

Algo's Gone Wild

Risk in the World of Automated Trading Strategies

By Bernard S. Donefer

Picture this: a trader with a large order executes an algorithmic strategy, either from his broker or proprietary to his own firm. It has a bug. Perhaps it relied on incorrect historical data in its creation, an analyst pulls the wrong data file with one mistyped character, or the correct strategy is sent to market with the wrong parameters. Perhaps a poorly set pegging order roils the market. Or today, the real time data the algo uses to update itself is delayed, even by a single second. Operating on incorrect information, its trades are routed to ten or more light and dark markets searching for liquidity. Like a dog chasing its tail, it moves the NBBO canceling and correcting itself to adapt to the new self-created market conditions. Other algos and strategies, stat arb, market makers or liquidity seekers spot the movement and begin to trade on the unusual market activity. Dark pools execute tens of thousands of shares against the new NBBO. Correlated securities now react and indices move. A decade ago, regulators might see this activity as coming from a single source, a single fat fingered trade, but now we just see many small orders across multiple markets. Is it "smart money" -- does someone know something? Keynes' animal spirits take over and the herd charges and in doing so the contagion spreads to related assets and derivatives reinforcing the panic. Momentum traders and aggressive quant traders trying to game and get ahead of other firm's strategies add to the trading. It is not easily identified as a single algo; it is amorphous and widespread. With naked access by the client, the broker whose infrastructure is being utilized may not see the orders until after they are executed, too late for risk tools, short sale rules or credit limits to be exercised. With our fragmented market structure, no single marketplace sees enough of the suspect order flow to identify it as "their problem". Could an automated strategy ever result in such market chaos?

On Sept 8, 2008, a six-year-old headline announcing the bankruptcy of United Airlines erroneously hit the news feeds.¹ Within about 12 minutes, shareholders lost approximately \$1 billion as UAL stock dropped from \$12 to \$3 a share before later recovering upon realization that the headline was a mistake. Again, a rapid drop in price brought in additional panicked sellers reacting to the market price movement, most not even knowing the precipitating cause. However, according to the *New York Times*, "Human error seems to have played only a minor role. The financial damage was mostly the result of the interplay between the algorithms that search and compile information from the Web and the ones that Wall Street firms and hedge funds use to make trades

automatically.”² Actual people may not have been fooled by the incorrect headline, but computer models took over the trading in UAL.

A month before the UAL fiasco, Bloomberg news published and then retracted an obituary of Apple CEO Steve Jobs. The incident took place after market hours, but imagine the impact on Apple’s stock price had it appeared earlier in the day, when the same news reading algorithms might have taken Apple on the same ride they took United Airlines two weeks later.

On October 19, 1987, the S&P dropped from 282 to 225 points, losing over 20% in waves of panicked selling. A loss of that magnitude was so statistically unlikely that its occurrence wouldn’t have been expected in millions of years of trading.

While the market may have initially declined for good reasons that day, two automated trading strategies were identified as likely drivers of such a massive panic: portfolio insurance and index arbitrage strategies³. In both cases, market data fed back in a loop, generating further selling to protect assets held by institutional money managers. While portfolio insurance made sense on an individual investor basis, when the strategy is simultaneously replicated over many portfolios, it resulted in cascading cycles as each investor tried to protect themselves. Unable to stem the tide, NASDAQ market makers walked away from their desks and NYSE specialists risked and lost much of their capital. These events, and likely others we haven’t yet unidentified, were the result of errors in automated models and strategies, *algos gone wild*.

Experts estimate that from 60%-75% of *all* equity trading in the U.S. is generated by orders from computer models reacting in sub seconds to market news and real time price movements, without human intervention.⁴ Bob Iati of the Tabb Group estimates, that these strategies represented industry revenues of \$21B (though recently he has revised it downward to the \$7-9B range), so we can assume that it is unlikely these techniques will go away any time soon. Further, we can expect it will be extended to European and Asian markets and across asset classes individually and in combination.

Estimates of automated/high frequency trading volumes come from surveys, as these orders, unlike program trades (baskets of 15 or more stocks worth \$1M or more), are not specifically identified. I once casually suggested that automated trades be identified for real time regulatory monitoring and post-trade analysis, e.g., 10 days after the fact, as are reserve orders on NASDAQ. Participants responded that mandating a strategy indicator on all orders required them to change all of their EMSs/OMSs, FIX engines etc., and testing them on an industry basis was too expensive. Furthermore, many firms would resist disclosing their proprietary strategies because competitors could possibly

data mine the order data and reverse engineer strategies and trade ahead or against them. We have seen how miniscule mistakes can explode into market-moving messes, but in the absence of tracking by regulators, the scope of the problem remains largely unknown and certainly outside the ability of regulators to stop during harrowing market conditions. I expect that this reluctance may change in the near future and regulators will have the ability to halt “non-productive” stat arb and rebate trading during periods of market turbulence.

