Call Markets with Adaptive Clearing Intervals

Extended Abstract

Buhong Liu
King's College London, UK
buhong.liu@kcl.ac.uk

Maria Polukarov
King's College London, UK
maria.polukarov@kcl.ac.uk

Carmine Ventre
King's College London, UK
carmine.ventre@gmail.com

Lingbo Li
Turing Intelligence Technology, UK
lingbo@turintech.ai

Leslie Kanthan
Turing Intelligence Technology, UK
leslie@turintech.ai

ABSTRACT

Trading mechanisms play a fundamental role in the health of financial markets. For example, it is believed that continuous double auctions constitute fertile soil for predatory behaviour and toxic order flows. To this end, frequent call markets have been proposed as an alternative design choice to address the latency arbitrage opportunities built in those markets. This paper studies the extent to which adaptive rules to define the length of the clearing intervals affect the performance of frequent call markets.

KEYWORDS

Market Microstructure; Market Trading Mechanisms; Call Markets; High-Frequency Finance

ACM Reference Format:

Buhong Liu, Maria Polukarov, Carmine Ventre, Lingbo Li, and Leslie Kanthan. 2021. Call Markets with Adaptive Clearing Intervals: Extended Abstract. In *Proc. of the 20th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2021), Online, May 3–7, 2021*, IFAAMAS, 3 pages.

1 INTRODUCTION

Continuous-time double auctions (CDAs) are a very popular trading mechanism applied in modern financial exchanges. However, they are believed to lead to the latency arms race problem [8, 26] and highly volatile markets [18]. Instead, frequent call markets (a.k.a., batch auctions) have been shown to successfully address this problem [8, 30] and outperform CDAs in many aspects including market efficiency, total surplus and size of the spread. Much of the previous research on batch auctions focused on what we call deterministic call markets (DCM), in which the clearing interval length is fixed. We explore the extent to which adaptive call markets (ACMs) where the clearing interval is not constant but moves in rhythm with the market can "improve" the market over deterministic batch auctions. To obtain solid conclusions from the simulations, we apply an *empirical game-theoretic analysis* (EGTA) to compute the empirical equilibria that take into account the strategic responses of traders.

We conclude that market performance is only linked to the clearing frequency. We also show that adaptivity combined with market-based clearing rules can also lead to markets performing better. Furthermore, we explore other market-based clearing rules and draw a picture that supports the exploration of different combinations of termination rules (depending on market conditions) that could be used to make the market perform as intended.

2 EXPERIMENTAL SETUP

Our model is inspired by Wah et al. [28] since it is believed to capture the qualitative phenomena found in real financial markets [5]. There are 40, 80 and 160 agents trading a single security in a thin market, medium market and thick market, respectively. Agents are allowed to submit limit orders when they wish to trade. The limitation of the size of each order is set to 1 unit except when we test the performance with extreme orders. To simplify, we adopt fine-grained but discrete prices and times to simulate both the CDA and the frequent call markets. We also put a price range of the security from 0 to 1000 to avoid unnecessary complexity. The trading occurs over a finite horizon T, which is set to be 200.

We introduce a mean-reverting stochastic process f_t to represent the true value at different times, defined as $f_t = r\bar{f} + (1-r)f_{t-1} + s_t$ where $r \in (0,1)$ is the reversion rate and $s_t \sim N(0, \sigma_s^2)$. The parameters r and σ_s control the average shift of fundamental value and are set to be 0.8 and 100, while $\bar{f}$ is 500. The agents generate their own valuations containing common and private component following the setup in [5, 28]. The common component is $\lambda_{i,t} + f_t$, where $\lambda_{i,t}$ denotes the bias, independently generated from a normal distribution $N(0, 400)$. The private component is a measurement of the personal valuation of holding a position through a vector Θ_i. Assume that the maximum size allowed to long or short is 1. The elements $\theta_{i,q}$ then represent the marginal surplus of obtaining one more unit of the asset when agent i longs q units for non-negative q, or shorts q units for negative q, and are independently generated from a normal distribution $N(0, 50)$ and sorted in descending order to fill the vector Θ_i.

