

Algorithmic Trading, Market Efficiency and The Momentum Effect

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ABSTRACT

The evidence put forward by Zhang (2010) indicates that algorithmic trading can potentially generate the momentum effect evident in empirical market research. In addition, upon analysis of the literature, it is apparent that algorithmic traders possess a comparative informational advantage relative to regular traders. Finally, the theoretical model proposed by Wang (1993), indicates that the informational differences between traders fundamentally influences the nature of asset prices, even generating serial return correlations. Thus, applied to the study, the theory holds that algorithmic trading would have a significant effect on security return dynamics, possibly even engendering the momentum effect.

This paper tests such implications by proposing a theory to explain the momentum effect based on the hypothesis that algorithmic traders possess Innovative Information about a firm's future performance. From this perspective, Innovative Information can be defined as the information derived from the ability to accumulate, differentiate, estimate, analyze and utilize colossal quantities of data by means of adept techniques, sophisticated platforms, capabilities and processing power. Accordingly, an algorithmic trader's access to various complex computational techniques, infrastructure and processing power, together with the constraints to human information processing, allow them to make judgments that are superior to the judgments of other traders.

This particular aspect of algorithmic trading remains, to the best of my knowledge, unexplored as an avenue or mechanism, through which algorithmic trading could possibly affect the momentum effect and thus market efficiency. Interestingly, by incorporating this information variable into a simplified representative agent model, we are able to produce return patterns consistent with the momentum effect in its entirety.

The general thrust of our results, therefore, is that algorithmic trading can hypothetically generate the return anomaly known as the momentum effect. Our results give credence to the assumption that algorithmic trading is having a detrimental effect on stock market efficiency.

DECLARATION

I, Rafael Alon Gamzo, declare that this research report is my own work except as indicated in the references and acknowledgements. It is submitted in partial fulfilment of the requirements for the degree of Master of Management in Finance & Investment in the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

Rafael Alon Gamzo: 

Signed at Wits Business School

On the 1st day of August 2013

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My first appreciation goes to Hashem, G-d, King of the universe, the most precious thing in my life. No words can fully express my deep affection, awe and reverence.

“My soul thirsts for You, my flesh longs for You, in a dry and weary land without water. So may I look for You in the sanctuary to see Your power and Your glory. Because your love is better than life, my lips will glorify you. I will praise you as long as I live, and in your name I will lift up my hands”. (Tehillim:63.)

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CHAPTER 1: INTRODUCTION

Eugene Fama's (1970) Efficient Market Hypothesis (EMH) has arguably become one of the most fascinating and highly contested subjects amongst financial professionals and academics alike. Indeed, the foundation of capital market equilibrium lies on the Efficient Market Hypothesis¹.

Essentially, the Efficient Market Hypothesis is "an extension of the zero profit competitive equilibrium condition from the certainty world of classical price theory to the dynamic behavior of prices in speculative markets under conditions of uncertainty²" (Jensen, 1978, p. 3). Inherent in the above supposition is that – given the available information - security prices are likely to exhibit unpredictable behavior. Accordingly, by and large, no group of investors should be able to consistently "beat the market" by making consistent positive excess returns.

Security return dynamics as well as potential trading strategies are fundamentally influenced by the nature and thus *unpredictability* of security prices, implicit in this Efficient Market Hypothesis (Karemera, Ojah, & Cole, 1999). Broadly speaking, the extent to which a financial market is efficient has felicitous consequences for investment and resource allocation in an economy. This hypothesis has been continuously and extensively documented, tested and challenged ever since its inception³.

However, there has been a growing body of financial literature recently⁴, highlighting aspects of stock price and return behavior, which seem to deviate

¹ It is of critical importance that the (EMH) holds, or most of the statistical techniques in analyzing capital market equilibrium such as the Capital Asset Pricing Model (CAPM) are open to question (Huang & Yang, 1999).

² Accordingly, a market can be called efficient when "prices always fully reflect available information" (Fama, 1970, p. 383).

³ Its prominence in financial literature became most noticeable in the 1960s under the rubric of the 'Random Walk Hypotheses'

⁴ The growing availability of intraday data in the 80s and 90s allowed researchers to test informational effects on stock prices within minutes (Gosnell, Keown & Pinkerton, 1996). However, this period also

from what is considered the norm, regarding the traditional paradigm. These abnormalities are both baffling and difficult to reconcile with market efficiency due to their implications regarding predictability. These irregularities are referred to as market anomalies. Among these anomalies, the momentum effect is probably the most difficult to explain and represent, perhaps, the strongest evidence against the Efficient Market Hypothesis⁵.

Following Hong and Stein (1999), the momentum effect can be viewed as an umbrella term encompassing two pervasive, interconnected phenomena. That is, firstly, the phenomena of excess stock returns tending to exhibit unconditional positive serial correlation in the short to medium-run (short-term momentum) and secondly, the phenomena of excess returns tending to exhibit negative serial correlation in the long-run (long-term reversals). Taken together these two interconnected phenomena represent the momentum effect in its entirety. Indeed, studies on this subject have begun to view short-term momentum and long-term reversals as inseparable phenomena. (Hong and Stein, 1999). This momentum effect is regarded as one of the most puzzling anomalies of finance. Questions surrounding the underlying causes for the above anomaly have been and may remain empirically unresolved for a while.

Adding to the complexity of the issue, financial markets are seen to have undergone tremendous structural changes since the aforementioned studies were conducted. Recent technological innovations have facilitated an extraordinary evolution in capital market structure, as well as considerably *altering the processes underlying security returns*.

witnessed the intellectual dominance of the efficient market hypothesis becoming far less universal. For example, Keim and Stambaugh (1986) found stock prices can be predicted using certain forecast techniques based on certain predetermined variables.

⁵ These abnormalities “cast a considerable doubt on the validity of the Capital Asset Pricing Model, and hence, market efficiency.” (Alagidede & Panagiotidis, 2009, p. 9). Indeed, Fama and French (1996) point out that the momentum effect constitutes the “main embarrassment” for their three-factor model (see also Fama and French (2008))

All things considered it seems indecorous to neglect these technological innovations and its possible effects on market efficiency when analyzing the issues highlighted above - this remains a central theme of our research.

One of the key developments stemming from these technological advances falls under the rubric of algorithmic trading. According to Zhang (2010), as of 2009, algorithmic trading accounted for as much as 78% of all U.S. equity trading volume.

Algorithmic trading is commonly defined as the “use of computer algorithms to automatically make trading decisions, submit orders, and manage those orders after submission” (T. Hendershott & Riordan, 2009, p. 2). Algorithms have evolved into some of the most sophisticated trading programs, making use of cutting edge mathematical models and extraordinary processing power in order to implement profitable trading strategies. They employ relevant statistical and econometric techniques via advanced computer and communication systems at extremely high speeds and are capable of anticipating and interpreting relatively short-term market signals, in order to implement profitable trading strategies.

A debate comprising widely opposing opinions has transpired regarding the benefits and risks associated with algorithmic trading. The “Jury is still out”, however, regarding its overall effect on the *efficiency* of financial markets. Proponents of algorithmic trading have linked its presence to increased liquidity⁶ and/or improved price discovery⁷ in both foreign exchange and equity markets. (Hendershott, Jones & Menkveld, 2011; Chaboud, Hjalmarsson, Vega &

⁶ Hendershott, Jones and Menkveld (2011) argue that for all stocks, and especially large-cap stocks, automated trading increased liquidity. Chaboud, Hjalmarsson, Vega and Chiquoine (2009), using the 1993 to 1997 period, posit that automated trading tends to slightly increase liquidity provisions in the foreign exchange markets after exogenous market events such as news announcements.

⁷ Brogaard (2010) in his analysis on the impact of algorithmic trading on market quality finds that algorithmic trading adds to the process of price discovery, but finds mixed results on its ability to supply liquidity to the market. Hendershott and Riordan (2011) examined the impact of algorithmic trading on the price discovery process in US equity markets. Overall the authors observed that marketable algorithmic trades actively drive prices towards their long-term fundamental value, thereby aiding the price discovery process.

Chiquoine, 2009; Brogaard, 2010, and Hendershott & Riordan, 2011). Whilst, opponents argue that it creates an atmosphere of instability and information inefficiency (Smith, 2010, and Zhang, 2010). Evidence to date is still inconclusive.

Consistent with the momentum effect, Zhang (2010) finds that algorithmic trading hinders the incorporation of fundamental information into asset prices. His paper reveals that prices deviate systematically from their fundamental values when algorithmic trading is more evident, resulting in their regression in subsequent periods. Relying on U.S. equity market data, Zhang showed that in terms of economic magnitude, one standard deviation increase in algorithmic trading also increased price reaction to fundamental information by 8%.

Although not *explicitly* considered in his paper, the findings suggest the presence of a momentum effect- which was previously attributed to behavioral factors such overconfidence and subjective self-attribution bias⁸- and that this effect can be better explained by algorithmic trading. Moreover, Smith (2010) finds that algorithmic trading is influencing the microstructure of equity transactions, exhibiting drastically higher degrees of self-similarity⁹.

Evidence thus far seems to lend itself to the possibility of a relationship between algorithmic trading and the momentum effect. However, attributing causality- by accrediting algorithmic trading with engendering the momentum effect- remains premature.

⁸ See for example, Daniel, Hirshleifer and Subrahmanyam, 1998, or section 2.3.1 of this paper, possible explanations for the momentum effect, for a more detailed description of overconfidence and subjective self-attribution bias.

⁹ Self-similarity is usually calculated using the Hurst exponent, H , which measures the relative degree of self-similarity from pure Markovian Brownian Motion. For more information see Smith (2010). His analysis posits that, as a result of algorithmic trading, markets are beginning to exhibit feedback effects at extremely short timescales.

In brief, the momentum effect and thus return predictability has dominated discussions on the Efficient Market Hypothesis, yet no clear reasons or causes of the phenomena have been established. The initial perception fails to take into account the tremendous changes that have taken place in financial markets, consequently, neglecting the role played by algorithmic trading in this complex dynamic relation. Further, the evidence put forward by Zhang (2010) indicates that algorithmic trading can potentially generate the momentum effect evident in the research, however, due to algorithmic trading's relatively recent emergence, the literature is yet to examine this directly. More precisely, the literature is yet to produce a theoretical model that investigates whether algorithmic trading can generate the momentum effect.

Therefore, this research intends to investigate the contemporaneous and dynamic relationship between algorithmic trading, the momentum effect and stock market efficiency by focusing, foremost, on the impact algorithmic trading has on security pricing and return dynamics (market efficiency). More specifically, algorithmic trading's ability to generate short-run momentum and subsequent long-term reversals (the momentum effect).

If one takes into consideration the well documented nexus between the momentum effect and stock market efficiency as well as considering the possibility of algorithmic trading engendering this observed phenomenon, it seems appropriate to investigate algorithmic trading, the momentum effect and stock market efficiency in unison.

1.2) Purpose of the Study

The main purpose of this research is to examine the available literature on capital market efficiency in order to provide a premise with which to discuss and evaluate the critical issues raised by the anomalistic feature of the Efficient Market Hypothesis, namely, the momentum effect.

This analysis intends to complement still inconclusive academic literature on these topics by drawing upon both conceptual frameworks and indicative

evidence observed in the U.S. markets. More importantly an assessment will be made on whether this observed phenomenon can be explained by algorithmic trading in the capital market.

In an effort to advance on causality, this study will attempt to produce a representative model, incorporating features that fit well with the stylized facts about algorithmic trading.

This is done in order to identify the theoretical mechanism through which algorithmic trading may possibly generate this observed phenomenon.

1.3) Context of the Study

i) The Efficient Market Hypothesis

When Fama (1970) assembled a comprehensive review of theoretical and empirical evidence of market efficiency he proposed a theory known as the Efficient Market Hypothesis (EMH). Accordingly, a market can be called efficient when “ prices always fully reflect available information”(Fama, 1970, p. 383)

The concept of an efficient market can be illustrated by the following short story:

A student and her finance professor are both walking down the busy campus hall when they both notice a \$100 note lying on the floor. As the student bends down to pick up the money she notices a disappointed look on her professor's face. The professor subsequently says to the student, 'Don't bother. If the money was really there, someone else would have picked it up already' (Malkiel, 2003).

The Efficient Markets Hypothesis is simple in principle, but remains elusive. Under the rubric of the Random Walk Hypothesis, the Efficient Market Hypothesis suggests that the path that a stock price follows should display no discernible pattern, thus precluding any knowledge of past prices as a means of predicting future stock prices. A simple version of the Random Walk Hypothesis is that the

price of a stock today is the price of a stock yesterday plus an unpredictable error term:

$$Y_t = a + Y_{t-1} + e_t$$

More precisely the above equation is referred to as a random walk with a drift¹⁰. This idea has been applied extensively to theoretical models and empirical studies of financial securities prices, generating considerable controversy as well as fundamental insights into the price-discovery process¹¹. The importance of the Random Walk Hypothesis cannot be understated. "It is crucially important that the random walk hypothesis holds, or most of the statistical techniques in analyzing capital market equilibrium such as CAPM are open to question" (Huang & Yang, 1999, p. 3).

ii) Evolution and Forms of Market Efficiency

A market is said to be efficient *regarding some particular information* if that information is not effective in earning positive excess returns. Historically the evolution of empirical work on market efficiency began primarily with what is referred to as weak form tests. Here, studies were concerned merely with past price (or return) histories. This type of test is considered the outcome of random walk literature. After numerous tests confirmed efficiency at this level, studies began to focus on semi-strong form tests which were concerned with the time taken for prices to adjust to all publically available information¹². Finally, strong form tests, where, monopolistic access to information by any investors, was of interest. As a result three different forms of market efficiency emerged. These forms are elaborated below:

¹⁰ In the true random walk model a would = 0.

¹¹ "If stock prices are generated by a random walk (possibly with drift), then, for example, the variance of monthly sampled log-price relatives must be 4 times as large as the variance of a weekly sample." (Lo & MacKinlay, 1988, p. 53)

¹² For example, dividend announcements, seasoned public offerings or stock splits.

A) Weak-Form Efficiency

This type of efficient market suggests that the current price of a share reflects its own past prices. In other words all information about *historical prices* has already been incorporated into the current share price. Thus prices “fully reflect” the historical information of past prices and returns.

B) Semi-Strong Form Efficiency

Semi- strong form efficiency is regarded as the most controversial efficiency form. It proposes that all *publicly available information*¹³, including all historical information is reflected in the share price.

C) Strong-Form Efficiency

With strong form efficiency, all information, both public and private is reflected in current market prices. This form of efficiency is probably best viewed as a benchmark against which any deviations from market efficiency can be analyzed.

It is of particular interest to note that any information set in the strong form includes the information set in the semi strong form, which in turn includes the information set in the weak form and therefore the particular sets of information used in the three forms of market efficiency are considered *nested*.

Figure 1, below, displays the three information sets for market efficiency.

¹³ Information such as annual reports, news announcements and economic data.

Figure 1

Information Sets for
Market Efficiency

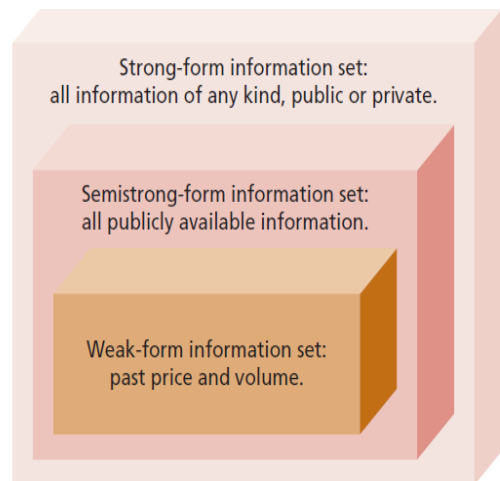


FIGURE 1- INFORMATION SETS FOR MARKET EFFICIENCY - SOURCE: FUNDAMENTALS OF INVESTMENTS, VALUATION AND MANAGEMENT. 2012. P.229.

iii) The Price Adjustment Process Implicit in Efficient Market Hypothesis

Stock price changes are as a result of frequent purchases and sale of shares. In an efficient market, investment decisions are based on a determination of a share's fundamental value¹⁴. According to the Efficient Market Hypothesis any unexpected firm-specific news announcement should result in an instantaneous price adjustment, where the new price fully reflects the available information, and hence, its fundamental value. Unexpected news announcements might include, for example, dividend increase announcements. This type of announcement is a positive news announcement¹⁵ and should result in one of three possible price adjustment processes. The three possible processes are as follows:

¹⁴ . Fundamental value refers to the value of a security which is intrinsic to or contained in the security itself. It can be ascertained by calculating the present value of future cash flows, discounted at the appropriate risk-free rate.

¹⁵ Miller and Rock (1985) hypothesize that investors draw inferences about implied changes in expected cash flows from corporate dividend announcements, suggesting dividend increases represent good news for investors.

- *Efficient Market Reaction:* The price should immediately adjust to its new fundamental value which reflects all available information. There should not be a tendency toward subsequent changes.
- *Delayed Price Reaction:* The price displays partial adjustment and therefore trends towards its fundamental value. However a significant amount of time elapses before it reflects this new information.
- *Overreaction and Correction:* The price initially overreacts to the new information, eventually correcting to its intrinsic value.

Figure (2) provides an example of the three ways in which prices can react to positive unexpected news.

Figure 2

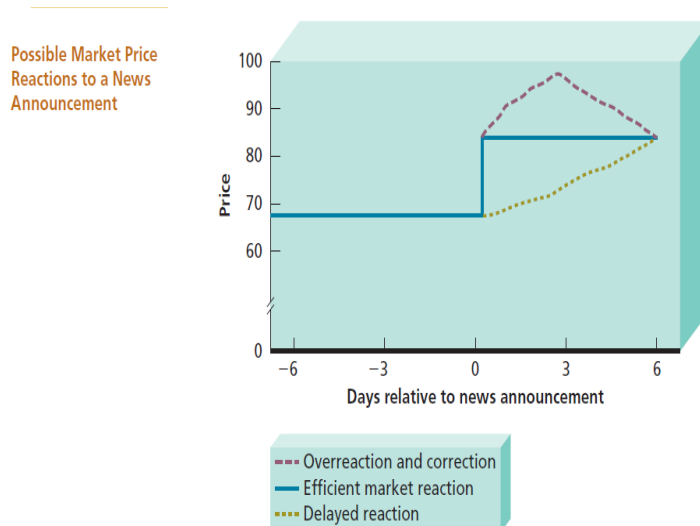


FIGURE 2- POSSIBLE MARKET PRICE REACTIONS TO A NEWS ANNOUNCEMENT- SOURCE: FUNDAMENTALS OF INVESTMENTS, VALUATION AND MANAGEMENT. 2012. P229

iv) Market Efficiency and the Momentum Effect

Despite decades of research, an extensive body of recent financial literature has produced evidence on security returns that sharply contrasts the traditional view that securities are rationally priced to reflect all publicly available information. These findings confirm the presence of a market anomaly known as the momentum effect. Evidence of the momentum effect amount to the most controversial aspect of the debate on stock market efficiency. Two of the more pervasive phenomena associated with the momentum effect have thus far been identified.

- 1) Positive short to medium term autocorrelation of returns (short-term momentum).
- 2) Negative autocorrelation of prior short-term returns (long-term reversal).

In fact, prominent theoretical models in this area such as Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998) and Hong and Stein (1999) all treat short-term momentum and long-term reversals as inseparable phenomena.

The longer term aspect of the momentum effect, long term reversals, was first documented by De Bondt and Thaler (1985). They show that over 3- to 5-year holding periods stocks that were extreme “losers” over the initial 3 to 5 years achieve higher returns than stocks that performed well over the same period.

Following De Bondt and Thaler, Jegadeesh and Titman (1993) provide evidence of shorter-term, return continuations. That is, prior to the negative return correlations documented by De Bondt and Thaler (1985), excess returns tended to exhibit positive serial correlations in the short to medium horizon. They show that stocks that perform best over a 3 to 12 month period tend to continue to perform well over the subsequent 3 to 12 months and stocks that perform the worst over a 3 to 12 month period tend to continue to perform poorly over the subsequent 3 to 12 months.

The evidence implies that the combinations of a positive return correlation at short horizons and eventual mean reversion at long horizons constitute the momentum effect in its entirety.

However, the available literature has found mixed empirical evidence regarding the momentum effect, depending on exchange specific variables, such as stage of development, relative time and frequency of transactions. The available literature has yet to pinpoint the exact mechanism through which this anomaly takes place.

