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**NAVAL
POSTGRADUATE
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MONTEREY, CALIFORNIA

THESIS

**ADJUSTING THE CAPITAL ASSET PRICING MODEL
FOR THE SHORT-RUN WITH LIQUIDITY PROXIES,
WHILE ACCOUNTING FOR DENIALS AND
DECEPTIONS IN FINANCIAL MARKETS**

by

John J. Mooney IV
March 2014

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**ADJUSTING THE CAPITAL ASSET PRICING MODEL FOR THE SHORT-RUN
WITH LIQUIDITY PROXIES, WHILE ACCOUNTING FOR DENIALS AND
DECEPTIONS IN FINANCIAL MARKETS**

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Submitted in partial fulfillment of the
requirements for the degrees of

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ENGINEERING**

and

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from the

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ABSTRACT

William Sharpe's 1964 capital asset pricing model relies heavily on an accurate assessment of the asset's sensitivity to the broader market, termed β . By modifying the classic approach to incorporate liquidity of the asset, designated β' , short-term return estimates may be improved. Specifically, in this research, the limit order book is used as a short-term proxy for liquidity assessments. Unfortunately, precise data were unavailable to test: however, detailed realistic examples are outlined in order to explore both rationale and critiques of the adjusted model.

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LIST OF ACRONYMS AND ABBREVIATIONS

AMH	adaptive market hypothesis
ATS	alternative trading system
BPS	basis point
CAPM	capital asset pricing model
CL	complex liquidity
CTFC	commodity futures trading commission
D-CAPM	downside-adjusted-CAPM
DJIA	Dow Jones industrial average
DM	developed markets
DoD	Department of Defense
ECN	electronic communications network
EEFI	essential elements of friendly information
EM	emerging markets
EMH	efficient market hypothesis
FO	free option
FTT	financial transaction tax
HFT	high-frequency trading
IO	information operations
IOC	immediate-or-cancel
IOI	indicators of interest
ITS	inter-market trading system
IW	information warfare
JP	joint publication
LOB	limit orders book
MILDECc	military deception
MPT	modern portfolio theory
NE	non-execution
OPSEC	operations security
R-CAPM	revised-CAPM
Reg NMS	regulation national market systems

SEC	Securities and Exchange Commission
SL	simple liquidity
SVI	search volume index
TCL	total complex liquidity
TP	transformation procedures

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An investment in knowledge pays the best interest.
—Benjamin Franklin

The more I see, the less I know for sure.
—John Lennon

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I. INTRODUCTION

If you've heard this story before, don't stop me because I'd like to hear it again.

—Comedian Groucho Marx (1890–1977)

A. THE FOURTH THURSDAY OF OCTOBER

Everyone knew it was coming; it was just a matter of when. In the days leading up to that fourth Thursday of October, and as the rumors grew to consensus, newsmen, bankers, and their chauffeurs were waiting anxiously for the organized support they believed was inevitable. After all, it was not the first time the markets faced such a crisis. Just seven months before, Charles E. Mitchell, president of the powerful National City Bank, stepped in and reassured the markets that the boom times would continue. He offered \$25 million loans to show his support to the call side, leveraged speculators (Galbraith, 1961, pp. 42–43). Though it was unclear in what form the inevitable support would materialize, or who precisely would do the organizing, it was understood that the worse was over, and the titans of industry and finance would put a stop to the unreasonable fall in prices. After all, on Tuesday, Mitchell himself declared that “the decline had gone too far” and the economy was “fundamentally sound” (Galbraith, 1961, p. 102).

By Wednesday, the market was looking ambiguously unsound, as the *Times*, Dow Jones Industrial Average fell by nearly 7.5% from 415 to 384 (Galbraith, 1961, p. 103). The morning hours of the next day, Thursday, were characterized by chaos, confusion, and fear, as boardrooms around the country saw near vertical price declines bleed across the ticker. Ticker printers themselves were falling more and more behind, desperately and futilely trying to keep up with volume twice as great as the previous record-holder, and four-fold greater than a typical day of heavy trading. By noon, the panic had subsided. It wasn't that federal bureaucrats released positive data about the economy, nor that a particularly large firm, like General Electric or Ford Motor Company reported better-

