## The Role of Stop-Loss Orders in Market Efficiency and Stability: An Agent-Based Study

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- Keywords: Market Simulation, Agent-Based Simulation, Limit Order Book, Stop-Loss Cascade, Market Manipulation.
- Abstract: Stop-loss orders can have large and ranging effects on the behaviours and outcomes for participants within financial markets. We develop and demonstrate an approach to studying the effect of stop-losses on price dynamics within a financial market. Using our high-fidelity agent-based market simulator that draws on historical limit order book data, we illustrate that the introduction of stop-loss orders leads to volatility, creating the potential for *stop-loss cascades* that result in large price movements. We study a market containing an agent that is able to trigger such events and profit from them. We indicate that the structure of the stop-loss order book may be used by such an agent to inform trading decisions and to generate volatility within markets for their benefit. Finally we demonstrate how the agents closing strategy effects both the profitability of the agent, as well as the price trajectory of the market.

## **1 INTRODUCTION**

Stop-loss orders are a common risk management tool used by traders in financial markets to minimise losses. They allow the automatic closing of a position and use a similar mechanism as a margin call, to limit investors' losses. If the price of the traded good drops below a given threshold, they will execute a sell in order to cover their position, realising a loss. However, stop-loss orders can also amplify market volatility and lead to large price movements.

Stop-loss orders are widely used and their use is common practice among professional traders (Vytelingum, 2006). They impact market dynamics and are of immense interest in the study of markets and agent strategies. We approach the study of stoploss orders and consequent price volatility, including cascades, using agent-based market simulation. Our agent-based framework enables the study of market effects. Our simulation approach also facilitates the study of individual agent strategies. Here, in particular, we examine strategies that attempt to trigger and profit from price volatility.

To the best of our knowledge, we are the first to develop an agent-based simulation to investigate how stop-loss orders can affect agent outcomes and price volatility.

## 2 PRELIMINARIES

**Continuous Double Auction (CDA)** The CDA is a common market mechanism used to store and match orders, thus facilitating trading. In a CDA, there is a fixed-duration trading period during which buy orders ("bids") and sell orders ("asks") may be submitted. When bids and asks are compatible in terms of price and quantity, a trade is executed. If new orders are not compatible, the order is placed in the Limit Order Book (LOB) for future execution (Vytelingum, 2006).

#### **Limit Order Book**

The LOB maintains a list of bids and asks (with their associated price level and quantity) that have been submitted to the exchange. When an order is submitted it is initially checked against existing orders within the LOB. Orders that may be filled are executed, whilst those that cannot be matched will be added to the LOB.

## **Order Types**

Importantly we distinguish two main order types that can be used in a CDA: *limit orders* and *market orders*. Limit orders specify the price at which a trade is made. They will only be executed if there is an

#### 280

Liston, P., Gretton, C. and Lensky, A. The Role of Stop-Loss Orders in Market Efficiency and Stability: An Agent-Based Study. DOI: 10.5220/0012371400003636 Paper published under CC license (CC BY-NC-ND 4.0) In Proceedings of the 16th International Conference on Agents and Artificial Intelligence (ICAART 2024) - Volume 1, pages 280-288 ISBN: 978-989-758-680-4; ISSN: 2184-433X Proceedings Copyright © 2024 by SCITEPRESS – Science and Technology Publications, Lda. opposing order that satisfies this price requirement. Limit orders that are not executed remain in the LOB. Market orders, in contrast, are executed immediately and will pay the best available price for the given quantity. Market orders do not enter the LOB if they are partially or wholly unfulfilled.

#### Stop-Loss Orders

Stop-loss orders, a sub-type of market and limit orders, allow a market participant to buy or sell a good if its value reaches a certain trigger price. Often used to close a position these orders are typically used in an attempt to limit an investors' losses. If the price of the traded good reaches the given threshold, the trader's order is executed (usually as a market order), covering their position.

