Algorithmic Trading and Statistical Arbitrage

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The history of statistical arbitrage goes back to the early 1980s, where it was born as the now venerable "pairs trading" business, exploiting a simple motion in the relative prices of similar stocks, the "popcorn process."[1] After 20 years of excellent profitability and evolution to grander form as "statistical arbitrage," the discipline suffered from paltry returns in 2003–2005. Many reasons contributed, in different degrees and for short or long term effects, to the performance attenuation. Prominent among these, and with growing significance over time (where other contributors had instantaneous step change impact or ephemeral influence), is algorithmic trading. There is some irony here: the general adoption of statistically based trading tools eating away the trading performance of the classic statistical arbitrage strategy … a sort of algorithmic cannibalism. The irony doesn't end there—or perhaps the next phase is not ironic? As algorithms take over more of the business of implementing investors' decisions, their very pervasiveness is itself generating new, sustained, systematic patterns of stock price behavior—just the fodder required by systematic exploitation strategies.

The shift of trading from the floor of the NYSE to internal exchanges in the guise of computer algorithms designed by large brokerage houses and investment banks has cumulatively become a change with glacier-like implacability. Slow. Massive. Irresistible. Crushing. One major structural consequence, fed also by technical developments in the credit markets and the development of ETFs, through not explicitly tied to algorithmic trading, is literally the forming anew of patterns of price behavior determined by the interaction of computer algorithms as agents for share dealings. A frequently remarked facet of the evolving dynamics is the decline of market volatility. Where has market volatility gone? In large part the algorithms have eaten it. Reduce the voice of a single participant yelling in a crowd and the babble is unaffected. Quiet a significant proportion of participants and the reduced babble is oddly deafening. Now that computer programs "manage" over 60% of U.S. equity trades among "themselves," the extraordinary result is akin to ministering a dose of ritalin to the hyperactive market child. In the commentary on low volatility two themes stand out: one is a lament over the lack of Keynes' animal spirits, a concern that the entrepreneurial genius of America is subdued even as Asian giants are stirring. The other is a fear that investors have forgotten the risks inherent in investment decisions, and that inadvisable decisions are therefore being made that will have negative consequences in the near future. The inconsistency in those two characterisations is stark, but it can be rationalized. Contrary to the first notion, the spirit is quite animated—with a billion and a half shares changing ownership daily on the NYSE mart alone, what other conclusion should one draw? There is plenty of spirit; simply its animus is satisfied with less overt fuss. Algorithms don't have emotions.

Low volatility was the cause of statistical arbitrage performance decline, according to many evaluations. It is a simple-to-remember thesis and when voiced seems to require no elaboration. The implication inherent in the statement, that statistical arbitrage reaped return from volatility, was indeed true, so what more needed to be said? Add to that the thesis advocated here, that the rise of algorithmic trading has forever eliminated part of the volatility historically seen in stock prices, and a conclusion that statistical arbitrage is dead seems unavoidable. In fact, the story is a lot more complex, and algorithmic trading has emerged as one of the most significant driving forces in local market dynamics.

The past year saw a resurgence of performance from those statistical arbitrage practitioners who persisted through the extremely challenging dynamic changes of 2003–2005. Interestingly, while there are new systematic patterns in the movements of relative equity prices, some old patterns have also regained potency. Notwithstanding the emerging primacy of algorithmic trading as progenitor of exploitable stock price patterns just claimed, the classic popcorn process may have received last rites prematurely.

MARKET DEFLATION

Exhibit 1 depicts the market for buying and selling stocks, a generic market where buyers and sellers come together to agree on a price for mutually acceptable exchange of ownership. There are many buyers and many sellers. Lots of individual excitors. Many points of agreement. Substantial volatility.

Exhibit 2 depicts the arriving market for buying and selling stocks. The many individual buyers and sellers come together by the intermediating management of a handful of computer algorithms which internally cross a substantial portion of orders and satisfy the residual by restrained, unexcitable exchange in the central market. There are many buyers and sellers. Many points of agreement. But less unmitigated agitation than the traditional bazaar. Constrained volatility.