than-expected earnings, or even that some opportunistic politician announced a government spending program to get the economy back on track. In fact, word began to spread that an emergency meeting was being held at 23 Wall Street, then headquarters of J. P. Morgan and Company. At the head of the table was the much extolled, though later maligned, Charles Mitchell, also in attendance were the chairmen of both Chase National Bank and National City as well as the president of the Guaranty Trust Company; all hosted by the senior partners of J. P. Morgan (Galbraith, 1961, pp. 104–106). It was a room full of the nation's most influential financiers, and what many hoped was an answer to the question of who would organize. While estimates vary greatly, most agree that the financiers purchased somewhere between \$40 million to \$240 million worth of securities, and by the end of the day, it was irrefutable that the support worked (Galbraith, 1961, p. 106). Disastrous morning losses were all but recouped before the markets closed that Thursday. Goldman Sachs, once trading down nearly 20 percent, recovered to close down a fraction above 1 percent. U.S Steel, a vocal target by the *organized support*, opened at 205½, dropped to 193½, and closed at 206 – a net gain on the day of 2 points (Galbraith, 1961, p. 108). With great success, the commended financial leaders of Wall Street had stepped in to provide sanity and liquidity to an increasingly irrationally volatile market. The worst had past, or so common knowledge would have suggested.

The next two trading days after Black Thursday went largely unchanged, rising modestly Friday, and falling by night the same Saturday morning (the New York Stock Exchange did not remain closed on all Saturday's until the 1950s) (Galbraith, 1961, pp. 110–111). The calmer weekend markets gave the financial saviors ample opportunity to dispose of the shares they acquired propping up the market Thursday afternoon. So after a tranquil Sunday, the markets opened Monday morning when the real troubles returned in earnest. Just like the previous Thursday, the bottom fell out as the *Times* industrials shed more than 10% (Galbraith, 1961, p. 114). Regrettably, on Monday, unlike the past Thursday, support neither organized nor materialized in the waning open hours of the market. While the bankers did meet after the market closed, a statement released after the meeting adjourned, made it clear that the oracles of the financial district were not there, “to maintain any particular level of prices or to protect anyone's profit” (Galbraith, 1961,

p. 115). The next day, Tuesday, October 29, 1929, would be the most devastating day in the New York stock market for 60 years. Shedding percentages nearly as great as Monday, with volumes well exceeding those of the past record setting Thursday, on Black Tuesday the financial leaders were silent. And so with a crash, an era branded by unemployment, stagnation, and hardship, the Great Depression had begun (Galbraith, 1961, pp. 116–117).

What, if any, lessons can be learned from these events? Furthermore, do these hard-earned lessons apply today, after nearly 85 years, in what seems to be a very different economy? Intuition unconsciously, yet confidently, answers yes; truths, models, and conclusions can both be drawn and applied from the circumstances of the Great Crash. Nevertheless, prudence dictates that if interpretations are too broad, then practitioners risk misapplying those lessons or neglecting to identify qualifying assumptions. Conversely, interpret too narrowly, or dismiss the findings entirely, and the prudent theorist may soon find the refrain of history’s ballad playing once again. With that disclaimer addressed, the first and most apparent conclusion is that, at the market close on Black Thursday, the price of securities was not based on fundamentals. This is made near conclusive by the sudden drops both before Black Thursday and in the days after the bankers refused to intervene. If, at least in the *short run*, security prices reflect something other than fundamentals—a benign conclusion that comes as little surprise to even the most casual observer of the market today—then, how should the short-run investor price securities? Admittedly, this is an almost esoteric question that may be satisfied by any number of answers. This thesis will explore one potential answer, drawing on a variety of disciplines and fields including information sciences, economics, military deception, operations security, capital asset pricing, and contemporary market conditions.

B. PROBLEM STATEMENT

In contemporary market conditions, how can short-run investors use information operations frameworks to incorporate trading indicators, such as liquidity, in order to improve the accuracy of the capital asset pricing model? Additionally, how do

contemporary market conditions, specifically dark pools and high-frequency trading, affect those indicators and the revisions of the pricing model?

