Impact of Pinging in Financial Markets: An Agent Based Study

Sriram Bharadwaj Rangarajan[1] [a] and Carmine Ventre[2] [b]

[1] *UKRI Centre for Doctoral Training in Safe and Trusted AI, Department of Informatics, King's College London, London, U.K.*

[2] *Department of Informatics, King's College London, London, U.K.*

{*sriram_bharadwaj.rangarajan, carmine.ventre*}@*kcl.ac.uk*

Keywords: Agent Based Modeling, Financial Markets, Dark Pools, Market Impact, Pinging, Market Manipulation, Empirical Game-Theoretic Analysis.

Abstract: Institutional traders in the financial markets rely on hidden trading venues to execute significantly large trades with lower execution costs and reduced information leakage. One such trading venue, known as dark pool, offers institutional traders better execution costs through hidden order books and delayed trade reporting. Despite their advantages, dark pools are susceptible to market manipulation practices such as 'pinging'. Due to low transparency in dark pools, the incentives of pinging agents and their impact on market participants has not been studied in detail. In this paper, we present an agent-based model of the financial markets to study market impact of trading strategies and the dynamics of pinging in dark pools. We identify the scenarios and market conditions under which pinging is a profitable manipulation strategy and compute its impact on execution costs of informed institutional trading agents. Further, we consider agent incentives and use empirical game theory to compute the equilibrium state of the market and quantify the additional costs imposed by pinging agents on informed traders. This study aims to bridge the existing research gap by providing a framework for analyzing market manipulation in dark pools and is a foundational step towards designing safer dark pools.

1 INTRODUCTION

The financial markets operate as highly sophisticated ecosystems and are shaped by the diverse interactions of market participants including retail investors, liquidity providers and institutional traders. Institutional traders, such as investment banks, frequently need to acquire or liquidate large quantities of securities to implement their investment mandates. However, executing large orders in the financial markets can significantly impact market prices and lead to higher execution costs. Market impact (also known as price impact) refers to the difference in market price trajectories when a trade is executed compared to the counterfactual price trajectory that would have occurred had the trade not been executed (Said, 2022). A strategy used by institutional traders to reduce market impact is to distribute their trading activity across 'lit' markets (financial markets with transparent order reporting) and dark pools (financial markets with hidden trading activity).

Dark pools are private trading venues that allow participants to execute trades without disclosing their intention to the wider market. These venues help informed traders to reduce market impact and provide them with anonymity with regards to their trading activity (Brogaard and Pan, 2021; MacKenzie, 2019). The ability of dark pools to trade in a hidden manner helps their participants to prevent information leakage (Buti et al., 2017; Bayona et al., 2023). Dark pools have evolved significantly since their inception in the late 20th century. Modern day dark pools such as Crossfinder are predominantly established and operated by investment banks. However, the lack of transparency and public data on orders presents challenges for modeling and understanding the nuances of dark pool dynamics (MacKenzie, 2019). Controversies surrounding dark pools have underscored their systemic implications. Numerous lawsuits against dark pools operators and fines levied by regulators in the recent past highlight the insufficient policing within these venues [1]. Unlike 'lit' markets, where market information is publicly available, the opaque structure

[a] https://orcid.org/0009-0006-4310-4004

[b] https://orcid.org/0000-0003-1464-1215

[1] See https://www.tradersmagazine.com/departments/brokerage/ubs-pays-record-14-million-fine-for-dark-pool-violations/.

Rangarajan, S. B. and Ventre, C.
Impact of Pinging in Financial Markets: An Agent Based Study.
DOI: 10.5220/0013312900003890

In *Proceedings of the 17th International Conference on Agents and Artificial Intelligence (ICAART 2025) - Volume 1*, pages 172-183
ISBN: 978-989-758-737-5; ISSN: 2184-433X

of dark pools limits the ability of researchers and regulators to study their operations (Buti et al., 2022).

Besides the lack of transparency and inability to study these markets, market manipulation is a significant concern in dark pools, since it disrupts the 'lit' market efficiency and increases execution costs for genuine participants. While market manipulation (Lin, 2017) in 'lit' markets has been well studied (Liu et al., 2022), detection of manipulation in dark pools is much harder due to its low transparency. This opens up dark pools to market manipulators, who may misuse these venues for profiting at the expense of legitimate market players (Aquilina et al., 2024). An example of a dark pool manipulation strategy is 'pinging', where the manipulation agent places small quantity orders in the dark pools to detect the presence of large hidden institutional trading orders (Martínez-Miranda et al., 2016). Once a large order is detected, the manipulation agent would front-run the institutional agent by placing orders in the 'lit' market and profiting from the impending market moves. Pinging undermines the purpose of dark pool trading, reduces market confidence, leads to information leakage and increases execution costs (Stenfors and Susai, 2021). Despite the negative effects of pinging in dark pools, it remains relatively unexplored in literature. Our paper aims to address this research gap by using agent based modeling (ABM) to study the dynamics of pinging in dark pools and its impact on institutional trader's execution costs.

This paper aims to integrate computational multi-agent system design with financial market manipulation analysis by presenting a novel incentive-aware ABM of the financial markets with an associated dark pool. By presenting a novel pinging agent definition, we aim to enhance our understanding of how pinging impacts the financial markets and its participants (like institutional traders). To our knowledge, this is the first study that analyzes pinging based market manipulation in dark pools, and quantifies the impact of pinging on market impact and execution costs of informed traders. The main contributions of our work are:

- We propose a novel incentive aware ABM of the financial markets with a dark pool for studying the market price impact of institutional trading strategies. Our ABM is able to replicate price impact characteristics in classical literature (Obizhaeva and Wang, 2013; Almgren and Chriss, 2001) as well as model the impact of trading in dark pools.
- We define a novel pinging market manipulation agent (in Section 3.6) that probes the dark pool markets for hidden orders and profits by trading ahead of large institutional trades.
- Using our ABM and pinging agent, we are able to ascertain the market scenarios under which pinging is a profitable manipulative activity, and we show the impact of pinging on execution costs.
- We use empirical game-theoretic analysis (EGTA) (Wellman, 2006) to compute the market strategy equilibrium of the institutional and pinging trader's actions and compute the impact of pinging in the market equilibrium.

2 RELATED WORK

2.1 Agent Based Modeling

The study of financial markets using computational agent based models has grown significantly in recent times, leveraging advancements in ABM (Liu et al., 2022; Wah et al., 2015; Brinkman and Wellman, 2017). ABM allows researchers to study the complexities of the financial markets and observe the emergent market dynamics. Some of the earliest research works in this field (Chiarella, 1992; Gode and Sunder, 1993) consider market participants like fundamentalists and zero-intelligence agents to study emergent market phenomenon. Subsequent research (Majewski et al., 2018) further improves on the Chiarella model by enhancing the fundamental price to include a drift component and thereby modeling diverse market regimes. ABM has further been used in conjunction with the ABIDES framework (Byrd et al., 2020) to estimate market impact of an institutional trader. While there is extensive research on the use of ABMs for modeling market impact, the modeling of market impact of execution strategies using an ABM while replicating temporary and permanent impact components remains unexplored.