ARISE BLACK BOXES

Having invented the pairs trading business two decades previously, Morgan Stanley was at the forefront of the creation of a new business in the early 2000s: a less risky, more sustainable business that, in a wonderful example of commercial parricide, systematically destroyed opportunities for old line pairs trading. Algorithmic trading was born. Huge order flow from institutions and hedge funds, much of which is electronically matched in house, provides multiple opportunities for bounty beyond the expected brokerage fees. Combining the insight and knowledge learned from proprietary trading (beginning with the classic pairs trading business) with analysis of a warehouse of order flow data, brokers[2] built trading tools that incorporate models for forecasting market impact as a function of order size and time of day, moderated by specific daily trading volume stock by stock. It was a masterfully timed development. Coming as new statistical arbitrageurs were appearing with abandon, it allowed vendors to seduce those whom their tools would eventually help destroy, along with existing clients thirsting for any new edge that had the promise of lower transaction costs or marginal improvements in execution price. The genius of the business was compounded as the institutional and statistical arbitrageurs' order flow provided an ongoing feast of raw material for the data miners.

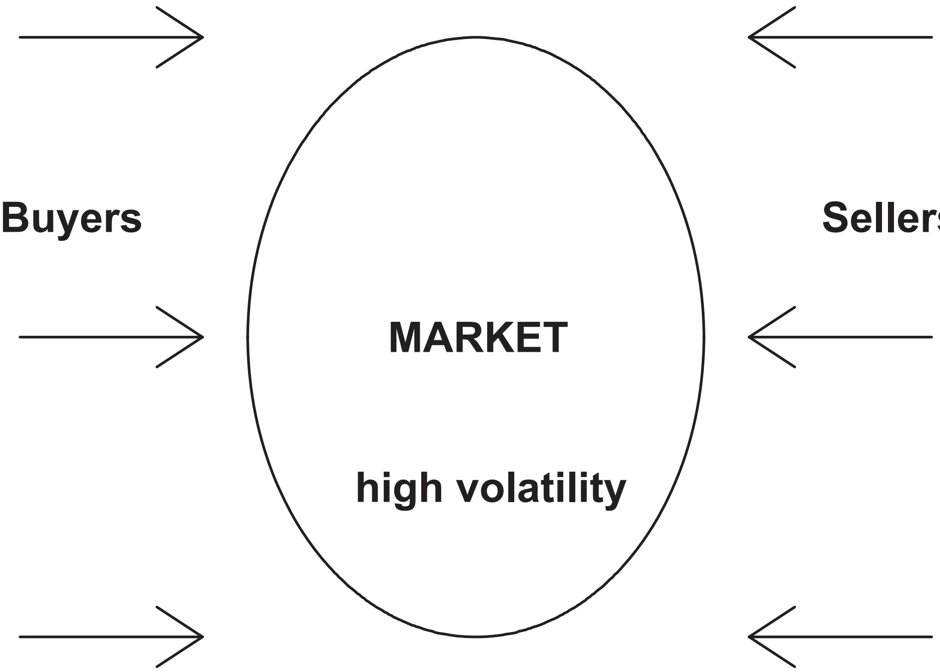
Patterns of transaction volume by stock, by day of the week, by time of day, by current day's trading volume were constructed from the mined data. The mere ability to predict with measurable efficacy how much would be given up from current price to buy or sell a specific number of shares in a fixed period was a stunning development to traders. Hedge funds had for years made their own attempts; with their much less rich data than broker archives it is unlikely that many matched the brokers' success.[3] Regardless, an edge was eliminated.

Fitting logistic type models to order flow and fill data quickly produced the first generation of models, allowing traders to obtain quantitative answers to frequently faced, urgent questions:

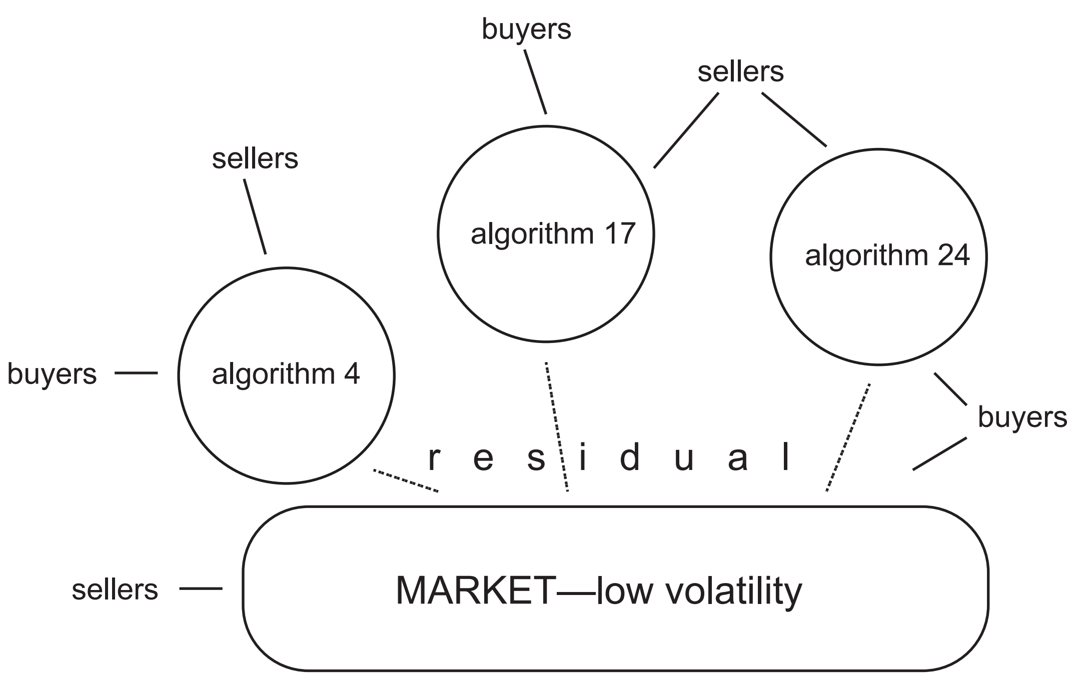
- How much will I have to pay to buy x thousand shares of XYZ in the next half hour?
- How much if I allow the remainder of the trading day?
- How much can I sell of XYZ in one hour keeping impact to k cents?

An unadvertised beauty of the tools is the self-propagating nature of the opportunity set. As traders switched

E X H I B I T 1
The Way the Market Was



E X H I B I T 2
A "Deflated" Market Model



to the technology a new set of order flow information was presented to and collected by vendors. Now it was possible to examine the trading of the impatient "pay up and get it done" and the relaxed "wait and see" players. Models of client profiles, built from the client order flow, trading tool configuration, and fill/cancel-correct records, practically generate themselves. With the ability to gauge how much a client would be willing to pay for a fill, and estimates of how long it would take to get the trade done at lower market impact … the many possibilities fairly screamed themselves to researchers, echoing and amplifying the old line pairs trade screams heard by a previous generation two decades earlier.

All of this opportunity set offered itself for reaping without requirement of capital commitment. The risk of proprietary trading was eliminated and the "new" business is infinitely scalable.[4]

MODELING EXPECTED TRANSACTION VOLUME

The place to begin is the data mine. What data is available and which of it is pertinent to answering the "How much…?" questions? Suppose that for stock XYZ there is a history of daily transaction volume data by individual trade, for over 10 years. That is 2,500 days of daily transaction material. The first thing to do is examine the cumulative trade volume by day: every stock has a distinctive character to its pattern of trading over the day, a footprint if you like. Using a one-shoe-fits-all approach, forecasting an elephant's footprint using a generic mammal footprint, may work but will suffer from needlessly large inaccuracies (noise or error variance). Worse would be to use an asp's footprint (try to describe it…). You can see the problem.

Begin looking at the data with a view to identifying a trading day pattern in transaction volume. How to characterize it? While it is unlikely that the daily pattern 10 years ago is close to the daily pattern today, it would be inadvisable to assume so. Remember that reversion patterns exploited by the original pairs trade persisted with economically exploitable frequency and magnitude for a decade and a half before technological and market developments caused a dramatic change. Examine some daily cumulative transaction volume charts from 10 years ago, some from five years ago, some from this year. You notice a similar form to the graph (curve), but obvious differences—faster cumulation early in the day and again late in the day comparing recent patterns to earlier patterns. Better to not simply aggregate all the data and estimate an average curve, then.

Look more closely at daily patterns for the last three months. That is 60 charts. Examine a three-month set from 10 years ago. You notice quite a lot of overlap in the basic shapes. But look at the scales: the stock trades at much higher volumes now than it did a decade ago. Hmmm. Rescale the graphs to show cumulative percent of daily total volume. Now all graphs are on the same 0 – 100 scale. Aha! There is much less variability in the patterns of the last quarter. So … whether a given day is relatively high or relatively low volume, a similar pattern for the trading over the day is revealed.