C. RESEARCH METHODS

This effort employs a comparative analysis of academic and industry case studies involving emerging trading strategies and asset valuations. Initial research methods primarily involve secondary research focused on military operations security methods and techniques along with corresponding deception approaches. High-frequency/low latency trading and automated trading systems research, case studies and the myriad published academic papers are examined to determine the role of fragmentation in current market conditions. A linkage between the two disciplines is established and a model proposed to more accurately measure near instantaneous valuation. Unfortunately, due to resource constraints and the absence of reliable datasets, the model is limited to face validation and future research may provide validation or rejection as appropriate. Finally, the model itself, and the model's proxy metric, will be used as an example to show operations security concerns and how deception techniques can be used to manipulate the information landscape available to modern traders and investors.

D. CAPITAL MARKETS

1. A Brief History

It is critical to begin with a common understanding of the nature capital markets and their derivative, financial markets. The original purposes of capital markets were, and remain today, two-fold: to raise money from investors, and to expand commercial enterprise. In turn, investors receive a return on their investment, which is either fixed or variable depending on the investment class. Two, and only two, vehicles exist for commercial enterprises to raise this capital.

The first vehicle, and the means with which many are most familiar, are equity markets. In equity markets, investors exchange capital (i.e., savings) for equity in a particular company. This equity, commonly referred to as stock or shares of a particular company, represents a portion of ownership the investor has acquired through the exchange (Fama & Miller, 1972, p. 64).

Usually this equity grants the investor part ownership of the company, which, in turn, entitles that investor to certain rights as an owner. These rights include profit sharing, voting for board members, and the approval of bylaws (Fama & Miller, 1972, p. 64, 67–68). On a side note, not all share classes are created equal, and today many companies are issuing increasingly controversial share class termed non-voting, where ownership does not ensure shareholders views, are reflected in company decisions (Franks & Mayer, 2006 p. 4). While the rights associated with this equity, as the name implies, are considerably more restricted, nevertheless, the value of non-voting equity fluctuates up or down as the underlying enterprise expands or contracts.

The second, less understood, though considerably larger capital market, is the debt market (Tang, n.d.). While the purpose is the same, to raise money for commercial enterprises, the vehicle used in the debt market is a bond, rather than a stock in the equity market. A bondholder, or debt investor, is entitled to different rights than the shareholder in the equity market. For one, the bondholder is not entitled to company profits, nor are they entitled to vote for board members. Nevertheless, a bondholder's repayment, plus interest, is guaranteed on an established timeline, except in the case of bankruptcy restructuring. A shareholder has no such right, and in the event of bankruptcy is typically the last to receive any form of compensation (Barrett & Sullivan, 1988, p. 1). Through many of the theorems and discussions may apply equally to bond markets, equity markets and their derivatives will be the primary focus of this thesis.

Over time, capital markets have evolved into the more broadly defined financial markets. While financial markets encompass stock and bond markets, they also include some complex financial derivatives of those investment classes. Today options, leveraged positions, mutual funds, exchange traded funds, and future contracts are investment tools readily available to investors of all levels. For purposes of this thesis, two distinct types of investors are defined. First, there is the individual investor who is commonly referred to as a retail investor. The retail investor typically has limited access to capital, fewer positions, and less advanced trading resources than the institutional investor (Richter, 1989, p. 1, 5). Institutional investors typically have more sizeable pools of capital, access to a wider assortment of trading tools, and considerably more resources invested in

research and capital management. Institutional investors also range in composition. A few examples of institutional investors today include large corporations, pension plans, mutual funds, private equity and hedge firms. Increasingly, institutional investors are conducting more of the trades in both the capital markets and global financial markets. While retail or individual investors owned an estimated 90% of the stock market in the 1950s, that number has eroded in every decade since, to about 60% in the aftermath of the crash of 1987 (Richter, 1989, p. 5). This decline is shown in Figure 1.