To simulate the bidding process, we assume that during each time interval $[t, t+1)$, every agent has one opportunity to submit a limit order (in which case any outstanding order from previous intervals is cancelled) or take no action. The order in which the agents choose a strategy is randomised. In a call market, the agents can only observe the price quotes at the point in which the market last cleared.

We assign the agents with a required surplus range $[\alpha_{\min}, \alpha_{\max}]$, where $\alpha_{\min}$ is the minimum expected surplus from trading and $\alpha_{\max}$ is the maximum expectation. Each agent enters the market with a probability β every time the fundamental value changes. The strategy space is inspired by [5].

Proc. of the 20th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2021), U. Endriss, A. Nowé, F. Dignum, A. Lomuscio (eds.), May 3–7, 2021, Online.

3 EXPERIMENTS AND ANALYSIS

The key features of the market we are concerned here with are the market efficiency, spread measuring the liquidity, and volume measuring the activeness of the market.

3.1 Random Call Markets

We first compare the performance of CDAs, DCMs and Random Call Markets (RCMs) – where the length of clearing interval is not fixed and is generated from a distribution parameterised by a fixed length of time. We consider the thickness of the market, as from above. The results are shown in Figure 1.

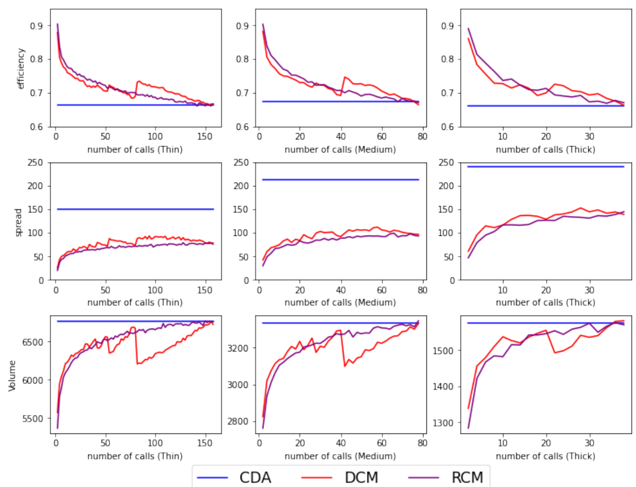

Figure 1: Market Measures: CDA vs DCM vs RCM

The conclusion is that the market performance is only relevant to the clearing frequency, but irrelevant to the generation of irregular clearing intervals. So, deterministic and random call markets have very similar performances as long as the frequency is equal.

3.2 Stability-driven Adaptive Call Markets

Aiming at having a stable market, we analyse so called Stability-driven Adaptive Call Markets (SACMs). A stable market is believed to produce an efficient economic outcome [17]. Let M denote the mid-price right after the previous clearing and let M' be the virtual mid-price, updated as new orders are collected. A SACM with threshold d clears if $\frac{|M-M'|}{M} \leq 100d$, where d denotes the percentage of change in mid-price that we allow before we clear. Since the price grid is sparse, we set up seemingly large thresholds d in $\{0.1, 0.2, 0.3\}$. Figure 2 shows that the market is able to maintain a high efficiency by controlling the stability level d.

3.3 Volume-driven Adaptive Call Markets

We consider two termination rules related to the volume. The first one tracks the aggregate volume during the clearing interval and clears when it reaches a threshold. We call it cumulative-volume ACM (CVACM). The second tracks the ratio between the cumulative volume of effective ask orders and bid orders, and is called extreme-volume ACM (EVACM). We run experiments to test an