Typically, exchanges maintain two separate order books. A LOB, visible to all traders in a market, and a stop-loss order book, visible only to the exchange. This separation and opacity of the stop-loss order book are justified and necessary to help prevent *snowball* effects and stop-loss cascades, as have been studied in (Osler, 2005).

#### Stop-Loss Cascade

A *stop-loss cascade* is a rapid, self-reinforcing price movement or "price cascade" catalyzed by the triggering of stop-loss orders. In a stop-loss cascade, an asset moves in a particular direction, triggering a small number of stop-loss positions to be activated. This execution subsequently moves the price further in the given direction, triggering further stop-loss orders, and so on.

## **3** SIMULATOR

Using a method similar to (Spooner et al., 2018; Liston et al., 2022; Liston et al., 2023) we developed a market simulator for a single asset. Relying on reconstruction from historical data, our approach has been shown to be highly realistic, and makes minimal assumptions about the market.

## 3.1 Data

Historical trade data was obtained from the cryptocurrency exchange Binance. We use the currency pair Bitcoin/Tether (BTCUSDT). This choice was motivated by the desire to simulate a well-known and heavily traded market. Furthermore, it has been shown in (Alexander et al., 2021) that due to market arbitrage and a high correlation of Bitcoin price with prices of altcoins, BTCUSDT traded on Binance is the main source of volatility and price movement that flows to all other related markets and exchanges. Hence, this data should reliably allow us to make general statements about the LOB structure and dynamics, which should also be able to be generalized to other markets and exchanges.

Tick-level data was used to guide the simulation, with each entry representing a single trade.

A trade record consists of: trade ID, time, price, quantity, quote quantity, and direction.

LOB data, containing 20 levels on both Bid and Ask sides (price levels and quantity), was also obtained and updated when a new order was added or removed from the LOB. All data used was from November 2021.

### 3.2 Simulator

We simulate a financial market using a hybrid of real order book data and synthetic trades placed by agents.

Important within the system is the timing, size and direction of trades placed.

The simulator utilises a real historical order book to guide price levels within the market, while Zero-Intelligence (ZI) agents place market orders at previously observed tick intervals. These market orders subsequently "shift" the order book, such that the agents' orders drive the direction of the market, while the limit order book determines the size of the move and the structure of the market. Agents determine their trade size by sampling from a distribution constructed from historical trades.

#### Limit Order Book Extension

Given that the available LOB data contains only the top 20 price levels, agents' market orders can exceed the depth of the real order book. This may occur when an agent's order size is very large, or in particular when we investigate the injection of a *shock*. To address this problem, we developed a series of multilayer perceptron (MLP) models to approximate the proceeding 480 levels. These are recursively called when the limit order book depth is not sufficient to fill the agents' market orders, extending the book indefinitely until the agent's order may be completely filled.

#### Stop-Losses

We perform simulation experiments in markets both with and without stop-loss orders. In simulations where stop-loss orders are permitted, a separate stoploss order book is created and agents may place stoploss orders in addition (and in opposition) to their market order. To determine the price of the stop-loss order a log-normal distribution was used, sizing the stop-loss difference/level inversely from the agents' trade size (Acar and Toffel, 2001).

Stop-loss orders remain in the stop-loss order book until their trigger price is reached, exceeded, or they are cancelled. Before the selection of an agent and execution of a market order, the market price is checked against all orders within the stop-loss book. Any order within the stop-loss book that has a trigger price that has been reached is then activated. The order is triggered, executed and hence causes the LOB to shift. After the execution of a single stop-loss order, the LOB is shifted accordingly, and the stop-loss book is checked again to determine if the trigger price of any other orders has been reached. Once this process ends, standard order placement is resumed.<sup>1</sup>

It is important to note that market orders take execution precedence over stop-loss orders. Hence, while a market order is being executed no stop-loss orders can be triggered. After the market order is *completely* filled the stop-loss order book is reviewed, and stop-loss orders that have reached their trigger price are executed.