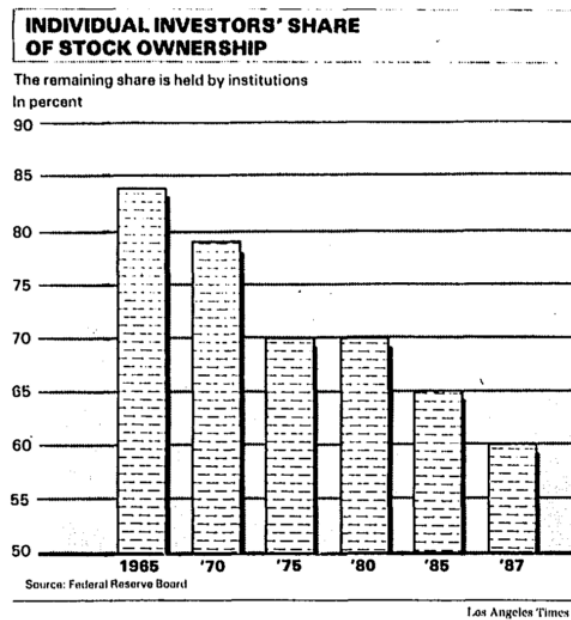


Figure 1. Individual Investors' Share of Stock Ownership (from Richter, 1989, p. 5)

In fact, the decline of individual ownership has only hastened since the late 1980s to less than an estimated 30% in 2009 (Evans, 2009, p. 1105). Beyond ownership, individual investors account for only about 2% of the daily trading on the New York Stock Exchange (Evans, 2009, p. 1105). This is in stark contrast to the 20% of daily trading attributed to them less than two decades prior (Richter, 1989). Conversely, over the past 60 years, large institutional investors have risen as retail investment has fallen, in both equity ownership and daily trading.

In addition to the rising trends toward institutional ownership and trading, two other inescapable modern facets of the market landscape are high-frequency trading,

(HFT) and alternative trading systems (ATS). HFT is intrinsically linked with another practice, algorithmic trading (AT) (Zhang, 2010, p. 5). While digital implementation of these practices is not required in principle, in reality, HFT could not exist without the computing power provided by the information age. While experts disagree on what exactly defines HFT, in general HFT involves algorithm based buying and selling in rapid succession (Gehm, 2010, p. 58). Additionally, HFT firms carry few positions over night, closing nearly all trades before the market closes, claiming their added liquidity adds a net value to the marketplace that would not be afforded in their absence (Zhang, 2010, pp. 1–2).

Furthermore, while algorithm based trading is not a new concept and has been employed at various levels since the 1980s, the rise in market share of daily trading volumes of HFT in the past decade have been staggering (Richter, 1989, p. D1) Daily trading volume statistics on this meteoric rise are shown in Figure 2.

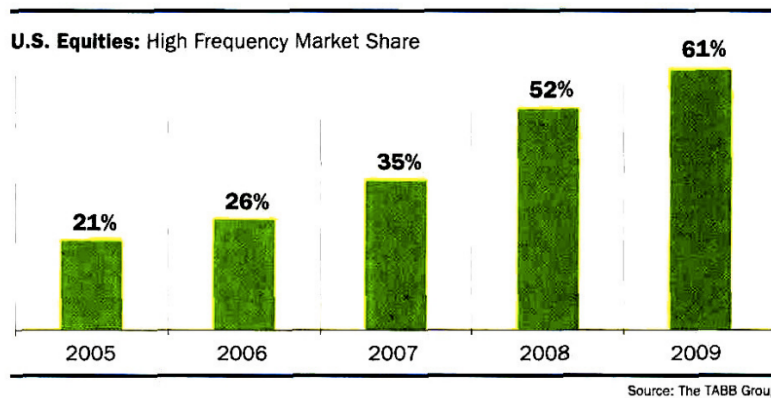


Figure 2. High-Frequency Trading Daily Trading Volume Market Share (from Gehm, 2010, p. 59)

In 2009, HFT daily trading accounted for more than 60% of the overall daily trading volume. That is, on average in 2009, 60% of stock market trades were decided not by fund managers or financial advisors, but by computer algorithms acting on their behalf (Gehm, 2010, pp. 58–60).

In addition to the changes in how trades are occurring (i.e., fast and via computer algorithms), dramatic changes are happening in where, electronically, the exchanges are

taking place. Alternative trading systems (ATS) are “venues or mechanisms containing anonymous non-displayed trading liquidity, available for execution” (Banks, 2010, p. 3). As a consequence of the anonymous, non-displayed liquidity characteristics, ATSs have come to be commonly referred to as dark pools. Though ominous sounding, in reality dark pools are similar to their lit counterparts, but offer some distinct advantages that have contributed to their rapid growth in popularity. Since regulation and introduction in 1998, daily trades in dark pools have grown to an estimated 20% over the overall market (Banks, 2010, pp. 6–8). Some of the advantages offered by dark pools, over conventional lit exchanges, include confidentiality, reduction in market impact, cost savings, and profit opportunities/price improvement. These advantages and their links to the information operations disciplines of operations security as well as deception will be further explored in following chapters.

