Forecasting of Volatile Assets using Artificial Swarm Intelligence

Louis Rosenberg
Unanimous AI
San Francisco, USA
louis@unanimous.ai

Gregg Willcox
Unanimous AI
San Francisco, USA
gregg@unanimous.ai

Martti Palosuo
Judge Business School
University of Cambridge
Cambridge, UK
prm50@jbs.cam.ac.uk

Ganesh Mani
Carnegie Mellon University
Pittsburgh, USA
ganeshm@andrew.cmu.edu

***Abstract*— Swarm Intelligence (SI) is a natural process that has been shown to amplify decision-making accuracy in many social species, from schools of fish to swarms of bees. Artificial Swarm Intelligence (ASI) is a technology that enables similar benefits in networked human groups. The present research tests whether ASI enables human groups to reach more accurate financial forecasts. Specifically, a group of MBA candidates at Cambridge University was tasked with forecasting the three-day price change of 12 highly volatile assets, a majority of which were *cult* (or *meme*) stocks. Over a period of 9 weeks, human forecasters who averaged +0.96% ROI as individuals amplified their ROI to +2.3% when predicting together in artificial swarms (p=0.128). Further, a $5,000 bankroll was managed by investing in the top three buy recommendations produced each week by ASI, which yielded a 2.0% ROI over the course of the 9-week study. This suggests that swarm-based forecasting has the potential to boost the performance of financial traders in real-world settings.**

Keywords—Artificial Swarm Intelligence, Swarm Intelligence, Human Forecasting, Financial Forecasting, Investing, Group Forecasting, Cult Stocks, Meme Stocks, Collective Intelligence, Wisdom of Crowds, Human-Machine Teaming.

I. Introduction

It is well known that groups of forecasters can outperform individuals by aggregating estimates using statistical methods [1-3]. Often called the Wisdom of Crowds (WoC) or Collective Intelligence (CI), this phenomenon was first observed over a century ago and has been applied to many fields. The most common methods involve polling human groups and then aggregating their input as a simple or weighted mean [4].

Recently, a new method has been developed that is not based on aggregating input from isolated individuals but involves synchronous groups of forecasters working together as real-time systems. Known as Artificial Swarm Intelligence (ASI) or Swarm AI, this method has been shown in numerous studies to significantly increase the accuracy of group forecasts [5-13].

In a recent study at the Stanford University School of Medicine, groups of doctors were asked to review chest X-rays and predict the likelihood that each patient had pneumonia. When working together in artificial swarm, diagnostic errors were reduced by over 30% [14]. In another study, groups of financial traders were asked to predict common market indicators including the price of gold, oil, and the S&P 500. Results showed a 36% increase in forecasting accuracy when participants used ASI as compared to traditional methods [20].

While prior studies have shown ASI to significantly amplify the group accuracy in controlled settings, the present work assesses whether swarm-based forecasting of highly volatile assets (mostly so-called *cult* or *meme* stocks), achieves similar improvements. To address this, a nine-week pilot study tasked a group of MBA candidates at Cambridge University with making weekly forecasts of 12 high-volatility assets, comparing individual forecasts to swarm-based predictions. Performance was also compared to traditional *Wisdom of Crowd* methods.

II. Background

A. Swarm Intelligence (SI)

The decision-making process that governs honeybee swarms has been researched since the 1950s and has been shown at a high level to be quite similar to decision-making in neurological brains [15,16]. Both employ populations of simple excitable units (i.e., neurons and bees) that work in parallel to integrate noisy evidence, weigh competing alternatives, and converge on decisions in real-time. In both brains and swarms, outcomes are arrived at through competition among groups of excitable units. In honeybees, this enables hundreds of scout bees to collect information about their local environment and then deliberate in synchrony, converging on a single optimal decision [17-20].