What are these algorithms and who uses them? As the terms “algorithmic” and “high frequency” trading have often been used with conflicting meanings, I offer my own definitions. They all represent automated trading strategies that use historical data to model individual asset trading patterns, use real time data to control execution patterns and need direct, high speed access to get orders to market. To capture profits or meet trading objectives, infrastructure latency (time delays) has gone from seconds to milliseconds and marketplaces, brokers and traders are now targeting microsecond speeds (millionths of a second) in order to access liquidity the fastest.

The users of these practices can be divided into four groups. :

1. **Liquidity seekers** – the users of **algorithmic trading** are buy side institutions and their brokers with large blocks to buy and sell. In order to minimize market impact, they often slice and dice the block into smaller orders across multiple venues (there are up to 40 markets, light and dark, to choose from for equities). These may target the VWAP price or minimize implementation shortfall from the arrival price at the trading desk. No matter the trading strategy, their goal is to buy or sell a security for a longer investment period. Choice of the asset is made by a money manager. These algorithms are offered by brokers and independent software vendors as alternatives to sell side traders “working the order” or upstairs trade facilitation.
2. **Automated market makers** – firms (dealers) who continuously buy and sell a fixed list of securities (equities, options) hoping to profit on the spread of as little as a penny per share. Instead of using human traders to manage their positions, computer systems examine the real-time market data and using predetermined logic, publish quotes in the market. Their aggressiveness in pricing determines the business they attract. In some cases they only accept immediate or cancel orders (IOC) and do not want the fiduciary responsibility of holding limit orders. These are sometimes called “ping destination” for the technique of quickly pinging (testing) the site looking for an immediate fill. Market makers typically do

not want to hold positions and attempt to maintain balanced books with small inventories.

The strategies commonly attributed to **very high frequency traders**:

3. **Stat Arb Strategy traders**— analyze individual and groups of assets' historical time series data looking for trading patterns and correlations, then monitor real time data and identify opportunities to profit by temporary dislocations from expected norms. Resulting trades range from sub-second round trips to holding periods of minutes, hours and occasionally days or weeks. Examples include pairs trades, where hundreds of pairs of correlated securities may be chosen and traded, with the expectation that 55%-60% of the time it will result in a profitable prediction of the change in their spread relationship. These strategies may be implemented across asset classes, such as stocks, options and futures, across markets, indices and volatilities. They rely on convergence, regression to the mean and the expectation that markets quickly correct any imbalances and irrationalities. These strategies underlying logic may be similar to those used by automated market makers without the expectation that they will be continuously in the market. Remember, perfectly rational markets would never offer such opportunities and the existence of frequent profitable opportunities brings the efficient market hypothesis into some question.

I will also add a subset category, the “gamers” who try to game the system by looking for the footprints of buy side algorithmic strategies and attempt to trade ahead or against them. It is not illegal, but reminds me of the home made robots battling to the death in Battlebot™ competitions or warfare with each side becoming more sophisticated and continually raising the stakes in a game of hiding and discovery.

For automated agency marketplaces, alternative trading systems (ATSs), who do not participate in the trade, commissions are earned, not spreads, typically on a maker/taker model. Posting a bid/offer, the maker earns a rebate of about a quarter of a cent per share and the taker, who hits or takes the market, pays a higher commission of about a third of a cent. The objective is to encourage liquidity and attracting more profitable taker trading to the venue. However, these business decisions lead to another strategy.

4. **Rebate seekers** – these traders rely on the rebates offered by market places to provide liquidity, typically a quarter of a penny per share. They post, execute and post on the other side at the same price hoping to earn both rebates. They are subject to gains or losses on price movements in the security. These are the *ultra high frequency* traders, with individual firms often executing 50-100MM shares a day, concentrating their trading on one or two marketplaces. Clearing brokers, trying to gain a reputation for speed and accuracy in their back office often charge minimal or no clearing costs to ultra high frequency traders, enabling this strategy to be profitable. Should markets become too volatile, they can stop at any time, dramatically lowering the available liquidity in a market and potentially trapping institutional traders in their liquidity strategies.