V) Algorithmic Trading

Recent technological innovations have revolutionized the way in which financial markets operate. These advances have resulted in tremendous changes in the structure of financial markets and have an important bearing on the processes underpinning security pricing and return dynamics.

Two important interconnected technological changes have been associated with this development. Firstly, computer technology has enabled investors the ability to automate their trading processes and secondly, exchanges have re-organized themselves to the extent that mostly all markets are now electronically operated.

The process by which the securities trading became electronic can be traced as far back as the 1970s, when, NASDAQ¹⁶, previously known as the National Association of Securities Dealers (NASD) embarked on a computer-assisted system for automated quotation in the United States (Freund, 1989). This led to the obsolescence of physical trading floors, allowing for automated electronic trading systems to dominate. Information technology has progressed to such a level that it can now be found at every stage of the trading process.

A key development stemming from these advances falls under the rubric of algorithmic trading. Essentially, algorithmic trading is computer-determined trading, utilizing super computers and complex algorithms that directly interface

¹⁶ National Association of Securities Dealers Automated Quotations.

with trading platforms at high speed, placing orders without immediate human intervention. They employ relevant statistical and econometric techniques via advanced computer and communication systems and are capable of anticipating and interpreting relatively short-term market signals in order to implement profitable trading strategies¹⁷. Consequently, algorithmic trading has become a crucial competitive factor for capable market participants.

A distinctive sub category of algorithmic trading that has grown recently is known as high frequency trading. However, to date, there has not been a unanimously accepted academic or regulatory definition of high frequency trading¹⁸. According to Brogaard (2010), high frequency trading is computer determined trading whereby stocks are bought and sold by an automated algorithm at high speeds and held for a very short period, usually seconds or milliseconds. However since the typical properties of high frequency trading could also define algorithmic trading, it becomes extremely challenging to distinguish between the two. Adding to the complexity of the issue, some high frequency trading strategies are seen to have no special speed requirement. (Tradeworx 2010a).

In order to elucidate the distinction between algorithmic trading and high frequency trading we take a more general approach, by assuming that algorithmic trading is a hyponym including all its subsets, including but not limited to high frequency trading. This view is supported by Abergel, Bouchaud, Foucault, Lehalle, and Rosenbaum (2012). This approach allows us to avoid the false dichotomy often associated with algorithmic trading and high frequency trading. The focus then becomes on the nature of the trading strategies coded by the algorithms themselves.

Therefore, to summarize, algorithmic trading is defined as computer-determined trading, utilizing super computers and complex algorithms which directly interface

¹⁷ Brogaard (2010) posits that algorithmic traders generate gross trading profits of approximately \$2.8 billion annually and sharp ratios of about 4.5

¹⁸ See Gomber, Arndt, Lutat and Uhle (2011), Appendix II- Academic and Regulatory Definitions of Algorithmic Trading, pp. 74.

with trading platforms at high speed, placing orders without immediate human intervention. It (algorithmic trading) employs cutting edge mathematical models, adept computational techniques and extraordinary processing power via advanced computer and communication systems and is capable of anticipating and interpreting relatively short-term market signals in order to implement profitable trading strategies.

VI) The Evolution of Algorithmic Trading

Detailing the progression of algorithmic trading requires that algorithms be classified into four generations. This is based on the work of Almgren (2009) and includes information from Johnson (2010) and Leinweber (2009) as well as, Gomber, Arndt, Lutat and Uhle (2011).

First generation trading algorithms were the result of a natural progression in basic order slicing. They involved the realization of specific pre-determined benchmarks, such as the Time Weighted Average Price (TWAP)¹⁹. These early algorithms were likely statically driven and based on specific trading schedules. However, due to the anticipatory nature of these trading schedules, market participants would often take advantage of their regular trading patterns.

Second generation algorithms were more multifarious than their predecessors and sought to manage the trade-off between market impact and timing risk. The most prominent second generation algorithms were implementation shortfall algorithms. Implementation shortfall algorithms tried to reduce the market impact of large orders by considering the possibility of adverse price reactions during the execution process (timing risk). In order to avoid this, these algorithms predetermine an execution plan based on historical data, and split an order into

¹⁹ An example is given by Gomber, Arndt, Lutat and Uhle (2011): "TWAP algorithms divide a large order into slices that are sent to the market in equally distributed time intervals. Before the execution begins, the size of the slices as well as the execution period is defined. For example, the algorithm could be set to buy 12,000 shares within one hour in blocks of 2,000 shares, resulting in 6 orders for 2,000 shares which are sent to the market every 10 minutes. TWAP algorithms can vary their order sizes and time intervals to prevent detection by other market participants." (p. 24)

as many as necessary but as few as possible sub orders. (Gomber, Arndt, Lutat & Uhle, 2011)

Third generation algorithms, often referred to as adaptive algorithms, follow a much more sophisticated approach. Instead of following a pre-determined schedule, they are adaptive in nature. Meaning they are able to re-evaluate and change their execution schedule with changing market conditions.

The most recent development in the algorithmic trading domain concerns the so called fourth generation algorithm. These algorithms use increasing levels of mathematical and econometric sophistication and include models of market forecasting, market impact and market risk. They have access to a wide variety of securities and derivatives and combine quantitative and non-quantitative methods in order to forecast relatively short-term market movements. These complex algorithms are capable of accumulating, estimating and utilizing colossal quantities of information in order to detect the kind of patterns and events that traders look for themselves. However they do this for hundreds or thousands of securities simultaneously at very high speed.

Most importantly, they seek to exploit information beyond the traditional data, including news, pre-news and other forms of information. (Leinweber, 2009)

Considering that contemporary relevance demands a neoteric perspective, we focus primarily on these so called fourth generation algorithms.

VII) Algorithmic Trading and Financial Institutions

In order to generate additional income, large financial institutions and investment banks increasingly employ state-of-the-art algorithmic and information technology as part of their trading activities²⁰. In fact income from these trading activities is progressively replacing revenue from traditional activities such as

²⁰ Conceptually, a financial institution's trading portfolio contains relatively short term -liquid assets, ranging from as short as one day to one year.

deposit taking and lending²¹. Institutional investors utilize advanced algorithms in order to conduct, for example, basic position trading and risk arbitrage.

With position trading, institutions buy large blocks of securities on the expectation of a favorable price move. While risk arbitrage entails, purchasing blocks of securities in anticipation of some information release. Institutions that engage in algorithmic trading use advanced computer programs to access and process vast amounts of data in order to successfully initiate the above trades. Also by utilizing algorithms they are able to trade large quantities gradually over time, thereby minimizing market impact and implementation costs (Saunders & M. Cornett, 2011).

VIII) Algorithmic Trading and the Momentum Effect

Academic research concerning the impact of algorithmic trading is still in its infancy and, as such, papers documenting its association with specific market anomalies such as the momentum effect remain, relatively unexplored.

However, that being said, a recent paper by Frank Zhang (2010) equates to, perhaps, the closest work documenting this association.

A short summary of the findings will be discussed below.

By using a sample that contains all stocks covered by the Center for Research in Security Prices (CRSP) and the Thompson Reuters Institutional Holdings database between the 1st quarter of 1985 and the 2nd quarter of 2009, Zhang (2010), attempted to examine algorithmic trading's association with both price volatility and the market's ability to incorporate fundamental news into stock prices.

²¹ This results in financial institutions having to manage a growing earnings uncertainty (market risk).

As algorithmic trading is not directly observable, Zhang (2010) proposed a novel way of estimating it, that is, by equating it to all the trading activities not included in the 13f database. The reasoning behind this approach is as follows.

The United States Securities and Exchange Commission (SEC) require institutions with over \$100 million in Assets under Management (AUM) to report their long term holdings in the 13f quarterly report of equity holdings. These institutions include hedge funds, investment companies, pension funds, insurance companies, university endowments, banks and many other types of professional investment advisors. Crucially short positions are not required to be disclosed and thus excluded from the report. Thus by measuring trading volume relative to institutional portfolio changes in quarterly 13f filings, Zhang (2010) was able to capture trading frequencies greater than those of long term traditional investors (Securities and Exchange Commission, 2013).

Overall, the evidence indicated that algorithmic trading increases stock volatility. “The positive correlation between algorithmic trading and stock price volatility is stronger for stocks in the investable universe, stronger for stocks with high institutional holdings, and stronger during periods of high market uncertainty” (Zhang, 2010, p. 24)

However, the reason that his research equates to, perhaps, the closest work documenting the association between algorithmic trading, the momentum effect is seen in the second aspect of his investigation, namely algorithmic trading’s association with the markets ability to incorporate fundamental news into stock prices.

By using analysts’ earnings revisions and earnings surprises to proxy for fundamental news, Zhang determined that algorithmic trading detracts for the markets ability to incorporate news into prices, whereby, prices tended to overshoot their fundamental values, resulting in their regression in subsequent periods. Interestingly this algorithmic trading-related price reaction and subsequent reversal is consistent with the momentum effect documented in financial markets.

Zhang's article provides valuable insight into the dynamic relationship between algorithmic trading, the momentum effect and stock market efficiency. However, the underlying theoretical mechanism behind this relationship remains unknown, increasing the necessity for further investigation.

1.4) Problem Statement

The momentum effect and thus return predictability has dominated discussions on market efficiency, yet no clear reasons or causes of the phenomena have been established. The initial perception fails to take into account the tremendous changes that have taken place in financial markets, consequently, neglecting the role played by algorithmic trading in this complex dynamic relation.

- **Sub Problem**

The evidence put forward by Zhang (2010) indicates that algorithmic trading can potentially generate the momentum effect evident in the research, however, due to algorithmic trading's relatively recent emergence, the literature is yet to produce a theoretical model that examines this relation directly.

1.5) Research Objectives

This research intends to investigate the relationship between algorithmic trading, the momentum effect and stock market efficiency by focusing, foremost, on the impact algorithmic trading has on security pricing and return dynamics. More specifically, algorithmic trading's association with short-run momentum and subsequent long-term reversal.

Sub Aims

- To analyze from the literature, the theoretical mechanism through which, algorithmic trading can possibly generate the momentum effect.
- Propose a theoretical model that is better suited to describe the world of algorithmic trading.

- Produce a representative model, incorporating features that fit well with the stylized facts about algorithmic trading, in order to ascertain whether, theoretically, algorithmic trading can generate the momentum effect.

1.6) Research Questions

- Can algorithmic trading potentially generate the momentum effect?
- If algorithmic trading can generate the momentum effect, what is the underlying mechanism?
- Can this mechanism be modelled by a representative agent model?

1.7) Significance of the Study

The aim of this paper is to make a contribution to the research on market efficiency and its associated anomaly, the momentum effect, by studying the impact of algorithmic trading on security pricing and return dynamics. The main focus will be on U.S. equity markets.

Primary investigations into the Efficient Market Hypothesis yield extensive support for market efficiency. However, it is important to note that the majority of these studies were conducted before the advent of algorithmic trading. Adding to this, there has been a growing body of empirical literature of late which does not support the efficient market hypothesis. Could an analysis of algorithmic trading be a catalyst for the further growth of such contradictory evidence?

Previous studies on the relationship between market efficiency and the momentum effect have been limited by their *exclusion* of new developments' such as algorithmic trading in their analysis. Thus, there is a need for further investigation that is consistent with the current state of the capital market.

Due to algorithmic trading's relatively recent emergence, this paper seems to be one of the first to directly investigate whether, theoretically, algorithmic trading can generate the momentum effect.

Evaluating the relationship between algorithmic trading and its relative effects on market efficiency is of interest to both investment practitioners and financial academics. In addition, the finding of the study is expected to assist policymakers understand the relative impact algorithmic trading has had on financial markets in the U.S., thus allowing them to gauge the relative risks associated with it, in order to make informed policy decisions.

1.8) Structure of the Research

I. Chapter 2 presents a review of the previous works on market efficiency, the momentum effect and algorithmic trading, as well as considering the theoretical links between these three factors.

II. Chapter 3 provides an overview of the research design and methodology utilized in this study to ascertain the effects of algorithmic trading on market efficiency. The econometric methodology is also discussed in this chapter.

III. Chapter 4 presents a theoretical model

IV. Chapter 5 reports the results of the study.

IV. Chapter 6 provides the conclusion of the study and recommendations for further research.

CHAPTER 2: LITERATURE REVIEW

2.1) Introduction

This section provides a review of the previous works on market efficiency, the momentum effect and algorithmic trading, as well as considering their theoretical links.

2.2) Review of the Current Literature Concerning the Efficient Market Hypothesis

According to Eugene F. Fama (1970):

The primary role of the capital market is allocation of ownership of the economy's capital stock. In general terms the ideal is a market in which prices provide accurate signals for resource allocation: That is, a market in which firms can make production -investment decisions, and investors can choose among the securities that represent ownership of firms' activities under the assumption that security prices at any time "fully reflect" all available information. A market in which prices always "fully reflect" available information is called efficient. (p. 383).

The question, as to what the phrase "fully reflect" means, thus arises. Its ambiguity results in a situation where it lacks the ability to be empirically testable. In order to create a situation in which it is testable, there is a need for greater specification regarding the price formation process. In determining what is meant by the phrase "fully reflect", one could argue that market equilibrium can be stated in terms of expected returns, whereby, conditional on a specific informational set, the equilibrium expected return is a function of its risk (Fama, 1970). Generally expected return theories can be described algebraically as follows:

$$E(\tilde{p}_{j,t+1}|\theta_t) = [1 + E(\tilde{r}_{j,t+1}|\theta_t)] p_{jt},$$

Where:

- E = expected value operator
- p_{jt} = price of security j at time t
- $\tilde{p}_{j,t+1}$ = price of security j at time $t + 1$
- $\tilde{r}_{j,t+1}$ = percentage return at time $t + 1$
- θ_t = the set of “fully reflected” information in the price at time t

Where; $\tilde{p}_{j,t+1}$ and $\tilde{r}_{j,t+1}$ are random variables at time t .

The specific chosen expected return theory would determine $E(\tilde{r}_{j,t+1}|\theta_t)$, the value of the expected return in equilibrium, on the basis of the information set θ_t . The equation implies that the information in θ_t is fully utilized in determining equilibrium expected returns, therefore θ_t is “fully reflected” in the formation of the price p_{jt} . By assuming that conditions of market equilibrium can be stated in terms of expected returns and that equilibrium returns are formed on the basis of information in θ_t has major empirical implications: “they rule out the possibility of trading systems based only on information in θ_t that have expected profits or returns in excess of equilibrium expected profits or returns”(Fama, 1970, p. 385). The above model of market efficiency is often referred to as the expected return or “fair game” model.

However, the fair game model merely says that conditions of market equilibrium can be stated in terms of expected returns, and it has little to say about the stochastic process generating returns (Fama, 1970). Therefore, the random walk model, where the sequence of past returns is of no consequence in determining distributions of future returns, should be viewed as an extension of the expected return model. It creates a more detailed statement about the specific economic environment. There are many variations of the random walk model²², but formally it is defined as follows:

²² See page 7 of this paper.

$$F(r_{j,t+1}|\theta_t) = F(r_{j,t+1}),$$

Where future price changes are independent and identically distributed.

In his paper on stock price behavior, Eugene Fama (1970) reviewed the theoretical and empirical literature on the efficient markets model. His primary objective was to create a clear, up-to-date picture of the work conducted thus far. His work established the first coherent summary of the different aspects of market efficiency; in so doing, Fama (1970) created a formal separation and categorization of information subsets into *weak*, *semi-strong* and *strong* form tests of market efficiency. After thorough investigation the argument was made that there was minimal (if any) evidence against the strong form test and no evidence against the weak and semi-strong form tests.

Evidence against the strong form tests were disregarded because, at the time, there was no indication of monopolistic access to information being a prevalent issue among investors. Interestingly, the current questions surrounding algorithmic trader's access to more sophisticated information seems to create an atmosphere in which to contest the above finding. Are the above results still applicable, or could they simply be a product of the time instead of describing fundamental results?

At the time, the majority of evidence seemed consistent with the Efficient Market Hypothesis. Any results indicating equity return predictability were summarily found insignificant, and prices were viewed as following a random walk. Support for the Random Walk Hypothesis was evident from the results of Osborne (1959) and Cootner (1964) when testing the hypothesis using historical data. Similarly, the serial correlation tests of Moore (1962) also seemed to indicate evidence in support of the model. In the studies, successive price changes displayed serial correlation coefficients that were extremely close to zero, thus ruling out change dependency.

A plethora of subsequent studies emerged as a result of the strong support for the Efficient Market Hypothesis. A common theme was to investigate equity price reactions to unexpected news announcements (Ball & Brown, 1968). The results

typically showed that stock prices adjusted somewhat instantaneously to the event, an inference that is in line with the Efficient Market Hypothesis.

The growing availability of intraday data in the 80s and 90s allowed researchers to test informational effects on stock prices within minutes (Gosnell, Keown, & Pinkerton, 1996). However, this period also witnessed the intellectual dominance of the Efficient Market Hypothesis becoming far less universal. Many financial economists and statisticians began to believe that stock prices are at least partially predictable. Papers began to uncover empirical evidence pointing to stock return predictability. For example, Keim and Stambaugh (1986) found stock prices can be predicted using certain forecast techniques based on certain predetermined variables.

In addition, Lo and MacKinlay (1999) reject the Random Walk Hypothesis after finding several statistically significant short-term serial correlations. A positive serial correlation in this context would be viewed as evidence of short-term momentum. This creates an opportunity for investors to earn excess returns through an investment strategy of buying after periods with positive returns and selling after periods of negative returns.

2.3) Review of the Current Literature Concerning the Momentum Effect

Despite decades of research, an extensive body of recent financial literature has produced evidence on security returns that sharply contrasts the traditional view that securities are rationally priced to reflect all publicly available information. These findings confirm the presence of a market anomaly known as the momentum effect. Evidence of the momentum effect amount to the most controversial aspect of the debate on stock market efficiency. The pervasive anomalous returns associated with the momentum effect are described as being anomalous because they cannot be explained by the capital asset pricing model (CAPM) of Sharp (1964) and Linter (1965).

Two of the more pervasive phenomena associated with the momentum effect have thus far been identified.

- 1) Positive short to medium term autocorrelation of returns (short-term momentum).
- 2) Negative autocorrelation of prior short-term returns (long-term reversal).

In fact, prominent theoretical models in this area such as Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998) and Hong and Stein (1999) all treat short-term momentum and long-term reversals as inseparable phenomena.

The longer-term aspect of the momentum effect, long term reversals, was first documented by De Bondt and Thaler (1985). They show that over 3 to 5 year holding periods stocks that were extreme “losers” over the initial 3 to 5 years achieve higher returns than stocks that performed well over the same period.

Following De Bondt and Thalers, Jegadeesh and Titman (1993) provide evidence of shorter-term return continuations. That is, prior to the negative return correlations documented by De Bondt and Thaler (1985), excess returns tended to exhibit positive serial correlations in the short to medium horizon. They show that stocks that perform best over a 3 to 12 month period tend to continue to perform well over the subsequent 3 to 12 months and stocks that perform the worst over a 3 to 12 month period tend to continue to perform poorly over the subsequent 3 to 12 months.

The evidence implies that the combinations of a positive return correlation at short horizons and eventual mean reversion at long horizons constitute the momentum effect in its entirety.

Subsequently investigating the momentum effect in stock markets became a worldwide phenomenon (Kang, Liu & Ni, 2002; Hong, Lee & Swaminathan, 2003 ; Snyman 2011). Evidence to date seems to indicate that, in terms of countries, the momentum effect is shown to be stronger in the developed markets, than in

the emerging markets²³. This seems to suggest that stock market development plays an important role in the momentum effect.

2.3.1) Possible Explanations for the Momentum Effect

Fama (1998) identified profitable momentum strategies as the one outstanding anomaly in modern finance. One of the premier explanations for this anomaly revolves around investor psychology and belongs to a field of study aptly named behavioral finance. Behavioral finance seeks to better understand how emotions and cognitive errors influence investors in the decision-making process. As previously stated the momentum effect encompasses two interconnected phenomena. That is both short-term momentum and long-term reversals. However models consistent with both these effects are relatively scarce.

Some behavioral models are able to explain short-term momentum but not long-term reversals (Berk, Green & Naik, 1999; Holden & Subrahmanyam, 2002; Makarov & Rytchkov, 2012.) Other models can justify long-term reversals but not short-term momentum. For example, Wang (1993) presents a dynamic asset-pricing model under the assumption that investor's possess different information regarding the expected future growth rate of returns. By differentiating between informed and uninformed investors, he determines that information asymmetry among market participants can result in higher price volatility and negative autocorrelation in returns. His discovery of an association between information asymmetry and negative auto correlations provides significant insight into the possible process underlying the reversal aspect of the momentum effect. Wang (1993) attributes the negative serial correlation to the mean reversion in the underlying variables that affect expected excess returns. He assumes that information asymmetry enhances this negative correlation when uninformed participants only learn about these state variables from realized returns, thus increasing expected future returns dependence on past returns. (See also Lewellen & Shanken, 2002 and Fama & French, 2008).

