with more fluctuation produce less TSR, market share and profit (see figure 5). High deviating markets obtain low market share during their high charging peaks and get higher market share during their low charging periods. In both cases, they get less profit because either these markets are charging too low or there are few traders in their markets to charge. In addition, since high deviation in charging policy changes the balance of intra and extra-marginal traders in a market, the calculated equilibrium of previous trading days are less accurate for the current day, which contributes to less TSR.

As mentioned in (Gruman & Narayana 2008), having lower fees compared to other markets would not necessarily attract traders to a market once traders are settled. This means that if fluctuation in fees is so high that causes loss of market share, fee reduction would not guarantee the return of traders. Therefore, more fluctuating markets gain less market share. The results obtained in this experiment are restricted to the following conditions: 1) all of the markets charge the same profit fee (almost 0.3) and charge 0 for other fees; and 2) all the markets have the same policies except for their charging policy. However, in general markets are attracted to lower charging markets (Niu et al. 2007). As a result, if a market is in competition with more powerful markets, in terms of market policies, higher fee charges and higher fee deviations result in more negative outcomes for the specialist.

CAT 2008 Final

Eleven teams participated in CAT final after going through the trial stage. We demonstrate the overall results of CAT final in Table 6 considering the three separate games combining a total of 1100 trading days. Comparing CAT game metrics, PersianCAT has the highest profit, almost 65% more than the second team, and the highest market share, which indicates the privilege of PersianCAT market among traders. PersianCAT was only second in TSR with less than 0.002 difference from the first team. In general PersianCAT team was ranked 1'st in the final.

Conclusion

In this paper, we introduced the PersianCAT's equilibrium price estimation and described its positive features. Our work is beneficial for two reasons: 1) it introduces a market with high overall outcomes; and 2) it shows the importance of establishing a market on equilibrium price, which causes positive market outcomes if the EQ estimation is accurate enough. We believe that any valuable market mechanism should be based on both the data of previous trading days and the estimated market equilibrium price. We also show that high deviation and instability in charging fees lead to negative market outcomes when comparing the same markets with almost equal average fees throughout the game. Moreover, this paper confirms and strengthens the outcomes already discussed in previous papers: single markets produce higher efficiency and lower convergence coefficient compared to the global values of homogeneous markets.

The results presented in this paper are limited to the combination of traders and markets mentioned in the experiments. In future work, we try to strengthen the results obtained here by increasing the number of runs over longer periods and also by considering other combinations of traders and specialists. In addition, we try to investigate other possible EQ price estimations that would improve market outcomes.

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