Sources of Properties of Security Market Pricing: Institutional Design and Agent Rationality

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Modern stock exchanges are largely organized as continuous-trading limit order books, a type of market structure that significantly encourages high frequency trading (Budish *et al.*, 2015). The alternative to continuous-time market design is discrete-time trading where investors can send orders at any time during the day but prices are set at specific points in time.

There is an ongoing debate over the relative advantages of continous- and discrete-time trading mechanisms. In June 2014, the SEC declared that batch auction can be a *"more flexible, competitive"* exchange design. In November 2018, the European Securities and Market Authority (ESMA) launched a call for evidence about the effect of periodic and frequent batch auctions systems on the price determination process and market transparency. According to Mary Jo White, who served as the 31st Chair of the Securities Exchange Commission (SEC), the topics of market structure policy are of particular importance and the advances in this field should help ensure that *..."markets continue to operate openly, fairly, and efficiently to benefit investors and promote capital formation."*

Inspired by the latter statements, we investigate in this paper the emergence of aggregate market properties (volatility, liquidity, efficiency) in various securities markets subject to a variety of institutional designs. We also allow these market structures to be populated with heterogeneous investors having specific sets of resources (budget, knowledge) and capabilities. Computational simulations allow us to compare how different market mechanisms behave in an all else equal setting of strictly similar initial conditions (number of trading rounds, number of market participants, number of held stocks,...).

The market structures we consider are both analyzed extensively in the literature and widely used in the industry and include: full matching, batch auction, Walrasian auction, discrete time market architecture called "share exchange" (initially presented in Biondi and Giannoccolo (2015)), quote driven architecture in presence of a market maker (specialist market), and order driven architecture (continuous-time central order book) with continuous trading. These market designs are summarized in Table 1.

The markets we simulate may be populated by one of four categories of traders. We start with simple atomistic zero intelligence agents called *ZER*. This type of trader randomly picks, from a given interval, an expected price (focal value) $E_{i,t}(p_{t+1})$, that determines the price limit

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of his orders. We assume that these traders buy or sell with equal probabilities. Since traders belonging to this category receive no information, have no learning capabilities and act randomly, the effects on price dynamics are the outcome of market design.

Similarly to *ZERs*, *ARTs* determine their focal value $E_{i,t}(p_{t+1})$ randomly; this value is uniformly drawn from a given interval. However, *ARTs* buy if they expect that the price will continue to rise, i.e. $E_{i,t-1}(p_t) < E_{i,t}(p_{t+1})$ and sell otherwise. The next category of agents, called *TRF*, trade on fundamental and momentum information. They determine their focal value as $E_{i,t}(p_{t+1}) = p_t + \psi_i(p_t - p_{t-1}) + \phi_i(F_t - F_{t-1})$ where ψ_i and ϕ_i are parameters that capture their sensitivity to trend and to changes in fundamental information, respectively. These investors sell (buy) when the last clearing price is higher (lower) than their focal price expectations, i.e. when $p_t > E_{i,t}(p_{t+1})$ $(p_t < E_{i,t}(p_{t+1}))$. They rely on limit orders, and their price limits are equal to their estimated focal values. Agents with strategic order placement *TRS* follow the same rules as *TRFs* to form their expectations but rely on completely different schemes for final order pricing. These investors check the best bid and the best ask available in the order book to optimize their final trade. *TRS* buyers quote a price that does not fully reflect their focal value, betting that a possible seller would accept this relatively low bid. Therefore, they submit their bids at $p_{t,i} \sim U[b_t, E_{i,t}(p_{t+1})]$, where $p_{t,i}$ denotes a bid quote submitted by agent i at moment t, b_t being the best bid at moment t. Similarly, *TRS* sellers propose a price that is higher than their reservation price, expecting that there will be a bidder willing to buy at such high price. *TRS* submit ask orders at $p_{t,i} \sim U[E_{i,t}(p_{t+1}), a_t]$, where $p_{t,i}$ denotes an ask quote submitted by agent i at moment t, a_t being the best ask at moment t. Hence, *TRS* agents determine the direction and price of their orders based on the last market price and the current status of the order book. These four trading strategies are summarized in Table 2.

The combination of four types of agent strategies and six types of institutional designs results in the 24 simulation protocols analyzed in depth in this paper. We investigate different dimensions of market quality: i) volatility measured by range, kurtosis and standard deviation of daily returns ii) informational efficiency measured by the deviation from fundamentals, and iii) allocative efficiency measured by the number of transactions and the number of waste (unexecuted) orders. [1]

We first focus on the volatility generated by each trading protocol. As mentioned above, if agents have zero-intelligence (ZER and ART), the statistical properties of returns are the sole outcome of the underlying market mechanism and do not stem from agents' strategies. In other words, it is the underlying market structure that drives the results. We find that the Full matching market structure displays the largest distribution of returns with amplified losses and gains. Markets with market makers feature smaller swings in returns. Moreover, returns in the dealership market are the least volatile, with standard deviations of returns twice lower compared to limit order central book, and insignificant kurtosis. The latter can be explained by the fact that market makers set their quotes based on the total bid/ask volume imbalance at the previous round and the last trading price. This reduces the impact of individual orders, which results in less dispersed prices compared to other market mechanisms where pricing results directly from individual quotes of thousands of market participants (as in a continuous trading central order book). We thus conclude that, without strategic agents, the order-driven market mechanism is the one that features the largest swings in both profits and losses.

To check the robustness of these results in presence of intelligent agents, we consider mar-

[1] This measure is introduced by LiCalzi and Pellizzari (2007).