2.2 Dark Pools and Market Manipulation

Dark pools are market venues that allow their participants to trade in an anonymized manner. Classical finance literature contains theoretical models on the dynamics of dark pools. Buti et al. (Buti et al., 2017) investigate the impact of the dark pool market on the 'lit' market and identify the conditions under which dark pool participation is higher. Kratz and Schoeneborn (Kratz and Schöneborn, 2014) propose a mathematical equilibrium market model for optimal liquidation of portfolios in the lit and dark pool markets. Different kinds of dark pools have been studied in literature by Zhu (Zhu, 2013). The most prevalent type is known as crossing networks, which enables trading at the midpoint of the lit market. One prior research work (Mo et al., 2013) has used ABM for modeling the benefits of dark pool trading and highlight the risk of lower order fills in dark pools.

Market manipulation and predatory strategies in the financial markets have been studied with a focus on spoofing and pinging strategies. Liu et al. (Liu et al., 2022) study the impact of spoofing on the lit market using ABM and EGTA, and show the resistance of an alternative market design called frequent call markets. Martınez-Miranda et al. (Martínez-Miranda et al., 2016) study pinging strategies using a reinforcement learning framework to study the trading dynamics of these agents. While there is extensive research on market manipulation in the lit markets, the impact of market manipulation in dark pools remains unexplored. Furthermore, an analysis of pinging based market manipulation using agent incentives and using ABM is an unexplored area too.

3 EXPERIMENTAL SETUP

Our study employs an agent-based financial market model that is inspired by frameworks utilized in prior research (Liu et al., 2022). All trading is permitted on a single security only. Our model allows trading agents to submit orders in two parallel market mechanisms namely the Continuous Double Auction (CDA) and the Dark Pool (DP) market, enabling a versatile analysis of market phenomenon. In our market setup, orders are submitted at discrete intervals of time ($t = 0, 1, ..., N$, where N is the total length of simulation) with order prices being restricted to integer multiples of the market tick size (set to 1 in this instance). We leverage ABM to analyze market dynamics and apply EGTA to compute the equilibrium behavior of the pinging agent and the institutional trading agent. The computational ABM market model was implemented in Python using the *mesa* library (Kazil et al., 2020) with separate Python modules built for each trading agent type and market matching mechanisms. Additionally equilibrium analysis using EGTA (Wellman, 2006) was performed using the open source *egtaonline* and *quiesce* libraries.

3.1 Market Environment

Our study uses a market environment that builds on frameworks commonly used in financial market ABM studies (Liu et al., 2022; Brinkman and Wellman, 2017). It features a population of N background agents, whose market arrival times are governed by a Poisson process with an arrival rate parameter λ. On arrival, agents may either cancel existing outstanding orders and/or submit new orders to either the CDA or dark pool markets. A fundamental price time series, representing the consensus value of the traded security, is expected to be present and known to all the agents in the environment. At each time step t, the fundamental price f is governed by a mean-reverting stochastic process described as below:

$$f_t = r\bar{f} + (1-r)f_{t-1} + s_t \quad s_t \sim N(0, \sigma_s^2) \qquad (1)$$

Here, f_t represents the fundamental price time series, $r \in (0,1)$ is the mean reversion rate, s_t is a noise term sampled from a normal distribution and $\bar{f}$ is the mean of the fundamental value. The parameters r and σ_s^2 can be adjusted to produce fundamental price time series with different levels of mean reversion and volatility. The initial value of the fundamental series $f_0 = \bar{f}$.

3.2 Valuation Models

At each time step t, when the fundamental value changes, agents in the market update their security valuations based on their private and common components consistent with the approach in prior research (Brinkman and Wellman, 2017; Liu et al., 2022). The common component of an agent's valuation is a noisy estimate of the true fundamental value. This estimate is modeled as a combination of the true fundamental and an agent-specific valuation bias $b_{i,t}$, which is sampled from a normal distribution $N(0, \sigma_{bias}^2)$. The agent's private component, denoted as θ_i, reflects the agent's marginal utility of acquiring an additional unit of the security. It is represented as a vector of length $2Q$ (where Q is the maximum permitted agent inventory) and is expressed as $(\theta_{i,-Q}, \theta_{i,-Q+1}, ..., \theta_{i,0}, ..., \theta_{i,Q-2}, \theta_{i,Q-1})$. Each element $\theta_{i,q}$ corresponds to the marginal utility of one additional security for agent i, when its current inventory is q. This vector θ_i is generated by sampling $2Q$ values from a normal distribution $N(0, \sigma_{pv}^2)$ and sorting them in descending order. The total valuation of agent i at time t with an inventory q is calculated as:

$$v_{i,t,q} = \begin{cases} f_t + b_{i,t} + \theta_{i,q}, & \text{if buying} \\ f_t + b_{i,t} - \theta_{i,q-1}, & \text{if selling} \end{cases} \qquad (2)$$

3.3 Market Mechanisms

In this study, we explore two distinct market mechanisms - Continuous Double Auction (CDA) and dark pool market, which co-exist in the overall market environment. We would like to examine the market dynamics when an institutional trading agent interacts with the CDA and dark pool markets through different strategies. The CDA is a widely employed mechanism where agents place buy (sell) limit orders with an associated price at which they would like to trade at. All orders are stored in the limit order book (LOB) and trades occurs when a new incoming order matches with an existing one in the LOB. We implement an ABM functioning as per the CDA market framework, similar to those presented in prior research (Liu et al., 2022; Brinkman and Wellman, 2017). The dark pool market, in contrast, is a less prevalent market design more popular in certain geographies (MacKenzie, 2019). While the dark pool market also allows participants to submit buy or sell orders in continuous time like the CDA, the order book is hidden from the participants thereby allowing them to hide their trading intentions (Buti et al., 2017; Bayona et al., 2023). In this study, we implement a dark pool market that acts as a crossing mechanism between buyers and sellers with trades occurring at the midpoint of the best bid and offer prices in the CDA market. Our dark pool market model is inspired by prior research work (Mo et al., 2013), however we use a more heterogeneous background agent strategy set. The market model in our study allows trading agents to trade either in the CDA or the dark pool market or adopt a mixed trading strategy.

3.4 Background Agents

We use three kinds of background agents in our market simulations to study the market dynamics in the presence of an institutional trading agent and a pinging market manipulation agent. The three agent types we use are - zero intelligence (ZI) strategy, fundamental traders (FT) and market makers (MM). Further, we also employ noise trading agents to enhance the order book depth at various levels.