#### Limitations

This method of simulation makes limited assumptions and has previously been shown to be highly accurate (Spooner et al., 2018), however, it should be noted that agents' actions do not affect the structure of the limit order book. Agents' trades alter the price of the market and shift the limit order book price levels, but do not result in the addition or removal of orders from the limit order book.

Additionally, despite the efforts that have been made to extend the LOB for cases where agents' order size exceeds the depth of the book. This extension by its nature may not always truly replicate reality.

However, as noted in (Torii et al., 2015) the aim of this study is to arrive at a qualitative description of the mechanisms and influences of stop-losses and stop-loss agent strategies, not to reproduce the characteristics of real markets.

## 3.3 Simulator Verification

To verify the ability of the simulator to create realistic price dynamics we first visually inspect samples. Figure 1 shows the price dynamics for 50 simulations containing 100,000 trades on 11/20/2021. We observe similar price patterns emerge and that the simulator produces plausible realisation and price paths.

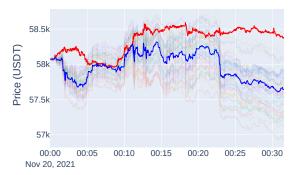


Figure 1: Simulated price dynamics for 50 Simulations of 100,000 trades for BTCUSDT on 11/20/2021. Blue solid lines represent the average simulated price, and red represents the observed (real) price from historical ticks. The faded lines show the various trials.

Further, we utilise standard procedures stipulated in (Cont, 2001) to examine the stylized facts of the market and compare them to those observed in reality for the same dates. Note that some stylized facts are inherent features of the simulation approach we have pursued. Because the limit order book used to guide the price was taken from the observed data, it is not necessary to validate the statistical properties of the structure of the limit order book. Similarly, such interrogation is not required for trade sizing as we sample from historical data. Additionally, given that all ZI trades are aligned to execute at times when real trades occurred within the historical data, no consideration for trade arrival time is necessary.

Our validation work is focused on the statistical properties of simulated returns. We consider the logarithmic-returns of the price, focusing on the skew, kurtosis, volatility autocorrelation, and price autocorrelation. Table 1 illustrates that the stylized facts of the simulation fall within the range for all measurements undertaken, indicating that simulations can largely emulate realistic price dynamics. While we do note that there is generally lower autocorrelation for both volume and log-returns for simulated markets, this is likely due to the use of ZI agents. Although real markets may exhibit long-range dependency of trade directions, the purely random trade directions generated by the ZI agents deviate from this market characteristic and is a familiar limitation of this simulation approach. This may have small impacts at the granular level, however, it should not materially affect the broader outcomes of this study.

## **4 EXPERIMENTAL EVALUATION**

We have performed 3 major experiments. Initially, we create a market that allows stop-loss orders. We

<sup>&</sup>lt;sup>1</sup>When executing stop-loss orders, no additional stoploss orders may be placed.

Table 1: Aggregated stylised facts at tick level, computed over 50 trials of 100,000 ticks for each day between 11/01/2021 and 11/30/2021. Compared to the stylised facts observed for 100,000 ticks on each day between 11/01/2021 and 11/30/2021. We report the mean, maximum and minimum observed values.

	Skew	Kurtosis	Return Autocorr.	Volatility Autocorr.
Observed	3.09 (-1.04-5.43)	1,007 (523–1888)	-2.64(-3.200.63)	-6.50(-0.61-7.0)
Simulated	0.22 (-2.30-1.50)	1,186 (302–1.144)	-8.40(-6.20-0.29)	-17.0 (-12.00.54)

analyse the impact and compare volatility between markets with and without stop-loss orders. We then construct an agent that inputs large shock orders into these markets and observe its effect. Finally, we investigate closing strategies that this agent may use and how these affect both the agents' profitability, as well as the market as a whole.