²³ (Rouwenhorst, 1998; Griffin, Ji, & Martin, 2003; Muga & Santamaria, 2007.)

However, regarding the momentum effect in its entirety, there are a small number of models consistent with both these phenomena. Two of the most notable exceptions are the positive feedback model of De Long, Shleifer, Summers, and Waldmann (1990) and the investor overconfidence hypothesis of Daniel, Hirshleifer and Subrahmanyam (1998).

a) The Positive Feedback Model

De Long, Shleifer, Summers, and Waldmann (1990) in their study of investor behavior, present an empirically significant argument against the standard perception that rational speculators stabilize asset prices. Their analysis posits that in the presence of positive feedback traders²⁴, the actions of rational speculators can destabilize prices. They argue that when there are numerous feedback traders in a specific market, actions of rational speculators exaggerate price trends.

An example of this is given by De Long *et al.* (1990). Accordingly, when a rational speculator receives good news, they recognize that subsequent trading on this information will result in a price increase, which would incentivize feedback traders to purchase the shares. In anticipation of such a reaction, informed investors buy more today, and so they drive prices up today more than is implied by the fundamental news event. “Tomorrow”, the uninformed investors buy in response to the prior price increase and thus keep prices above their fundamentals, even as rational investors sell out their positions and stabilize prices.

Their model generates a “positive correlation of stock returns at short horizons, as positive feedback traders respond to past price increases by flowing into the market, and negative correlations of stock returns at long horizons, as prices eventually return to their fundamental”(De Long *et al.*,1990,p.381). Thus, their model is able to generate the momentum effect in its entirety.

²⁴ For example, investors that purchase securities when prices rise and sell when prices fall. See De Long *et al.* (1990).

b) The Overconfidence Hypothesis

Daniel, Hirshleifer and Subrahmanyam (1998) postulate that security markets initial overreaction and subsequent reversal is a result of two well-known personal psychological biases, namely: *Investor overconfidence* regarding private information and *subjective self-attribution*.

Accordingly, an overconfident investor is “one who overestimates the precision of his private information signal, but not of information signals publicly received by all” (Daniel et al., 1998, p. 4).

Self-attribution bias²⁵ on the other hand, suggests that investors attribute their success to their own personal ability, yet failures are attributed to external uncontrollable forces, thus giving weight to their achievements instead of their failures.

By including self-attribution bias in their model, confidence levels change from being fixed to an outcome dependent variable. Thus, an investor’s confidence rises if subsequent public information confirms their private signal, but falls only by a small amount if the public information does not confirm the private signal. As a result, the self-attribution bias will often reinforce overconfidence.

By demonstrating that short-run positive autocorrelations can be consistent with long-run negative autocorrelations, their analysis confirms the patterns found by previous literature on the momentum effect.

2.3.2) Rational Models and Information

With the exception of a minor compendium of behavioral models, rational models usually follow the informed/ uninformed- investor paradigm (Grossman, 1976). According to Grossman (1976) informed investors are those that have information about the future states of the world, while the uninformed investors do not. This

²⁵ A theory strongly related to cognitive dissonance where the individual disregards information that conflicts with past choices. See Bem (1965).

differential informedness aspect of markets, commonly referred to as information asymmetry, implies that some investors are better than others when it comes to interpreting financial information and are, as a consequence, better at forecasting future market movements. According to Brown, Richardson and Schwager (1987), this superiority is mostly driven by informed investor's access to both more timely information and a broader set of information on which to base forecasts.

By and large, the interplay between market participants and information has proven to be an important trend in model development and research design. The current approach emphasizes the information content of accounting data and its association with current and future firm value²⁶. This methodology and philosophy highlights not only stock behavior in reaction to accounting data but also its association with future earnings.

2.3.3) Concluding Remarks on Explanations for the Momentum Effect

Behavioral finance seems to provide a plausible explanation for the observed momentum effect. However behavioral economics is an evolving discipline, and as such, requires constant revisions and adaptations in order to be applicable in the current environment. In an environment where up to 77%²⁷ of total volume traded is a result of algorithmic trading, it seems somewhat inappropriate to neglect algorithmic trading and its possible effects in the analysis of the momentum effect.

²⁶ . Where, the information content in accounting data is primarily measured by the market's reaction to earning announcements. (White, 2006)

²⁷ See Brogaard (2010).

2.4) Review of the Current Literature Concerning Algorithmic Trading

The traditional *paper systems* that brokers, dealers, and specialists used during trading quickly lost its appeal during the 1960s due to the massive growth in trading volume. This “paperwork crisis” put significant pressure on floor traders and seriously affected operations on the NYSE. The result was the introduction of the first electronic order routing system by 1976.

Then in the 1980's the NYSE upgraded their order system to SuperDot. This development facilitated the growth of a type of programmed trading, where investors could execute large orders of multiple trades' simultaneously. This type of trading is not algorithmic trading, per se, but shares many of its characteristics.

By the 90s, the advances in telecommunications and computer technology resulted in many extensive changes. A key example of this was the introduction of alternative trading platforms such as the ECN²⁸, where buyers and sellers orders could be matched at *much faster rates* and without traditional brokers or dealers.

In 2000, a truly groundbreaking development occurred. This was the decimalization of the price quotes on US stocks. Decimalization made it much easier for computer algorithms to trade and conduct arbitrage. It created a platform in which algorithmic trading could thrive (Smith, 2010).

Being a relatively new phenomenon, research that examines algorithmic trading directly is still limited. A serious obstacle in conducting research on this topic is data availability. That being said, a small but growing group of academic papers have begun to address questions surrounding algorithmic trading, mainly focusing on market quality parameters and issues regarding its profitability and fairness. The evidence to date is still inconclusive.

²⁸ Electronic Communications Network.

The majority of evidence indicates that algorithmic trading is having a positive influence on the market. Yet there is growing literature which is seemingly critical of algorithmic trading. Below is a short review of the most noteworthy evidence in favour of and against algorithmic trading.

a) Evidence in Favour of Algorithmic Trading

An important model that examines the theoretical impact of algorithmic trading on market quality²⁹ was conducted by Cvitanic and Kirilenko (2010). They create a theoretical model that adds algorithmic traders (machines) into a market populated by non-algorithmic traders. In their model algorithmic traders do not possess any informational advantages over the traditional investor. The only difference between normal and algorithmic traders – ‘machines’ – is that the latter have the advantage of having the ability to submit and cancel orders at faster rates than traditional traders

They find that by introducing the algorithmic traders into the model, transaction costs and their distributions tend to change. Cvitanic and Kirilenko (2010) show that the introduction of the machine improves the overall forecastability of transaction costs as they are more centered around the mean.

In line with the above study, Jarnecic and Snape (2010) categorize algorithmic traders into one of 6 groups. The 6 categories are as follows:

- Retail investors
- Low latency³⁰ participants
- Small institutions
- Investment banks
- Large institutions
- Traditional market makers

²⁹ More specifically, investigate the impact of algorithmic trading on transaction prices, trading volume and inter-trade duration.

³⁰ High speed market participants that react to market events in the millisecond environment. With “latency” defined as the time taken to discover an event.

Their results indicate that algorithmic traders tend to improve liquidity * over time and are more likely to dampen volatility than increase it.

Furthermore, Angel, Harris and Spatt (2011) studied the impact of regulatory and structural changes in U.S. equity markets for period 1993 to 2009. They show that algorithmic trading has significantly improved market quality, pointing to the dramatic decrease in execution speeds and bid ask spreads. They also propose that trading costs have declined and liquidity has increased in the presence of algorithmic trading.

On their investigation into low latency trading (Algorithmic trading), Hasbroak and Saar (2011) observe that low latency trading successfully lowers bid ask spreads, increases equity market depth and lowers short term volatility. Their work was consistent with that of Chaboud, Hjalmarsson, Vega and Chiquoine (2009), who posit that automated trading tends to slightly increase liquidity provisions in the foreign exchange markets after exogenous market events such as news announcements during 1993 to 1997.

However, they do note that algorithmic trading systems have less diverse strategies and exhibit higher correlation than those of human traders. Also, in then Euro-Dollar and Dollar-Yen markets, the two most traded currency pairs, algorithmic trading has less impact on price discovery than their traditional human counterparts.

Brogaard (2010), in his analysis on the impact of algorithmic trading on market quality finds that algorithmic trading adds to the process of price discovery, but finds mixed results on its ability to supply liquidity to the market. Brogaard (2010) also finds that algorithmic trading generates large revenues³¹. However he neglects to take into account how these positive excess returns impact market efficiency. Interestingly the findings suggest that a large portion of algorithmic traders tend to follow a price reversal strategy.

³¹ Generating gross trading profits of approximately \$2.8 billion annually and sharp ratios of about 4.5.

Lastly Martinez and Rosu (2011) show that as algorithmic traders enter the market, the market exhibits less volatility and becomes more stable.

b) Evidence Against Algorithmic Trading

Predominantly, algorithmic traders attempt to forecast relatively short-term market movements. Therefore, it may be appropriate to begin with a short review of the research concerning the behavior and thus, impact that short-term trading has on market efficiency.

There have been several academic papers that have focused on short-term trading and its relative impact on the equity market. The majority of these studies were conducted even before the inception of algorithmic trading and resulted in evidence that was in sharp contrast to the classic Efficient Market Hypothesis. The two most influential papers are briefly discussed below.

Froot, Scharfstein and Stein (1992) conducted research more than a decade before the algorithmic trading era, focusing primarily on the implications of short-term trading. They find that short-term investment horizons affect the nature of asset prices, leading to a specific type of informational inefficiency. Accordingly, short-term speculators seem to exhibit a form of herding that may result in decisions being made on the premise of information unrelated to the asset's fundamental value. They conclude that short-term traders focus too heavily on short term information and, as a consequence, they decrease the informational quality of market prices and adversely affect the Efficient Market Hypothesis.

In a similar vein, De Long, Shleifer, Summers and Waldmann (1990) conducted their research on the impact of short-term investing as well as noise trading³². They found that their presence' resulted in asset prices diverging from their fundamental values, implying that the traditional trading activities of traders can be seen as a response to noise rather than fundamental information.

³² "Noise trading is trading on noise as if it were information." Black (1986, p.531)

Taken together, the above evidence *seems an implicit suggestion* that, in the current context, algorithmic trading would be detrimental to the informational quality of asset prices due to its short-term nature.

Evidence against algorithmic trading specifically will be discussed below:

A growing number of studies, some of which are based on more recent and more extensive data are producing results that are critical of algorithmic trading. This growth is arguably a result of a *single event* known as the “Flash Crash” of May the 6th, 2010. The “Flash Crash” resulted in the largest single-day point decline in the history of the Dow Jones Industrial Average (998.5). For about 5 minutes approximately \$1 trillion in market value had disappeared, only to bounce back just as quickly.

The two most affected markets appeared to be the futures market and the equities market. Although the exact degree to which algorithmic trading was responsible for the “Crash” remains unknown, it seems clear from the evidence below that it was a major contributing factor.

- **The “Flash Crash”**

According to a report published by the SEC (2010), two separate liquidity incidents occurred on that day:

- The liquidity crisis in broad index level in the E-Mini futures market
- The liquidity crisis in individual stocks

Below is a brief description detailing the events that led to the “Flash Crash” of May, 2010:

On the 6th of May 2010 a large sell order³³ was initiated by a trader via an automated trading algorithm, programed to feed orders into the E-Mini futures

³³ Set to 9% of the trading volume calculated over one minute earlier. See SEC (2010).

market. This “sell algorithm” was set to ignore market price and market timing and only focus on quantity.

The sell pressure was *initially* absorbed by 3 distinct market participants:

- Other algorithmic traders seeking to profit from the subsequent price increases.
- Traditional buyers in the futures market.
- Cross market arbitragers (who transferred this sell pressure to the equities markets by opportunistically buying E-Mini contracts and simultaneously selling individual equities in the S&P 500 Index)

The above net buyers subsequently accumulated temporary long-term positions. However, about 60 % of algorithmic traders net long positions were sold. The resulting growth in volume prompted the initial “sell algorithm” to feed more orders into the market, even though the previous orders had not yet been fully absorbed by the other participants. The result was a drop in E-Mini prices by about 3% in just 240 seconds. Nevertheless, by 2:45 pm the “Stop Logic Function” saw a pause in trading for about 5 seconds, resulting in a decrease in sell side pressure and an increase in buy side pressure. This was followed, almost immediately, by price stabilization and recovery. Overall in just the four and a half minutes from 2:41pm prices on the E-Mini had sunk by more than 5%, only to recover moments later.

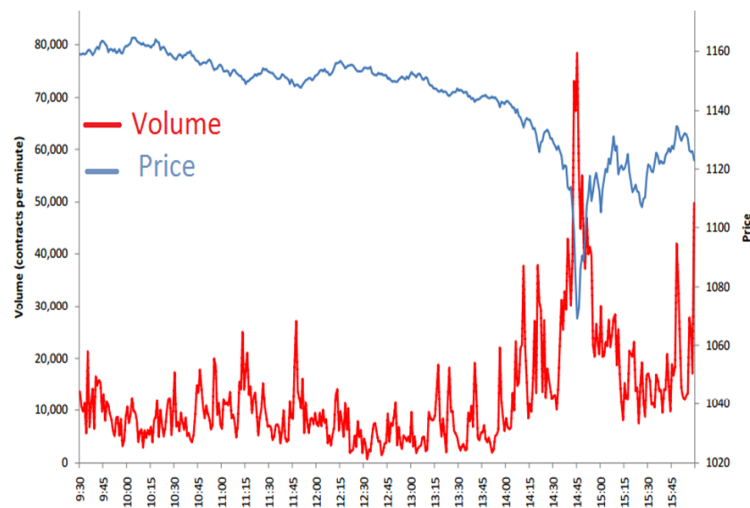


FIGURE 3- E-MINI VOLUME AND PRICE. SOURCE: SECURITIES, & COMMISSION, E. (2010). FINDINGS REGARDING THE MARKET EVENTS OF MAY 6, 2010. P. 19

The other liquidity crises occurred in the equities market approximately 30 seconds before trading resumed in the E-Mini market at about 2:45 pm. Around 8000 individual stocks were traded, with the majority displaying similar price declines and reversals as those in the E-Mini futures market. “Over 20,000 trades across more than 300 securities were executed at prices more than 60% away from their values just moments before”(SEC , 2010, p.1) By the end of the day, major futures and equities indices recovered to close at losses of about 3% from the prior day.

Although an intra-day event, the “Flash Crash” of 2010 cannot be considered inconsequential. On the contrary, many have argued that the “Flash Crash” of May the 6th 2010 represents the strongest evidence in support of the hypothesis that algorithmic trading has a destabilizing effect on the market.

Perhaps the rarity of officially commissioned studies further emphasizes its importance.

The SEC provided a short summary of the lessons to be learnt from the “Flash Crash” of 2010:

One key lesson is that under stressed market conditions, the automated execution of a large sell order can trigger extreme price movements, especially if the automated execution algorithm does not take prices into account. Moreover, the interaction between automated execution programs and algorithmic trading strategies can quickly erode liquidity and result in disorderly markets. As the events of May 6 demonstrate, especially in times of significant volatility, high trading volume is not necessarily a reliable indicator of market liquidity (SEC, 2010, p.6).

The “Flash Crash” brought to light algorithmic trading’s ability to exacerbate price movements in times of financial stress. The question now arises as to whether or not the same can be said under “normal” circumstances.

Zhang (2010) examined the impact of algorithmic trading in a broader economic context using the period 1985-2009. Using data from the CRSP and the Thomson Reuters Institutional Holdings databases in the U.S., he addressed two important economic issues surrounding algorithmic trading:

- Whether algorithmic trading was associated with price volatility.
- The effect that algorithmic trading had on the market’s ability to incorporate news concerning the firm’s fundamentals into stock prices.

After controlling fundamental firm-specific volatility, as well as other exogenous volatility variables, Zhang found a positive correlation between algorithmic trading and stock price volatility. He revealed that a one standard deviation increase in algorithmic trading activity is associated with a 5.6% rise in volatility.

Then, by using dividend surprises and analysts forecast revisions as proxies for firm fundamental information news, he provided evidence that algorithmic trading was negatively associated with the market’s ability to incorporate news about fundamentals into asset prices. His paper showed that prices seemed to deviate systematically from their fundamental values when algorithmic trading was more evident. In fact, one standard deviation increase in algorithmic trading also increased price reaction to fundamental information by 8%.

Although not explicitly considered in his paper, the findings suggest that the momentum effect, which was previously attributed to behavioral factors such as overconfidence, could be better explained by algorithmic trading activities. This remains a central theme of the research.

In 2011, Biais, Foucault & Moinas (2011) analyzed the effect of algorithmic trading on the market as a whole. Their work was one of the first to highlight the social impact³⁴ of algorithmic trading. By postulating a theoretical model, in which algorithmic traders have a speed advantage over ordinary traders, they found that the introduction of algorithmic trading can have two opposing effects. On the one hand it can increase an investor's chance of finding a counterparty to trade with, whilst, on the other hand, it is capable of generating *informational* asymmetries between slower traders' and algorithmic traders.

From the above it seems evident that "information" underpins the majority of algorithmic trading impact determinations, such as the price impact to information releases or even informational asymmetries between algorithmic traders and non-algorithmic traders. Thus, any analysis taking the informational aspects of algorithmic trading into account seems appropriate.

2.4.1) The Interplay Between Market Participants and Information

By and large, the interplay between market participants and information has proven to be an important trend in financial market research. Apropos market information, a large amount of literature has begun to address related issues of information differentials and its subsequent market effects (Grossman, 1976). This information differential, commonly referred to as information asymmetry, arises when information is known to some, but not all market participants. The

³⁴ In order to have a positive impact on society, a financial market should be fair, orderly and transparent and investors should be able to determine the best possible price for an asset with minimum effort. This type of market would tend to limit the information asymmetries between issuers, investors and their agents that could lead to a loss of confidence and desire to participate.

current approach emphasizes the distinction between informed and uninformed market participants.

Regarding this informed/ uninformed- investor paradigm, informed investors are seen to be those investors that have “private” information about the future states of the world, while the uninformed investors are those that do not (Grossman, 1976). This seems to imply that some investors are better than others when it comes to interpreting financial information and are, as a consequence, better at forecasting future market movements. According to Brown *et al.* (1987) this superiority or *advantage* is mostly driven by informed investor’s access to both more accurate and timely information as well as a broader set of information on which to base forecasts. Information asymmetry is closely related to the problem of adverse selection. According to Grossman (1979): “The problem of adverse selection arises as a manifestation of asymmetrical information in any market in which buyers and sellers are not equally informed about the characteristics of the heterogeneous commodities they exchange.”(p.336)

Consistent with the literature on information asymmetry, Wang (1993) presents a dynamic asset-pricing model under the assumption that investors possess different information regarding the expected future growth rate of returns. By differentiating between informed and uninformed investors, he determines that information asymmetry among market participants can result in higher price volatility and negative autocorrelation in returns.

2.4.2) Algorithmic Trading and Asymmetric Information

Academic research concerning the impact of algorithmic trading is still in its infancy. A serious obstacle in conducting research on this topic is data availability. That being said, a small but growing group of academic papers have begun to address questions surrounding algorithmic trading, mainly focusing on market quality parameters and issues regarding its profitability and fairness. The evidence to date is still inconclusive. The vast majority of studies regarding algorithmic trading have coalesced around the idea that algorithmic traders possess a comparative advantage relative to regular traders. The literature

(Hendershott & Riordan, 2011; Foucault, Biais & Monias, 2013; Brogaard, Hendershott & Riordan, 2012) has typically focused on a speed advantage. For example, Hendershott and Riordan (2011) observe that orders initiated by fast algorithmic traders have more of a permanent impact on prices than those initiated by slower, non-algorithmic traders, and that the advantage of being able to act on relevant information before other market participants is sufficient to overcome the bid-ask spread. Accordingly due to this “speed advantage”, Hendershott and Riordan view algorithmic traders as superiorly informed. Their results are consistent with those of Brogaard, Hendershott and Riordan (2012) who suggest that algorithmic traders, as a result of their speed advantage, impose adverse selection on regular traders.