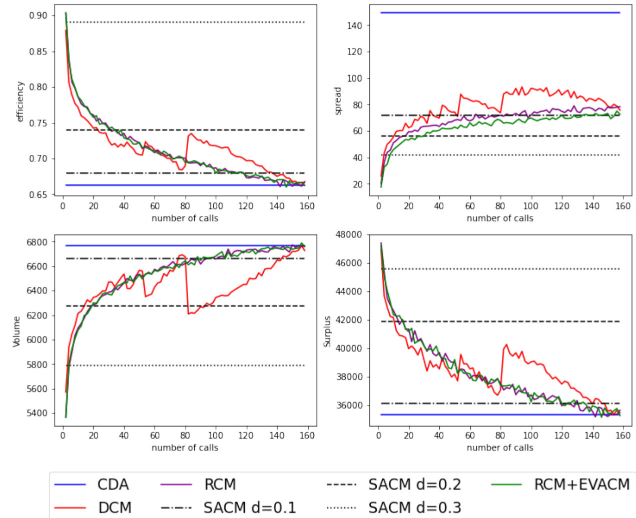

Figure 2: Market Measures: SACMs vs others

extreme scenario where the cumulative bid order size is 100 times the cumulative ask order size. We set the extreme-volume threshold to be 20. Table 1 shows that EVACM is helpful in stopping "flash crashes" and vertical increasing, and in turn contributes to the stability of the market.

Table 1: Changes in Price in Extreme Scenarios

Type	DCM	RCM	CVACM	EVACM
Proportion of change	32%	35%	41%	21%

3.4 Exploration of Combined Termination Rules

EVACM helps to avoid extreme loss, which indicates that it can be used as an additional termination rule. We take a first exploration of combined termination rules and examine the performance of RCMs with Extreme-Volume termination rule (RCM+EVACM for short). The experiment results are shown in Figure 2.

We conclude that in most markets measures, RCM+EVACM performs similarly to RCM. However, in the aspect of market spread, there is a constant decrease from RCMs to RCM+EVACMs, showing that the additional EVACM helps to narrow down the spread.

4 CONCLUSIONS

We observe that ACMs with stability-driven termination rules are able to provide a balance between good market performance and acceptable price stability, and extreme-volume adaptive call markets are helpful in reducing the risk of sharp price movements. These results thereby suggest that flexibility is the key advantage of ACMs over other markets, and studying combinations of clearing rules deserves further research.

REFERENCES

[1] Eric M Aldrich and Kristian López Vargas. 2018. Experiments in high-frequency trading: Testing the frequent batch auction. *Experimental Economics* 40 (2018).

[2] Eric M Aldrich and Kristian López Vargas. 2019. Experiments in high-frequency trading: comparing two market institutions. *Experimental Economics* (2019), 1–31.

[3] W Brian Arthur, John H Holland, Blake LeBaron, Richard Palmer, and Paul Tayler. 1996. Asset pricing under endogenous expectations in an artificial stock market. *The economy as an evolving complex system II* 27 (1996).

[4] Markus Baldauf and Joshua Mollner. 2014. *High-frequency trade and market performance.* Technical Report. working paper.

[5] Erik Brinkman and Michael P Wellman. 2017. Empirical mechanism design for optimizing clearing interval in frequent call markets. In *Proceedings of the 2017 ACM Conference on Economics and Computation*. 205–221.

[6] Tobias Brünner. 2019. Price formation in call auctions with insider information. *Studies in Economics and Finance* (2019).

[7] Eric Budish, Peter Cramton, and John Shim. 2014. Implementation details for frequent batch auctions: Slowing down markets to the blink of an eye. *American Economic Review* 104, 5 (2014), 418–24.

[8] Eric Budish, Peter Cramton, and John Shim. 2015. The high-frequency trading arms race: Frequent batch auctions as a market design response. *The Quarterly Journal of Economics* 130, 4 (2015), 1547–1621.

[9] Ya-Kai Chang, Robin K Chou, and J Jimmy Yang. 2020. A rare move: The effects of switching from a closing call auction to a continuous trading. *Journal of Futures Markets* 40, 3 (2020), 308–328.

[10] Dave Cliff. 2009. ZIP60: Further explorations in the evolutionary design of trader agents and online auction-market mechanisms. *IEEE Transactions on Evolutionary Computation* 13, 1 (2009), 3–18.

[11] Dave Cliff and Janet Bruten. 1998. Zero is Not Enough: On The Lower Limit of Agent Intelligence For Continuous Double Auction Markets. (1998).