How do we use this insight? One goal is to represent the curve (of cumulative percentage trade volume in a day) in a way in which it will readily yield the proportion of a day's trade volume in the market at a specific time. In other words, to provide a ready answer to questions such as: How much of the volume is transacted by 2 p.m.? Cumulative density functions of probability distributions provide a natural function set, since distributions are precisely what are being examined here. A convenient form for statistical model building is the logistic function.

Pick a function. Fit it to the data. You can now readily make sensibly quantified stock specific responses to the question: How much of the day's volume is transacted by 2 p.m.? *On average*……

MODELING MARKET IMPACT

The foregoing analysis considered only transaction volume—what about price information in the record? In the set of 60 days of trading data for XYZ there are many individual buy and sell transactions for order sizes as small as 100 shares to as large as 100,000 shares. The fill information for all orders is also recorded. Plotting order size against the change in price from the order price (or market price at time of order) and the average fill price shows a definite relationship (and a lot of variation). Once again some of the variation magically disappears when each day is scaled according to that day's overall volume in the stock. Orders, up to a threshold that one might label a "visibility threshold," have less impact on large volume days.

Fitting a mathematical curve or statistical model to the order size–market impact data yields a tool for answering the question: How much will I have to pay to buy 10,000 shares of XYZ? Note that buy and sell responses may be different and may depend on whether the stock is moving up or down that day. Breaking down the raw data set and analyzing up days and down days separately will illuminate that issue. More formally, one could define an encompassing statistical model including an indicator variable for up or down days and test the significance of the estimated coefficient. Given the dubious degree to which one could reasonably determine independence and other conditions necessary for the validity of such statistical tests (without a considerable amount of work), one will be better off building prediction models for the combined data and for the up/down days separately and comparing predictions. Are the prediction differences of *practical* significance? What *are* the differences?

One drawback of fitting separate models to the distinct data categories is that interaction effects (between volume, up/down day, buy/sell, etc.) cannot be estimated. If one is looking for understanding, this is a serious omission as interactions reveal subtleties of relationships often not even dimly suggested by one factor at a time analysis. If one is looking for a decent prediction, the omission is intellectually serious (if there are interactions) but practically (depending on the nature of the interactions) of less import.

Time of day is also significant in market impact estimation—recall the analysis of the cumulative trading volume pattern over the day. Filling an order during the "slow" or more thinly traded part of the day requires either more patience for a given slippage limit or a willingness to increase that limit. An obvious approach is to slice the data into buckets for the slow and not slow parts of the day (or simply do it by, say, half hour segments) and estimate individual models for each. While the statistical modeling and analysis can be made more sophisticated—formally modeling parameters across time slices with a smooth function, for example, employing classification procedures such as regression trees to identify natural groupings (time may be better sliced than by the half hour with more intervals around the market, open and close, volume weighting is another possibility)—imagination is the only limit. The simple bucketing procedure posited here serves to exemplify the opportunity and the approach.

A NEW PARADIGM FOR STATISTICAL ARBITRAGE

Since early 2004, spread motions have been observed to exhibit an asymmetric process where divergence is slow and continuous but convergence—the "reversion to the mean" of old—is fast(er), even sudden by comparison. Convergence is not necessarily "to the mean," though it is in the direction of a suitably local view of "the mean." The first two characteristics contrast with those of the popcorn process, which exhibits a faster paced departure from the norm and a slower return. The third characteristic, the degree of reversion to an underlying mean, also distinguishes the two processes: in the newly emerging process the extent of the retrenchment move is far more variable than was the case for the popcorn process.

