New York Law Journal
Corporate Update
WWW.NYLJ.COM
An ALM Publication
VOLUME 247—NO. 50
THURSDAY, MARCH 15, 2012

CORPORATE SECURITIES

Not Accounting for Algorithmic Trading May Skew Settlements


By **Joshua Ronen**
And **Kenneth A. Sagat**

Since 2005, algorithmic trading, particularly high-frequency trading executed in milli-seconds (HFT), has dramatically changed the secondary equity securities markets, both absolutely and as a proportion of total trading volume. Algorithmic trading, particularly HFT, does not typically rely on the integrity of market prices or fundamental information pertaining to issuers. As the Wall Street Journal reported on Feb. 23, 2012, "[Securities and Exchange Commission (SEC)] Chairman Mary Schapiro said a large portion of equities trading has little to do with 'the fundamentals of the company being traded.'"[1]

If economists retained by litigants in Rule 10b-5 securities class action litigation do not eliminate most, if not all, of algorithmic trading when estimating damages for settlement purposes, the number of class members in certified classes may be overestimated, resulting in exaggerated estimates of aggregate damages. In turn, exaggerated estimates of aggregate damages may magnify the in terrorem effect of class actions, resulting in skewed settlements.

In a 2010 Concept Release on Equity Market Structure,[2] the SEC recognized this dramatic change in the secondary markets, stating that "[t]he secondary market for U.S. listed equity securities has changed dramatically in recent years. In large part, the change reflects the culmination of a decade-long trend from a market structure with primarily manual trading to a market structure with primarily automated trading." The predominant form of automated trading—algorithmic trading—is executed electronically by means of computer algorithms, with the algorithm either initiating the order or governing its execution in terms of timing, price or quantity. Examples include dividing large orders to obtain better priced executions, exploiting minute price differences among markets, executing based on developing price trends,[3] and exploiting perceived anomalies in pricing based upon historical price relationships.

A form of algorithmic trading is HFT—quantitative trading characterized by extremely short holding periods—which may occur in milliseconds and may involve traders having direct access to trading facilities.[4] HFT typically employs strategies such as statistical[5] or event arbitrage[6] and often involves the use of rapid fire buy and sell orders.[7] In November 2010, the SEC stated that "HFT alone has been estimated to account for more than 50 percent of U.S. equities market volume." Other estimates have put it as high as 70 to 80 percent, although HFT, as a subset of algorithmic trading, is often referenced interchangeably with algorithmic trading in general.

However one views it, algorithmic trading, inclusive of HFT, dominates the equities markets. HFT traders, initiating and executing trades in milliseconds, and other algorithmic traders, seeking to exploit pricing anomalies and arbitrage opportunities,[8] are not executing trades relying upon fundamental information or the premise that stock prices reflect all available fundamental information. HFT trading may contribute to market efficiency and liquidity by eliminating minute pricing disparities,[9] but it certainly does not involve reliance upon fundamental information embedded in prices for making trading decisions. Likewise, other algorithmic traders, engaged in inter-day or intra-day trading and using computer algorithms to implement trading strategies, are predominantly not relying on stock prices as a fair reflection of fundamental information concerning the future cash flows of issuers.

Applying a rebuttable presumption of reliance on stock prices based upon market efficiency, as enunciated by the U.S. Supreme Court in the seminal case of *Basic Inc. v. Levinson,*[10] to high-frequency traders and most algorithmic traders does not make sense. Inherently, these traders are not relying upon the fairness of the market price based upon the market taking into account all available public fundamental information; rather, they are exploiting pricing anomalies, arbitrage opportunities and strategies to lower transaction costs. For this reason alone, algorithmic traders should be excluded from any Rule 10b-5 classes. Otherwise, and in any event, a cumbersome examination of each algorithm utilized by each algorithmic trader would be necessary, raising a predominance of individual issues likely defeating class certification. To the extent there might remain a small minority of non-HFT algorithmic traders who might theoretically be able to establish reliance on the integrity of the market price of a security, they are no doubt sophisticated investors who can fend for themselves so that excluding them broadly from the class definition in order to protect class action certification for others is sensible.

> Settlement negotiations that do not fully take into account the predominance of algorithmic trading due to the inadequacy of economic models are skewed to the high side.

JOSHUA RONEN *is a professor at the Stern School of Business, New York University and co-editor-in-chief of the forthcoming JAAF, a journal of accounting, finance, and law.* KENNETH A. SAGAT *is a partner in Sagat Burton.*

Even if algorithmic traders are not carved out of the class definition, their individual claims would ultimately likely fail since any presumption of reliance would be rebuttable in most instances—assuming they would even submit claims subjecting their individual proprietary algorithms to scrutiny. Whether as a result of carve out from class certification, the unlikelihood of algorithmic traders submitting claims, or the rejection of individual claims as result of the rebuttal of the presumption of reliance, estimates of potential damages for settlement negotiation purposes would be sharply reduced.

A form of algorithmic trading is high-frequency trading—quantitative trading characterized by extremely short holding periods—which may occur in milliseconds and may involve traders having direct access to trading facilities.

Virtually, if not all, economic models currently utilized to estimate damages in aftermarket securities litigation, whether plaintiff or defendant oriented, do not explicitly recognize, and thus do not exclude, the high volume of algorithmic trades. The negotiation of settlements is the actual outcome determinant for the great majority of Rule 10b-5 class actions since most that are not initially dismissed are settled and do not go to any verdict. Those few that do go to verdict and are lost by defendants have been resolved by settlement prior to the entry of a final judgment after an adjudication concerning the applicability of a rebuttable presumption of reliance to submitted individual claims.