In the natural world, swarming organisms establish real-time feedback loops among group members. To achieve this among groups of networked humans, ASI technology allows distributed users to form closed-loop systems moderated by swarming algorithms [5-9]. The goal is to enable groups of distributed users to work in parallel to (a) integrate noisy evidence, (b) weigh competing alternatives, and (c) converge on decisions in synchrony, while also allowing all participants to perceive and react to the changing system in real-time, thereby closing a feedback loop around the full population of participants.

B. Swarm Software

The software used to enable ASI in this study is called the Swarm® platform from Unanimous AI and is shown in Figure 1. Using this software, groups answer questions in real time by collaboratively moving a graphical puck to select among a set of answer options. Each participant provides input by moving a graphical magnet to pull on the puck, thereby imparting their personal intent on the system as a whole. The input from each user is not a discrete vote, but a stream of time-varying vectors.

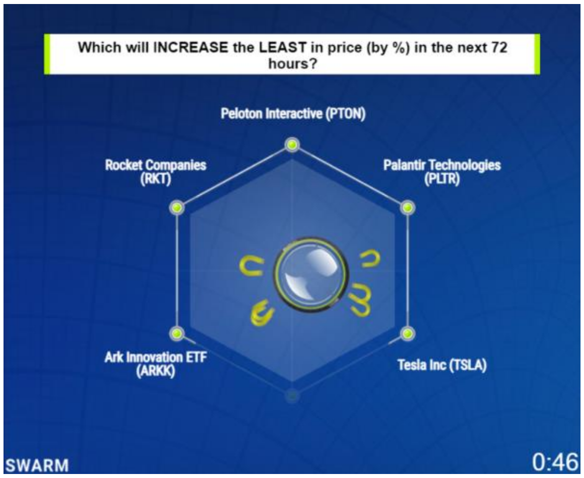

Fig. 1. Users engaging Swarm software to rank assets.

Because all users can adjust their intent continuously in real-time, the puck moves based on interactions among all members, empowering the group to converge in synchrony. Participants must continuously update their input throughout the real-time process or lose their influence over the outcome. This enables the intelligence algorithms to continuously monitor the changing behaviors of all members, modulating the aggregation. Figure 2 shows an example of the underlying human behaviors. More details on the Swarm software can be found in [21, 22].

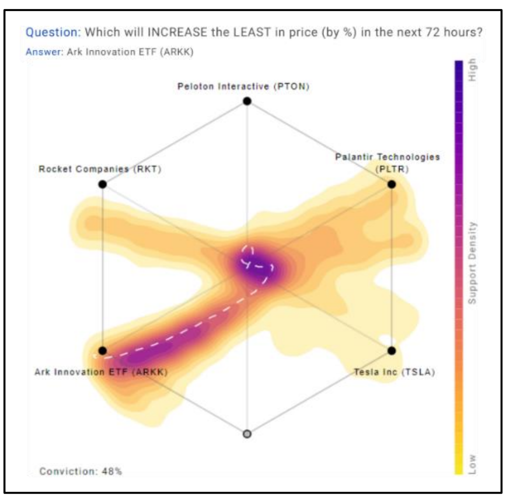

Fig. 2. Behavioral plot of the real-time decision making process. Darker areas convey higher conviction. The dotted line shows the puck trajectory.

III. METHODOLOGY

To assess the ability of human groups to forecast cult stocks, we conducted a nine-week study using volunteers from the Cambridge Judge School MBA program. Volunteers self-identified as interested in cult stocks and followed at least one stock closely. In other words, they were all representative of the high-level demographic driving the cult-stock movement. Each weekly group of between 8 and 16 participants came from the same pool of volunteers. To establish a baseline, all participants provided their weekly forecasts as individuals using a standard online survey. The group then congregated online in real-time and used the Swarm platform and make collective forecasts.

In each week of the study, participants first predicted the price change of the 12 assets over the next three days in a survey. The survey asked participants to buy or short up to 2 units of their virtual bankroll for each asset, and to predict which asset would increase the most and which would decrease the most respectively. The Wisdom of the Crowd (WoC) response to each question was calculated as the most popular response provided by the survey participants (i.e. the statistical Mode).