In line with the above, Foucault, Biais and Monias (2013) indicate that this speed advantage allows these traders (algorithmic traders) to forecast future market movements somewhat effectively. As written by Foucault, Biais and Monias (2013), “the ability of fast traders to collect and process market information that will be also available to slow traders, but a few seconds or milliseconds later, is a form of foreknowledge.” (p.6). Fittingly, Hirshleifer (1971) defines foreknowledge as the knowledge of events that will occur in due time.

Nevertheless, apart from the speed dimension there remains an additional aspect inherent in algorithmic trading affording firms a comparative advantage relative to traditional traders. In fact Kirilenko, Andrei, Pete Kyle, Mehrdad Samadi, and Tugkan Tuzun (2011), write that “possibly due to their speed advantage or superior ability to predict price changes, algorithmic traders are able to buy just before the prices are about to increase.” (p.20). Their analysis highlights the *possibility* of an alternative to the speed differential being the only source of inequity.

However the question arises as to how, if not as result of their speed advantage, algorithmic traders can be viewed as superiorly informed?

In order to identify and explicate an alternate source of inequality between algorithmic traders and non-algorithmic traders, we provide a brief overview of

the informational sources available to algorithmic trading practitioners, as well as considering their relevance to informational asymmetry.

2.4.3) Information Driving Algorithmic Trading

Information is an indispensable component of the algorithmic trading organization, essentially driving their trading activities. The question arises as to what kind of information is being used by algorithmic traders in their decision making process. Brogaard (2011) was one of the first to highlight some of the different types of information driving algorithmic trading activities. Accordingly his work addressed a variety of different information avenues available to the algorithmic traders. Information was summarily categorized as belonging to either legitimate or illegitimate sources. According to Brogaard (2011), the most important legitimate sources are as follows:

- Order book dynamics
- Trade dynamics
- Past stock returns
- Cross asset correlations
- Cross stock correlations

Order Book Dynamics

By listing interested transacting parties³⁵, the order book contains important information regarding the supply and demand aspects of an asset. Research has pointed out that order books contain significant predictive information (Parlour, 1998). Numbers, Size, Best bid and offer proximity, Sequence, Duration and even cancelled orders are all useful signals contained in order books. Thus, via the use of sophisticated computers that utilize very advanced mathematical models, algorithmic traders are able to analyze and utilize all the information contained in order books, in quantities that seem intrinsically impossible for human traders.

³⁵ Be it those who are looking to buy or those who are willing to sell.

Trade Dynamics

Information relevant to the short term directional patterns of stock prices is often contained in actual trades. Data such as size of past trades, number of trades per period and even time of day all provide useful information to algorithmic traders.

Past Stock Returns

Past stock returns provide valuable insight into the stock price discovery process. Price and return reactions to specific events such as dividend announcements can be useful, informative decision-making tools for algorithmic traders when combined with past trade and order book dynamics.

Cross Stock Correlations

Some stocks tend to move together. Indeed a pairs trading strategy is a well-documented and profitable initiative. In essence “pairs are stocks that are close substitutes according to a minimum-distance criterion using a metric in price space” (Gatev, Goetzmann, & Rouwenhorst, 2006, p. 826). A pair trading strategy is thought to be the brainchild of Nunzio Tataglia. In the mid-1980s, Tataglia assembled a team of physicists, mathematicians and computer scientists to uncover arbitrage opportunities in financial markets. “His group of former academics used sophisticated statistical methods to develop high-tech trading programs, executable through automated trading systems” (Gatev et al., 2006, p. 799), essentially replacing the intrinsically limited human processing ability with sophisticated computer trading programs. A significant discovery that had previously eluded human traders was made by the programs when it identified pairs of securities whose prices tended to move together. This incentivized Tataglia to follow a pairs trading strategy said to have generated close to 50 million dollars. Pairs trading has since grown in popularity and is being utilized by many individual as well as institutional traders.

Today pairs trading is essentially linked to algorithmic trading, in that they are built on computerized models that use historical data mining and analysis techniques to identify correlated stocks.

Cross Asset Correlations

Compared to cross stock correlation, cross asset correlation can display an even stronger relationship. Just like with pairs trading, algorithmic traders can engage in potentially profitable trading strategies because of their ability to identify correlated assets. Most of the time, cross asset correlations simply induce rebalancing trades. In fact correlations in asset returns are an essential element of Markowitz's modern portfolio theory³⁶.

2.4.3.1) Other Sources of Information Available to Algorithmic Traders

Brogaard's (2011) investigation provides valuable insight into informational capacities of algorithmic traders. However according to Leinweber (2009), algorithmic traders of today seek to exploit information *beyond* the traditional data described above. This extended information set includes news, pre-news and other influential material. Many advanced algorithms currently employ complex analytical techniques to discern the likely impact of news announcements on the market. These algorithms integrate textual systems with the more established market data described in Brogaard (2011) using increasing levels of mathematical and econometric sophistication as well as sophisticated data mining techniques.

The literature (Gomber, Arndt, Lutat & Uhle, 2011) commonly refers to this type of algorithm as a fourth generation algorithm.

- **Fourth Generation Trading Algorithms and Information**

Trading on financial markets is strongly influenced by public firm-specific, macroeconomic and other related information flows. Markets react sensitively to textual information updates— "news" —which is announced on a recurrent and intermittent basis. However, there is a limit to the amount of information a human trader can analyze. This has prompted the development of so called fourth

³⁶ See Fabozzi, Gupta and Markowitz (2002).

generation algorithms³⁷. Recently, major news providers have started offering algorithmic traders access to low latency, electronically processable news feeds and provide algorithmic traders with valuable numerical and textual information.

Algorithmic trading practitioners employ various advanced techniques to extract actionable information from these numerical and textual news feeds. These techniques include - statistical methods, time series analytics, artificial intelligence, machine learning, neural networks, support vector machines tools, data mining as well as text mining. These techniques emphasize the importance of text based recognition and reasoning alongside the analysis of numerical information.

For example, earning announcements do not simply relay numerical data, they contain valuable text as well. In fact, the text contained in these financial statements is crucial when it comes to interpreting the data. Sometimes footnotes will even change the meaning of the numbers.

The discretionary nature of income recognition³⁸ inherent in the U.S. generally accepted accounting practice (GAAP) often results in a degree of management manipulation – where the text included in the footnotes of financial statements is frequently the only indication of these activities.

Two of the most noticeable trends follow under the guise of either income smoothing or big bath accounting. Empirical evidence indicates that management can and do engage in such behavior. (Bartov 1993; Fried, Dov, Haim Mozes, Donna Rapaccioli, & Allen Schiff, 1996; Ronen & Sadan, 1981; Moses, 1987)

³⁷ These automated algorithms facilitate the use of news in both processed and raw forms.

³⁸ See, e.g. White (2011).

With income smoothing, many firms reduce earnings in “good years” and inflate earnings in “bad years” in order to present stable earnings³⁹.

With big bath accounting, the hypothesis suggests that, unlike income smoothing, management will report additional losses in bad years in the hope that by taking on all available losses at one time, they will clear the decks once and for all. *Crucially, this activity implies that future reported profits will rise.*

Importantly, regarding algorithmic trading, the use of statistical methods, time series analytics, artificial intelligence, machine learning, neural networks, support vector machines tools, data mining as well as text mining, provides algorithms with the ability to identify these subtle errors and deficiencies. By doing so, advanced algorithms are able to identify hidden layers of information as well as forecast possible future stock changes and shocks associated with the eventual corrections of these errors.

This ability to process text as well as numerical data from hundreds if not thousands of sources has given these algorithmic traders a competitive edge relative to traditional traders.

2.4.4) A Possible Explanation for Algorithmic Traders Informational Superiority

In general, with regards to algorithmic trading, information asymmetry appears to occur because some investors have either (a) superior speed in accessing or exploiting information, or (b) more advanced techniques, platforms and capabilities. Traditionally, the market microstructure literature, e.g., Foucault, Biais and Monias (2013), has mainly focused on the first type of information asymmetry. In contrast, the latter component has received little attention. Our paper fills the gap.

³⁹ Concerning the earning reduction aspect of income smoothing, some firms will defer gains and recognize losses in these so called good years. While in an attempt to inflate earnings in bad years, some firms attempt to recognize gains and defer losses.

Essentially, we take a novel approach, and assume that algorithmic traders have access to an information variable, which we term ‘Innovative Information’ – and this aspect affords algorithmic traders a comparative advantage relative to traditional traders.

More precisely, we define Innovative Information as:

The information derived from the ability to accumulate, differentiate, estimate, analyze and utilize colossal quantities of data by means of adept techniques, sophisticated platforms, capabilities and processing power.

From this perspective, an algorithmic trader’s access to various complex computational techniques, infrastructure and processing power, together with the constraints to human information processing, allow them to make judgments that are superior to the judgments of other traders. In fact, according to Qin (2012), advances in the capabilities and processes of computers has fundamentally influenced the accuracy of forecasting.

This is supported by Easley, Lopez de Prado and O’Hara (2012) who hypothesize that an algorithmic trader’s relative advantage lies in their superior capabilities and techniques. They argue that contrary to popular perception, speed is not the defining characteristic that sets algorithmic trading apart. In their evaluation, algorithmic trading is not characterized by a speed dimension, but rather an ability to make superior strategic decisions via the use of advanced techniques⁴⁰.

Regarding the techniques utilized by algorithmic traders, the nature of their sophistication cannot be understated. Indeed, the use of adept and complex techniques is a crucial component of an algorithmic practitioners trading strategy.

⁴⁰ This is supported by Das, Hanson, Kaphart and Tesauro (2001), who, by attempting to determine whether computer traders can be considered superiorly informed relative to their human counterparts, designed a simulated human versus machine experiment consisting of six challenges. By dividing the simulated population into human traders, fast computer agents and slow computer agents, Das *et al.* (2001), demonstrates that the computerized agents outperformed their human counterparts in all six challenges. Interestingly this result held for both fast and slow computerized agent populations, indicating that speed was not the sole factor accounting for the agents’ edge in performance.

Johnson (2010) is quoted as saying:

“These techniques offer the potential to improve short-term predictions for key market variables...This is because they can incorporate a much wider range of factors in their forecast models. They may also be able to cope with today’s more complex marketplaces, where trading is fragmented between multiple venues.” (p.489)

In effect, these adept computational techniques including statistical methods, time series analytics, artificial intelligence, machine learning, neural networks, support vector machines tools, data mining as well as text mining are all used in prediction of stock markets⁴¹. Below we summarize the adept computational techniques – a critical component of Innovative Information - utilized by algorithmic traders.

2.4.4.1) Advanced Computational Techniques used by Algorithmic Traders

Data\Text Mining

Data mining can be defined as the practice of isolating legitimate, unidentified, coherent and actionable information from large databases and using it to make critical business decisions.

This type of information may be inferred from correlations between assets, both in the same market, across different markets or even different asset classes⁴². (Johnson, 2010). Data mining can assist in the process of discovering these relations, allowing one to generate forecasting models based on wide ranges of data.

⁴¹ As suggested by Eiben and Smith (2003), these techniques have three overarching functions. More specifically, prediction, asset relationship identification and strategy generation.

⁴² For example lead/lag relationships may be found between different assets across different markets and classes. (See Johnson, 2010)

On the other hand, text mining concerns the automated classification of textual information by transforming unstructured information into machine readable format and using it to make astute transactional decisions.

Artificial Intelligence

Artificial Intelligence (AI) is a subset of computer science that seeks to develop intelligent machines, capable of making adroit decisions. AI systems are designed to adapt and learn from their environment and are able to resolve amenable information processing problems without any human intervention. It (AI) relies on state-of-the-art software and infrastructure, allowing for vast quantities of informational variants to be tested in parallel. In accordance with Barry, two primary categories of AI can be identified, namely, conventional AI and computational intelligence.

Conventional AI is a top down approach, based on logic and a complex collection of rules each designed to make informed decisions. Computational Intelligence on the other hand, takes a bottom up approach and is inspired by biological processes such as neural networks and support vector machines. It applies an advanced version of machine learning as part of its decision making process, i.e. the use of computer systems to identify deep patterns in market activity and make intelligent decisions based on this.

Databases with trillions of observations are now commonplace in financial firms. Machine learning methods, such as Nearest Neighbor or Multivariate Embedding algorithms search for patterns within a library of recorded events. This ability to process and learn from what is known as “big data” only reinforces the advantages of algorithmic trading. (Easley *et al.*, 2012)

Neural Networks

Neural network methods have gained prominence recently including plotting input-output vectors for cases where traditional models fail to hold. Neural networks are information processing paradigms with a remarkable tolerance for noise, ambiguity and uncertainty. Suhas and Patil (2011) explain neural

networks as “a collection of mathematical processing units that emulate some of the observed properties of biological nervous systems and draw on the analogies of adaptive biological learning” (p.2).

Neural networks are especially useful for recognizing relationships in convoluted and complicated data sets and are only limited by the power of their relative platform or infrastructure. Their remarkable ability to derive meaning from vast, complicated and imprecise data allows them to detect patterns and identify trends that are too intricate to be noticed by humans alone. In fact in tests against other approaches, neural networks are always able to score very high (Berson, Smith and Thearling, 2000).

In fact, research has documented their ability to somewhat accurately forecast future market movements for a variety of different instruments and markets.

For instance, Walczak (2001) observes that a neural network was able to forecast foreign exchange rates for a variety of currencies. Hutchinson, Lo and Poggio (1994) compose a neural network for predicting Standard & Poor's 500 futures options prices. Whereas, Castiglione (2001) construct neural network models to predict a variety of financial time series.

Therefore by combining the search capabilities with the modeling power of the neural networks, a robust, usable predictive tool can be created. (Foster, 2002)

Support Vector Machines

In many ways support vector machine models share many of the same characteristics as neural networks, although their training is very different. Essentially, a support vector machine model is an alternative training method for polynomial, radial basis function and multi-layer perceptron classifiers in which the weights of the network are found by solving a quadratic programming problem with linear constraints – this is done instead of solving a non-convex, unconstrained minimization problem like those in standard neural network

training.⁴³ Importantly, their ability to cope with problems spanning multiple dimensions makes them an excellent prediction tool for algorithmic traders in today's convoluted financial markets.

For example, Van Gestel *et al.* (2001) used a support vector machine to forecast time series and associated volatility for US short-term interest rates along with German DAX stock index. Regarding the sign of forthcoming returns, support vector machines proved to have around 5% greater predictive accuracy when compared to traditional methods. In addition, Mills (1991) found that support vector machines are a superior forecasting method when it came to predicting the weekly direction of NIKKEI 225 Index.

2.4.4.2) Infrastructure and Processing Power

Evidently, fourth generation algorithms perform analytics at a very granular level. This implies that they have to process voluminous amounts of variables in parallel. However, the traditional relational database management systems of the past cannot cope with such vast amounts of data as their scalability is extremely limited. To manage these high data volumes, many algorithmic trading practitioners have turned to the large-scale data processing and execution platform known as 'MapReduce'. Indeed, "MapReduce rises in recent years as the de-facto tool for big data processing." (Qin, 2012, p.39)

This sophisticated processing platform has seriously advanced algorithmic traders capabilities and processing power. In effect, the adept computational techniques highlighted above⁴⁴ are useful only when they are executed on advanced processing platforms like MapReduce.

Recall that this analysis intends to evaluate whether the momentum effect can be explained by algorithmic trading in the capital market. To explore this issue,

⁴³ For a more detailed view of support vector machines see Bennett and Campbell (2000).

⁴⁴ Such as statistical methods, time series analytics, artificial intelligence, machine learning, neural networks, support vector machines tools, data mining as well as text mining.

this paper will propose a theoretical model - incorporating features that fit well with the stylized facts about algorithmic trading - in order to ascertain whether, theoretically, algorithmic trading can generate this effect.

In this context, following the literature, we succinctly highlight the stylized facts about algorithmic trading. This can be seen below.

2.4.5) Stylized Facts about Algorithmic Trading

Quintessentially we define algorithmic trading⁴⁵ as computer-determined trading whereby, super-computers and complex algorithms directly interface with trading platforms, placing orders without immediate human intervention. It (algorithmic trading) employs cutting edge mathematical models, adept computational techniques and extraordinary processing power via advanced computer and communication systems and is capable of anticipating and interpreting relatively short-term market signals in order to implement profitable trading strategies.

However, an overview of the available academic and regulatory definitions (as seen in Gomber, Arndt, Lutat & Uhle, 2011) indicate that there is yet to be a unanimously accepted academic and regulatory definition of algorithmic trading.

Rather than adding another definition to the list, we will try to extract the main characteristics/facts from the existing literature - highlighted in this paper - that are non-contradictive with existing definitions. This is done in order to excerpt common notions that incorporate most of the existing characteristics of algorithmic trading.

Below we delineate the stylized characteristics/facts about algorithmic trading identified from the literature. However, it is important to note that the first characteristic (below), represents the principal component of algorithmic trading.

⁴⁵ Considering that contemporary relevance demands a neoteric perspective, we focus primarily on so called fourth generation algorithms.

By implication, the succeeding facts can be viewed as somewhat secondary characteristics of algorithmic trading. This should become clearer as we proceed.

1. Algorithmic traders have a comparative advantage relative to traditional traders.

This comparative advantage relates to an informational advantage as a result of their access to Innovative Information. Where Innovative Information is more precisely defined as *the information derived from the ability to accumulate, differentiate, estimate, analyze and utilize colossal quantities of data by means of adept techniques, sophisticated platforms, capabilities and processing power.*

From this perspective, an algorithmic trader's access to various complex computational techniques, infrastructure and processing power, together with the constraints to human information processing, allow them to make judgments that are superior to the judgments of other traders. This informational paradigm means that algorithmic traders are capable of anticipating and interpreting relatively short-term market signals. In fact Kirilenko *et al.* (2011), write that possibly due to their superior ability to predict price changes, algorithmic traders are able to buy before prices increase. In addition, according to Qin (2012), advances in the capabilities and processes of computers has fundamentally influenced the accuracy of forecasting. See section (2.4.4) for more on how algorithmic trader's advanced informational capabilities has allowed them to somewhat accurately forecast future return and price changes.

2. Algorithmic traders have access to a wide variety assets.

Accordingly, their access to multiple markets allow them to search through trillions of observations and identify elaborate patterns in market activity – this then allows them to implement profitable trading strategies without any direct human intervention. Moreover, algorithms are capable of accumulating, estimating and utilizing colossal quantities of information from different securities and in different markets in order to detect the kind of patterns and events that traders look for themselves. However, they do this for hundreds or

thousands of securities simultaneously. According to Easley *et al.* (2012), an algorithmic trader's ability to process this "bid data" from multiple venues only reinforces their advantage over traditional traders.

3. Algorithmic traders are able to identify correlations between assets, both in the same market, across different markets or even different asset classes. In fact many of their trading strategies are linked to this capacity.

Their remarkable ability to derive meaning from vast, complicated and imprecise data allows them to detect patterns and identify trends that are too intricate to be noticed by humans alone. This ability allows them to identify correlations between assets, both in the same market, across different markets or even different asset classes. In this context algorithmic traders can engage in potentially profitable trading strategies such as pairs trading.

This is supported by Brogaard (2011) who posits that pairs trading is essentially linked to algorithmic trading, in that they are built on computerized models that use complex computerized techniques in order to identify correlated stocks.

Also, like with pairs trading, algorithmic traders can engage in potentially profitable trading strategies because of their ability to identify correlated assets. Interestingly, most of the time cross asset correlations simply induce rebalancing trades⁴⁶.

4. Algorithmic traders seek to exploit information beyond the traditional data. This includes information derived from news and pre-news sources. By emphasizing the importance of text based recognition and reasoning alongside the analysis of traditional numerical information- both prior to, and in conjunction with news announcements - these traders are able to discern the likely impact of these announcements as well as forecast future possible market changes associated with it.

⁴⁶ Indeed, asset return correlations are an essential element of Markowitz's modern portfolio. See e.g. Fabozzi, Gupta and Markowitz (2002).

Empirical evidence indicates that markets react sensitively to textual information updates— so called “news” —which is announced on a recurrent and intermittent basis.

However, there is a limit to the amount of information a human trader can analyze, both prior to, and during the event itself. This has prompted the development of so called fourth generation algorithms⁴⁷. Recently, major news providers have started offering algorithmic traders access to low latency, electronically processable news feeds and provide algorithmic traders with valuable numerical and textual information.

Algorithmic trading practitioners employ various advanced techniques to extract actionable information from these numerical and textual news feeds. These techniques include statistical methods, time series analytics, artificial intelligence, machine learning, neural networks, support vector machines tools, data mining as well as text mining. These techniques emphasize the importance of text based recognition and reasoning alongside the analysis of numerical information.