[12] Sanmay Das. 2008. The effects of market-making on price dynamics. In *Proceedings of the 7th international joint conference on Autonomous agents and multiagent systems-Volume 2*. International Foundation for Autonomous Agents and Multiagent Systems, 887–894.

[13] Norman Ehrentreich. 2003. A corrected version of the santa fe institute artificial stock market model. *Complexity* (2003), 23.

[14] Doyne Farmer and Spyros Skouras. 2012. Review of the benefits of a continuous market vs. randomised stop auctions and of alternative priority rules (policy options 7 and 12). *Manuscript, Foresight. Government Office for Science* (2012).

[15] Dhananjay K Gode and Shyam Sunder. 1993. Allocative efficiency of markets with zero-intelligence traders: Market as a partial substitute for individual rationality. *Journal of political economy* 101, 1 (1993), 119–137.

[16] M Haas and Marius A Zoican. 2016. Discrete or continuous trading? HFT competition and liquidity on batch auction markets. *Université Paris-Dauphine* (2016).

[17] Ottmar Issing. 2002. Why stable prices and stable markets are important and how they fit together. In *Speech at the First Conference of the Monetary Stability Foundation*, Vol. 5.

[18] Andrei Kirilenko, Albert S. Kyle, Mehrdad Samadi, and Tugkan Tuzun. 2017. The Flash Crash: High-Frequency Trading in an Electronic Market. *The Journal of Finance* 72, 3 (2017), 967–998.

[19] Blake LeBaron. 2002. Building the Santa Fe artificial stock market. *Physica A* (2002), 1–20.

[20] Blake LeBaron. 2006. Agent-based computational finance. *Handbook of computational economics* 2 (2006), 1187–1233.

[21] Richard G Palmer, W Brian Arthur, John H Holland, Blake LeBaron, and Paul Tayler. 1994. Artificial economic life: a simple model of a stockmarket. *Physica D: Nonlinear Phenomena* 75, 1-3 (1994), 264–274.

[22] Vladimir Petrov, Anton Golub, and Richard B. Olsen. [n.d.]. Intrinsic Time Directional-Change Methodology in Higher Dimensions. *SSRN* ([n. d.]). https://ssrn.com/abstract=3440628

[23] Chris Preist and Maarten van Tol. 1998. Adaptive agents in a persistent shout double auction. In *Proceedings of the first international conference on Information and computation economies*. 11–18.

[24] Charles R Schnitzlein. 1996. Call and continuous trading mechanisms under asymmetric information: An experimental investigation. *the Journal of Finance* 51, 2 (1996), 613–636.

[25] L Julian Schvartzman and Michael P Wellman. 2009. Stronger CDA strategies through empirical game-theoretic analysis and reinforcement learning. In *Proceedings of The 8th International Conference on Autonomous Agents and Multiagent Systems-Volume 1*. 249–256.

[26] Chris Sparrow. 2012. The failure of continuous markets. *The Journal of Trading* 7, 2 (2012), 44–47.

[27] Perukrishnen Vytelingum, Dave Cliff, and Nicholas R Jennings. 2008. Strategic bidding in continuous double auctions. *Artificial Intelligence* 172, 14 (2008), 1700–1729.

[28] Elaine Wah, Dylan Hurd, and Michael Wellman. 2016. Strategic market choice: Frequent call markets vs. continuous double auctions for fast and slow traders. *EAI Endorsed Transactions on Serious Games* 3, 10 (2016).

[29] Elaine Wah, Sébastien Lahaie, and David M Pennock. 2016. An Empirical Game-Theoretic Analysis of Price Discovery in Prediction Markets.. In *IJCAI*. 510–516.

[30] Elaine Wah and Michael P Wellman. 2013. Latency arbitrage, market fragmentation, and efficiency: a two-market model. In *Proceedings of the fourteenth ACM conference on Electronic commerce*. 855–872.

[31] Michael P Wellman. 2006. Methods for empirical game-theoretic analysis. In *AAAI*. 1552–1556.

[32] Mason Wright. 2016. Using reinforcement learning to validate empirical game-theoretic analysis: A continuous double auction study. *arXiv preprint arXiv:1604.06710* (2016).