2. Lit Exchange Standard Operating Procedures

Before the advantages of ATSs are addressed, it is important to first provide some background, review the lit exchange protocols, common order types and order execution rules for comparison purposes. Of the dozens of orders types accepted across various exchanges, most are derivatives of two distinct types, market or limit orders. In general, market orders specify the quantity and the security that the buyer wishes to purchase, while limit orders also specify maximum (minimum) the buyer (sell) is willing to pay (accept) for the security. If the limit order bid (offer) the buyer (seller) is willing to pay (accept) is lower (higher) than the current market rate, then that limit order is added to the limit order book, LOB, on either the bidding or offering side depending on whether it is a buy or sell order, respectively (Kane, Liu, & Nguyen, 2011, p. 64). Because the limit order is not necessarily immediately executed, as is the case with market orders, the limit order *adds* liquidity to the market, and as a corollary, the limit buyer/seller is a *liquidity supplier*. Conversely, because a market buy (sell) order is executed immediately at the lowest (highest) available price listed in the LOB, the market order *removes* liquidity from the market and the market buyer/seller is a *liquidity taker* (Pascual & Veredas, 2009, p. 527). While it varies by exchange, typically *liquidity takers* are charged a fee for the removal of liquidity, while *liquidity suppliers* are offered a rebate for adding liquidity.

The fee is usually larger than the rebate, and the difference is collected by the exchange to cover operating expenses (Banks, 2010, pp. 94–95). Other types of orders exist. For instance, the NYSE has 27 different orders, each with its own characteristics, but most are derivatives of the basic market and limit orders discussed (Euronext, 2013).

The LOB then becomes two simple tables of limit orders, one buy side table, and one sell side table. Although it varies by exchange, the minimum information required for each row in the table is a unique order identifier (identifying both the order and the trading institution or broker who placed the order), quoted price, order quantity, quantity traded, and order type. Usually more information is provided such as how much, if any, of the order has been partially filled, along with the date and time of order was entered or removed, or whether the order was pre-maturely canceled before execution (Kozhan & Salmon, 2010, p. 6). The quoted price on the buy side table is referred to as the *bid* price, while on the sell side it is referred to as the *offer* price (Kane, Liu, & Nguyen, 2011, pp. 64–65). A simplified LOB is shown in Figure 3.

				<u>Last Traded Price</u> \$10.00				
<u>Buy-Side</u>					<u>Sell-Side</u>			
<u>Date/Time</u>	<u>Unique ID</u>	<u>Order Quantity</u>	<u>Bid Price</u>		<u>Date/Time</u>	<u>Unique ID</u>	<u>Order Quantity</u>	<u>Offer Price</u>
5/12/2013 09:54:23	445141	300	\$9.58		5/12/2013 09:54:21	434286	200	\$10.02
5/12/2013 09:54:69	395848	100	\$9.58		5/12/2013 09:53:94	332176	300	\$10.03
5/12/2013 09:54:23	131944	700	\$9.56		5/12/2013 09:54:23	384672	800	\$10.03
5/12/2013 09:54:99	495549	900	\$9.55		5/12/2013 09:54:92	32917	300	\$10.05
5/12/2013 09:53:23	319243	3000	\$9.54		5/12/2013 09:54:03	385075	2000	\$10.06
5/12/2013 09:53:13	176871	4000	\$9.54		5/12/2013 09:54:41	126302	3000	\$10.06
5/12/2013 09:54:93	448411	8000	\$9.52		5/12/2013 09:53:87	62852	1000	\$10.08

Figure 3. Sample Simplified Limit Order Book at Time t

Although each exchange has slightly different execution rules, generally limit orders are executed in their entirety, in accordance with both quote price, and in the order in which they arrive. For example, if an additional sell limit order arrived at $t+1$ in the sample, Figure 3, with a unique ID of 3245322, order quantity of 300 at an offer price of \$10.02, then order 296618 would need to have the 200 shared filled before order 3245322 could begin execution (Kane, Liu, & Nguyen, 2011, p. 64).

