

Call Markets with Adaptive Clearing Intervals

Extended Abstract

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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

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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 α_{\min} is the minimum expected surplus from trading and α_{\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].

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.

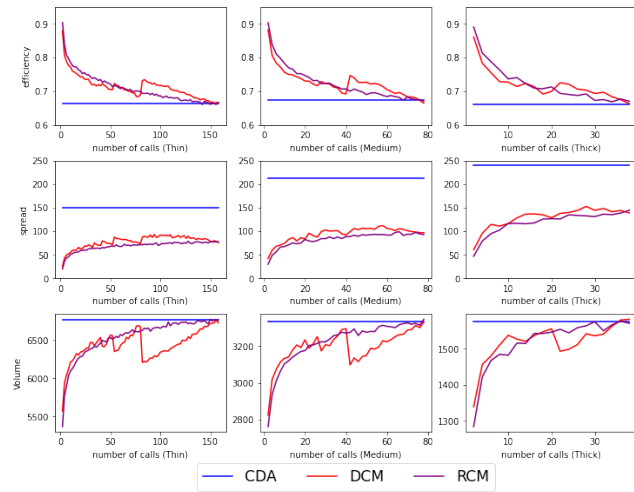


Figure 1: Market Measures: CDA vs DCM vs RCM

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

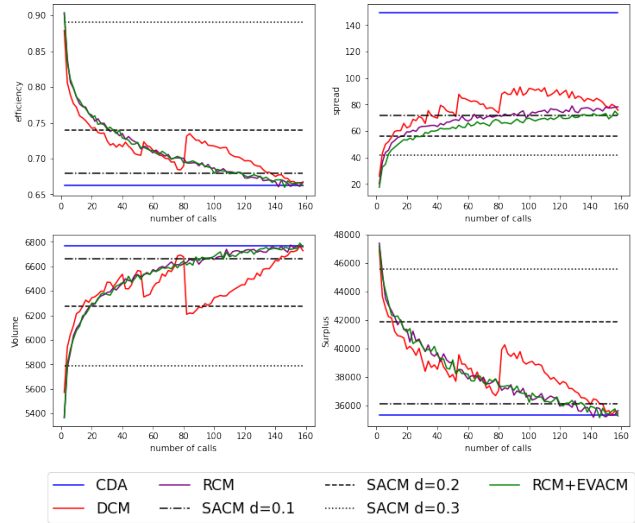


Figure 2: Market Measures: SACMs vs others

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.

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