Zero Intelligence Strategy. Zero intelligence (ZI) traders place limit orders with prices determined based on the market fundamental value and private valuations only, without considering the state of the order book. The ZI strategy used in our paper is inspired by prior research (Brinkman and Wellman, 2017) and this agent determines their order prices by shifting their agent valuation using an offset drawn from a uniform distribution $U \sim [R_{min}, R_{max}]$. ZI agents usually carry low inventory and therefore the inventory limit for our study is set as $Q = 3$. On entering the market, the ZI agent samples an expected surplus from the uniform distribution and adjust their valuation by this surplus to calculate their order price. The order price submitted by agent i with current inventory q at time t is calculated as below:

$$p_{i,t,q} = \begin{cases} v_{i,t,q} - U[R_{max}, R_{min}], \text{ if buying} \\ v_{i,t,q} + U[R_{min}, R_{max}], \text{ if selling} \end{cases} \quad (3)$$

Fundamental Trader Strategy. Fundamental traders (FT) are those who seek long-term value and base their trading decisions on the dislocations between the market quote-mid and their security valuations, aiming to capture significant deviations between the two. In comparison to ZI agents, FT agents are more risk-averse and require a substantial surplus to be motivated to trade. Drawing from the hypothesis and findings from prior research (Majewski et al., 2018), we model the FT agent demand as a polynomial function of the market price's deviation from the agent valuations. The aggregate demand for all FT agents at time t is given by:

$$D_{i,t} = \beta_1(v_{i,t} - P_t) + \beta_2(v_{i,t} - P_t)^3 \quad (4)$$

where P_t represents the market mid price at time t, β_1 and β_2 are the coefficients for the linear and cubic terms respectively, $v_{i,t}$ is the agent valuation. FT agents enter the market following the Poisson process presented in Section 3.1, place orders near the market mid price to adjust their inventory to align with their computed demand function value.

Market Maker Strategy. Market making (MM) refers to a category of trading strategies aimed at providing liquidity to the market and profiting from the bid-offer spread (Chakraborty and Kearns, 2011). Our MM strategy agent is inspired by Karvik et al. (Karvik et al., 2018) and has been streamlined to reduce computational complexity. The MM agent considered in our model enters the market and adjusts its buy and sell orders (Bid_k, Ask_k) at each time $t \in (0, T)$. Our MM agent monitors the volume of arriving buy and sell orders, constructs indicators of market imbalance and modifies its orders as described in prior research (Ho and Stoll, 1981). On observing a higher demand to buy (sell), the MM infers the market sentiment and adjusts its prices upward (downward). They also effectively manage inventory risk by adjusting prices upward (downward) to effectively manage decreases (increases) in holding inventory. At each time t, the MM calculates its mid-price $mmp_{i,t}$ and series of quotes (Bid_k, Ask_k) as expressed below:

$$mmp_{i,t} = mmp_{i,t-1} + \alpha_{demand}.DI + \alpha_{inv}.IC \quad (5)$$

$$DI = (N_{aggbids,t-1->t} - N_{aggasks,t-1->t}) \quad (6)$$

$$IC = (q_{i,t} - q_{i,t-1}) \quad (7)$$

$$Bid_k = mmp_{i,t} - \frac{MMSpr_i}{2} - (k-1)ticksize \quad (8)$$

$$Ask_k = mmp_{i,t} + \frac{MMSpr_i}{2} + (k-1)ticksize \quad (9)$$

where $k = 1,2,3,....MMLvls_i$, $mmp_{i,0} = f_0$ (fundamental mean), $N_{aggbids,t-1->t}$ and $N_{aggasks,t-1->t}$ are the total quantity of aggressive bids and asks respectively between $t-1$ and t, $q_{i,t}$ is the MM agent inventory at time t, DI represents demand imbalance, IC represents inventory change, α_{demand} is the market demand adjustment factor, and α_{inv} is the agent inventory adjustment factor, $MMSpr_i$ is the fixed MM agent spread, $MMLvls_i$ is the number of quote levels on both the buy and sell sides.

Noise Trader. Noise traders are uninformed market participants who lack intrinsic valuations of the traded security and typically trade near the market mid price. These types of agents are frequently employed in financial market simulations (Ponomareva and Calinescu, 2014; Farmer et al., 2003) due to the ability to account for upto 96% of the variance observed in market spreads. In this study, noise trader agents submit buy or sell orders shifted from the market mid price by a value sampled from a uniform distribution $U \sim [R_{min}, R_{max}]$. The submitted price by noise trader i at time t is given by:

$$p_{i,t} = \begin{cases} P_t - U[R_{max}, R_{min}], \text{ if buying} \\ P_t + U[R_{min}, R_{max}], \text{ if selling} \end{cases} \quad (10)$$

where P_t is the market mid price at time t

3.5 Institutional Trading Agent

In our study, we use an institutional trader agent implementing a time-weighted average price (TWAP) strategy for our analysis of market impact in CDA and dark pool markets. The TWAP strategy entails executing the total order volume at a consistent rate over the entire execution period, aiming to match the market's time-weighted average price. To achieve this, the strategy splits the total execution volume into equal portions, executing one portion per time interval. The order quantity executed by the TWAP agent during the k-th interval is given by $n_k = X/N_{TWAP}$ (where N_{TWAP} if the number of intervals for the strategy). To analyze the impact of executing orders in the dark pool market mechanism, we extend the vanilla TWAP strategy to create multiple TWAP strategy variants, each of which differ in the proportion of the trade volume executed in the CDA vs dark pool. In this study, we analyze four different TWAP strategy variants, as presented in Table 1. For example the strategy $S_{0\%DP}$ executes the entire trade volume in the main CDA market while the $S_{10\%DP}$ executes 10% of the trade volume in the dark pool and 90% in the CDA market.

Table 1: TWAP Strategy Variants - Each of these strategies differ by the fraction of the overall trade executed in the dark pool vs CDA markets.

Strategy	DP Fraction	CDA Fraction
$S_{0\%DP}$	0%	100%
$S_{10\%DP}$	10%	90%
$S_{20\%DP}$	20%	80%
$S_{30\%DP}$	30%	70%

3.6 Pinging Agent

Pinging (Martínez-Miranda et al., 2016) refers to a market manipulation strategy (Budish et al., 2015) where the agent submits small orders (typically near the best bid or offer price of the market) to detect the presence of large hidden institutional orders. In this paper, our main focus will be on pinging based market manipulation in dark pool (DP) markets. As discussed in classical finance research (Kratz and Schöneborn, 2014), pinging agents in dark pool markets aim to probe the presence of large orders in dark pool markets and subsequently place orders in the main CDA markets with the aim of profiting from future market moves. Pinging can often be harmful to market participants since the market price is no longer indicative of the true security value and this increases execution costs for institutional trading agents.