For example, news events such as earning announcements do not simply relay numerical data, they contain valuable text as well. In fact, the text contained in these financial statements is crucial when it comes to interpreting the data. Sometimes footnotes will even change the meaning of the numbers.

The discretionary nature of income recognition inherent in the U.S. generally accepted accounting practice (GAAP) often results in a degree of management manipulation. Indeed, empirical evidence indicates that management can and do engage in somewhat serpentine activities – often falling under the guise of either income smoothing or big bath accounting (Bartov 1993; Fried, Dov, Haim Mozes, Donna Rapaccioli, & Allen Schiff, 1996; Ronen & Sadan, 1981; Moses, 1987).

⁴⁷ These automated algorithms facilitate the use of news in both processed and raw forms.

Often the text included in the footnotes of financial statements is the only indication of these activities.

Importantly, the use of *adept computational techniques* provide algorithmic traders with the ability to identify the subtle errors and deficiencies associated with the somewhat serpentine reporting activities accompanying earnings announcements. By doing so, advanced algorithms are able to identify hidden layers of information as well as forecast possible future stock changes and shocks associated with the eventual corrections of these errors.

This ability to utilize adept computational techniques in anticipation of, and in conjunction with, news announcements has given these algorithmic traders a competitive edge relative to traditional traders.

As noted previously, a major objective of this paper is to propose a theoretical model – incorporating features that fit well with the stylized facts about algorithmic trading – in order to ascertain whether, theoretically, algorithmic trading can generate the momentum effect. In order to propose such a model, we need to identify existing theoretical models consistent with some of the above mentioned facts/ characteristics of algorithmic trading.

This will provide us with the theoretical foundations necessary for our distinct model.

2.4.5.1) Existing Theoretical Models Consistent with some of the Characteristics of Algorithmic Trading

Below we delineate the individual stylized facts about algorithmic trading accompanied by the details of existing models consistent with each stylized fact.

1. Algorithmic traders have a comparative informational advantage relative to traditional traders.

Evidently, this comparative informational advantage seems to lend itself to related issues of information asymmetry. Apropos asymmetric information, a large

amount literature has begun to address related issues of information differentials, and its subsequent market effects (e.g. Grossman, 1976). This information differential arises when information is known to some, but not all, market participants. The current approach emphasizes the distinction between informed and uninformed market participants. Regarding this informed/ uninformed investor paradigm, informed investors are seen to be those investors that have “private” information about the future states of the world, while the uninformed investors are those that do not (Grossman, 1976). This seems to imply that some investors are better than others when it comes to interpreting financial information and are, as a consequence, better at forecasting future market movements.

Consistent with the literature on information asymmetry, Wang (1993) presents a dynamic asset-pricing model under the assumption that investors possess different information regarding the expected future growth rate of returns. By differentiating between informed and uninformed investors, Wang (1993) determines that information asymmetry among market participants can result in higher price volatility and negative autocorrelation in returns.

However, it is extremely important to note that in context of computerized trading, this comparative informational advantage relates to an algorithmic traders access to Innovative Information. As stated previously, Innovative Information refers to *the information derived from the ability to accumulate, differentiate, estimate, analyze and utilize colossal quantities of data by means of adept techniques, sophisticated platforms, capabilities and processing power.*

From this perspective, an algorithmic trader's access to various complex computational techniques, infrastructure and processing power, together with the constraints to human information processing, allow them to make judgments that are superior to the judgments of other traders.

For a paper consistent with this so-called advanced judgment paradigm, consider Daniel and Titman's (2006) investigation into long-term return anomalies. The authors propose an interesting theory on observed anomalies, relating to how investors assess and react to different types of information.

Specifically, they decompose information into tangible and intangible components. Accordingly, tangible information relates to the explicit, publicly disclosed, performance measures which can be observed directly by all and is available from the firms' accounting statements. Whilst, on the other hand, intangible information relates to the more *abstruse* information about growth opportunities judged or interpreted privately by owners. Their analysis indicates that long-term return anomalies "arise because future returns are cross-sectionally related to past realizations of intangible information." (Daniel and Titman, 2006, p. 1638)

One can thus take the Innovative Information as being intangible information. This information is not directly observable but reflects the more "decrypted" information - signaling the firm's future performance. It is available to algorithmic trading firms as a result of their access to various complex computational techniques, infrastructure and processing power – and essentially allows them to make judgments that are superior to the judgments of other traders. Indeed, an investor's ability to evaluate information that is relatively vague is consistent with Daniel and Titman's (2006) classification of intangible information⁴⁸.

The Innovative Information concept is also related to the research conducted by Miao and Albuquerque (2008). In their paper they present a rational expectations heterogeneous investor model with asymmetric information in order to address the trading behavior of different types of investors when some of them possess '*advanced* information' – information about a firm's future performance, such as shocks to earnings - in a rational expectations framework. In the model, investors are regarded as being either informed or uninformed. By assuming that informed investors possess both private information as well as private advanced information, they attempt to account for the under reaction and overreaction phenomena. Accordingly, advanced information makes "prices move in ways that are unrelated to fundamentals.

⁴⁸ See Daniel and Titman (2006, p. 1640)

To reiterate, for the sake of clarity, we emphasize that this aspect – an algorithmic trader's access to Innovative Information - functions as the key characteristic of algorithmic trading.

2. Algorithmic traders have access to a wide variety of assets.

The recent advent of electronic trading has undeniably facilitated the expansion of markets. In fact, increasing numbers of order and execution management systems (OMS, EMS) now provide unified platforms for trading across a wide range of asset classes. Somewhat unsurprisingly, this expansion has also led to an increased level of market complexity - as it invariably results in trading across different platforms, currencies and time zones. Indeed, with today's more complex marketplaces, trading has become fragmented between multiple venues⁴⁹.

However, new algorithmic trading technologies are creating new capabilities that no human trader could ever offer, such as assimilating and integrating vast quantities of data and making multiple accurate trading decisions across multiple venues. In fact, an algorithmic trader's access to multiple trading venues is one of the key advantages that algorithmic trading hold over traditional trading methods.

The assumption that algorithmic traders have access to an expanded opportunity set is consistent with Merton's (1987) Investor Recognition Hypothesis (IRH). In his paper, Merton attempts to rectify the variation in stock returns that remain unexplained by fundamental variables, such as earnings and cash flows. In this context Merton refers to the number of investors who know about an asset as the degree of 'investor recognition' for that asset.

The key behavioral assumption invoked by Merton's (1987) IRH is that investors only use assets that they know about in constructing their optimal portfolios. He reveals that in cases where a relatively limited number of investors know about

⁴⁹ Barry Johnson (2010) states that "algorithmic traders are able to cope with today's more complex marketplaces, where trading is fragmented between multiple venues."(p.489)

a particular asset, the only way for markets to clear is for these investors take sizable undiversified positions in the security. These investors then require higher expected returns to compensate them for the increased idiosyncratic risk. Accordingly, the varying degree of 'investor recognition' affects an assets equilibrium pricing.

Crucially, the IRH implies that a subset of investors⁵⁰ have a *larger* investible universe. This assumption is particularly pertinent to algorithmic traders, with regards to the above mentioned expanded opportunity set.

3. Algorithmic traders are able to identify correlations between assets, both in the same market, across different markets or even different asset classes.

Below, we introduce two existing models that are in their own unique way, consistent with this aspect of algorithmic trading.

A securities market performs two important functions or roles. More precisely, *allocating* risk and communicating information among investors. How efficiently the market performs these two functions crucially depends on market structure. Yet, over time, the structure of securities markets change as new securities are introduced and technologies develop. (Huang and Wang, 1997).

The literature primarily confronts the impact of these changes on a markets informational role. However, according to Grossman (1995), this informational role is intrinsically linked to the markets above mentioned allocational role. With this in mind, Huang and Wang (1997) analyze the impact of market structure development by considering the interaction between the allocational and informational roles of a securities market.

Using a fully rational expectations framework with heterogeneously informed investors, Huang and Wang (1997) break away from the traditional two-asset economy, by including a third, non-traded asset. In so doing, Huang and Wang

⁵⁰ In our case, algorithmic traders.

show that, in addition to providing information to less informed traders⁵¹, the introduction of a non-traded asset changes the information content of existing security prices - this seems to occur because it changes allocational trading.

Importantly, their assumption that *stock dividends are correlated with the non-traded assets returns* is particularly pertinent to our analysis of algorithmic trading. In their model, the identified correlation structure generates allocational trade in the market. Moreover, their analysis implies that in many cases - provided that *stock dividends are identified by traders to be correlated with the non-traded assets returns* - the introduction of a non-traded asset can increase stock risk premium and price volatility under asymmetric information.

In a similar vein, Wang (1994) investigates the relation between the nature of investor heterogeneity and the behavior of trading volume, and its association with the markets underlying price dynamics.

Regarding the nature of investor heterogeneity, Wang develops a model in which investors – informed and uninformed - are both informationally as well as opportunistically heterogeneous. More specifically, investors are heterogeneous in their information as well as their private investment opportunities.

Regarding uninformed investors, their investment universe consists of public assets *only*; a risky stock and a risk- free bond. Informed investors on the other hand, can invest in both publicly traded assets as well as a private investment opportunity whose *returns are identified to be positively correlated with earnings*.

In the model, informed investors rationally trade for both informational and noninformational reasons. Informational trading occurs when informed investors receive private information about the stocks future cash flow. Alternatively, noninformational trade occurs when informed investors optimally rebalance their portfolio as their private investment opportunity changes. Crucially, according to

⁵¹ Via the non-traded assets prices

Wang (1994), the model predicts that informational trading and noninformational trading give rise to a very different dynamic relation between volume and returns. Detail on this relation is extensive in his paper. However, for the sake of associative simplicity, we do not exhaust the relative findings. Instead, we focus on the aspect of noninformational trading – an aspect most associated with algorithmic traders ability to identify correlated assets.

From this perspective, we identify the underlying factor in his model that gives rise to this noninformational trading. Thus, we focus on Wang's (1994) distribution assumptions.

More precisely, Wang assumes that informed investors have identified a positive correlation between stock returns and private investment returns. By implication, the stock and the private technology become substitutes to the informed investor. Consequently, the informed investor's stock demand depends not only on the stocks expected return, but also on the private investments expected return.

As the informed investors private opportunity changes over time, they optimally adjust their private investment and stock holdings. Importantly this need of portfolio rebalancing generates trade in the market. By analyzing the noninformational trading paradigm, Wang (1994) generates new insights into the dynamic relation between volume and returns.

In the context of algorithmic trading, Wang's model implies that - assuming algorithmic traders are able to identify correlated assets - private information about one stock may well provide private information about other assets in the algorithmic trader's portfolio and by effect induce rebalancing trades.

4. Algorithmic traders seek to exploit information beyond the traditional data. That is, information both prior to, and in conjunction with news announcements.

Characterizing algorithmic traders' use of information both in anticipation of and in conjunction with public announcements is a complicated problem in the context of a rational model of trade. Typically, models of trade eschew the above

mentioned complication by supposing that investors utilize information *either* in anticipation of *or* in conjunction with public announcements. For example, many papers base their analysis exclusively on the assumption that investors utilize information in anticipation of an announcement. (E.g. Demski & Feltham, 1994; McNichols & Trueman, 1994; Abarbanell *et al.*, 1995.)

On the other hand, Varian (1989), Holthausen and Verrecchia (1990), and Indjejikian (1991), all base their analyses on the assumption of information in conjunction with announcements.

In addition to being less rich as a description of real markets, models based exclusively on one type of information are often empirically misspecified.

As mentioned above, rational models generally restrict themselves to the analysis one type of information variable in isolation. However, one exception is Kim and Verrecchia (1997), who are able to combine both variables in a unified manner. In fact, Kim and Verrecchia (1997) produce a rational trading model that incorporates both information in anticipation of, as well as, information in conjunction with public announcements - more precisely defined by Kim and Verrecchia (1997) as pre-announcement information and event-period information respectively.

In their paper pre-announcement private information refers to the information that investors actively gather prior to a news release. Conversely, event-period information denotes the new information arising from the interaction between information contained in the public announcement and private information gathered prior to the announcement, which becomes useful only in conjunction with the announcement itself.

Intuitively, advanced agents would trade in the wake of an earnings announcement not just because of the information contained in the announcement itself, but also because their private event-period information leads them to *interpret the reported amounts differently* than others who lack this information. In fact, event-period private information is often defined as “uniquely

privately inferred information about future earnings.” (Barron, Harris & Stanford, 2005. p.404)

According to Kim and Verrecchia (1997):

“All anticipated events or announcements motivate pre-announcement private information gathering. In addition, event-period private information is used in all announcements to provide a context or interpretation to the disclosure. Consequently, event-period information also seems a pervasive feature of disclosure.” (p. 396)

Essentially, a public release of information triggers agents with diverse processing capabilities, to generate new idiosyncratic information from the public announcement.

Kim and Verrecchia’s (1997) results are consistent with the assumption that accounting disclosures trigger the generation of idiosyncratic information by elite information processors such as algorithmic traders.

2.4.5.2) Concluding Remarks

Recall that this paper intends to determine whether, theoretically, algorithmic trading is capable of engendering the momentum effect. In this context, we proposed the development of a theoretical model - incorporating features that fit well with the stylized facts about algorithmic trading - in order to ascertain whether, theoretically, algorithmic trading can generate this effect. Summarily, following the literature, we highlighted the stylized facts about algorithmic trading.

However as should be clear by now, algorithmic trader’s access to Innovative Information is presumably the most representative stylized fact of algorithmic trading. This is because, essentially, all the all the other characteristics relate in some way or another to this component.

CHAPTER 3

3.1) Introduction

The research methodology used in this study is introduced in this section. The hypothesis of this study, the research design and identification of relevant variables are defined and discussed.

3.2) The Central Hypothesis of This Study

The evidence put forward by Zhang (2010) indicates that algorithmic trading can potentially generate the momentum effect evident in the research. In addition, upon analysis of the literature, it is apparent that algorithmic traders possess a comparative informational advantage relative to regular traders. Finally, the theoretical model proposed by Wang (1993), indicates that the informational differences between traders fundamentally influences the nature of asset prices, even generating serial return correlations. Thus, applied to the study, the theory holds that algorithmic trading would have a significant effect on security return dynamics, possibly even engendering the momentum effect.

This paper tests such implications by proposing a theory to explain the momentum effect based on the hypothesis that algorithmic traders possess Innovative Information about a firm's future performance.

However, since our analysis needs to be relevant to algorithmic trading, we follow Leinweber (2009) and decompose Innovative Information into (A) pre-announcement Innovative Information and (B) event-period Innovative Information.

It should be noted at this time however, that it is actually event-period Innovative Information that generates the momentum effect. Nevertheless, since event-period Innovative Information is driven by pre-announcement Innovative Information in our model, our hypothesis remains appropriate. This will become clearer in the next section as we proceed with the model.

In section (3.2.1), we discuss the broader meaning of Innovative Information before detailing its composition (i.e. pre-announcement, event-period Innovative Information).

3.2.1) Identification of Relevant Variables and Setting Prior Expectations

- Innovative Information

Proposing a theory to explain the momentum effect based on the hypothesis that algorithmic traders possess Innovative Information requires clarification. Specifically, on what classifies as Innovative Information.

Academic research concerning the impact of algorithmic trading is still in its infancy. A serious obstacle in conducting research on this topic is data availability. That being said, a small but growing group of academic papers have begun to address questions surrounding algorithmic trading, mainly focusing on market quality parameters and issues regarding its profitability and fairness. The evidence to date is still inconclusive. The vast majority of studies regarding algorithmic trading have coalesced around the idea that algorithmic traders possess a comparative advantage relative to regular traders. The literature (Hendershott & Riordan, 2011; Biais Foucault & Monias, 2011; Brogaard, Hendershott & Riordan, 2012) has typically focused on a speed advantage. For example, Biais, Foucault & Monias (2011) analyzed the effect of algorithmic trading on the market as a whole. By postulating a theoretical model, in which algorithmic traders have a speed advantage over ordinary traders, they found that the introduction of algorithmic trading can have has two opposing effects. On the one hand it can increase an investor's chance of finding a counterparty to trade with, whilst, on the other hand, it is capable of generating *informational* asymmetries between slower traders' and algorithmic traders. In addition, Hendershott and Riordan (2011) observe that orders initiated by fast algorithmic traders have more of a permanent impact on prices than those initiated by slower, non-algorithmic traders, and that the advantage of being able to act on relevant information before other market participants is sufficient to overcome the bid-ask spread. Accordingly due to this "speed advantage", Hendershott and Riordan

view algorithmic traders as superiorly informed. Their results are consistent with those of Brogaard, Hendershott and Riordan (2012) who suggest that algorithmic traders, as a result of their speed advantage, impose adverse selection on regular traders.

Nevertheless, apart from the speed dimension there remains an additional aspect inherent in algorithmic trading affording firms a comparative advantage relative to traditional traders. In fact Kirilenko, Andrei, Pete Kyle, Mehrdad Samadi, and Tugkan Tuzun (2011), write that “possibly due to their speed advantage or superior ability to predict price changes, algorithmic traders are able to buy just before the prices are about to increase.” (p.20). Their analysis highlights the *possibility* of an alternative to the speed differential being the only source of inequity.

However the question arose as to how, if not as result of their speed advantage, algorithmic traders can be viewed as superiorly informed?

By drawing on inferences from the literature⁵² we identified algorithmic trader’s access to Innovative Information as the possible alternate source of their informational superiority.

More precisely we defined Innovative Information as:

The information derived from the ability to accumulate, differentiate, estimate, analyze and utilize colossal quantities of data by means of adept techniques, sophisticated platforms, capabilities and processing power.

From this perspective, an algorithmic trader’s access to various complex computational techniques, infrastructure and processing power, together with the constraints to human information processing, allow them to make judgments that are superior to the judgments of other traders. In fact, according to Qin (2012),

⁵² See section 2.4.4 of this paper.

advances in the capabilities and processes of computers has fundamentally influenced the accuracy of forecasting.

This is supported by Easley, Lopez de Prado and O'Hara (2012) who hypothesize that an algorithmic trader's relative advantage lies in their superior capabilities and techniques. They argue that contrary to popular perception, speed is not the defining characteristic that sets algorithmic trading apart. In their evaluation, algorithmic trading is not characterized by a speed dimension, but rather an ability to make superior strategic decisions via the use of advanced techniques.

Consider Daniel and Titman's (2006) investigation into long-term return anomalies. They propose an interesting theory on observed anomalies, relating to how investors assess and react to different types of information. Specifically, they decompose information into tangible and intangible components. Accordingly, tangible information relates to the explicit, publicly disclosed, performance measures which can be observed directly by all and is available from the firms' accounting statements. Whilst, on the other hand, intangible information relates to the more *abstruse* information about growth opportunities judged or interpreted privately by owners. Their analysis indicates that long-term return anomalies "arise because future returns are cross-sectionally related to past realizations of intangible information." (p. 1638)

One can thus take the Innovative Information as being intangible information. This information is not directly observable but reflects the more "decrypted" information - signaling the firm's future performance. It is available to algorithmic trading firms as a result of their access to various complex computational techniques, infrastructure and processing power – and essentially allows them to make judgments that are superior to the judgments of other traders. Indeed, an investor's ability to evaluate information that is relatively vague is consistent with Daniel and Titman's (2006) classification of intangible information⁵³.

⁵³ See Daniel and Titman (2006, p. 1640)

The Innovative Information concept is also related to the research conducted by Miao and Albuquerque (2008). In their paper they present a rational expectations heterogeneous investor model with asymmetric information in order to address the trading behavior of different types of investors when some of them possess *advanced* information – information about a firm’s future performance, such as shocks to earnings - in a rational expectations framework. In the model, investors are regarded as being either informed or uninformed. By assuming that informed investors possess both private information as well as private advanced information, they attempt to account for the under reaction and overreaction phenomena. Importantly, we can relate our concept of Innovative Information to Miao and Albuquerque’s (2008) advanced private information.

However, as noted in the foregoing, our analysis needs to be relevant to algorithmic trading. Thus we take things further, by decomposing Innovative Information into (A) pre-announcement Innovative Information and (B) event-period Innovative Information. This apportionment follows Kim and Verrecchia (1997) and is driven by the assumption that algorithmic traders utilize information both prior to, and in conjunction with news announcements (Leinweber, 2009).

Pre-announcement Innovative Information and event-period Innovative Information are discussed below:

➤ Pre-announcement Innovative Information

Pre-announcement Innovative Information refers to information relating to an expected error in a forthcoming earnings announcement. Following Kim and Verrecchia (1997), this error arises from the application of random, liberal, or conservative accrual-based accounting practices and estimates in announcements.