Next, participants logged into the Swarm platform to synchronously answer these same questions as a group—first allocating their virtual bankroll for each stock, and then creating two rankings of assets: the most likely to decrease and the most likely to increase over the next three days. For these rankings, the top 5 longs and top 5 shorts were considered. All individuals were anonymous to one another while swarming.

Swarm sessions started approximately 15 minutes after the close of the market and lasted approximately half an hour. The price of each security was recorded at the open of the market the day after the swarm, and also at the close of the market three days after the swarm. The price of bitcoin (BTC) was recorded as soon as the swarm ended, as BTC trades continuously.

The percentage price change in each stock was calculated using the price of the equity upon market open the day after the swarm and the price at close of market three days after the swarm. The top three individuals whose virtual bankroll showed the highest ROI over the three-day period were awarded bonuses: $15 for first place, $10 for second place, and $5 for third place. This bonus was to incentivize participants to use their best efforts in the forecasting surveys.

Finally, we managed a real bankroll over the duration of this experiment: starting with $5,000, we invested in the three stocks the Swarm ranked as most likely to increase in price. Bonuses were awarded to participants based on the overall performance of the swarm-managed bankroll. This was done to motivate best efforts from members during the swarming portion of the study.

A. Data Analysis

Of the 108 asset movements collected, the mean movement was 1.62% upwards, which was skewed higher by the presence of a small number of outliers that increased in price by more than 20%. No price ever decreased by more than 20%.

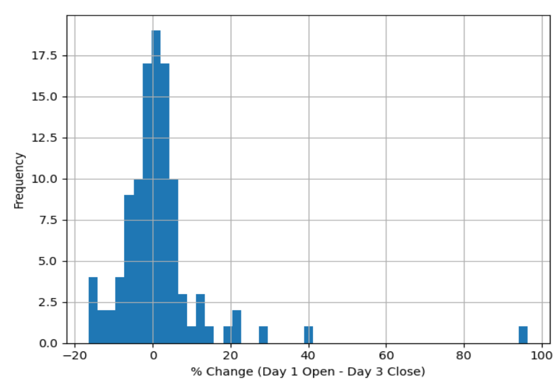

Fig. 3. Distribution of Observed Price Movements

Such extreme outliers distort the analysis and interpretation of these results by biasing towards a handful of data and may be unrealistic in practice: a trader or hedge fund manager would likely reduce exposure to these wild events by using stop losses (and perhaps profit targets). As a result, we consider a clipping function that restricts the maximum movement of these stocks in the three-day window to a fixed interval: either 10% or 20%.

For reference, the 12 assets forecast consisted of stocks (GME, AMC, RKT, TLRY, PLTR, TSLA, PTON, AAPL and SPCE), ETFs (ARKK and social-media driven BUZZ) and Bitcoin (BTC, a volatile cryptocurrency). A chart of the average price change of each asset is provided in Figure 4. The vast majority of price movements were under 5% during each trading period, though some assets exhibited larger volatility.

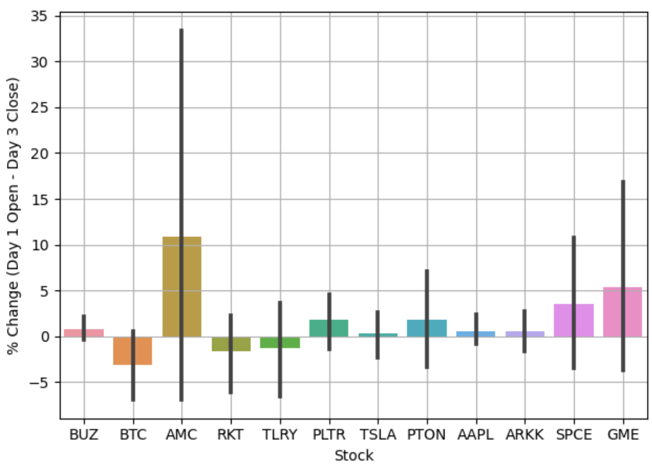

Fig. 4. Average Movement across 12 Assets with 95% Confidence Interval shown as black bars.