For our experiments, we employ a simplistic pinging agent that performs two activities in parallel. First, the pinging agent places small buy or sell trades (buy or sell direction chosen at random) of quantity 1 unit in the dark pool market in regular intervals (in this case at $t = 0, 10, 20...., T-10, T$) to detect the presence of large dark pool orders. The pinging agent uses the information gained from the previous 10 pings (on a rolling basis) to ascertain whether there is hidden buy or sell side demand in dark pool market. Second, the pinging agent executes aggressive buy or sell trades in the CDA market to achieve its target inventory, which is determined based on the information acquired from the dark pool pinging process. The target inventory for the pinging agent is set to the maximum positive (negative) inventory if a large hidden buyer (seller) was detected in the pinging process. The target inventory for pinging agent is set as:

$$TI_{Ping} = \begin{cases} +Q_{Ping}, \text{ if buyer in } 70\%+ \text{ pings} \\ -Q_{Ping}, \text{ if seller in } 70\%+ \text{ pings} \\ 0, \text{ otherwise} \end{cases} \quad (11)$$

where TI_{Ping} is target inventory of the pinging agent and Q_{Ping} is the maximum inventory for the pinging agent ($Q_{Ping} = 10$ in our study).

Table 2: Environment Parameters.

Parameter	Value	Parameter	Value
$\overline{f}$	500	N	110
r	0.2	$N_{noise-agents}$	20
σ_s^2	10	λ_{ZI}	0.01
σ_{bias}^2	10	λ_{FT}	0.005
T	2000	$(\alpha_{inv},\alpha_{demand})$	(1,-1)
R_{min}	0	R_{max}	5
$MMSpr_i$	4	$MMLvls_i$	5
σ_{pv}^2	5	β_1	-5
β_2	-6.4e-3		

3.7 Environment Parameters

During the course of experiments and analysis in this paper, the general market parameters remain fixed. To estimate the market impact of different strategies, we vary the execution strategy under consideration (as described in Section 3.5) and the total order quantity executed (as described in Table 3). The security price is allowed to fluctuate between 0 and 1000 with a market tick size of 1. The market consists of $N = 110$ ($N = N_{ZI-CDA} + N_{FT-CDA} + N_{MM-CDA} + N_{ZI-DP}$) background agents, which are split between the CDA and dark pool markets. As per the findings in prior research (Ye, 2024) that dark pool markets attract informed speculatory agents and uninformed trading agents, we will assume our market model to contain 50 FT agents ($N_{FT-CDA} = 50$), 25 ZI agents ($N_{ZI-CDA} = 25$) and 10 MM agents ($N_{MM-CDA} = 10$) in the CDA market while the dark pool market will contain 25 ZI agents alone ($N_{ZI-DP} = 25$). We do not include any MM agents in the dark pool as per the findings in prior research (Zhu, 2013). ZI and FT agents arrive at the market following a Poisson process with respective arrival rates λ_{ZI} and λ_{FT}, while the MM agent is present at every time step. To account for market variance, we maintain a fixed number of noise trader agents $N_{noise-agents}$ in the CDA market. The demand function factors for FT agents are specified in Table 2. These parameter choices are motivated by the findings in prior research (Majewski et al., 2018). The simulation length is set to $T = 2000$ time steps. The summary of environment and background agent parameters discussed in this section is shown in Table 2, with each of these parameters chosen to be in line with prior research (Liu et al., 2022; Brinkman and Wellman, 2017; Karvik et al., 2018).

3.8 Execution Scenarios and Metrics

We outline certain execution scenarios to analyze market impact of various execution strategies. These scenarios differ based on the total order volume executed in each scenario. For each scenario, an institutional trader agent trades a total order volume as defined by the respective scenario beginning at $t = 0$ and completing execution at $t = 1000$. The scenarios under which we will be evaluating market impact are specified in Table 3. These execution scenarios were chosen with the order quantities aligned with 10%, 15%, 20% and 25% of the typical trading volume in one simulated trading day of $T = 2000$ time steps. To evaluate market impact in a CDA-dark pool market model, we focus mainly on temporary/permanent impact and execution costs as defined in prior research (Said et al., 2017). The list of market metrics we will use are temporary impact, permanent impact, implementation shortfall and agent surplus. These are defined as follows:

Table 3: Execution Scenario Definitions.

Scenario	Execution Order Volume
$Scen_{100}$	Agent buys 100 units of security
$Scen_{150}$	Agent buys 150 units of security
$Scen_{200}$	Agent buys 200 units of security
$Scen_{250}$	Agent buys 250 units of security

- Temporary Impact - Temporary impact is defined as the peak change in market price observed during the execution period relative to the execution strategy's arrival price.
- Permanent Impact - Permanent impact refers to the new equilibrium price level post execution completion relative to the execution strategy's arrival price.
- Implementation Shortfall - Implementation Shortfall (also known as execution cost) is the effective cost incurred by the execution agent, i.e., the average cost incurred by the agent per unit of security purchased.
- Agent Surplus/Profits - The terminal surplus of an agent is the sum of cash and value of terminal security holdings (Brinkman and Wellman, 2017).

3.9 Agent Strategy Space and EGTA

Our ABM simulation is formulated as a financial profit maximization game between an institutional trader and a pinging agent. Also as defined in Section 3.4, the market model consists of $N = 110$ background agents who act as per their fixed strategies and do not adapt their strategies as per the market scenario. We assume that the time period of the institutional agent activity and pinging agent activity is too short for the background agents to detect and adapt to and therefore each of the background agents (ZI, MM and FT) follow fixed strategy profiles.

On the other hand, the two players in our financial market game with dynamic strategies are the institutional trader agent (described in Section 3.5) and the pinging agent (described in Section 3.6). While we do analyze all combinations of these strategies in Sections 4.1 and 4.2, we model the market simulation as a 2-player game in Section 4.3 to compute the equilibrium state. The institutional trader chooses its strategy from the strategy set $\{S_{0\%DP}, S_{10\%DP}, S_{20\%DP}, S_{30\%DP}\}$ (described in Table 1). The pinging agent chooses between 2 strategies - 'Idle' (dormant) or 'Active' (agent acts per Section 3.6). Both of these agents pick their strategy in the market equilibrium to maximize their profits. Since we are unable to apply theoretic Nash equilibrium models to a financial market ABM, we use EGTA (Wellman, 2006) for analyzing our market game. First, we consider all strategy combinations for the institutional trader agent (4 possible strategies) and pinging agent (2 possible strategies) and run 100 simulations for each strategy profile. Next, we analyze and calculate the agent surplus for each simulation. Finally, we compile these strategy profiles with their payoffs, construct the payoff matrix and perform EGTA.

4 EXPERIMENTS AND ANALYSIS

4.1 Market Impact in Hybrid CDA-Dark Pool Strategies

In this section, we show the ability of our financial market ABM to model market impact of an institutional trader agent under various execution scenarios while following different strategies.