The risk of these automated strategies is a function of the context in which they trade. Consider these five market constituencies which must address these potential problems:

1. The buy side firm executing the strategy.
2. The executing broker or software provider providing the algo/strategy and may include infrastructure, including direct market access (DMA), the smart router, data pipes and connectivity. They may offer naked access, use of their name to access the market without orders going through their risk infrastructure. Bypassing all these controls can leave brokers open to risks they may not be prepared for. Regardless, speed is king and being in second place means missing the opportunity.
3. The clearing broker, responsible to the clearing house for the trade.
4. The marketplace executing the trades.
5. Systemic risk across the entire market.

Each looks at the risks from their own perspective and must establish their own processes and controls to mitigate the possible failure scenarios that they must face. Beyond the individual firms, the larger issue is systemic risk across financial markets. Here the regulators have oversight responsibility and must be prepared to act on a timely basis, but how can they identify when an algo goes wild in real-time, before the damage becomes systemic? What can they do about it?

The Canadian Market Regulation Services⁵ were concerned enough that in January 2008 they published a Market Integrity Notice and a March 2009 follow-up reminding brokers that they are responsible for all orders sent to market by their clients and that

the broker has the obligation to stop unreasonable trades or orders. U.S. markets may benefit from a reminder like this.

I would like to suggest a number of possible best practices, including requirements for additional transparency that might minimize the potential for the risks of *algos gone wild*.

- ◆ Prohibit the practice of clients bypassing their broker's and clearing broker's risk management systems by directly accessing markets, i.e., naked access
 - This will give a potential advantage to broker's own proprietary trading desk over hedge funds. However, only the original algorithm need be vetted and the follow on trades can go directly to the market.
- ◆ Mark all automated trades by one of four types: institutional buy side (regardless of who is controlling the algo), market making, statistical arbitrage or rebate seeking.
 - Get a better understanding of the impact of these trades on liquidity and volatility.
 - Enable regulators to prohibit certain types of trading during market crises, similar to stopping program trades in market downturns.
- ◆ Establish standard order types for all market places. Ensure that orders are interpreted in exactly the same way in all venues and implement an industry test to guarantee compliance.
- ◆ Report all trades within 1 second, rather than the current 90 seconds.
 - Enable more timely tracking of potential problems
 - Require reporting the actual marketplace where the order was executed
 - Markets should report their trades, shares matched and orders and shares routed in a consistent way.
- ◆ Regulators clearly delineate the responsibility of executing and clearing brokers for algo/HF trades.
 - Demonstrate intraday short sale, capital sufficiency rules were met.
 - Demonstrate ability to monitor pre-trade and intra-day risk.
- ◆ Firms offering algos should be audited by FINRA/SEC to show sufficient due diligence in their creation and real time controls to monitor their performance.

Will we see an event caused by algos gone wild in our markets? I believe it is inevitable. I am further convinced that with no planning, method to identify the cause or regulatory framework, it will be virtually impossible to stop before significant systemic market damage is done. My hope is that we as an industry all do our parts to minimize any such event.

Remember, beware of geeks bearing gifts.

1 A Mistaken News Report Hurts United, New York Times, Sept 8, 2001

2 Got the News Instantaneously, Oh Boy, New York Times, Sept 13, 2008

3 A Brief History of the 1987 Stock Market Crash with a Discussion of the Federal Reserve Response, Mark Carlson, 2007, Accessed at

<http://www.federalreserve.gov/pubs/feds/2007/200713/200713pap.pdf>

4 The Real Story of Trading Software Espionage, Advanced Trading, Bob Iati of the Tabb Group July 10, 2009

<http://www.advancedtrading.com/algorithms/showArticle.jhtml;jsessionid=A010HBV40ZCSGQSNLPSKH0CJU>

5 IIROC Specific Questions Related to Supervision of Algorithmic Trading March 20, 2009

http://docs.iiroc.ca/DisplayDocument.aspx?DocumentID=66E3E5D143F74DB6BE34458361C4AFD6&Language=enNN2JVN?articleID=218401501&_requestid=475870#undefined

Author

Bernard S. Donefer is Distinguished Lecturer and Associate Director of the Subotnick Financial Services Center at Baruch College, City University of NY and Adjunct Associate Professor at NYU Stern Business School. He is Principal of Conatum Consulting LLC. bernard.donefer@baruch.cuny.edu