Indeed, concerning earnings announcements-as noted in section (2.4.3.1) of this paper- management can and do engage in the somewhat serpentine activities such as income smoothing and big bath accounting. However, an

algorithmic traders ability to accumulate, differentiate, estimate, analyze and utilize colossal quantities of data by means of adept techniques, sophisticated platforms, capabilities and processing power (Innovative Information) – results in a situation in which algorithmic traders are able to identify the subtle errors and deficiencies associated with the above mentioned serpentine practices.

Stated differently: The use of Innovative Information in the pre- announcement period provide algorithmic traders with the ability to identify the subtle errors and deficiencies accompanying the somewhat serpentine reporting activities associated with earnings announcements. By doing so, advanced algorithms are able to identify hidden layers of information as well as forecast possible future errors.

➤ Event-period Innovative Information

Event-period Innovative Information denotes the new information that arises as a result of the interaction between information contained in the public announcement itself and the pre-announcement Innovative Information gathered prior to the announcement. As will become clear, once earnings are announced, the pre-announcement Innovative Information can be combined with the earnings announcement itself to assess the true value of earnings not reported in the announcement. Thus it triggers a uniquely private signal about the following period's idiosyncratic shock in the form of event-period Innovative Information. Indeed, as a result of their ability to accumulate, differentiate, estimate, analyze and utilize colossal quantities of data by means of adept techniques, sophisticated platforms, capabilities and processing power advanced algorithms are able to identify hidden layers of information as well as forecast possible future stock changes and shocks associated with the eventual corrections of prior period errors.

Intuitively, algorithmic traders would trade in the *wake* of an earnings announcement not just because of the information contained in the announcement itself, but also because their pre-announcement Innovative Information leads them to interpret the reported amounts differently than others who lack this information.

As noted earlier, an appropriate approach in making progress on identifying the existence of a relationship between the momentum effect and algorithmic trading, is to focus on the details of a theoretical mechanism through which algorithmic trading could possibly generate this return anomaly and to document it's working.

Therefore we propose that the underlying mechanism by which algorithmic trading can generate the momentum effect is through their access to “Innovative Information”. More precisely, their access to pre-announcement Innovative Information as well as event-period Innovative Information. In order to test such an assumption, we present a simplified single agent model where the representative agent or algorithmic trader possesses both pre-announcement Innovative Information as well as event-period Innovative Information. This is done in order to assess the impact of Innovative Information specifically. The relative stylized facts about algorithmic trading identified in section (2.4.5) - that we have not commented on here - will also be incorporated into our unique model.

3.3) Research Design and Modelling

Our model is based on the seminal study of Wang (1993). However, since our analysis needs to be relevant to algorithmic trading, we make some additional assumptions corresponding to the stylized facts of algorithmic trading – highlighted in section (2.4.5) of this paper. Therefore our model is nested in the study of Wang (1993). The presence of these stylized facts complicates our analysis significantly and requires a solution technique different from that in Wang (1993).

Firstly, following stylized fact (1), we assume that the algorithmic trader has access to what we define as Innovative Information. This information variable is similar to that of Daniel and Titman's (2006), intangible information and has many of the same characteristics of Miao and Albuquerque's (2008) private advanced information. Secondly, we decompose Innovative Information into (A) pre announcement and (B) event- period Innovative Information. This relates to Kim and Verrecchia's (1997) pre- announcement and event-period private information and corresponds to stylized fact (4). Furthermore, we follow Merton (1987) and

assume that the algorithmic traders' investment universe consists of a risky stock, a riskless bond and a private investment opportunity - stylized fact (2).

Also, and in line with stylized fact (3), we assume that returns on the private investment opportunity are positively correlated with stock earnings. Thus, the private investment opportunity and the stock can be considered substitutes to the algorithmic trader. Note that this correlation is only identified at time 1.

However, it is important to note that, unlike Wang's (1993) model, which incorporates heterogeneous investors, we propose a simplified single algorithmic trader agent model in order to provide intuition into algorithmic trading's possible association with the momentum effect. Furthermore this allows us to keep this analysis tractable.

3.4) Research Methodology

Popper (1972) rationalizes that defining what we observe must be led by the formulation of theory and hypotheses; therefore scientific methods involve testing theories in ways where the results can possibly support theory. This rationale is based on the principle that theory precedes research and statistical justification of conclusions developed from empirically testable hypotheses form the fundamental tenets of scientific knowledge advancement.

Corresponding with the above philosophy, this paper will adopt what is known as the 'Representative Agent' paradigm approach in order to test the hypothesis.

The three commonly expressed rationales for the use of representative agent modeling are as follows: "Representative agent models allow the researcher to avoid the Lucas critique⁵⁴, they are of help in the construction of Walrasian (general equilibrium) models, and they may be used to establish microfoundations for macroeconomic analysis." (Grabner, 2002).

⁵⁴ The shortcomings associated with predicting the impact of a change in economic policy exclusively on the basis of relationships observed in historical data.

The fact that they form the microeconomic groundwork necessary for macroeconomic studies resonates as the premier justification for this methodology. In fact modern macroeconomics is formed explicitly on microeconomic grounds.

Due to the 'particular' nature of the subject area, this research method is appropriate in isolating the effects of Innovative Information in order to determine algorithmic trading's relationship with the momentum effect.

CHAPTER 4: THE MODEL

As prior noted, our model is based on the representative agent approach. However, as representative agent models are well established in the literature, we will be succinct in describing this paradigm. We begin by taking a typical rational expectations trading model, based on the existence of pre-announcement private information, and adapting it to include event-period private information similar to the type suggested by Kim and Verrecchia (1997).

There are four points in time, time 0, 1, 2 and 3 and three assets in the economy. The assets comprise of two publically traded assets, as well as a non-traded, private investment opportunity. The two traded assets consist of a riskless bond and a riskier stock. This private investment opportunity is afforded to the agent in the spirit of Merton's (1987) Investor Recognition Hypothesis,⁵⁵ as well as a key stylized fact of algorithmic trading.

In our model, time 0 characterizes the pre-announcement period. In this period, the agent obtains and observes private information about an error in a forthcoming public announcement, which we assume to be an earnings announcement. As discussed below, we define this private information as pre-announcement Innovative Information.

However, it is crucial to note that this information is only useful at time 1 (the event-period), in conjunction with the earnings announcement itself. Thus, although pre-announcement Innovative Information is acquired in time 0, we do not view it as an actionable signal until time 1 when it can be combined with the public announcement itself. Additionally, since pre-announcement Innovative Information is not informative at time 0, no trading occurs in the pre-announcement period.

⁵⁵ Merton's Investor Recognition Hypothesis concerns informed investor's investment opportunity set. It theorizes that informed investors have a larger investible universe. See Merton (1987).

Time 1 characterizes the event-period. Three important events occur during the event-period. First a public announcement occurs at time 1, this public announcement is assumed to be an earnings announcement. Second, once earnings are announced in time 1, time 0's pre-announcement Innovative Information can be utilized by the algorithmic trader to form a uniquely private information signal – which we define as event-period Innovative Information. This information (event-period Innovative Information), concerns new idiosyncratic information about an expected shock to earnings in time $t + 1$ of the event-period. Essentially, one can say that, by combining pre-announcement Innovative Information with the announcement itself, the algorithmic trader is able to generate new idiosyncratic information from the public announcement in the form of event-period Innovative Information. Third, the agent identifies a key correlation structure between specific assets. That is to say, a *positive* correlation between dividends and the private investment returns. By implication, the private investment opportunity and the stock become substitutes to the agent from time 1 onwards. Thus, the algorithmic trader's stock demand depends not only on the stocks expected return, but also on the expected return on the private investment opportunity. Since trading only commences in the event-period, this assumption is reasonable.

Model specifics are provided below in section (4.1).

4.1) A Representative Algorithmic Trader-Agent Model

The Pre-Announcement Period

As discussed in the foregoing, time 0 is subsumed under the pre-announcement period. In time 0 we assume that the algorithmic trader obtains private pre-announcement Innovative Information in the form of an error in a forthcoming public announcement. Accordingly, this announcement is set to occur in the event-period (time 1).

Following Bizrat Hashem this error arises from the application of random, liberal, or conservative accrual-based accounting practices and estimates in

announcements. Indeed, concerning earnings announcements-as noted in section (2.4.3.1) of this paper- management can and do engage in the somewhat serpentine activities such as income smoothing and big bath accounting.

However, an algorithmic traders ability to accumulate, differentiate, estimate, analyze and utilize colossal quantities of data by means of adept techniques, sophisticated platforms, capabilities and processing power – results in a situation in which, for all intends and purposes, algorithmic traders can be viewed as distinctly different to traditional market participants. This is because, unlike traditional market participants, algorithmic traders have the ability to identify the subtle errors and deficiencies associated with the above mentioned serpentine practices.

Stated differently: The use of Innovative Information in the pre- announcement period provide algorithmic traders with the ability to identify the subtle errors and deficiencies accompanying the somewhat serpentine reporting activities associated with earnings announcements. By doing so, advanced algorithms are able to identify hidden layers of information as well as forecast possible future errors.

Therefore, as applied to our model, we assume that the agent obtains a private signal about *this* expected error in the pre-announcement period, time 0. We define this private information signal as pre-announcement Innovative Information and denote it by $G_0 = L - \epsilon_2$.

Critically, $G_0 = L - \epsilon_2$ is *only* useful in the event-period, at time 1, in conjunction with the earnings announcement itself, and is consequently, of no use in the pre-announcement period. Therefore, the agents' actions and equilibrium are unaffected by this private signal in the pre-announcement period. Accordingly,

no trading occurs in this period. Since no trading occurs in this period, market clearing conditions are automatically satisfied⁵⁶.

Essentially, although G_0 is gathered in the pre-announcement period, we do not view it as an actionable signal until the event-period (time 1).

The Event-Period

Recall that - due to the lack of trading activity - equilibrium remains static in the pre-announcement period. Thus, for the sake of simplicity we begin to index time by the letter t from the event-period (time 1) onwards. In addition – since no trading occurs in the pre-announcement period – we ultimately have to contend that the momentum effect occurs in the event-period following an earnings announcement. This gives credence to our above time classification. With no loss of generality, and in order to extricate the event period from the pre-announcement period, we henceforth refer to time 1 and 2...of the event-period as t and $t + 1 \dots$ respectively. This simplifies our analysis significantly. This time classification is a crucial component of our model.

A. Agent Preferences

Note that the preferences highlighted below also apply to the pre-announcement period, however, since there is no trading in the pre-announcement period, we have defined the agent's preferences in the event-period.

The agents utility is a constant absolute risk aversion function derived from the subsequent periods wealth, ω_{t+1} . Preferences are illustrated below in equation (1):

$$E_t\{-e^{-\gamma\omega_{t+1}}\} \quad (1)$$

⁵⁶ See De Long, Shleifer, Summers and Waldmann's (1990) (B).

Where E_t is the expectations operator at time t conditional on all available information, and γ , the coefficient of absolute risk aversion or risk aversion parameter.

B. Investable Universe

In the spirit of Merton's investor recognition hypothesis⁵⁷, as well as the documented stylized facts about algorithmic trading, the sophisticated agent has access to two publicly traded assets, in addition to a private investment opportunity. The public assets include a risk-free storage technology (safe-asset) and a riskier stock.

i) The Risk-Free Storage Technology

The risk-free storage technology is assumed to have an infinitely elastic supply at a positive constant rate of return r . Let $R = 1 + r$ be the gross rate of return on the risk free asset⁵⁸. We can therefore assume that $R > 1$.

ii) The Risky Stock

The riskier stock generates a flow of output (dividend) and is in fixed supply normalized to one unit. Without a loss of generality, shares of the stock are perfectly divisible. Dividend or earnings is denoted by the upper case Roman letter D_t . The underlying mechanisms governing the earnings process forms a critical tenant of our model and can be seen by our decomposition of earnings into two components à la Wang (1993). Suppose that the dividend process, D_t , is modeled as the sum of a permanent component, L_t , and a temporary component, ϵ_t^D . Equation (2), seen below, illustrates the process governing D_t :

$$D_t = L_t + \epsilon_t^D \quad (2)$$

⁵⁷ Merton's investor recognition hypothesis concerns informed investor's investment opportunity set. It theorizes that informed investors have a larger investible universe. See Merton (1987).

⁵⁸ Generally recognized as a short term government treasury bill.

With,

$$L_t = \alpha_L L_{t-1} + \epsilon_t^L, \quad 0 < \alpha_L < 1. \quad (3)$$

Where persistence is given by α_L .

Also,

$$\epsilon_t^D = \alpha_{\epsilon_t^D} \epsilon_t^D + \epsilon_{2,t}. \quad (3.1)$$

It is important to note that ϵ_t^L and $\epsilon_{2,t}$ are the permanent and temporary disturbances in (or shocks to) the dividend process while L_t and ϵ_t^D are the permanent and temporary components of the dividend process. Also, ϵ_t^L and $\epsilon_{2,t}$ have means of zero and variances, σ_L^2 and σ_D^2 respectively. Let P_t be the (ex- dividend) share price of the stock. The stock ultimately yields a dividend D_t and a capital gain $P_t - P_{t-1}$. We define $X_{t,ri}^e$ to be the excess return on one share of stock. This amounts to the return minus the financing cost at the risk free rate. Therefore, following Wang (1993), $X_{t,ri}^e = P_t + D_t - RP_{t-1}$.⁵⁹ Note that $X_{t,ri}^e$ is the excess return on one share of stock and not the excess return on one dollar invested in the stock. The excess return on one share of stock is the excess *share* return while the excess return on one dollar invested in the stock is the excess *rate* of return. The rate of return is calculated by dividing the share return by the share price.

iii) The Private Investment Opportunity

In addition to the public assets described above, a private investment⁶⁰ is also afforded to the algorithmic trader. The private investment has constant returns to scale with its return between t and $t + 1$ represented by $R + X_{t+1,pri}^e$, where $X_{t+1,pri}^e$ is the excess rate of return for $t + 1$. ($X_{t,pri}^e$ should not be confused with

⁵⁹ See Wang (1993, p.254).

⁶⁰ A non-traded asset in Miao and Albuquerque (2008).

$X_{t,ri}^e$, the excess return on one share of public stock). $X_{t+1,pri}^e$, or private investment excess returns, satisfies:

$$X_{t+1,pri}^e = J_t + \epsilon_{t+1}^{X_{pri}^e} \quad (4)$$

Where $\epsilon_{t+1}^{X_{pri}^e}$ is the temporary component and J_t is the persistent component. Assume J_t follows an $AR(1)$ process:

$$J_t = \alpha_J J_{t-1} + \epsilon_t^J, 0 < \alpha_J < 1. \quad (5)$$

It is also assumed that shocks to the respective variables $\epsilon_{t+1}^{X_{pri}^e}$ and ϵ_t^J are normal random variables with means of zero and variances $\sigma_{X_{pri}^e}^2$, σ_J^2 , respectively. By construction, assuming that $0 < \alpha_J < 1$, we are also assuming that J_t follows a stationary process.

Events in the Event-Period

Three crucial events occur in the event-period. They are as follows:

1. A public announcement occurs at time 1. This public announcement is an earnings announcement and *communicates* $D_t = L_t + \epsilon_t^D$.
2. Time 0s forecasted public announcement error (pre-announcement-Innovative Information) is utilized by the algorithmic trader, and, when combined with the earnings announcement itself, triggers a uniquely private signal in the form of event-period Innovative Information. This event-period Innovative Information concerns information about a firm's future performance, such as future shocks to earnings.
3. The agent identifies a key correlation structure between specific assets at time 1. That is to say a positive correlation structure between dividends and the returns on the private investment opportunity (i.e. $\sigma_{X_{t,ri}^e, X_{t,pri}^e} > 0$) or $E[\epsilon_t^D, \epsilon_t^{X_{pri}^e}] = \sigma_{D, X_{pri}^e} > 0$. This assumption is similar to that made by

Wang (1993) and implies that the private investment and stock can be considered substitutes for one another. The intuition for this follows a key characteristic of algorithmic trading⁶¹. By implication, the algorithmic trader's stock demand depends not only on the expected return on the stock in the event-period, but also the expected return on their private investment opportunity.

More detail is provided below.

As mentioned above, time 1 characterizes the event-period. In this event-period a public earnings announcement occurs. This earnings announcement communicates $D_t = L_t + \epsilon_t^D$.

Once earnings are announced and D_t is known, $G_0 = L - \epsilon_2$, the forecasted error in the public announcement (pre-announcement Innovative Information), can be utilized by the agent. Thus, as noted prior, G_0 is only useful in the event-period - time 1 - in conjunction with earnings announcement itself. When combined with the earnings announcement, G_0 generates:

$$D_t - G_0 = \epsilon_t^D + \epsilon_2.$$

Where ϵ_2 has mean zero and variance σ_D^2 .

This is then used by the algorithmic trader to assess the true value of earnings not reported in the earnings announcement itself. It triggers a uniquely private signal about $E[D_{t+1}]$. More specifically, it triggers a uniquely private signal about $E[\epsilon_{t+1}^D]$. This private signal is referred to as event-period Innovative Information.

Event-period Innovative Information is denoted by H_t and is modeled as a noisy signal about time $t + 1$ idiosyncratic shock:

$$H_t = \epsilon_{t+1}^D + \epsilon_t^H \tag{6}$$

⁶¹ See section (2.4.5) of this paper.

Where, ϵ_t^H is a normal variable with mean zero and variance σ_H^2 .

We can now provide more information about the investor's expectation about D_{t+1} , where:

$$E_t[D_{t+1}] = E_t[L_{t+1} + \epsilon_{t+1}^D] = \alpha_L L_t + E_t[\epsilon_{t+1}^D] = \alpha_L L_t + \frac{\sigma_D^2}{\sigma_H^2 + \sigma_D^2} H_t.$$

Therefore, the public release of information in the event-period triggers new private information in the form of H_t . In essence, following Kim and Verrecchia (1997), one can say that agents with advanced information-processing capabilities are able to generate new idiosyncratic information from the public announcement. This new idiosyncratic information concerns an expected shock to earnings at $t + 1$ of the event-period. Indeed, advanced algorithms are able to identify hidden layers of information as well as forecast possible future stock changes and shocks associated with the eventual corrections of prior period errors.

Event-Period Decisions and Equilibrium

Crucially, although pre-announcement Innovative Information drives event-period Innovative Information, it is actually event-period Innovative Information in the event-period that generates the momentum effect (short-term momentum and long-term momentum).

There are two fundamental principles here that are crucial to understanding our paper. These are as follows:

- (1) The agent obtains pre-announcement Innovative Information at time 0, the pre-announcement period. However, pre-announcement Innovative Information can only be utilized by the trader when it is combined with the earning announcement itself – and this announcement is only set to occur in the event-period (time 1).
Nonetheless, once earnings are announced at time 1, the combination of pre-announcement Innovative Information and the announcement itself produce event-period Innovative Information.

- (2) Since trading only commences in the event-period, we contend that the momentum effect must occur following the earnings announcement. This indicates that the event-period Innovative Information is actually generating the momentum effect.

As a consequence of the above, for the remainder of the paper, we focus primarily on the event-period.

Assuming that prices are taken as given, the algorithmic trader solves the following problem in the event-period:

$$\max - E_t[\exp(-Y\omega_{t+1})]^{62},$$

The agent achieves this by choosing stock holdings , S , and private asset holdings, α_t , subject to the constraint⁶³:

$$\begin{aligned}\omega_{t+1} &= S_t(P_{t+1} + D_{t+1}) + \alpha_t(R + X_{t+1,pri}^e) + (\omega_t - (S_t P_t + \alpha_t)) R \\ &= S_t X_{t+1,ri}^e + \alpha_t X_{t+1,pri}^e + \omega_t R\end{aligned}\tag{7}$$

Where like Wang, we have imposed a market clearing condition of $S_t = 1$

PROPOSITION 1. The economy has a steady-state rational expectations equilibrium in which the equilibrium stock price is

$$P_t = PV + \Pi_t,$$

It contains an intrinsic component and a premium component. For proof see Appendix A.

⁶² Stated differently, the algorithmic trader maximizes Eq. (1), by choosing stock holdings, and private asset holdings, subject to the budget constraint, Eq. (7).

⁶³ Following (Albuquerque & Miao, 2008, p.9, Eq. (12)).

$PV = E_t[\sum_{s=1}^{\infty} R^{-s} D_{t+s}]$ is the intrinsic component or fundamental component, equal to the expected present value of future cash flows⁶⁴ discounted at the appropriate risk free rate (R_f). Whilst Π_t is the risk premium due to dividend, private asset returns and finally, event-period Innovative Information signal risk.