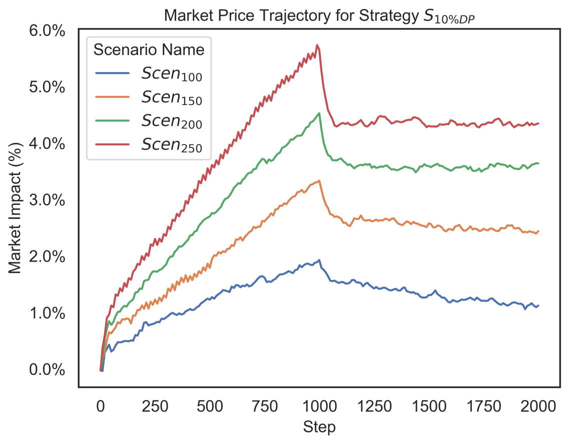

Figure 1: Market Price Trajectory under different execution scenarios for Strategy $S_{10\%DP}$.

4.1.1 Experimental Procedure

First, we use an ABM based on the financial market model described in Sections 3.1-3.3 and the parameters in Table 2. Second, we introduce an institutional trader agent (as defined in Section 3.5) into the market model in different market scenarios. The institutional trader agent is simulated under each of the execution scenarios defined in Table 3 while following each of the TWAP strategy variants defined in Table 1. The purpose of these scenario and strategy variants is to understand the relationship between the total order execution volume and the market impact metrics, as well as the relationship between the CDA-dark pool execution volume splits and market impact metrics. Finally, under each of these scenarios and strategies, we observe the emergent system dynamics and compute the market impact metrics defined in Section 3.8.

4.1.2 Results and Analysis

The resulting price trajectory for one of the TWAP strategies $S_{10\%DP}$ under each of the execution scenarios is as shown in Figure 1. Based on the emergent market dynamics observed in Figure 1, we observe that the market price impact peaks around $t = 1000$ for all of the execution scenarios, which is when the institutional trader agent concludes its execution. The market price then swiftly converges to a new price equilibrium by the end of the simulation day around $t = 2000$. Across the execution scenarios, a larger volume executed corresponds to a higher price impact. The initial peak in market price impact is measured as temporary impact and this peak is due to the temporary demand-supply mismatch. The subsequent convergence to a new price equilibrium is due to the subsequent arrival of FT agents, who in turn absorb most of the demand from the institutional trader. This price dynamics is as expected by classical finance literature (Obizhaeva and Wang, 2013). We also notice that the price impact trajectory in Figure 1 shows a concave shape in line with theoretical finance models (J. Doyne Farmer and Waelbroeck, 2013).

The market impact metrics for each of the execution scenarios and strategies is as shown in Figure 2. As the fraction of the trade volume executed in the dark pool increases, we observe a decrease in temporary impact, permanent impact and execution cost. For example in Figure 2(a)-(c), temporary impact, permanent impact and execution cost decreases as we move from $S_{0\%DP}$ to $S_{30\%DP}$ (left to right in Figure) for a given scenario. On investigating our ABM simulations, we find that this is due to the dark pool market trades being hidden from other participants and thereby the anonymity leads to lower price impact

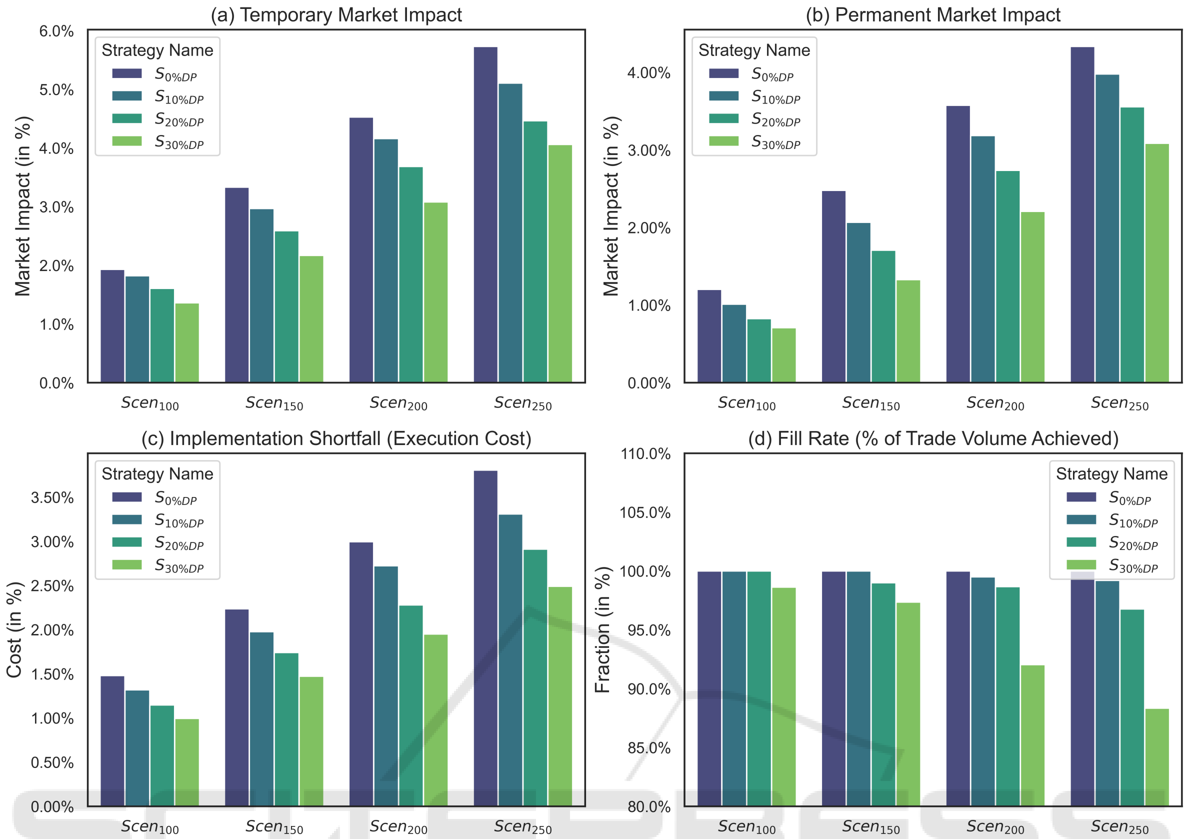

Figure 2: Market Impact Metrics under different execution scenarios and TWAP strategies. The X-axis for each of these subplots contains the execution scenario under analysis (as per Table 3). (a) Temporary Market Impact, (b) Permanent Market Impact, (c) Implementation Shortfall (a.k.a Execution Cost), (d) Fill Rate (% of Trade Volume Achieved).

of the dark pool trades. We also notice a larger reduction in temporary impact, permanent impact and execution cost from more dark pool trading for the larger volume scenarios (such as $Scen_{250}$). This can be attributed to two factors. First, as the execution scenario volume increases, a larger quantity is being executed in the dark pool market and thereby higher cost savings. Second factor is the un-executed trades in the larger volume execution scenarios such as $Scen_{250}$. As can be seen from Figure 2(d), there is a reduction in the trade fill rate as we move from $Scen_{100}$ to $Scen_{250}$, especially while employing strategy $S_{30\%DP}$. This shows that there is limited liquidity available in the dark pool market and thereby attempting to execute large volumes would lead to non-executed trades and thereby a lower agent surplus. Thereby institutional traders need to balance the benefits of cost-efficient execution in dark pools with the higher risk of un-executed trades in dark pools.