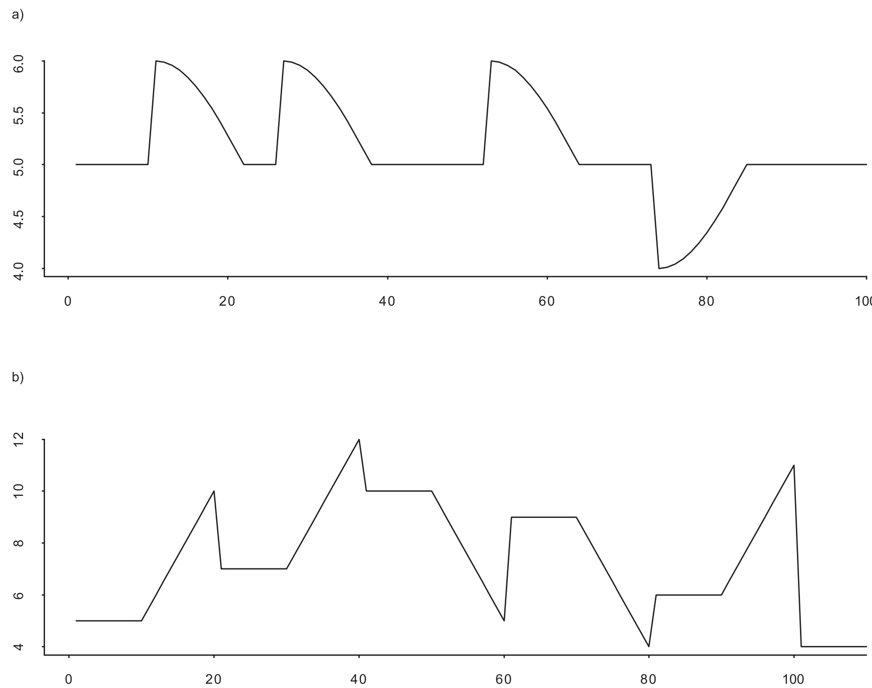
Contrast the classical popcorn process with the new process using Exhibit 3. The notable features of the new process are: a slow, smooth divergence from local equilibrium; fast reversion toward that former equilibrium; *partial* reversion only (in most cases); repeated moves in "quick" succession delineating a substantive "local" trend away from the "underlying equilibrium." (The latter is, as in all archetypal illustrations, depicted as a constant level. In practice it is superimposed on longterm trend movements—for a positive trend turn the page anticlockwise by several degrees to view the archetype.)

The critical departure in this new "catastrophe" model is the appearance of local trends within the period classically depicted as sufficiently local to be constant. The local trend (within a trend) *must* now be depicted and formally incorporated in the analysis because it is part of the opportunity driver and is crucial to the successful exploitation of the new reversionary moves. It cannot be ignored as noise on an underlying (popcorn) process.

The combination of variable amounts of "reversion" and multiple moves in the same direction before a larger directional shift (singly or, again, multiple small events) is driven by the interaction of algorithmic trades. Patient algorithms "ease up" when prices move repeatedly penny by penny by penny—moves which specialists are keen on following the change to decimalization and which are undoubtedly programmed into some algorithms. What used to be a certain inertia to moves when tick size was substantive, an eighth, is now eagerness to repeatedly penny. Pennying was ridiculously lucrative at first when human traders still dominated order flow. The patience and discipline of algorithms having replaced direct trader involvement has altered the dynamics of the interaction. The results that seem now to be clear are the catastrophe moves described.

EXHIBIT 3

a) Archetype of Popcorn Process Showing Reversion to a Mean. b) New Archetype: Catastrophe Process