Finally, to meaningfully compare data, we ran statistical significance tests comparing each investment strategy to each other investment strategy by bootstrapping 1,000 times over the data points produced by each metric. For example, to bootstrap the Swarm Top Picks metric over the 9 weeks of the study, we randomly selected 18 of the swarm's Top Long and Top Short picks with replacement from the set of 18 data points (9 weeks, one Long and one Short per week) we have for this metric.

B. Results

When using a 20% clipping function, the swarm's top-ranked picks netted an average ROI of 2.3% week-over-week, which outperformed the Individual (0.96%, p=0.13) and WoC (1.6%, p=0.18) top-ranked picks, as shown in Figure 5. As a result, we can be more than 80% confident that the top-ranked Swarm picks outperformed the WoC and Individual rankings due to more than random chance. Over the 9-week course of this study, the Swarm Top Ranking strategy's weekly average ROI corresponds to an estimated cumulative ROI of 22.7%.

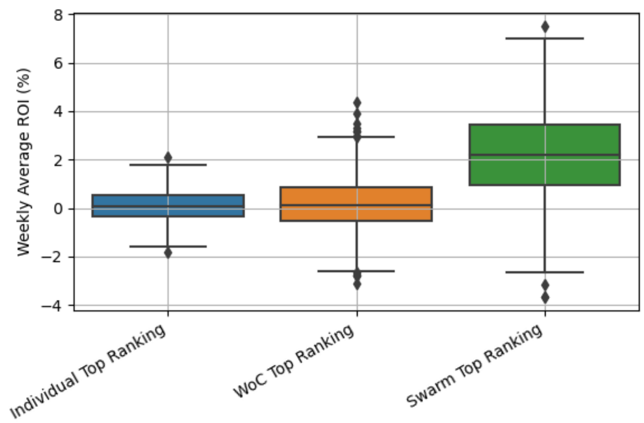

Fig. 5. Investment Performance using 20% Clipping.

To examine how sensitive these results are to changes in the clipping, we next limited the stock movements further using a 10% clipping function. In this context, the swarm achieves a 1.77% ROI, which outperforms the average individual (-0.26% ROI, p=0.110) and the WoC (-0.39% ROI, p=0.106). As a result, we can be more than 85% confident that the Swarm Rankings outperformed both the average individual and the median individual response in this respect due to more than random chance alone. We also see that there's a reasonable range of clipping limits for which the Swarm Top Rankings outperform the WoC and Individual top rankings.

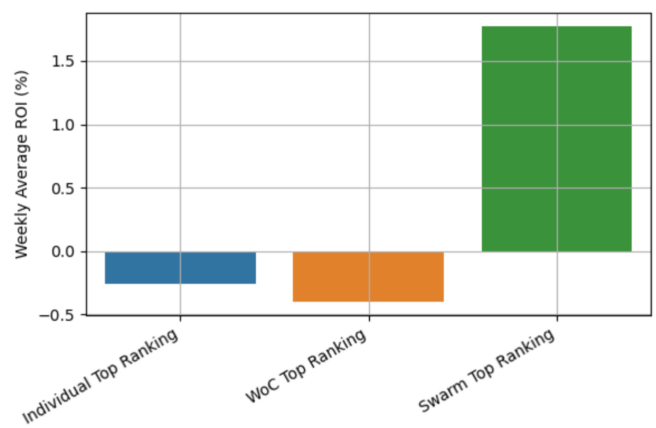

Fig. 6. Investment Performance using 10% Clipping.