Settlement negotiations that do not fully take into account the predominance of algorithmic trading due to the inadequacy of economic models are skewed to the high side. This is not to blame the economists. Even before the significant change in equities trading, the models generally applied to estimating damages were not usable for the purpose of entering judgment since they could not reliably estimate damages due to differences in the trading behavior of investors in different companies and to an absence of data prior to the submission of actual claims. But, if those models were previously considered adequate for the negotiation of settlements, they are not today when they do not take into account the high volume of algorithmic trading.

The principal fallacy of existing models is that they attempt to provide a quantitative construct by examining institutional holdings on a quarterly basis from SEC data and then allocating the change in institutional holdings to every day in the class period based upon the total daily volume in the stock. This, however, does not make any sense when there is considerable disparity in trading behavior among institutions, especially when institutions engage in HFT and other algorithmic trading. The available data from SEC filings simply does not pick up intra-quarter changes much less intra-day changes in equity holdings. The velocity of trading among institutions can differ considerably and a relatively small number of institutions engaging in very fast trading, especially HFT, can be responsible for most of the reported daily volume of the trading of an equity security.

There are difficulties in measuring potential damages in securities class actions to take into account the predominance of algorithmic traders due to a paucity of data concerning algorithmic trading that should not be underestimated. HFT traders are particularly difficult to identify, often trading through "dark pools" that hide their identities. Nevertheless, it is important to recognize that properly excluding algorithmic trading from estimated damages can result in a reduction in damage estimates by a substantial order of magnitude reaching in some instances as high as 90 percent of estimates produced by models commonly used by plaintiffs and 50 to 75 percent of estimates commonly produced by models utilized by defendants—based solely on shares traded and not differences in the economic estimates of price inflation.

The changes in the secondary equity markets since 2005 due to the predominance of algorithmic trading, especially HFT, can only be ignored at the risk of significantly skewing 10b-5 class action settlements. This may benefit those class members actually submitting claims, but it may misallocate resources to the detriment of current shareholders and other current corporate constituencies.

1. Scott Patterson and Andrew Ackerman, "SEC May Ticket Speeding Traders," The Wall Street Journal, Feb. 23, 2012, at C1.

2. Concept Release on Equity Market Structure, Exchange Act Release No. 61358, 75 Fed. Reg. 3594 (Jan. 21, 2010).

3. Traders using this strategy use moving averages to determine the general direction of the market and to generate trade signals. Traders employing a trend-following strategy do not aim to forecast or predict specific price levels; rather, they simply jump on the trend and ride it. See, for example, Michael W. Covel, "Trend Following: How Great Traders Make Millions in Up or Down Markets," (Financial Times Prentice Hall 2004) (Updated Edition 2009).

4. D. Easley, M. López de Prado & M. O'Hara, "The Microstructure of the 'Flash Crash': Flow Toxicity, Liquidity Crashes and the Probability of Informed Trading," The Journal of Portfolio Management, Vol. 37, No. 2, 118-128 (Winter 2011).

5. Statistical arbitrage " refers to highly technical and short-term mean-reversion strategies involving large numbers of securities (hundreds to thousands, depending on the amount of risk capital), very short holding periods (measured in days to seconds), and substantial computational, trading, and information technology (IT) infrastructure." See Andrew W. Lo, "Hedge Funds: An Analytical Perspective" 260 (Princeton Univ. Press 2010) (New Edition); see also Narasimhan Jegadeesh, "Evidence of Predictable Behavior of Security Returns," Journal of Finance, Vol. 45 (1990), at 881-98; Bruce N. Lehmann, "Fads, Martingales, and Market Efficiency," Quarterly Journal of Economics, Vol. 105 (1990), at 1-28.

6. An example is merger arbitrage, sometimes called risk arbitrage where a trader invests in event-driven situations such as leveraged buyouts, mergers and hostile takeovers. The stock of an acquisition target typically appreciates while the acquiring company's stock price decreases. Such a strategy generates returns by purchasing the stock of the company being acquired, and in some instances, selling short the stock of the acquiring company. See Barclay Hedge Alternative Investment Databases, http://www.barclayhedge.com/research/definitions/Merger-Arbitrage-definition.html (last visited Feb. 24, 2012).

7. High-Frequency Trading or "black box trading" involves automated program trading that uses high-speed computers covered by complex algorithms to analyze data and transact orders in massive quantities at very high speeds. Among other things, HFT allows program traders to peek at major incoming orders and jump in front of them to skim profits off the top. See, for example, Ellen Brown, "Computerized Front Running," Counterpunch, http://www.counterpunch.org/2010/04/23/computerized-front-running/.

8. See, for example, Andrei Shleifer and Robert Vishny, "The Limits of Arbitrage," Journal of Finance, Vol. 52 (1997), at 35-55; Wei Xiong, "Convergence trading with wealth effects," Journal of Finance, Vol. 62 (2001), at 247-92; and Peter Kondor, "Risk in Dynamic Arbitrage: Price Effects of Convergence Trading," Journal of Finance, Vol. 64, No. 2 (2009), at 638-58.

9. See Terrence Hendershott, Charles M. Jones & Albert J. Menkveld, "Does Algorithmic Trading Improve Liquidity?," The Journal of Finance, Vol. 66, No. 1 (2011).

10. *Basic Inc. v. Levinson*, 485 U.S. 224, (1988); see also *Erica P. John Fund Inc. v. Halliburton Co.*, 131 S. Ct. 2179 (2011).