#### 4.1 Introduction of Stop-Loss Orders

In this experiment, our aim was to observe the effects of the market with stop-losses, noting their effect on price path formation and volatility. This is done by measuring the variance in logarithmic returns, as given by:  $\sigma^2 = \frac{1}{N-1} \sum_{t=1}^{N} (R_t - \bar{R}_t)^2$ . Here,  $\sigma^2$  is the variance/volatility,  $R_t$  is the log return at time t,  $\bar{R}_t$  is the mean of all log returns for the given period, and N denotes the number of observations considered (Poon and Granger, 2003).

We enable the execution of stop-loss orders as specified previously and consider two scenarios. One where stop-losses are not permitted, and the other where stop-losses are permitted. This experiment is run 50 times for each date within 11/01/2021 - 11/30/2021. The resulting volatility measures are shown in Table 2, and Figure 2 displays the market output for the first 100,000 ticks on 11/20/2021.

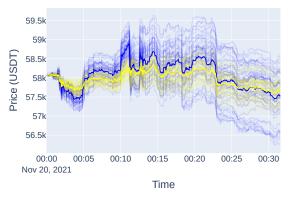


Figure 2: Price dynamics for the without stop-loss orders (yellow) and with stop-loss orders (blue) for 20/11/2021.

The volatility of the market is increased when stop-loss orders are introduced (Table 2). In particular, an approximate 27% increase in mean volatility and the minimum volatility was observed in the market containing stop-losses exceeding the maximum volatility observed when a market did not contain any stop-loss orders. This indicates a clear distinction that the addition of stop-loss orders has the potential to have a large impact on volatility.

Further, we visualise the effects of the addition of stop-loss orders in Figure 2. We observe both an increase in volatility throughout the simulation and the generation of moments of singular large volatility/price movements (shocks), most notably around the 10 minute mark.

The presence of price shock moments indicates the execution of sequential stop-loss orders. As such, this suggests an agent with sufficient capital may be able to submit a large order to create a market shock, and thus trigger this sequential execution and hence a stop-loss price cascade.

#### 4.2 Triggering Stop-Loss Cascades

Having shown that markets with stop-loss orders may experience movements of large price volatility, we seek to introduce an agent that may induce such stoploss cascade events. We construct an agent that places a large order that acts as an impulse or a shock to the market. Drawing inspiration from (Balch et al., 2019), the impulse is sized to correspond to 500% of the total volume within the limit order book for the given time. The agent then injects this impulse order either in an upward (buy) or downward (sell) direction, consuming the entire volume within the order book and triggering stop-loss orders in that direction.

We compare the market's reaction when the agent submits an impulse with/without stop-losses orders in the simulated market. We also compare the outcomes of this shock when placed as a buy or a sell. We perform 50 trials under each computational set-up, with each trial containing 100,000 ticks, for the date of 11/21/2021. Figure 3 displays the visual impact these shocks had on the market, and Table 2 shows the volatility observed for each experimental set-up.

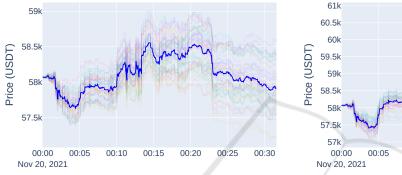
Comparing Figure 3(c) with Figure 3(d). We note that when a shock is injected into the market the reaction within the market that does not contain stop-loss orders is relatively muted compared to the market that allows stop-loss orders. This is further supported by

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(a) Down shock injected, stop-loss orders are not permitted.



00:00 00:05 00:10 00:15 00:20 00:25 00:30

(c) Upward shock injected, stop-loss orders not permitted.

(d) Upward shock injected, stop-loss orders are permitted.

Figure 3: Comparison of price dynamics when stop-loss orders are permitted (b, d) and not permitted (a, c). When a downward (a, b) or upward (c, d) shock was injected.

Table 2: Volatility of returns for various market conditions	. 50 Simulations of 100,000 trades for BTCUSDT on $11/20/2021$ .