The intrinsic component and the premium component are given by

$$PV_t = R^{-1} \left(\frac{\alpha_L}{1-R^{-1}\alpha_L} L_t + \frac{\sigma_D^2}{\sigma_H^2 + \sigma_D^2} H_t \right) \quad (8)$$

And,

$$\Pi_t = - \frac{Y \left(V_{X_{ri}^e} V_{X_{pri}^e} - V_{X_{ri}^e X_{pri}^e}^2 \right)}{V_{X_{pri}^e}} \frac{1}{R-1} - \frac{R^{-1} V_{X_{ri}^e X_{pri}^e}}{V_{X_{pri}^e}} \left(\frac{J_t}{1-R^{-1}\alpha_J} + \bar{\sigma} H_t \right), \quad (9)$$

Where: $V_{X_{ri}^e} \equiv Var_t(X_{ri}^e, X_{ri}^e), V_{X_{pri}^e} \equiv Var_t(X_{pri}^e, X_{pri}^e),$

And,

$$\bar{\sigma} \equiv \frac{\sigma_D X_{pri}^e}{\sigma_H^2 + \sigma_D^2}, \quad V_{X_{ri}^e X_{pri}^e} \equiv Cov_t(X_{ri}^e, X_{t+1, pri}^e) = \frac{\sigma_D X_{pri}^e \sigma_H^2}{\sigma_H^2 + \sigma_D^2}, \quad (10)$$

Note that $\sigma_D X_{pri}^e > 0$, therefore, $V_{X_{ri}^e X_{pri}^e} > 0$ and thus the public stock and private asset are substitutes for one another⁶⁵. This represents the algorithmic trader's event-period hedging incentive to rebalance his portfolio (the reason for trade). $V_{X_{ri}^e}$ and $V_{X_{pri}^e}$ are also constant. (See Appendix A for their derivation).

$-\frac{Y \left(V_{X_{ri}^e} V_{X_{pri}^e} - V_{X_{ri}^e X_{pri}^e}^2 \right)}{V_{X_{pri}^e}} \frac{1}{R-1}$, in equation (9) represents the discount required to compensate the risk-averse algorithmic trader for bearing dividend risk. The other

⁶⁴ Dividend.

⁶⁵ If $\sigma_D X_{pri}^e < 0$, then the private investment and the stock are compliments since $V_{X_{ri}^e X_{pri}^e} < 0$ by Eq. (10).

terms in equation (9) reveal how uncertainty affects the risk premium Π_t . Both uncertainty regarding the expected return on the private asset J_t and event – period Innovative Information signal, H_t affect the risk premium. Below we will illustrate how changes either J_t or H_t result in rebalance trades and thus impact stock prices.

The solution for the excess stock returns can then be expressed as:

$$X_{t+1,ri}^e = D_{t+1} + PV_{t+1} - E_t(D_{t+1} + PV_{t+1}) + \Pi_{t+1} - R\Pi_t, \quad (11)$$

From which conditional expected excess return or risk premium can be derived.

$$\begin{aligned} \mu_{t,X_{ri}^e} &= E_t [X_{ri,t+1}^e] = E_t [\Pi_{t+1} - R\Pi_t] \\ &= \frac{Y \left(V_{X_{ri}^e} V_{X_{pri}^e} - V_{X_{ri}^e X_{pri}^e}^2 \right)}{V_{X_{pri}^e}} + \frac{V_{X_{ri}^e X_{pri}^e}}{V_{X_{pri}^e}} (J_t + \bar{\sigma} H_t) \end{aligned} \quad (12)$$

The equation above highlights an important tenant of the model by showing that, in the event-period, following an earnings announcement, the expected excess return varies and its change is driven by both the expected return on the private asset, as well as, event-period Innovative Information signal. The fundamental argument is made that μ_{t,X_{ri}^e} , the variation in expected return at time t of the event-period, is the determinant for momentum and reversal effects in stock returns and, most importantly, it is driven by the event-period Innovative Information H_t . Thus, the event-period Innovative Information signal is the critical component in generating momentum and reversals from time 1, onwards.

To express the fundamental argument numerically, we follow Miao and Albuquerque (2008), and use the law of iterated expectations to

derive $E \{X_{ri,t+n_e+1}^e | X_{ri,t}^e\} = E \{\mu_{X_{ri,t+n_e}^e} | X_{ri,t}^e\}$, for any $n_e \geq 0$.

We have used the Roman lower-case letter n_e instead of the traditional n , to indicate that we are referring to points in time after the pre-announcement period. More, specifically, we are referring to time in the event-period.

Then by using equation (12) we can derive that:

$$E\{X_{ri,t+1}^e | X_{ri,t}^e\} = \frac{Y(V_{X_{ri}^e} V_{X_{pri}^e} - V_{X_{ri}^e X_{pri}^e}^2)}{V_{X_{pri}^e}} + \frac{V_{X_{ri}^e X_{pri}^e}}{V_{X_{pri}^e}} \frac{Cov(J_t + \bar{\sigma} H_t, X_{ri,t}^e)}{Var(X_{ri,t}^e)} X_{ri,t}^e, \quad (13)$$

$$E\{X_{ri,t+n_e}^e | X_{ri,t}^e\} = \frac{Y(V_{X_{ri}^e} V_{X_{pri}^e} - V_{X_{ri}^e X_{pri}^e}^2)}{V_{X_{pri}^e}} + \alpha_J^{n_e-1} \frac{V_{X_{ri}^e X_{pri}^e}}{V_{X_{pri}^e}} \frac{Cov(J_t + X_{ri,t}^e)}{Var(X_{ri,t}^e)} X_{ri,t}^e, \quad (14)$$

For $n_e \geq 2$.

If $Cov(X_{ri,t+n_e}^e, X_{ri,t}^e) > 0$, it says that excess returns exhibit momentum at horizon n_e of the event-period.

If $Cov(X_{ri,t+n_e}^e, X_{ri,t}^e) < 0$, it says that excess returns exhibit reversals at horizon n_e of the event-period.

Importantly, equations (13) and (14) indicate that momentum and reversals occur in the event-period and are determined by the signs of $Cov(J_t + X_{ri,t}^e)$ and $Cov(H_t, X_{ri,t}^e)$. In order to show what happens when event-period Innovative Information is not present in this period, equation (11) is used. Using (11), we calculate:

$$Cov(J_t, X_{ri,t}^e) = \frac{V_{X_{ri}^e X_{pri}^e}}{V_{X_{pri}^e}} \frac{R\alpha_J - 1}{R - \alpha_J} \frac{\sigma_J^2}{1 - \alpha_J^2} \quad (15)$$

And,

$$Cov(H_t, X_{ri,t}^e) = R^{-1} \frac{\sigma_D^2 (1 - \rho_{D X_{pri}^e}^2)}{\sigma_H^2 + \sigma_D^2 (1 - \rho_{D X_{pri}^e}^2)} (\sigma_H^2 + \sigma_D^2) > 0. \quad (16)$$

The conditional correlation coefficient between $\epsilon_t^{X_{t,pri}^e}$ and ϵ_t^D is represented by

$\rho_{D X_{pri}^e} \in (0,1)$. Thus crucially, without event-period Innovative Information, one can get either momentum at all horizons or reversals at all horizons following a news announcement. The logic is that, when, in the absence of event-period Innovative Information, equation (14) would hold for all $n_e \geq 1$. Since

$Cov(J_t, X_{ri,t}^e) < 0$ only if $R \alpha_J < 1$, equation (14) implies that

$Cov(X_{ri\ t+n_e}^e, X_{ri\ t}^e) < 0$ if and only if $R \propto_j < 1$, for all $n_e \geq 1$. This means that in the absence of event-period Innovative Information, we can get either momentum at all the horizons or reversals at all the horizons of the event-period. This contradicts the empirical evidence that momentum occurs in the short-term and reversals in the long-term.

Consider a case where algorithmic traders possess event-period Innovative Information. Assuming $R \propto_j < 1$, we get $Cov(X_{ri\ t+n_e}^e, X_{ri\ t}^e) < 0$ for all $n_e \geq 2$ by equations (14) and (15).

Because $Cov(H_t, X_{ri\ t}^e) > 0$ by equation (16), it follows from equation (13) that event-period Innovative Information helps generate a positive correlation between $X_{ri\ t}^e$ and $X_{ri\ t+1}^e$.

When $\propto_j$ is sufficiently close to $1/R$ from below, $Cov(J_t + \bar{\sigma} H_t, X_{ri\ t}^e)$ is adequately close to $Cov(\bar{\sigma} H_t, X_{ri\ t}^e) > 0$. In this case, we make $Cov(J_t + \bar{\sigma} H_t, X_{ri\ t}^e) > 0$ and hence $Cov(X_{ri\ t+1}^e, X_{ri\ t}^e) > 0$.

Thus, by attributing event-period Innovative Information to the algorithmic trader and allocating it to the model, we can generate momentum and subsequent reversals following an earnings announcement. Note that this result applies only to the event-period (time1) onwards. Essentially, time 0 can be considered more of an information gathering or reference period.

Conceptually, assuming $R \propto_j < 1$, an increase in the stock price in time 1 would result in a higher $X_{ri\ t}^e$. This increase could potentially be explained by the low expected private asset return J_t . Thus a lower investment would be made in the private asset. This would imply less aggregate risk being borne in equilibrium, consequently driving down conditional expected excess returns (or risk premium). Therefore, high current excess returns would be associated with low expected future excess returns, generating reversals.

However, when an algorithmic trader possesses event-period Innovative Information at time 1, then positive news about $t + 1$'s idiosyncratic shock would also result in an increase in the stock price. Additionally, good event-period Innovative Information would provide a signal that the private asset return is also higher in the future as dividend innovations are positively related to innovations in private asset returns. Logically more would be invested in the private asset, causing the investor to bear more aggregate risk, which results in higher expected future excess returns. Importantly, event-period Innovative Information helps create $t + 1$ momentum following an earnings announcement.

A very interesting characteristic of event-period Innovative Information, is that once it materializes it becomes unusable. Thus, the future stock price would fall, causing n_e excess returns ($n_e \geq 2$) to be negatively serially correlated with current excess returns e.g. $Cov(X_{ri\ t+n_e}^e, X_{ri\ t}^e) < 0$, for any $n_e \geq 2$ subject to $R \propto_j$ being < 1 .

Therefore, an important contribution of the model is that event-period Innovative Information can generate, in the event-period, short-run momentum and long-term reversals simultaneously following a public announcement. However, the above mechanism is conditional on event-period Innovative Information inducing rebalancing trades⁶⁶. To see the derivation of the above see Appendix A, where we show in that:

$$E\{X_{ri\ t+1}^e | X_{ri\ t}^e\} = E\{\mu_{X_{ri\ t}^e} | X_{ri\ t}^e\} = Y \left(V_{X_{ri}^e} + V_{X_{ri}^e X_{pri}^e} E\{\alpha_t | X_{ri\ t}^e\} \right). \quad (17)$$

The explanation for event-period short-term momentum is based on the correlation between α_t and $X_{ri\ t}^e$. Remember, α_t is the investment in the private asset, and $X_{ri\ t}^e$ is the time 1, event-period excess stock returns. Assuming $V_{X_{ri}^e X_{pri}^e} > 0$, momentum occurs if the algorithmic trader invests a greater amount

of money in the private asset when the current stock return is high. There is a high probability of this happening in the presence of event-period Innovative Information because it drives both future returns on the private asset ($X_{pri,t+1}^e$), and the time 1 stock return ($X_{ri,t}^e$), in the same direction.

Now consider the logic behind the condition $R_{\alpha_j} < 1$.

When expected returns in the private asset, J_t , increase, P_t and $X_{ri,t}^e$ fall, *ceteris paribus*. On the other hand, a high J_t tends to follow a previously high J_t because this process is persistent. A previously high J_t causes the previous stock price and current excess stock returns $X_{ri,t}^e$ to rise. When the persistence of J_t , is low enough in that $R_{\alpha_j} < 1$, the first effect dominates, causing negative correlation between J_t and $X_{ri,t}^e$ and thus reversals in stock returns. Otherwise, excess stock returns tend to be positively serially correlated.

In summary, two conditions need to be met in order to generate short-term momentum and long-term reversals in the event-period following an earnings announcement. Primarily, the persistence of α_j must be adequately small. If it is too large, we cannot generate long-term reversals in the event-period. Secondly, given a small α_j we require $Covariance(H_t, X_{ri,t}^e) > 0$ otherwise we cannot generate short-term momentum in the event-period.

In conclusion, our analysis indicates that by attributing event-period Innovative Information to an algorithmic trader and allocating it to the model, we are able to generate the momentum effect following a news announcement. Interestingly, we also identify the origin of this event-period Innovative Information. That is to say, when pre-announcement Information (collected at time 0) is combined with an earnings announcement at time 1 we can produce event-period Innovative Information and thus, the momentum effect following an earnings announcement.

Our representative algorithmic trader agent model in which traders have access to both Innovative information in anticipation of, as well as, as a result of an announcement is valuable for understanding the economic mechanism through

which algorithmic trading can possibly affect the momentum effect in financial markets.

Thus, the representative algorithmic trader agent model with pre-announcement Innovative Information and $t + 1$ in advance, event-period innovative Information provides key insights into the possible underlying mechanism behind the momentum effect.

4.2) Limitations

While the representative agent model produced in this section demonstrates the role of Innovative Information in generating momentum and subsequent reversals, it suffers from a significant limitation. That is, the representative agent framework is a simplifying assumption and as such, ignores crucial interactions between different types of investors.

CHAPTER 5: DISCUSSION OF THE RESULTS

Recall that this research intended to investigate the relationship between stock market efficiency, algorithmic trading and the momentum effect, by focusing foremost, on the impact that algorithmic trading has on security pricing and return dynamics. More specifically, focusing on algorithmic trading's association with short-run momentum and subsequent long-term return reversals. This included the identification of a theoretical mechanism through which algorithmic trading may possibly generate this observed phenomenon

To corroborate the inferences drawn from the literature⁶⁷, algorithmic trader's access to Innovative Information was identified as the catalyst through which algorithmic trading could possibly impact the momentum effect. (See section 2.4.4 for how the Innovative Information component relates to algorithmic traders). Thus, based on this hypothesis, we produced a model incorporating this Innovative Information in an attempt to ascertain its validity. More precisely, Innovative Information was decomposed it into (A) pre-announcement Innovative Information and (B) event-period Innovative Information.

From this perspective, pre-announcement Innovative Information was attributed to an algorithmic trader in a period preceding an earnings announcement. Here, pre-announcement Innovative concerned information about an expected error in the upcoming earnings announcement. Since this announcement was only set to occur in the event-period (time 1), the pre-announcement Innovative Information was considered unusable until it could be combined with the earnings announcement itself at time 1.

Nevertheless, when combined with the earnings announcement itself in the event-period, pre-announcement Innovative Information triggered a uniquely private information signal – defined as event-period Innovative Information. Here, event-period Innovative Information concerned new idiosyncratic information

⁶⁷ Wang (1993), Daniel and Titman (2006), Miao and Albuquerque (2008) and Brogaard (2011).

about an expected shock to earnings at time $t + 1$ of the event-period. *The intuition for this followed our assumption that advanced algorithms are able to identify hidden layers of information as well as forecast future stock changes and shocks associated with the eventual corrections of prior period errors.* Crucially, event-period Innovative Information was able to engender return patterns that closely resemble the momentum patterns evident in financial markets.

The procedure issued in the preceding model will be summarized below:

We began by taking a typical rational expectations trading model, based on the existence of pre-announcement private information, and adapting it to include event-period private information similar to the type suggested by Kim and Verrecchia (1997).

There were four points in time, time 0, 1, 2 and 3 and three assets in the economy. That is, two publically traded assets, as well as, a non-traded, private investment opportunity- where the two publically traded assets consisted of a riskless bond and a riskier stock.

In our model, time 0 characterized the pre-announcement period. In this period, the agent obtained and observed private information about an error in a forthcoming public announcement, which we assumed to be an earnings announcement - we defined this private information as pre- announcement Innovative Information.

Although pre-announcement Innovative Information was acquired in time 0, we did not view it as an actionable signal until time 1(the event-period) since only at time 1 could this information be combined with the public announcement itself. Additionally, since pre-announcement Innovative Information was not useful at time 0, no trading occurred in the pre-announcement period.

Time 1 characterized the event-period. Three important events occurred during the event-period. *First* a public earnings announcement occurred at time 1. *Second*, once earnings were announced in time 1, time 0's pre-announcement Innovative Information was utilized by the algorithmic trader to form a uniquely

private information signal in the form of event-period Innovative Information. This information (event-period Innovative Information), concerned new idiosyncratic information about an expected shock to earnings in time $t + 1$ of the event-period. *Third*, the agent identified a key correlation structure between specific assets. That is to say, a *positive* correlation between dividends and the private investment returns. By implication, the private investment opportunity and the stock became substitutes to the agent from time 1 onwards. Thus, the algorithmic trader's stock demand depended not only on the stocks expected return, but also on the expected return on the private investment opportunity in the event-period. This represented the algorithmic trader's event-period hedging incentive to rebalance his portfolio.

Further, by defining the economy as a steady-state rational expectations equilibrium, our equilibrium stock price comprised an intrinsic component as well as a premium component. The intrinsic component or fundamental component equaled the expected present value of future cash flows⁶⁸ discounted at the appropriate risk free rate (R_f). Whilst the risk premium component represented the discount required to compensate the risk-averse algorithmic trader for bearing, dividend, private asset returns and finally, event-period Innovative Information signal risk.

Next, we identified two sources of uncertainty that affected the risk premium. That was, both uncertainty regarding the expected return on the private asset, as well as uncertainty regarding the event-period Innovative Information signal affected the risk premium.

The fundamental argument was made that the variation in expected returns in the event-period was the determinant for momentum and reversal effects in stock returns in and , most importantly , it was driven by the event-period Innovative

⁶⁸ Dividend.

Information H_t . Thus, the event-period Innovative Information signal is the critical component in generating momentum and reversals from time 1, onwards.

Intuitively, once an algorithmic trader attained event-period Innovative Information at time 1, then positive news about $t + 1$'s idiosyncratic shock would also result in an increase in the stock price. Additionally, good event-period Innovative Information would signal that the private asset return is also higher in the future as dividend innovations were identified to be positively related to innovations in private asset returns. Logically the algorithmic trader would invest more in the private asset, causing the investor to bear more aggregate risk, which results in higher expected future excess returns.

Importantly, event-period Innovative Information helps create $t + 1$ momentum following an earnings announcement. However, a very interesting characteristic of event-period Innovative Information, was that once it materializes it became unusable.

Therefore, an important contribution of our model is that event-period Innovative Information can generate, in the event-period, short-run momentum and long term reversals simultaneously, following a public announcement. This was, however, as noted above, conditional on event-period Innovative Information inducing rebalancing trades from time 1 onwards.

In conclusion, our analysis indicates that by attributing event-period Innovative Information to an algorithmic trader and allocating it to the model, we are able to generate the momentum effect following a news announcement. Interestingly, we also identify the origin of this event-period Innovative Information. That is to say, when pre-announcement Information (collected at time 0) is combined with an earnings announcement at time 1 we can produce event-period Innovative Information and thus the momentum effect following an earnings announcement.

Therefore, our representative algorithmic trader agent model in which traders have access to both Innovative information in anticipation of, as well as, Innovative Information as a result of an announcement is valuable for

understanding the economic mechanism through which algorithmic trading can possibly affect the momentum effect in financial markets.

CHAPTER 6: CONCLUSION AND RECOMMENDATIONS

The Efficient Market Hypothesis (EMH) has arguably become one of the most influential concepts in financial markets. Its prominence in financial literature became most noticeable in the 1960s under the rubric of the 'Random Walk Hypothesis'. Quintessentially, the Efficient Market Hypothesis is "an extension of the zero profit competitive equilibrium condition from the certainty world of classical price theory to the dynamic behavior of prices in speculative markets under conditions of uncertainty" (Jensen, 1978, p. 3). The supposition has been stated in a variety of different ways, but the easiest and most representative way to express it is the following:

A market is efficient "when prices exhibit unpredictable behavior, given the available information." (Karemera et al., 1999, p. 171). This means that information is "fully reflected" in prices and that these prices do not display a perceptible pattern.

However, there has been a growing body of financial literature recently, highlighting aspects of stock price behavior, which seem to deviate from what is considered the norm, regarding the above mentioned paradigm. These discoveries confirm the presence of a market anomaly known as the momentum effect. The momentum effect presents a major challenge to the EMH and to standard risk-based models.