Of course, this discussion on limit orders is only half of the equation. Without corresponding market orders, few trades would be executed and price discovery would likely be hindered. Market orders, unlike most limit orders, are immediately executed, so long as sufficient liquidity exists on the opposing side of the limit order book. Continuing the example in Figure 3, a market buy order at $t+1$ of 500 shares would be executed, filled against order 182411, 128920 would be partially filled against order 237997 - 300 for 182411, 100 for 128920, and the remaining 100 for 237997, leaving 600 unfilled for 237997 with the market order executed completely.

As a final caveat on limit orders, there is no requirement that buy limit order bids be submitted below the last traded price, or sell limit order offers above. In fact, many limit orders bids are submitted above the last traded price and sell orders below, effectively acting as market orders with guaranteed execution prices given a sufficient level of liquidity. These orders are generically referred to as marketable limit orders and act more similar to market orders than limit orders with respect to information leakage and order flow (Biais & Weill, 2009, p. 3).

3. Dark Pools Operating Procedures

While dark pools operate with the same basic mechanisms as their lit counterparts, the largest and defining difference is the amount of information available to the participating traders. For example, while the dark pool operators invariably keep and execute orders in accordance with a LOB, the contents of the LOB is considered proprietary and not released to the public or participating traders. Additionally, the execution rules that dictate which orders are executed and in what order are also considered proprietary. This has led many to refer to dark pool algorithms dictating which orders are filled, and in what order, as a “black box”, observing orders entering the box, with filled—or unfilled as the case may be—exit the other side. The implications of this black box approach to trading are considerable. Many of these implications are discussed in followed chapters and literature reviews.

4. The Exchange-Scape and Order Flow in the Ether

Further complicating the matter is the fact that the two exchanges discussed above, lit exchanges and dark pools, are the order fillers of last resort. Many orders never reach either exchange and are filled by “internalizers”. In many ways these internalizers resemble dark pools with black box algorithms and limited proprietary transactional data, such as hidden LOBs with none of the transparencies required by regulated lit exchanges. Figures 4 and 5, from two industry publications show notional lifecycles of orders. The Norges Bank Investment Management (NBIM), the asset management group of the Norwegian central bank, produced Figure 4, while Figure 5 is taken from the Tabb Group’s written statement to Congress discussed in detail in the literature review. Tabb goes on to detail the seven-step process each order could possibly take, should they remain unfilled prior to reaching the final exchange with the national best bid offer (NBBO).

- (1) Broker trades against the order.
- (2) Trade the order in the broker’s internal ATS.
- (3) Soliciting other clients to trade against the order.
- (4) Send the order to other internal brokers’ ATSS
- (5) Have other brokers solicit orders.
- (6) Send that order to a public exchange.
- (7) If the exchange can’t match the order at the best price, the exchange is mandated to route that order to the exchange displaying the NBBO (Tabb, 2012, p. 3).

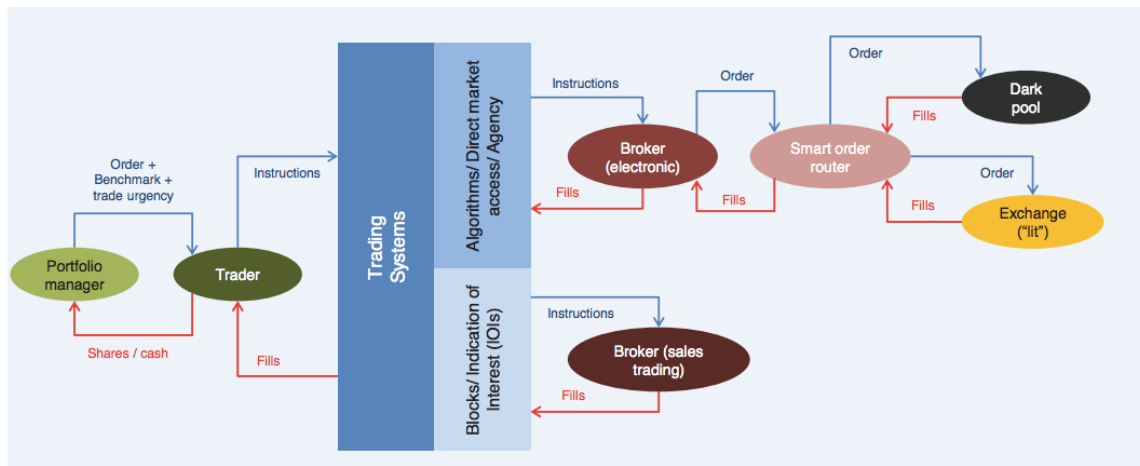


Figure 4. The Order Lifecycle (from NBIM, 2013, p. 3)