4.1.3 Key Outcomes

- We show the ability of our ABM to estimate market impact of an institutional trader strategy under different TWAP strategy variants.
- We also show that as the TWAP strategy executes a larger portion of the trade in dark pool, it benefits from lower market impact and execution costs due to hidden nature of activity in the dark pool.
- We observe that the benefits of executing higher volumes in the dark pool plateau based on the execution scenario and leads to un-executed trades due to limited dark pool liquidity.

4.2 Impact of Pinging Agent Manipulation

In this section, we show the impact of pinging based market manipulation on market impact and execution costs incurred by institutional trading agents. We analyze the scenarios and conditions under which pinging is a profitable strategy.

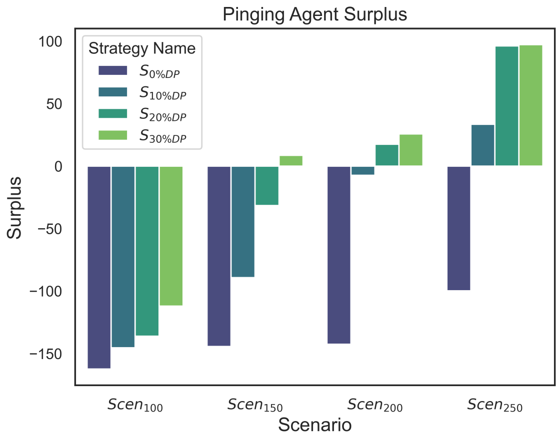

Figure 3: Pinging agent surplus under different execution scenarios and different TWAP strategies.

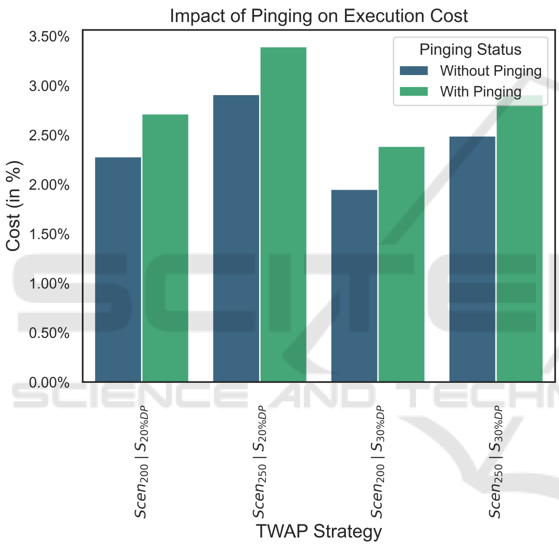

Figure 4: Execution cost impact caused by pinging agent when institutional trader adopts strategies $S_{20\%DP}$ and $S_{30\%DP}$, in the $Scen_{200}$ and $Scen_{250}$ execution scenarios.

4.2.1 Experimental Procedure

First, we use the same ABM setup as described in Sections 3.1-3.3. Second, we introduce an institutional trader agent into the market model under the same scenarios and TWAP strategy variants as used in Section 4.1. We also introduce a pinging agent (as described in Section 3.6) into the market environment. Finally, under each of these scenarios and strategies, we observe the emergent system dynamics, analyze the conditions under which the pinging agent is profitable and also understand its impact on execution costs.

4.2.2 Results and Analysis

First we analyze the conditions under which pinging based market manipulation is profitable by looking at the pinging agent profits (surplus) as shown in Figure 3. We can see that the profits accumulated by the pinging agent increases as the fraction of volume executed in the dark pool market increases, i.e., as we move from strategy $S_{0\%DP}$ to $S_{30\%DP}$ for a given scenario. We find that a larger volume executed in the dark pool corresponds to larger supply demand mismatches in the dark pool, thereby allowing the pinging trader to reliably detect the presence of a hidden large institutional order. The pinging agent is then able to use this reliable signal of dark pool buy orders to execute manipulative trades in the CDA market and profit from the subsequent upward market move. Based on the profit numbers show in Figure 3, we observe that the pinging agent is only able to stay profitable (surplus > 0) under certain market conditions. For example, under market scenario $Scen_{200}$, the pinging agent is only profitable when the institutional trading strategies $S_{20\%DP}$ or $S_{30\%DP}$ are deployed. This is because these scenario/strategy combinations with large volumes executed in dark pools provide the pinging agent a reliable hidden order signal.

Next, we analyze the impact of pinging activity on the execution costs of institutional traders. The execution costs for an institutional trader agent under some of the impacted scenario/strategy combinations is as shown in Figure 4. We can see that pinging causes a significant increase in execution costs for the institutional trader agent in scenarios $Scen_{200}$ and $Scen_{250}$ when the strategies $S_{20\%DP}$ and $S_{30\%DP}$ are deployed. For example, when $S_{30\%DP}$ strategy is deployed in $Scen_{250}$ scenario, there is an increase in execution cost from 2.49% to 2.90%. In some other scenario/strategy combinations such as under the $Scen_{100}$ scenario, the impact of pinging on execution costs is much smaller or negligible due to the pinging agent being unable to reliably detect hidden dark pool orders.

4.2.3 Key Outcomes

- We show that pinging is profitable mainly under significant supply demand imbalances in the dark pool. This is because of the higher reliability of hidden order signals.
- We also show that pinging based market manipulation is harmful to institutional traders since it leads to an increase in market impact and a subsequent increase in execution costs.

4.3 Strategic Response and Market Equilibrium

4.3.1 Experimental Procedure

First, we use the same ABM setup as described in Sections 3.1-3.3. Second, we compute the Nash equilibrium strategy adopted by institutional trader agent under each of the execution scenarios in Table 3 in the absence of pinging agents. Third, we compute the Nash equilibrium strategy adopted by both the institutional trading agent and the pinging agent (per Section 3.9). Finally, we compare the Nash equilibrium with and without the pinging agent to quantify the impact of pinging on execution cost of institutional traders.