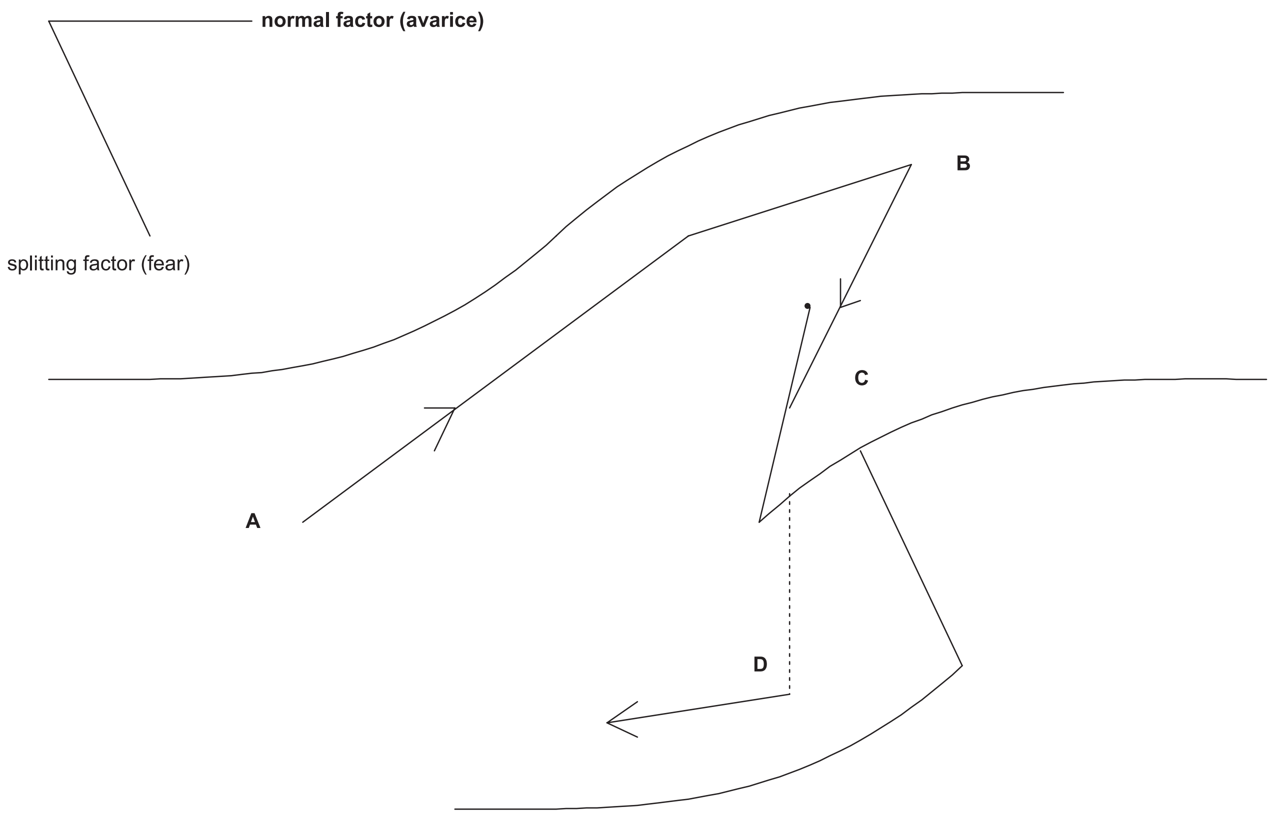
TADPOLE THEOREM[5]

Examine the catastrophe surface in Exhibit 4. The catastrophe move, a slow build up then a sudden drop, is created by continuous moves through a two-dimensional space. The dimensions correspond to a "normal" factor and a "splitting" factor in catastrophe theory parlance. At low levels of the splitting factor, variation in the normal factor causes smooth variation in the outcome surface. At high levels of the splitting factor, movement in the normal factor generates outcomes in two distinct regions, separated by a discontinuity—the catastrophic jump. The discontinuity is asymmetric: jumps 'up' and jumps 'down' occur at different levels of the normal factor for a constant level of splitting factor; this is known as hysteresis, commonly interpreted as inertia or resistance.

This is the classical description of the two-dimensional cusp catastrophe. Application to stock price development identifies "avarice" with the normal factor and "fear" with the splitting factor. Consider a movement over the surface beginning at A, with a low level of fear. The price develops smoothly in the direction of B with increasing avarice. As the price increases further to C (the surface is tilted upward along the splitting factor axis) fear begins to infect participants. Eventually fear surpasses avarice as the dominant concern and there is a quick price pull back. What is the nature of the fear? Simply that the divergence in price from the recent local trend is not fundamentally justified but is promoted by (algorithms') attempts to over-exploit buyers. (Algorithms don't actually experience fear, or have any experience at all, nor do they act from or demonstrate emotion. Bear with the informal use of descriptive language: this is a work in progress.) While algorithms have no conscious experience, they do encapsulate learning about price movement dynamics, knowledge of how much is to be given up or gained through backing away from the market, waiting. All this and information on current market moves feed into a calculated reaction which has the appearance of "fear"—pull back.

The depiction of fear and avarice factors represents the combination of participants—buyers, sellers, specialists—present in the market place through their algorithms. The avarice axis measures the maximum state

EXHIBIT 4
Catastrophe Trade Life Cycle



of avarice affecting traders and specialists: whoever has the greediest sentiment of the moment dominates interactions and price movements. In like manner the fear axis measures the maximum state of fear infecting participants.

As buy pressure is seen by the specialist, pennying begins. Trading algorithms, typically with some pricing room permitted to complete trades, follow the specialist up. Responding, the specialist's avarice increases and pennying continues (possibly picking up pace, though the description here does not require that level of specificity). As these interactions continue, price is moved higher until trading algorithms determine that it is time to suspend buying: calibrated on much previous data to "expect" how much will be necessary to complete trades, unemotional algorithms display saintly patience. Buy pressure eases. Immediately the specialists' avarice turns to "fear." Keeping price high will generate no profit if buyers stay mute and there is no business. Sellers share the fear. Price drops precipitously (in comparison with the rise) to rekindle buyer interest.