Name	Description
Full matching	All orders are sorted with price and time priority. Satisfies all orders which can find a match. Matching is performed starting from the best prices on both sides.
Walrasian	A trading session is divided into discrete time intervals, and, at each round, all orders are treated as having the same time stamp. The auctioneer proposes a tentative price and adjusts it based on aggregate excess demand. An auction ends when the proposed price clears the market ($D = S$). Walrasian auction perfectly matches the supply and the demand.
Batch	The price is at the intersection point of supply and demand curves.
Share exchange	$\frac{\overline{P}_{D,t}(\overline{P}_{S,t}-\underline{P}_{S,t})+\underline{P}_{S,t}(\overline{P}_{D,t}-\underline{P}_{D,t})}{(\overline{P}_{D,t}-\underline{P}_{D,t})+(\overline{P}_{S,t}-\underline{P}_{S,t})}$ if $\overline{P}_{D,t} \geq \underline{P}_{S,t}$
Market maker	$P_{t+1} = \triangle \cdot median(E_{i,t}(p_{t+1})) + (1-\triangle) \cdot P_t$, where $\triangle = \frac{\lvert \sum D - \sum S \rvert}{N}$.
Order book	Continuous market mechanism. A transaction occurs when the best bid $\geq$ best ask. Possibility of multiple transactions at each time step.

Table 1: Summary of market designs. $E_{i,t}(p_{t+1})$ is the expectation of agent i at moment t about the price at next time step. $\sum D$ is the total demand volume, $\sum S$ is the total supply volume, and N is the number of traders. $\overline{P}_{S,t}$, $\underline{P}_{S,t}$ are the minimum and maximum ask prices submitted by agents at moment t. $\overline{P}_{D,t}$, $\underline{P}_{D,t}$ are the minimum and maximum bid prices submitted by agents at moment t.

Acronym	Name	Description
ZER	Null intelligence behavior	Quotes of limits of orders are uniformly drawn from the interval $U[100;300]$, Bids and Asks are sent with the same probability
ART	Auto-regressive traders	Focal value is randomly drawn from the interval $U[100;300]$. Autoregressive process in price discovery. If expectations on future price $>$ previous focal value $\Rightarrow$ Bid. If expectations on future price $\leq$ previous focal value $\Rightarrow$ Ask
TRF	Agents trading on fundamental and momentum	Sensitive to momentum and fundamental signals. Define their focal value based on previous market price, trend dynamics and fundamental information. If last market clearing price $\leq$ focal price expectation $\Rightarrow$ Bid. If last market clearing price $>$ focal price expectation $\Rightarrow$ Ask.
TRS	Agent with strategic order placement	Form focal values similar to TRF. Do not submit at their expectations. Check current state of the order book to optimize their final trade. Submit bids at $p_{t,i} \sim U[b_t, E_{i,t}(p_{t+1})]$. Submit their at $p_{t,i} \sim U[E_{i,t}(p_{t+1}), a_t]$, where b_t and a_t are the best bid and the best ask at moment t.

Table 2: Summary of agents' strategies

kets populated by investors with some cognitive abilities like TRFs and TRSs. This allows us to study the dynamics produced by non-trivial interactions between investors' strategic behavior and market structure. Additionally, the synchronization between profit-oriented traders can be an endogenous source of bubbles and crashes. In this framework, we try to figure out which market structure prevents the occurrence of such extreme price movements. Our findings reveal that speculative bubble seeking seems especially material for the order-driven market, where positive swings of excess return reach considerable peaks. On the contrary, we observe that volatility is significantly reduced on dealership markets, share exchanges, Walrasian, and batch auction protocols.

We then turn to the analysis of informational efficiency by comparing the distributions of generated price series to those of fundamental signals. With agents having zero-intelligence (ZER and ATR), we get that a full-matching market design produces chaotic pricing with considerably large price distribution. Obviously, it does not fit the distribution of fundamentals. We find that batch auctions perform slightly better than a dealership market with regard to deviations from fundamentals. We also find that a continuous trading limit order book tends to disperse prices more than the distribution of fundamentals, with an average price deviation from fundamentals that is twice larger than under Walrasian or batch auction.

Finally, we study allocative efficiency, which we proxy by the percentage of excess volume (total volume of trades divided by the total volume submitted at the bid or the ask side of the order book). In each round, all agents try to make a transaction. A protocol should minimize the number of waste orders or efficiently set aside orders with extreme pricing which potentially could produce extreme price movements. The batch auction and the specialist dealership market designs generate minimal excess volume. In contrast, the continuous double auction is seriously wasteful. Only around 8% of all orders are executed under this market architecture if it is populated by zero-intelligence agents. Moreover, increasing trading intelligence tends to increase the number of waste orders, most notably in the continuous order-driven market, where only 5% of orders submitted by rational profit-oriented agents result in a trade.

The large positive and negative return swings and significant deviations from fundamentals produced under the continuous central order book mechanism show that this type of market does not perform relatively well regarding informational efficiency and volatility. The strong positive asymmetry of return distributions produced by strategic TRS agents interacting in the limit order book also suggests that this mechanism can foster the development of speculative bubbles. Overall, we find that the immediacy offered by the continuous-time market design comes at the expense of other dimensions of market quality. We also show that discrete time batch auction features better informational and allocative efficiency and reduced volatility. These results are of particular interest for market regulators, as the frequent discrete-time batch auction (lasting only several milliseconds) has rapidly gained a significant market share since the application of MiFID II.

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