Two of the more pervasive phenomena have thus far been identified with the momentum effect. That is, positive short term auto correlations of returns (short term momentum) and the negative autocorrelations of prior short term returns (long term reversals).

To date, the momentum effect is regarded as somewhat of an empirical regularity⁶⁹. What has been contentious surrounds the causes of such an

⁶⁹ Fama and French (1996) point out that the momentum result of Jegadeesh and Titman (1993) constitutes the "main embarrassment for their three-factor model.

anomaly. Adding to the complexity of the issue, several academics have proposed that new technological developments in equity markets have affected the efficiency of financial markets.

By adding to the foregoing debate on the causes of this momentum effect, this study intended to identify whether a relationship exists between algorithmic trading, the most important of the technological developments, and the momentum effect.

Following the literature⁷⁰, we identified a possible avenue through which algorithmic trading could generate the momentum effect. That was through their access to Innovative Information. We tested this proposition by developing a single agent model incorporating this informational variable, as well as other stylized facts about algorithmic trading in an attempt to ascertain its credibility.

The intuition behind Innovative Information as well as its relevance to algorithmic trading is as follows:

In effect, we defined algorithmic trading as computer-determined trading, whereby super computers and complex algorithms directly interface with trading platforms, placing orders without immediate human intervention. It (algorithmic trading) employs cutting edge mathematical models, adept computational techniques and extraordinary processing power via advanced computer and communication systems and is capable of anticipating and interpreting relatively short-term market signals in order to implement profitable trading strategies.

Academic research concerning the impact of algorithmic trading is still in its infancy. A serious obstacle in conducting research on this topic is data availability. That being said, a small but growing group of academic papers have begun to address questions surrounding algorithmic trading, mainly focusing on market quality parameters and issues regarding its profitability and fairness. The evidence to date is still inconclusive. The vast majority of studies regarding

⁷⁰ Wang (1993), Daniel and Titman (2006), Miao and Albuquerque (2008) and Brogaard (2011).

algorithmic trading have coalesced around the idea that algorithmic traders possess a comparative advantage relative to regular traders. The literature (Hendershott & Riordan, 2011; Biais Foucault & Monias, 2011; Brogaard, Hendershott & Riordan, 2012) has typically focused on a speed advantage.

Nevertheless, apart from the speed dimension there remains an additional aspect inherent in algorithmic trading affording firms a comparative advantage relative to traditional traders. In fact Kirilenko, Andrei, Pete Kyle, Mehrdad Samadi, and Tugkan Tuzun (2011), write that “possibly due to their speed advantage or superior ability to predict price changes”, algorithmic traders are able to buy just before the prices are about to increase. Their analysis highlights the *possibility* of an alternative to the speed differential being the only source of inequity.

By drawing on inferences from the literature⁷¹, we identified algorithmic trader’s access to Innovative Information as the possible alternate source of algorithmic trader’s informational superiority.

More precisely we defined Innovative Information as:

The information derived from the ability to accumulate, differentiate, estimate, analyze and utilize colossal quantities of data by means of adept techniques, sophisticated platforms, capabilities and processing power.

From this perspective, an algorithmic trader’s access to various complex computational techniques, infrastructure and processing power, together with the constraints to human information processing, allow them to make judgments that are superior to the judgments of other traders. Consider Daniel and Titman’s (2006) investigation into long-term return anomalies. They propose an interesting theory on observed anomalies, relating to how investors assess and react to different types of information. Specifically, they decompose information into tangible and intangible components. Accordingly, tangible information relates to the explicit, publicly disclosed, performance measures which can be observed

⁷¹ See section (2.4.4) of this paper.

directly by all and is available from the firms' accounting statements. Whilst, on the other hand, intangible information relates to the more *abstruse* information about growth opportunities judged or interpreted privately by owners. Their analysis indicates that long-term return anomalies "arise because future returns are cross-sectionally related to past realizations of intangible information." (Daniel and Titman, 2006. p. 1638). One can thus take the Innovative Information as being intangible information. This information is not directly observable but reflects the more "decrypted" information - signaling the firm's future performance. It is available to algorithmic trading firms as a result of their access to various complex computational techniques, infrastructure and processing power – and essentially allows them to make judgments that are superior to the judgments of other traders. Indeed, an investor's ability to evaluate information that is relatively vague is consistent with Daniel and Titman's (2006) classification of intangible information⁷².

The Innovative Information concept is also related to the research conducted by Miao and Albuquerque (2008). In their paper they present a rational expectations heterogeneous investor model with asymmetric information in order to address the trading behavior of different types of investors when some of them possess *advanced* information – information about a firm's future performance, such as shocks to earnings - in a rational expectations framework. In the model, investors are regarded as being either informed or uninformed. By assuming that informed investors possess both private information as well as private advanced information, they attempt to account for the under reaction and overreaction phenomena. Importantly, we can relate our concept of Innovative Information to Miao and Albuquerque's (2008) advanced private information.

However, as noted in the foregoing, and in an attempt to be relevant to algorithmic trading, we took things further, by decomposing Innovative Information into (A) pre-announcement Innovative Information and (B) event-

⁷² See Daniel and Titman (2006, p. 1640).

period Innovative Information. This apportionment followed Kim and Verrecchia (1997) and is driven by the assumption that algorithmic traders utilize information both prior to, and in conjunction with news announcements (Leinweber, 2009).

In this context, pre-announcement Innovative Information concerned information about an error in a forthcoming earning announcement. Following Kim and Verrecchia (1997), this error arose from the application of random, liberal, or conservative accrual-based accounting practices and estimates in announcements. Indeed, concerning earnings announcements management can and do engage in the somewhat serpentine activities such as income smoothing and big bath accounting. However, an algorithmic traders ability to accumulate, differentiate, estimate, analyze and utilize colossal quantities of data by means of adept techniques, sophisticated platforms, capabilities and processing power – results in a situation in which algorithmic traders are able to identify the subtle errors and deficiencies associated with the above mentioned serpentine practices.

Stated differently: The use of Innovative Information in the pre- announcement period provide algorithmic traders with the ability to identify the subtle errors and deficiencies accompanying the somewhat serpentine reporting activities associated with earnings announcements. By doing so, advanced algorithms are able to identify hidden layers of information as well as forecast possible future errors.

On the other hand, event-period Innovative Information denotes the new information that arises as a result of the interaction between information contained in the public announcement itself and the pre-announcement Innovative Information gathered prior to the announcement. Thus, once earnings are announced, the pre-announcement Innovative Information can be combined with the earnings announcement itself to assess the true value of earnings not reported in the announcement. Essentially, it triggers a uniquely private signal about the following period's idiosyncratic shock in the form of event-period Innovative Information. Indeed, as a result of their ability to

accumulate, differentiate, estimate, analyze and utilize colossal quantities of data by means of adept techniques, sophisticated platforms, capabilities and processing power, advanced algorithms are able to identify hidden layers of information as well as forecast possible future stock changes and shocks associated with the eventual corrections of prior period errors.

Intuitively, algorithmic traders would trade in the wake of an earnings announcement not just because of the information contained in the announcement itself, but also because their pre-announcement Innovative Information leads them to interpret the reported amounts differently than others who lack this information.

As noted earlier, an appropriate approach in making progress on identifying the existence of a relationship between the momentum effect and algorithmic trading, is to focus on the details of a theoretical mechanism through which algorithmic trading could possibly generate this return anomaly and to document it's working.

Therefore we hypothesize that the underlying mechanism by which algorithmic trading can generate the momentum effect is through their access to “Innovative Information”. More precisely, their access to pre-announcement Innovative Information as well as event-period Innovative Information. In order to test such an assumption, we present a simplified single agent model where the representative agent or algorithmic trader possesses both pre-announcement Innovative Information as well as event-period Innovative Information. Additionally, many of the relative stylized facts about algorithmic trading identified in section (2.4.5), were also incorporated into the model.

Our model is based on the seminal study of Wang (1993). We made additional assumptions corresponding to the above mentioned stylized facts of algorithmic trading.

Firstly, following stylized fact (1), we assume that the algorithmic trader has access to what we define as Innovative Information. This information variable is similar to that of Daniel and Titman's (2006), intangible information and has many of the same characteristics of Miao and Albuquerque's (2008) private advanced

information. Secondly, we decompose Innovative Information into (A) pre announcement and (B) event- period Innovative Information. This relates to Kim and Verrecchia's pre- announcement and event-period private information and corresponds to stylized fact (4). Furthermore, we follow Merton (1987) and assume that the algorithmic traders' investment universe consists of a risky stock, a riskless bond and a private investment opportunity - stylized fact (2).

Also, and in line with stylized fact (3), we assume that returns on the private investment opportunity are identified to be positively correlated with stock earnings from the event-period onwards. Thus, the private investment opportunity and the stock can be considered substitutes to the algorithmic trader.

Crucially, although pre-announcement Innovative Information drives event-period Innovative Information, it is actually event-period Innovative Information in the in the event-period that generates the momentum effect (short-term momentum and long-term momentum).

There are two fundamental principles here that are crucial to understanding our paper. These are as follows:

(1) The agent obtains pre-announcement Innovative Information at time 0, the pre-announcement period. However, pre-announcement Innovative Information can only be utilized by the trader when it is combined with the earning announcement itself – and this announcement is only set to occur in the event-period (time 1). Nonetheless, once earnings are announced at time 1, the combination of pre-announcement Innovative Information and the announcement itself produce event-period Innovative Information.

(2) Since trading only commences in the event-period, we contend that the momentum effect must occur following the earnings announcement. This indicates that the event-period Innovative Information is actually generating the momentum effect.

In conclusion, our analysis indicates that by attributing event-period Innovative Information to an algorithmic trader and allocating it to the model, we are able to

generate the momentum effect following a news announcement. Interestingly, we also identify the origin of this event-period Innovative Information. That is to say, when pre-announcement Information (collected at time 0) is combined with an earnings announcement at time 1 we can produce event-period Innovative Information and thus the momentum effect following an earnings announcement.

Thus, our representative algorithmic trader agent model in which traders have access to both Innovative information in anticipation of, as well as, as a result of an announcement is valuable for understanding the economic mechanism through which algorithmic trading can possibly affect the momentum effect in financial markets.

Consider an algorithmic trader that receives Innovative Information at time 0, the pre-announcement period, in the form of pre-announcement Innovative Information. As this signal is only actionable when combined with the earnings announcement itself, assume that the algorithmic trader waits until the event period (time1), before making any trade decisions.

Next, assume that once this earnings announcement come to fruition (time1), the agent combines pre-announcement Innovative Information with the earnings announcement itself, generating uniquely private information in the form of an expected $t + 1$ event-period shock. Suppose that this signal – defined as event-period Innovative Information - relays positive news about $t + 1$ dividend innovations (assume $t + 1$ of the event-period).⁷³

This would result in an increase in stock price. Also, good event-period Innovative Information would signal that the private asset return is also higher in the future because future dividend innovations are positively related to innovations in the private asset returns. Logically, the algorithmic trader invests more in the private asset causing him to bear more aggregate risk. Subsequently, this results in

⁷³ Recall, for instance, following under the guise of Big Bath Accounting, serpentine reporting activities often imply that future reported profits will rise. (See page 45 of this paper).

higher expected future excess returns. Thus event-period Innovative Information helps create $t + 1$ ahead momentum in the event-period.

In addition to triggering short-run momentum in excess stock returns, private event-period Innovative Information may also induce long-run excess stock return reversals in the event-period. This is because the impact of event-period Innovative Information on stock prices dies out quickly once the information materializes, and consequently excess returns revert themselves when the return on private investment opportunities is not persistent.

Generally, as long term reversals are defined as a negative return autocorrelation following a previous positive return autocorrelation, we are comfortable referring to this secondary effect as a long-term return reversal.

Thus, by assuming algorithmic traders have access to Innovative Information, subsequently allocating it to the model in the form of pre-announcement and event-period Innovative Information, we can generate $t + 1$ ahead momentum followed by long-term reversals following an earnings announcement. The general thrust of our results, therefore, is that algorithmic trading can hypothetically generate the return anomaly known as the momentum effect. Our results give credence to the assumption that algorithmic trading is having a detrimental effect on stock market efficiency.

6.1) Recommendations for Further Research

Evidence on the momentum anomaly remains, perhaps, the strongest evidence against the efficient market hypothesis. The questions surrounding the underlying causes for the above anomaly have been and may remain empirically unresolved for a while. Similarly, studies concerned with the nexus between the momentum effect and algorithmic trading are extremely limited.

Adding to the foregoing, this research takes an unconventional and interesting position towards the possible causes of this anomaly. We attribute it to algorithmic trader's access to Innovative Information. The academic discourse on this informational variable being the underlying linkage between the momentum effect

and algorithmic trading has largely begun with this study. However paucity of algorithmic trading data has had a limiting effect. That being said, as data becomes available, further investigations of the many outstanding issues not addressed by this study will become more feasible. There are many possible extensions to this study for which future research is desirable. They include, although not necessarily limited to the following:

Firstly, the results could be enriched by extending the single agent model into a heterogeneous agent model in order to investigate crucial interactions between algorithmic traders and non-algorithmic traders and assess its impact.

Secondly, isolating, including and analyzing actual algorithmic trading transactions may prove to be extremely beneficial. This would allow the researcher to make comparisons between the theoretical assumptions of the model and reality.

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Appendix A

A) Equilibrium Derivation

Substituting (7) into (1), first-order conditions can be derived:

$$V_{X_{ri}^e} + \alpha_t V_{X_{ri}^e, X_{pri}^e} = Y^{-1} \mu_{X_{ri}^e, t} \quad (A1)$$

$$V_{X_{ri}^e, X_{pri}^e} + \alpha_t V_{X_{pri}^e} = Y^{-1} \mu_{X_{pri}^e, t}, \quad (A2)$$

Where market clearing requires $S_t = 1$.

In the equations below, we will show that $V_{X_{ri}^e}$, $V_{X_{pri}^e}$ and $V_{X_{ri}^e, X_{pri}^e}$ are constant after solving for the equilibrium price.

$$\mu_{X_{ri}^e, t} = E_t[X_{t+1, ri}^e], \mu_{X_{pri}^e, t} = E_t[X_{t+1, pri}^e], V_{X_{ri}^e} = Var_t(X_{ri, t+1}^e),$$

$$V_{X_{pri}^e} = Var_t(X_{t+1, pri}^e), V_{X_{ri}^e, X_{pri}^e} = Cov_t(X_{t+1, pri}^e, X_{t+1, ri}^e).$$

Using (A.1) results in:

$$E\{X_{t+1, ri}^e | X_{t, ri}^e\} = E\{\mu_{X_{ri}^e, t} | X_{t, ri}^e\} = Y \left(V_{X_{ri}^e} + V_{X_{ri}^e, X_{pri}^e} E\{\alpha_t | X_{t, ri}^e\} \right).$$

Solving equations (A.1) and (A.2) results in:

$$\alpha_t = Y^{-1} \frac{\mu_{X_{t,pri}^e}}{V_{X_{pri}^e}} - \frac{V_{X_{ri}^e, X_{pri}^e}}{V_{X_{pri}^e}}, \quad (A3)$$

$$\mu_{t, X_{ri}^e} = \frac{V_{X_{ri}^e, X_{pri}^e} \mu_{X_{t,pri}^e}}{V_{X_{pri}^e}} - Y \left(\frac{V_{X_{ri}^e, X_{pri}^e}^2}{V_{X_{pri}^e}} - V_{X_{ri}^e} \right). \quad (A4)$$

With event-period Innovative Information concerning $t + 1$ of the event-period dividend innovations,

$$\mu_{X_{t,pri}^e} = J_t + E \left\{ \epsilon_{t+1}^{X_{pri}^e} \middle| H_t \right\} = J_t + \bar{\sigma} H_t, \quad (A5)$$

$$V_{X_{pri}^e} = Var \left\{ \epsilon_{t+1}^{X_{pri}^e} \middle| H_t \right\} = \sigma_{X_{pri}^e}^2 - \frac{\sigma_{D, X_{pri}^e}^2}{\sigma_H^2 + \sigma_D^2},$$

Where $\bar{\sigma} = \frac{\sigma_{D, X_{pri}^e}}{\sigma_H^2 + \sigma_D^2}.$

By the definition of μ_{t, X_{ri}^e} and

$$E_t[D_{t+1}] = E_t[L_{t+1} + \epsilon_{t+1}^D] = \alpha_L L_t + \frac{\sigma_D^2}{\sigma_H^2 + \sigma_D^2} H_t,$$

We obtain

$$\mu_{t, X_{ri}^e} = E_t[P_{t+1}] + E_t[D_{t+1}] - RP_t = E_t[P_{t+1}] + \alpha_L L_t + \frac{\sigma_D^2}{\sigma_H^2 + \sigma_D^2} H_t - RP_t.$$

We obtain a difference equation for P_t by using the above equation and substituting (A.5) into (A.4):

$$E_t[P_{t+1}] + \alpha_L L_t + \frac{\sigma_D^2}{\sigma_H^2 + \sigma_D^2} H_t - RP_t = \frac{V_{X_{ri}^e, X_{pri}^e} [J_t + \bar{\sigma} H_t]}{V_{X_{pri}^e}} - Y \left(\frac{V_{X_{ri}^e, X_{pri}^e}^2}{V_{X_{pri}^e}} - V_{X_{ri}^e} \right)$$

Solving the above equation results in:

$$P_t = -Y \frac{V_{X_{ri}^e} V_{X_{pri}^e} - V_{X_{ri}^e, X_{pri}^e}^2}{V_{X_{pri}^e}} \frac{R^{-1}}{1 - R^{-1}} + \frac{R^{-1} \alpha_L}{1 - R^{-1} \alpha_L} L_t - \frac{R^{-1} V_{X_{ri}^e, X_{pri}^e}}{V_{X_{pri}^e} (1 - R^{-1} \alpha_J)} J_t \\ + R^{-1} \left[\frac{\sigma_D^2}{\sigma_H^2 + \sigma_D^2} - \frac{V_{X_{ri}^e, X_{pri}^e} \bar{\sigma}}{V_{X_{pri}^e}} \right] H_t. \quad (A6)$$

We can compute PV_t , the intrinsic component of P_t , given in equation (8). By using the above price equation we can obtain equation (9). Next, we can calculate the excess stock return using (A.6):

$$X_{t+1,ri}^e = Y \frac{V_{X_{ri}^e} V_{X_{pri}^e} - V_{X_{ri}^e, X_{pri}^e}^2}{V_{X_{pri}^e}} + \frac{1}{1 - R^{-1} \alpha_L} \epsilon_{t+1}^L + \left(\epsilon_{t+1}^D - \frac{\sigma_D^2}{\sigma_H^2 + \sigma_D^2} H_t \right) \\ - \frac{R^{-1} V_{X_{ri}^e, X_{pri}^e}}{V_{X_{pri}^e} (1 - R^{-1} \alpha_J)} \epsilon_{t+1}^J + \frac{V_{X_{ri}^e, X_{pri}^e}}{V_{X_{pri}^e}} (J_t + \bar{\sigma} H_t) + R^{-1} \left[\frac{\sigma_D^2}{\sigma_H^2 + \sigma_D^2} - \frac{V_{X_{ri}^e, X_{pri}^e} \bar{\sigma}}{V_{X_{pri}^e}} \right] H_{t+1}.$$

Using this equation we can derive $V_{X_{ri}^e}$ and $V_{X_{ri}^e, X_{pri}^e}$.

$$V_{X_{ri}^e} = \frac{\sigma_L^2}{(1 - R^{-1} \alpha_L)^2} + \frac{\sigma_D^2 \sigma_H^2}{\sigma_H^2 + \sigma_D^2} + \left(\frac{R^{-1} V_{X_{ri}^e, X_{pri}^e}}{V_{X_{pri}^e} (1 - R^{-1} \alpha_J)} \right)^2 \sigma_J^2 \\ + R^{-2} \left[\frac{\sigma_D^2}{\sigma_H^2 + \sigma_D^2} - \frac{V_{X_{ri}^e, X_{pri}^e} \bar{\sigma}}{V_{X_{pri}^e}} \right]^2 (\sigma_H^2 + \sigma_D^2),$$

And,

$$V_{x_{ri}^e, x_{pri}^e} = E_t \left[(\epsilon_{t+1}^D - E_t \epsilon_{t+1}^D) \left(\epsilon_{t+1}^{X_{pri}^e} - E_t \epsilon_{t+1}^{X_{pri}^e} \right) \right] = \frac{\sigma_{D_{X_{pri}^e}} \sigma_H^2}{\sigma_H^2 + \sigma_D^2}.$$