One might ask, Why not a smooth decline? Because reaction to fear is different from satisfying avarice (whether it is fear of selling too cheaply or buying too expensively), notwithstanding algorithms. Remember that algorithms are designed and coded by people. Patience. Wait for a significant decline. Therefore, without intermediate activity, downward pennying accelerates and in many cases is observed as a multipenny catastrophic drop.

Satisfied that patience has paid off, the cycle begins anew, very likely from a starting price higher than the starting price of the original move as these short-term catastrophic retrenchments are usually partial. Enthusiasm, avarice, builds over quickly and price races ahead of the sustainable growth path. Realization sets in, fear, and equilibrium is quickly, if temporarily, restored.

IMPLICATIONS FOR RISK MANAGEMENT

A valuable risk management tool in the successful management of many statistical arbitrage models is the so-called hurdle rate of return. A model's forecast function provides an explicit expected rate of return for any contemplated bet. Managers typically specify a minimum rate of return, the hurdle, which must be satisfied before a bet is made to avoid collections of bets that are, in the aggregate, probabilistically sure losers. In times of perceived heightened general risk (and we are entering one such period as this is written on March 3rd), typically exemplified by increased volatility, actual or expected, a standard practice is to raise the hurdle. This prophylactic action is designed to avoid entering reversion bets early, while divergence is still a strong force, thereby avoiding initial losses and hence increasing return. The tactic is a broad sweep action appropriate when concern is of a general increase in variation not focused on specific market sectors or stocks. (The tactic can, of course, be directed toward specific market sectors or other collections of stocks if there is reason to be so concerned.)

For the popcorn process the basic forecast function is a constant, the value of which at any time reasonably computed as a ewma (with more sophisticated modelers employing local trend components too depending on the time scale over which the move is exploited). When the spread pops, the expected return is calculated as a fraction of the deviation between the spread and the forecast value. When volatility is expected to increase, the pops will be expected to increase in magnitude; waiting for larger pops is obviously sensible. (Slow, rather than sudden, increases in volatility are automatically managed, feeding into dynamic recalibration of models. The scenario we are concerned with here is an increase of sufficient magnitude in a short interval that is outside the capacity of automatic model adjustment. That is a risk scenario rather than ordinary evolutionary dynamics.) The point is that the expectation-based information is not accessible to the model from data analysis, but it can be communicated by the modeler.

Are the considerations of risk, sudden non-specific increases in volatility, any different from those just articulated when considering catastrophe moves? At first blush it does not appear so. Catastrophe moves are a convergence following a divergence, so rescaling for a spike in volatility is just as relevant as it is for popcorn (or other reversion) models. That first blush might be of embarrassment on further reflection. Since early 2004 when the catastrophe process emerged as the better descriptor of local price and spread motions, the general level of market (and spread) volatility has been historically low. We do not have much empirical guidance on what will happen when volatility spikes. Rescaling of local catastrophe moves may be the result. But it could easily be something different. A good argument can be made that increased volatility will swamp the catastrophes, certainly sinking the ability to identify and exploit them on line, leading to the return to primacy of the popcorn process. Is such a development more than theoretically conceivable if the hypothesis of algorithmic interaction driving price dynamics is and remains true? What would cause volatility to spike? People, of course. Algorithms are tools. Ultimately people drive the process.

CONCLUSION

Volatility will remain consumed by the algorithms. Instead of human to human interaction, either face to face on the floor of the NYSE or face to screen to face in electronic marts, we will see algorithm to algorithm exchange. A large and growing part of the emotion surrounding trading is removed, and with that removal goes volatility. Yet in this focus on algorithms we must not forget that people still drive the system. With trades managed by algorithms implemented on incredibly fast processing computers, what might be done by algorithms designed to go beyond passive market participation to active market determination? Probing other algorithms for weakness, for opportunities to subvert naivete or to mislead into false judgement. Warfare by another name. The attraction for certain managers and the challenge for certain programmers is irresistible.

Speculation of course. I think.

ENDNOTES

This article is based on material in the author's forthcoming book, "Statistical Arbitrage: Algorithmic Trading Insights and Tecniques," to be published by Wiley in September 2007.