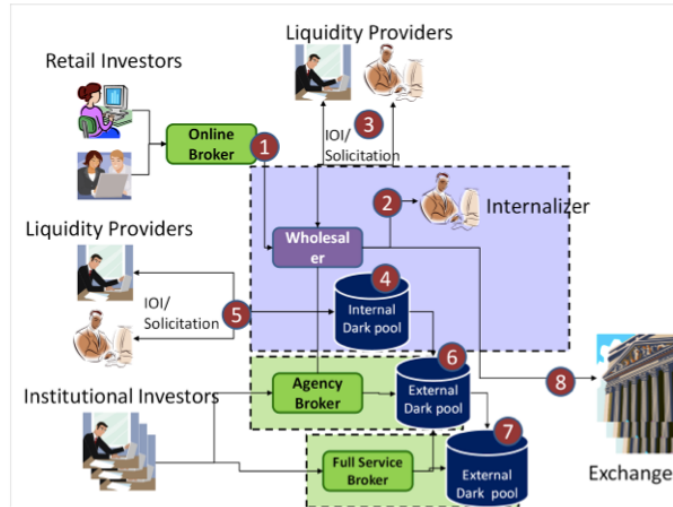


Figure 5. Equity Retail Order Flow Schematic (from Tabb, 2012, p. 3)

The trade is considered legal and in accordance with the Regulation National Market Systems (Reg NMS) so long as final execution is at or better than the NBBO price (Tabb, 2012, p. 3). The NBBO price is a result of the Reg NMS of 2007, which stipulated that all investors must have equal access to prices, and that trades must be executed at the best price nationwide (Banks, 2010, p. 10). Additionally, and to preclude any confusion moving forward, the term *ask* is used interchangeably with *offer*, and is synonymously defined as, the price at which a seller is willing to sell a given security.

5. A Return to Investor Value

While fascinating and nuanced, the question of what price an investor should be willing to pay for a fixed amount of equity in a given enterprise remains unaddressed. William Sharpe's 1964 work on capital asset pricing offers a viable starting point on how to measure such value. Much of Sharpe's theory on the appropriate price for capital assets (i.e., equity) rotates around the notion of risk. Generically, risk is defined as the degree of variability in consequence. For example, on a risk spectrum, if no variability in outcome exists, then the level of risk is zero; while if variability is infinite, then risk is infinite. Sharpe postulates that because portfolio theory has substantiated the claim that idiosyncratic or unique risk can be diversified away, the market will only compensate the investor for systematic or market risk. A more complete view and nuanced discussion of

Sharpe's work, along with his critics, will be explored in the chapter dedicated to a review of relevant literature. In Chapter III, this thesis will propose a modified CAPM, based on a change in current market interest vis-à-vis the broader market. The current state of the LOB will be used as both a simple-proxy and weighted proxy for both idiosyncratic and system-wide market interest. The model will target the volatility component of CAPM, β . The newly proposed β' attempts to increase CAPM valuation accuracy by integrating the product of a proxy for short-term volatility and the classic historical regression calculated as the covariance of the underlying security over the variance of the broader market. Volatility is targeted for refinement for two reasons: first, long term historical regression as a model for future volatility has been found to be a poor predictor when taken in isolation, and second current market conditions, namely HFTs and ATSS have been found to be a contributing factor toward volatility (Zhang, 2010, pp. 2–3, 7). Chapter IV offers a discussion on the complications anticipated by real world implementations of the model, the appropriateness of the proxy, obstacles presented by dark pools and internalizers. Finally, Chapter V ties information operations' paradigms to financial decision as well as pricing algorithms, proposes policy considerations, future work recommendations, and concludes.