PLIEI	No-SL,No Shock	No-SL,Up	No-SL,Down	SL,No Shock	SL,UP	SL,Down
Volatility	1.68	2.14	3.03	2.76	6.20	9.79
	(1.63-1.74)	(2.06-2.21)	(3.00-3.08)	(2.53-3.07)	(4.47-9.38)	(5.57-12.18)
Difference	0	+0.46	+1.35	+1.08	+4.52	+8.11

examining Table 2, which shows a clear and large increase in market volatility when a shock is present in a market with stop-losses as opposed to a market without stop-losses. With volatility increases of 6.76 and 4.06 in the downward and upward direction respectively. This once again shows the effect stop-losses have on price path generation, volatility and the market as a whole. With increased volatility and largely different price outcomes.

Considering the impact of shocks when placed in a downward (sell) and upward (buy) direction, we observe differences in the magnitude of reaction and price path deviation between Figure 3(*b*) and Figure 3(*d*). Notably, despite both orders being the same size, the shock submitted in the downward direction caused significantly larger price deviation ( $\sim$  \$3,000) than the shock in the upward direction ( $\sim$  \$1,000). Additionally from Table 2 we see that when this shock was submitted in the downward direction, the change in market volatility when injected into the stop-loss market had a much larger effect on market volatility (+6.76) compared to when it was submitted in the upward direction (+4.06). These results indicate that the structure of both the limit and the stop-loss order books are likely to play a large role in determining the size of the impact that large orders may have.

While we note that both the limit and stop-loss order books are likely to play a role in determining the outcomes of shock events, we consider the difference in volatility from the baseline that is generated. As seen in Table 2, while the introduction of shock events significantly increases volatility ( $\pm 1.35$  and  $\pm 0.46$ ) for downward and upward shocks, respectively, the increase in volatility due to a downward shock with the presence of stop-losses far exceeds that of the upward shock ( $\pm 8.11$  and  $\pm 4.52$ ). This indicates that the stop-loss order book plays a larger role in the impact of shocks. Hence, we suggest that the structure of the stop-loss order book provides vital information to inform agents' ability to trigger cascade events, particularly to maximise their return.

## 4.3 **Position Closing**

We have shown that the direction in which an agent attempts to cause a price cascade affects the price movement within the market and hence the profit an agent may obtain. Given the size of the agent's position it is also vitally important, both for the agent and for the market as a whole, to study how the agent closes their position.

We experiment with 3 strategies that the agent may use to close their position. We examine how this affects the agent's profit, as well as observe how this alters the price path observed within the market.

- 1. *Buy and hold*: An agent holds and receives a "marked to market" value of their shares at the conclusion of the simulation period. (Assume the agent closes their position without *slippage*.)
- 2. *Single Trade Closure*: An agent waits a set period *t* then **fully** closes their position. This ensures the agent's closing share balance is equal to their opening balance.
  - In our implementation the agent conducts a single order, 1,000 ticks after their initial large order.
- Spread Trade Closure: An agent makes multiple

   (n) trades, to close out their position and return to
   their initial share balance over time t.
   In our implementation, the agent conducts 10
   trades of equal size over the proceeding 10,000
   ticks after their initial large order.

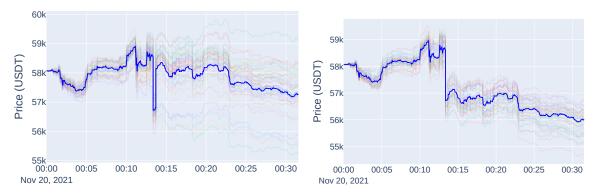
Each of the strategies was tested with both an upward (buy) and downward (sell) shock. Both conditions were tested with 50 simulations for 100,000 ticks on the date of 11/21/2021. Figure 4, and Figure 3 (*b*) and (*d*) display the visual impact these strategies. While Table 3 shows the profit generated by each strategy, and Table 4 displays the market volatility for each experimental set-up.