We also find that the Swarm Top Rankings achieved a significantly positive ROI in both the 20% clipping condition ($p<0.1$) and the 10% clipping condition ($p<0.1$). Neither the WoC nor Individual Top Rankings for either of these clipping conditions yielded a significantly positive ROI ($p>0.25$ in all cases). The distribution of all 1000 bootstrapped performances for each investment strategy is shown in Figure 7.

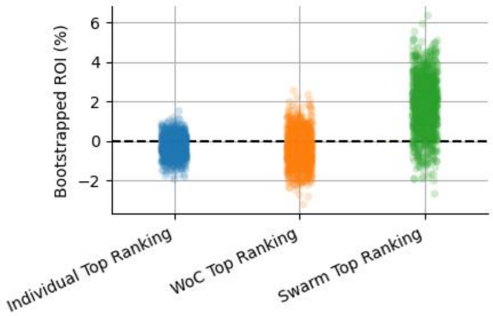

Fig. 7. Distribution of Bootstrapped Performance using 10% Clipping

To more accurately evaluate the quality of these strategies compared to the market, we can examine the performance of a benchmark index, the S&P 500 (SPY), over the same time intervals. We tabulated the price changes of SPY across the length of this study in the same way as the cult stocks. SPY on an average increased by +0.4% over the same time period we considered. The Swarm Top Rankings outperformed this benchmark metric using both the 10% clipping ($p<0.2$) and 20% clipping ($p<0.2$), while the Individual and WoC Top Rankings did not. As a result, we can conclude that Artificial Swarm Intelligence allowed this group to achieve a higher ROI in forecasting cult stocks than they would have achieved by investing in a market benchmark.

C. *Real Bankroll Analysis*

Before the experiment began, we allocated a real bankroll of $5,000 and invested weekly by splitting the full bankroll across the top three swarm-ranked buy picks for that week. At the end of the nine-week experiment, this bankroll had grown by 2.0%.

IV. Conclusions

This study highlights a promising technology for amplifying the real-world forecasting power of groups: Artificial Swarm Intelligence (ASI). In this study, ASI enabled a group of MBA candidates to forecast the price movements of 12 high-volatility financial assets (chiefly, equities) more accurately than if the group were forecasting as individuals or as a *crowd* aggregating their input statistically. The swarm-based forecasts yielded an impressive 22.7% cumulative ROI over the nine-week study by selecting one "top long" and one "top short" from the 12 assets under consideration each week. Further, the top three long picks were used each week to manage a real-world bankroll (with fees) and achieved +2.0% ROI over the nine-week test.

These results add to previous research demonstrating that human groups can use Swarm AI to make better collective assessments across a wide range of domains, from subjective judgements and medical diagnoses to market forecasting [5-14]. While this study was limited in that it only involved forecasting volatile *cult* stocks with groups of MBA students, the results support prior research showing success amplifying the accuracy of group financial forecasts using Swarm AI [12].

Acknowledgment

The authors thank the MBA candidates at the University of Cambridge, for their time. Thanks also to Culley Deisinger and Chris Hornbostel for moderating and organizing the sessions.

References

[1] Galton, F. (1907). Vox Populi. Nature, 75, 450-451.

[2] Steyvers, M., Lee, M.D., Miller, B., & Hemmer, P. (2009). The Wisdom of Crowds in the Recollection of Order Information. NIPS. 1785-93.

[3] Philip E. Tetlock and Dan Gardner. 2015. Superforecasting: The Art and Science of Prediction. Crown Publishing Group, New York, NY, USA.

[4] J Dana, P Atanasov, P Tetlock, B Mellers (2019), Are markets more accurate than polls. The surprising informational value of "just asking." Judgment and Decision Making 14 (2), 135-147.

[5] Rosenberg, L.B., "Human Swarms, a real-time method for collective intelligence." Proceedings of the European Conference on Artificial Life 2015, pp. 658-659.