4.3.2 Results and Analysis

First, we analyze the equilibrium market strategies played by the institutional trader agent in the absence of the pinging agent as displayed in Table 4. We see that in the scenarios $Scen_{100}$ and $Scen_{150}$, the institutional trader adopts the $S_{30\%DP}$ strategy which is the most cost effective strategy (as seen in Section 4.1). However, for scenarios with larger execution volumes $Scen_{200}$ and $Scen_{250}$, the trader adopts the $S_{20\%DP}$ and $S_{10\%DP}$ strategies respectively. This is because the $S_{30\%DP}$ strategy despite being the most cost-effective can lead to un-executed trades (as seen in Section 4.1). Next, we analyze the equilibrium market strategies played by the institutional trader agent and the pinging agent when they are both present in the market. As shown in Table 4, the pinging agent chooses to be inactive ('Idle') in scenarios $Scen_{100}$ and $Scen_{150}$ while its active in the other two scenarios. This is because the pinging agent makes negative surplus in the former two scenarios as a result of constantly pinging the market and not receiving any reliable signals. On the other hand, pinging agent makes positive surplus in scenarios $Scen_{200}$ and $Scen_{250}$ and stays active due to reliable hidden order signals.

The institutional trader has two main ways to respond to the actions of a pinging agent. It may either reduce its dark pool volume (by following a different strategy) and thereby stay under the radar of the pinging agent or it may choose to accept the negative cost impact of the pinging agent since reducing dark pool trading volume may increase costs even more. From Table 4, we see that the institutional trader plays the same strategies as in the market scenario without pinging, except when its in scenario $Scen_{150}$. In this scenario, the institutional trading agent switches from the most cost-effective strategy $S_{30\%DP}$ to the second most effective strategy $S_{20\%DP}$ to stay under the radar and avoid being manipulated by the pinging agent. The increased costs by switching to the second best strategy is overshadowed by the costs saved by evading the effects of pinging. Meanwhile, the institutional trader agent is unable to evade the presence of the pinging agent in scenarios $Scen_{200}$ and $Scen_{250}$ since the increased cost from pinging based manipulation is lesser than the cost of switching to a trading strategy with lower dark pool volume. Finally, we can see from Table 4, that pinging creates an increase in execution cost of 0.27%-0.48% of the overall trade value depending on the scenario. The only scenario that is unaffected by pinging is $Scen_{100}$, since the low execution volume is not conducive for the pinging agent.

4.3.3 Key Outcomes

- We show that the presence of pinging agents in the market can incentivize some institutional traders to reduce their volume executed in the dark pool market, thereby increasing their costs and market volatility, due the higher visibility of their trades.
- We also show that pinging agents do co-exist with institutional traders in the equilibrium state of market scenarios with high dark pool execution volume. Pinging agents profit at the expense of institutional traders by front-running their trades and leading to an increase in execution costs.

4.4 Market Implications and Regulation

The existence of dark pool pinging strategies has negative implications for market integrity. Since dark pools are mainly used by informed trading agents to hide their orders from the general market, pinging strategies that uncover these hidden dark pool orders undermine the purpose of dark pools. Dark pools with pinging activity no longer enable informed traders to execute their trades in a cost effective way and lead to information leakage (Mittal, 2008; Zhu, 2013). This could potentially lead to an erosion of trust and thereby reduced participation in dark pools. A reduction in dark pool participation could lead to reduced information acquisition, lower market price discovery and higher volatility (Ye et al., 2012).

Financial regulators have recognized the challenges caused by market manipulation activities like pinging and acknowledged the need for regulation in dark pools [2]. Improving transparency in dark pools while maintaining the hidden nature of trade execution could prove to be a crucial step towards combat-

[2] See https://www.forbes.com/sites/jonathanponciano/2021/08/04/sec-looking-closely-at-dark-pools-heres-what-they-are-and-why-reddit-traders-are-rallying/.

Table 4: Table shows the market equilibrium strategies played by Institutional trader agent with and without the presence of a pinging agent and the equilibrium pinging agent strategy when its present. The execution cost impact of introduction of a Pinging agent in different execution scenarios is displayed. The cost and impact are in % of the overall executed trade value.

		Pinging Strategy		Institutional Trader Strategy				Pinging Cost & Impact	
Pinging	Scenario	Idle	Active	$S_{0\%DP}$	$S_{10\%DP}$	$S_{20\%DP}$	$S_{30\%DP}$	Cost (in%)	Impact (in%)
Without	$Scen_{100}$			0	0	0	1	0.99%	
	$Scen_{150}$			0	0	0	1	1.47%	
	$Scen_{200}$			0	0	1	0	2.28%	
	$Scen_{250}$			0	1	0	0	3.30%	
With	$Scen_{100}$	1	0	0	0	0	1	0.99%	0%
	$Scen_{150}$	1	0	0	0	1	0	1.74%	0.27%
	$Scen_{200}$	0	1	0	0	1	0	2.71%	0.43%
	$Scen_{250}$	0	1	0	1	0	0	3.78%	0.48%

ing market manipulation. Besides transparency, there are concrete regulations that can be put in place to combat pinging. Imposing minimum dark pool order sizes could make it operationally expensive for pinging traders, thereby de-incentivizing them (Buti et al., 2017). Dark pool operators could also consider more robust market design options such as implementing randomized clearing with non-deterministic delays in the dark pool clearing process (Aquilina et al., 2021).

5 CONCLUSION

In this paper, we have proposed a novel incentive aware ABM of the financial markets with a dark pool, for investigating the impact of pinging on execution costs incurred by institutional traders. The key outcomes from our study are as follows:

- We show that our ABM can replicate market impact dynamics under various institutional strategies that split their trades between the CDA and dark pool. The market impact dynamics are in line with classical finance literature and we show that executing in dark pools is associated with lower execution costs and higher risk of non-execution.
- We propose a novel pinging agent for understanding the profitability of pinging under different market scenarios. We show that pinging is mainly profitable when there is significant supply demand mismatch in the dark pool. This is when the pinging agent can extract reliable signals of hidden large orders and profit from it.
- We show that the potential impact of pinging can incentivize institutional traders to reduce their dark pool activity to avoid being detected in some scenarios. Meanwhile, in other scenarios pinging agents can co-exist in the equilibrium with institutional traders leading to higher execution costs for the latter and poorer market price discovery.

There is plenty of scope for future work in the area of market manipulation analysis in dark pool markets using ABM. First, there is a need to model the incentives of background trader agents to understand which type of agents prefer dark pools and how this varies across market conditions. Second, there is a need to identify and test the potential of regulatory policies such as minimum order sizes and randomized clearing on combating market manipulation like pinging in dark pools. Third, there is need to identify more sophisticated pinging agent policies using reinforcement learning that may be more efficient at identifying large hidden orders. Finally, there is a need to ground ABM design with real world empirical data to produce more actionable insights.

ACKNOWLEDGEMENTS

This work was supported by the UKRI Centre for Doctoral Training in Safe and Trusted Artificial Intelligence [EP/S0233356/1].