We once again observe a difference in shock size between the buy/sell experiments. We therefore highlight the importance of the shock direction on the size of the cascade. This is shown both visually in Figure 4 and numerically by the increase in volatility noted in Table 4. Together this suggests that the structure, and likely the skew of the stop-loss order book largely contributes to the size of the cascade and that the existence of support/resistance has the potential to mute the effect of the shock. Therefore we hypothesise that knowledge of stop-loss order sizes and locations could be a key determinant in the success of such shock agents.

When considering the profitability of the agent we see that both the direction of the agent's trade and the closing strategy employed significantly alter its outcome. If an agent may only utilise a buy and hold strategy it is most advantageous to create a downward shock (\$2,210,000 vs. -\$2,530,000), and in fact the agent loses money if it initiates an upward movement. However, when undertaking either of the other strategies (single trade closure or spread trade closure) it is more profitable for the agent to cause an upward price movement (\$2,060,000 & \$2,140,000 for upward shocks compared to, \$98,100 & \$525,000 for downward shocks). This dichotomy highlights both that the closing strategy of the agent, and also that structure of the stop-loss book are vitally important in informing the agent's decision if it seeks to gain a profit. By examining Figure 3(b) it is possible to see why this effect may occur. When the agent undertakes the strategy of buy and hold it forces the price in a direction, however, if the agent waits too long to close it's trade, it allows time for the price path to progress and gives other agents within the simulation more of chance to influence the price progression. However, if the agent fully closes their trade within a smaller period of time, it is able to take advantage of the power it exerted over the market. This is illustrated by the single trade closure and spread trade closure strategies. In both cases, the agent closes its trade in a timely fashion after exerting control over the market. Although, in the case of the single trade closure the agent causes a "whiplash" effect within the market. Spiking the price almost as far in the opposite direction from its original trade, and diminishing the profit the agent generated. Whereas the spread trade closure strategy allows the agent sufficient time to minimise this whiplash effect, whilst also enabling it to close its position within a reasonable time allowing it to benefit from its previous price altering efforts.

Given this propensity to create whiplash effects within the market, it is interesting to examine the effects of these strategies on the volatility of the market as a whole. Table 4 describes the volatility of each scenario. Interestingly we see that when we compare the *buy and hold* closing strategy with *spread trade closure* strategy the level of volatility is very similar (within ~ 2%). Meanwhile, the *single trade closure* strategy results in overall volatility that is ~ 25% larger than *buy and hold*. This, once again emphasises the impact of the closure strategy, while also indicating that the triggering of stop-loss orders has a part to play in this. The single trade method is likely to reactivate newly placed stop-loss orders.

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(a) Downward shock injected, position closed in a single trade. (b) Downward shock injected, position closed incrementally.



(c) Upward shock injected, position closed in a single trade. (d) Upward shock injected, position closed incrementally.

Figure 4: Comparing price path effects for agents closing positions (a, c) immediately, and (b, d) incrementally. Under downward (a, b) and upward (c, d) shock conditions.

Table 3: Profits of Shock agent (in US Dollars) under varying shock direction and position closing strategy. 50 Simulations of 100,000 trades for BTCUSDT on 11/20/2021.

Shock	Buy & Hold	Single Trade Closure	Spread Trade Closure
Up	$-253 \times 10^4 \; (-273 - 210)$	$206 \times 10^4 (196-250)$	$214 \times 10^4 (196-234)$
Down	$221 \times 10^4 (196-240)$	$9.81 \times 10^4 \ (2.2-15.6)$	$52.5 \times 10^4 \ (23.5 - 75.8)$

In all, this simulation case study suggests that an agent can utilise stop-loss knowledge to create a more informed strategy to generate profit. While regular exchanges are prohibited by the Securities Exchange Commission (SEC) from utilising this insider information to trade against their clients, this is not the case for Cryptocurrency exchanges. This allows exchanges to obtain an informational advantage to trade against their users. Hence, opening up the possibility of exchanges orchestrating events similar to those shown in Figure 4 for their gain.