[1]I first heard the term "popcorn process" as a descriptor of spread dynamics, along with much else about statistical arbitrage, from Gregg van Kipnis in [1996].

[2]Morgan Stanley is not the only firm to have analyzed transaction data and offered tools to the marketplace encapsulating trading intelligence discovered therefrom. Goldman Sachs' operations on the floor of the NYSE—the Spear, Leeds, and

Kellog specialists bought in [2000]—represents a gold mine. Bank of America bought the technology of hedge fund Vector in 2002: "… computer algorithms will factor in a particular stock's trading characteristics *and BofA's own position in it* then generate buy and sell quotes" (Institutional Investor, June 2004, my italics). CSFB hired a former employee of the renowned and technologically advanced hedge fund D.E. Shaw, built a tool which "processes fully 40% of its [CSFB's] order flow" (Institutional Investor, June 2004). Lehman Brothers and more than a dozen others are also in the business.

[3]In addition to the latter remarks in (2), at least one new brokerage, Miletus, has been spun out of a billion-dollar hedge fund to monetize the value in the trading algorithms developed for the hedge fund's own trading. While severed from the hedge fund, the intelligence that is encapsulated in the trading algorithms lives on in the brains of the hedge fund. Now, how might that be useful?

[4]In another technology-driven development, beginning with Goldman Sachs in late [2006], at least two offerings of general hedge fund replication by algorithmic means have been brought to market. If these instruments gain popularity there are likely to be new systematic pattern generating forces added to the market. This is an exciting as well as exacting time for statistical arbitrageurs.

[5]I chose to call the new reversion pattern the catastrophe process, rather than popcorn 2 or some other label, because it is catchy and does capture the rather different move dynamic than is both suggested by the name and exhibited by the popcorn process. The development of an explanatory model of investor behavior that might represent why the new style moves occur is separated from the description and exploitation of those moves. The underlying elements of algorithm to algorithm interaction and growing popularity and use of trading algorithms in place of direct human action are undisputed. They are observed facts. Stock price histories are also incontrovertible facts. The patterns I have discerned in those histories are debatable: there is a lot of noise in any example I could show.

Trading models built to exploit the dynamics represented by the popcorn and catastrophe processes have undeniable track records. That is existential proof of model efficacy and supports the validity of the pattern descriptions, but it does not prove any theory of why the patterns are the way they are. The popcorn process has been so long established and so widely exploited at multiple frequencies that providing a rationale has not received much attention. The rise of a new pattern with the background of failure (in terms of economic exploitation) of the old also does not *require* a rationalization. If it persists and statistical arbitrageurs begin to discover it and churn out decent returns once again, investors will experience their own catastrophic shift from skepticism (fear of loss) to hope (greed).

While a rationalization is not necessary for the rise of the phenomenon of reversion by catastrophe, an understanding of market forces driving new dynamics and a cogent, plausible theory of how those forces interact and might produce emergent patterns is necessary to promote unbiased critical attention in the formative period. The simple catastrophe theory model presented in the text is offered as one possible way in which identified market forces recently introduced and growing in influence, as old behaviors and interactions are supplanted, might be understood. The catastrophe model is a plausible representation of what is currently known, but it is not a formal model from which predictions can be made. V.I. Arnold in *Catastrophe Theory* acidly remarks that "articles on catastrophe theory are distinguished by a sharp and catastrophic lowering of the level of demands of rigor and also of novelty of published results." You have been cautioned.

Arnold further remarks, "In the majority of serious applications … the result was known before the advent of catastrophe theory." The strong implication in our context, despite the lapse of 20 years since Arnold wrote, is that even if the representation and interpretation of the model presented are valid, it is probably better (more rigorously, more convincingly) constructed using tools other than catastrophe theory. I am, in fact, engaged in research using game theoretic tools to model trading algorithm interactions. This work is at too early a stage of development to report here. Finally, Arnold again, "in applications to the theory of the behavior of stock market players, like the original premises, so the conclusions are more of heuristic significance only." My premises are rather more than heuristic, algorithm to algorithm interaction and increasing dominance of algorithms and removal of direct human interaction, and patterns discerned from stock price data history being there for anyone to inquire of. Nonetheless, it is quite right to regard the catastrophe model of market agent behavior as heuristic. In keeping with Arnold's tone, it is proposed to describe the model as the *Tadpole theorem* with the explicit intention that it is just a little bit of Pole!

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