[6] Metcalf L, Askay DA, Rosenberg LB. Keeping Humans in the Loop: Pooling Knowledge through Artificial Swarm Intelligence to Improve Business Decision Making. California Management Review. 2019;61(4):84-109.

[7] Patel, B.N., Rosenberg, L., Willcox, G. et al. Human–machine partnership with artificial intelligence for chest radiograph diagnosis. npj Digital Medicine 2, 111 (2019). https://doi.org/10.1038/s41746-019-0189-7

[8] Rosenberg, Louis. (2016) "Artificial Swarm Intelligence vs Human Experts," International Joint Conference on Neural Networks (IJCNN).

[9] Rosenberg, Louis. Baltaxe, David and Pescetelli, Nicollo. "Crowds vs Swarms, a Comparison of Intelligence," IEEE 2016 Swarm/Human Blended Intelligence (SHBI), Cleveland, OH, 2016, pp. 1-4.

[10] Baltaxe, David, Rosenberg, Louis and N. Pescetelli, "Amplifying Prediction Accuracy using Human Swarms", Collective Intelligence 2017. New York, NY.

[11] Willcox G., Rosenberg L., Askay D., Metcalf L., Harris E., Domnauer C. (2020) Artificial Swarming Shown to Amplify Accuracy of Group Decisions in Subjective Judgment Tasks. In: Arai K., Bhatia R. (eds) Advances in Information and Communication. FICC 2019. Lecture Notes in Networks and Systems, vol 70. Springer, Cham.

[12] L. Rosenberg, N. Pescetelli and G. Willcox, "Artificial Swarm Intelligence amplifies accuracy when predicting financial markets," 2017 IEEE 8th Annual Ubiquitous Computing, Electronics and Mobile Communication Conference (UEMCON), NY, NY, 2017, pp. 58-62.

[13] L. Rosenberg and G. Willcox, "Artificial Swarm Intelligence vs Vegas Betting Markets," 2018 11th International Conference on Developments in eSystems Engineering (DeSE), Cambridge, UK, 2018, pp. 36-39.

[14] L. Rosenberg, M. Lungren, S. Halabi, G. Willcox, D. Baltaxe and M. Lyons, "Artificial Swarm Intelligence employed to Amplify Diagnostic Accuracy in Radiology," 2018 IEEE 9th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON), Vancouver, BC, 2018, pp. 1186-1191.

[15] Seeley T.D, Buhrman S.C 2001 "Nest-site selection in honey bees: how well do swarms implement the 'best-of-N' decision rule?" Behavioral Ecology and Sociobiology. 49(5), 416–427.

[16] Marshall, James. Bogacz, Rafal. Dornhaus, Anna. Planqué, Robert. Kovacs, Tim. Franks, Nigel. "On optimal decision-making in brains and social insect colonies." Soc. Interface 2009.

[17] Seeley, Thomas D., et al. "Stop signals provide cross inhibition in collective decision-making by honeybee swarms." Science 335.6064 (2012): 108-111.

[18] Seeley, Thomas D. Honeybee Democracy. Princeton Univ. Press, 2010.

[19] Seeley, Thomas D., Visscher, P. Kirk. "Choosing a home: How the scouts in a honey bee swarm perceive the completion of their group decision making." Behavioural Ecology and Sociobiology 54 (5) 511-520.

[20] Schumann, H., et. al. (2019) "'Human Swarming" Amplifies Accuracy and ROI when Forecasting Financial Markets. IEEE International Conference on Humanized Computing and Communication (HCC), 77-82.

[21] Rosenberg L., Willcox G. (2020) Artificial Swarm Intelligence. In: Bi Y., Bhatia R., Kapoor S. (eds) Intelligent Systems and Applications. IntelliSys 2019. Advances in Intelligent Systems and Computing, vol 1037. Springer, Cham. https://doi.org/10.1007/978-3-030-29516-5_79

[22] ASI White Paper - https://unanimous.ai/whitepaper