## 5 RELATED WORK

Agent-based simulations have risen in popularity over recent years. Their ability to conduct A/B testing and analyse events that may not have occurred historically

make them an almost ideal test-bed to understand the effects of regulation or rule changes, the performance of trading algorithms, and the disturbance of market conditions that have not been previously observed (Mizuta, 2016). As such Agent-based market simulations have contributed to analysis of price variation limits (Todd et al., 2016), whether short-selling regulations could aid in the prevention of bubbles and crashes (Yeh and Yang, 2010; in't Veld, 2016; Xiong et al., 2022), as well as the impact of tick sizes (Yagi et al., 2010), circuit breakers (Kobayashi and Hashimoto, 2011) and many other regulatory questions. Agent-based simulators have also been used to discover and test new trading regimes, and to understand the effects they may exhibit on markets. Notably, testing regime identification and trading policies (Amrouni et al., 2022); determining and mimicking agents' strategies (Mahfouz et al., 2021); and in-

Table 4: Market volatility for varying shock direction and closure strategies. 50 Simulations of 100,000 trades for BTCUSDT on 11/20/2021.

Shock	Buy & Hold	Single Trade Closure	Spread Trade Closure
Up	6.20 (4.40–9.33)	7.85 (5.47–11.23)	6.14 (4.47–9.38)
Down	9.79 (5.57–12.18)	12.34 (6.91–14.91)	9.98 (5.88–11.08)

vestigating methods for evaluating trading strategies (Balch et al., 2019).

#### A fundamental building block of agent-based simulation is of course the agents. Early market simulation relied solely on the concept of Zero-Intelligence (ZI) agents. First coined by Gode in 1993 (Gode and Sunder, 1993), these baseline ZI agents are a family of automated agents that submit random BID and ASK orders. ZI agents and their variations have formed the basis for many investigations into agent behaviour and market properties. For example, ZI agents were used by (Bollerslev and Domowitz, 2018) to analyze the structural impact of restricting the maximum depth of an order book. In (Duffy and Unver, 2006) they are used near-ZI agents to study asset price bubbles and crashes. Such agents also feature broadly in markert simulations when studying more complex agents adjacent to these in the exploration of market phenomena (Wang and Wellman, 2017; Byrd et al., 2020).

The concept of stop-loss cascades is not a new idea and has been commonly observed within FOREX markets. Osler (2005) provides evidence of self-reinforcing price movements or "price cascades" catalyzed by stop-loss orders. While (Noertjahyana et al., 2020) proposes a trading strategy that takes advantage of such cascading events to generate profit. Further, they have shown to be especially common in cryptocurrency markets (Machowski, 2021).

#### 6 CONCLUSION

In this paper, we have performed 3 major experiments. Initially, we created a market that allowed stop-loss orders. We compared and showed that the introduction of stop-loss orders increases generalised price volatility, as well as increasing the risk of large price movements. Further, we constructed an agent that submitted large (shock) orders and triggered stoploss cascades. We illustrated that the direction of these orders plays an important role in the size of the cascade and the market reaction. Finally, we demonstrated the impact the agent's closing strategy has both on its profit, as well as the market's price evolution. Illustrating that a slower re-accumulation strategy leads to more reliable returns and less volatility within the market.

#### **Future Work**

We focused on the impact of a single shock size on the market. It would be interesting to study how the size of the shock affects the market's response, and perform experiments similar to (Balch et al., 2019). Particularly, to investigate if large shocks result in new steady price levels being reached, and how the size of the stop-loss cascade and thus the movement away from previously placed stop-loss orders then affects the continuing market, or if in fact, smaller shocks simply see a return to previous price levels.

Further, our agent did not consider the structure of the stop-loss order book when placing its orders. A deeper analysis of the structure of the stop-loss order book and its effect on the size and the resulting price movements may greatly aid in understanding stop-loss cascades as a phenomenon.

Additionally, this information could be used to determine the optimal size and timing of the shock. Either leading to improved hand-crafted agents, or the application of reinforcement learning to create more profitable agents that drive these market effects.

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