REFERENCES

Almgren, R. and Chriss, N. (2001). Optimal execution of portfolio transactions. *Journal of Risk*, 3(2):5–39.

Aquilina, M., Budish, E., and O'Neill, P. (2021). Quantifying the high-frequency trading "arms race"*. *The Quarterly Journal of Economics*, 137(1):493–564.

Aquilina, M., Foley, S., O'Neill, P., and Ruf, T. (2024). Sharks in the dark: Quantifying hft dark pool latency arbitrage. *Journal of Economic Dynamics and Control*, 158:104786.

Bayona, A., Dumitrescu, A., and Manzano, C. (2023). Information and optimal trading strategies with dark pools. *Economic Modelling*, 126:106376.

Brinkman, E. and Wellman, M. P. (2017). Empirical mechanism design for optimizing clearing interval in frequent call markets. In *Proceedings of the 2017 ACM Conference on Economics and Computation*, EC '17, page 205–221, New York, NY, USA. Association for Computing Machinery.

Brogaard, J. and Pan, J. (2021). Dark pool trading and information acquisition. *The Review of Financial Studies*, 35(5):2625–2666.

Budish, E., Cramton, P., and Shim, J. (2015). The High-Frequency Trading Arms Race: Frequent Batch Auctions as a Market Design Response *. *The Quarterly Journal of Economics*, 130(4):1547–1621.

Buti, S., Rindi, B., and Werner, I. M. (2017). Dark pool trading strategies, market quality and welfare. *Journal of Financial Economics*, 124(2):244–265.

Buti, S., Rindi, B., and Werner, I. M. (2022). Diving into dark pools. *Financial Management*, 51(4):961–994.

Byrd, D., Hybinette, M., and Balch, T. H. (2020). Abides: Towards high-fidelity multi-agent market simulation. In *Proceedings of the 2020 ACM SIGSIM Conference on Principles of Advanced Discrete Simulation*, SIGSIM-PADS '20, page 11–22, New York, NY, USA. Association for Computing Machinery.

Chakraborty, T. and Kearns, M. (2011). Market making and mean reversion. In *Proceedings of the 12th ACM Conference on Electronic Commerce*, EC '11, page 307–314, New York, NY, USA. Association for Computing Machinery.

Chiarella, C. (1992). The dynamics of speculative behaviour. Working Paper Series 13, Finance Discipline Group, UTS Business School, University of Technology, Sydney.

Farmer, J. D., Patelli, P., and Zovko, I. I. (2003). The Predictive Power of Zero Intelligence in Financial Markets. Papers cond-mat/0309233, arXiv.org.

Gode, D. K. and Sunder, S. (1993). Allocative efficiency of markets with zero-intelligence traders: Market as a partial substitute for individual rationality. *Journal of Political Economy*, 101(1):119–137.

Ho, T. and Stoll, H. (1981). Optimal dealer pricing under transactions and return uncertainty. *Journal of Financial Economics*, 9(1):47–73.

J. Doyne Farmer, Austin Gerig, F. L. and Waelbroeck, H. (2013). How efficiency shapes market impact. *Quantitative Finance*, 13(11):1743–1758.

Karvik, G.-A., Noss, J., Worlidge, J., and Beale, D. (2018). The deeds of speed: an agent-based model of market liquidity and flash episodes. Bank of England working papers 743, Bank of England.

Kazil, J., Masad, D., and Crooks, A. (2020). Utilizing python for agent-based modeling: The mesa framework. In *Social, Cultural, and Behavioral Modeling*, pages 308–317, Cham. Springer International Publishing.

Kratz, P. and Schöneborn, T. (2014). Optimal liquidation in dark pools. *Quantitative Finance*, 14(9):1519–1539.

Lin, T. C. W. (2017). The new market manipulation. *Emory Law Journal*, 66:1253. Temple University Legal Studies Research Paper No. 2017-20.

Liu, B., Polukarov, M., Ventre, C., Li, L., Kanthan, L., Wu, F., and Basios, M. (2022). The spoofing resistance of frequent call markets. In *Proceedings of the 21st International Conference on Autonomous Agents and Multiagent Systems*, AAMAS '22, page 825–832, Richland, SC.

MacKenzie, D. (2019). Market devices and structural dependency: The origins and development of 'dark pools'. *Finance and Society*, 5(1):1–19.

Majewski, A., Ciliberti, S., and Bouchaud, J.-P. (2018). Co-existence of Trend and Value in Financial Markets: Estimating an Extended Chiarella Model. Papers 1807.11751, arXiv.org.

Martínez-Miranda, E., McBurney, P., and Howard, M. J. W. (2016). Learning unfair trading: A market manipulation analysis from the reinforcement learning perspective. In *2016 IEEE Conference on Evolving and Adaptive Intelligent Systems (EAIS)*, pages 103–109.

Mittal, H. (2008). Are you playing in a toxic dark pool? In *The Journal of Trading*.

Mo, S. Y. K., Paddrik, M., and Yang, S. Y. (2013). A study of dark pool trading using an agent-based model. In *2013 IEEE Conference on Computational Intelligence for Financial Engineering & Economics (CIFEr)*, pages 19–26.

Obizhaeva, A. A. and Wang, J. (2013). Optimal trading strategy and supply/demand dynamics. *Journal of Financial Markets*, 16(1):1–32.

Ponomareva, N. and Calinescu, A. (2014). *Revisiting Agent-Based Models of Algorithmic Trading Strategies*, pages 92–121. Springer Berlin Heidelberg, Berlin, Heidelberg.

Said, E. (2022). Market Impact: Empirical Evidence, Theory and Practice. Working Papers hal-03668669, HAL.

Said, E., Ayed, A. B. H., Husson, A., and Abergel, F. (2017). Market impact: A systematic study of limit orders. *Market Microstructure and Liquidity*, 03(03n04):1850008.

Stenfors, A. and Susai, M. (2021). Spoofing and pinging in foreign exchange markets. *Journal of International Financial Markets, Institutions and Money*, 70:101278.

Wah, E., Hurd, D., and Wellman, M. (2015). Strategic market choice: Frequent call markets vs. continuous double auctions for fast and slow traders. *EAI Endorsed Transactions on Serious Games*, 3(10).

Wellman, M. P. (2006). Methods for empirical game-theoretic analysis. In *Proceedings of the 21st National Conference on Artificial Intelligence - Volume 2*, AAAI'06, page 1552–1555. AAAI Press.

Ye, L. (2024). Understanding the impacts of dark pools on price discovery. *Journal of Financial Markets*, 68:100882.

Ye, M., Yao, C., and Gai, J. (2012). The externalities of high frequency trading. *SSRN Electronic Journal*.

Zhu, H. (2013). Do dark pools harm price discovery? *The Review of Financial Studies*, 27(3):747–789.