E. DISCLAIMER

Of note, while the aims of this research are not strategic, many of the concepts discussed may have strategic applications in global equity markets. In the aftermath of the 2008 financial crisis, it is clear that if national power can exert pressure on the fiscal sustainability of a threat, such exertion may be sufficient to achieve national goals. Some of the tactics, techniques, and procedures discussed herein may be applicable, on a larger scale, to the exertion of national power. Nevertheless, that is neither the intent nor the motivation behind this thesis. All of the research for this thesis is academic in nature. Discussions of deception techniques for financial gain are speculative, and should not be interpreted as an endorsement of such techniques for use by the U.S. government, the Naval Postgraduate School, or the author.

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II. LITERATURE REVIEW

Reading furnishes the mind only with materials of knowledge; it is thinking that makes what we read ours.

—Philosopher John Locke (1632–1704)

A. OVERVIEW

Surprisingly little research has been conducted demonstrating overlaps from the fields of study in information operations, financial markets, and appropriate capital asset evaluation. While this dearth of research is unanticipated, it offers an opportunity to bring a unique perspective to the discourse and contribute to the academic understanding and development of each field. Writing from each field of study is independently explored, and academic disciplines of each are reviewed in depth, to ensure a variety of perspectives and analysis. The capital asset pricing model serves as the foundation of the thesis. It is explored not only in its original form, but also in modified forms from a selection of academic critics and theorists. Current market shift and conditions, not present when the original model was proposed, are then reviewed in sections dedicated to high-frequency trading and alternative trading systems. Finally, information operation concepts, on which will be drawn in later chapters, including communication theory, operations security, and military deception are reviewed and their historical development chronicled.

B. CAPITAL ASSET PRICING MODEL AND ITS CRITICS

This equity market literature review concentrates on William F. Sharpe's (1964) capital assets pricing model (CAPM) and critics of CAPMs limitations over the past 40 years. Sharpe's CAPM was one of the first models to quantify the trade-offs between risk and return of underlying capital assets, be they stocks, bonds, real estate, or coin collections. Sharpe postulates that idiosyncratic risk, or unique risk, of individual investments should not be considered a factor when calculating the appropriate return for

a capital asset, a consequence of modern portfolio theory (MPT), which is addressed in due course. Sharpe's CAPM is defined such that

$$E[r_i] = r_f + \beta_i(E[r_m] - r_f) \quad (1)$$

where $E[r_i]$ is the appropriate return on asset i , r_f is the risk-free rate of return (i.e., commonly defined as treasury bills or other stable government issued securities), β_i is the ratio of the volatility of the asset and the overall volatility of the broader market, and $E[r_m]$ is the expected return of the broader market. Broken down into components

- $E[r_i]$ = risk-free return + risk premium of asset i
- Risk premium of asset $i = \beta_i(E[r_m] - r_f)$

As previously mentioned, Sharpe only considered systematic (broader market) risk a factor because, through adequate diversification, an investor can reduce the specific unique risk of each asset to zero, as demonstrated in Markowitz's (1952) Nobel Prize winning work on MPT, 12 years earlier. Sharpe believes the market would compensate only for the expected volatility of the underlying asset. This volatility is measured above by Sharpe as β_i , a ratio of the volatility of the asset and the overall volatility of the broader market such that

$$\beta_i = \frac{\text{cov}(r_i, r_m)}{\text{var}(r_m)} = \frac{\sigma_{im}}{\sigma_m^2} \quad (2)$$

Because the broader market is only a theoretical measurement, for specific calculations a broader index of equities is often used when calculating β , such as the S&P 500 (Sharpe, 1964, pp. 428–431).

While many still consider Sharpe and Markowitz's seminal work to be acceptable models for evaluating expected returns on individual assets, others, over the past four decades, have proposed variations on Sharpe's model and underlying assumptions.

Banz (1981) demonstrates a correlation between returns and market capitalization of underlying equities. Banz stipulates that while this correlation may be a result of a yet-unidentified third variable, the returns were shown to be independent of the risk class of the assets. This previously unidentified factor in returns was just the first in a series of critical looks at the fundamentals of CAPM.

More than a decade after Banz's original work, Fama and French (1992) proposed incorporating three factors into the estimate individual returns, as compared to the returns of the broader market. The Fama and French model integrates Sharpe's CAPM, referred to as the SLB model (Sharpe 1964, Lintner 1965, Black 1972), as well as Banz's work, demonstrating that equity returns also correlate with the market capitalization of the underlying asset compared to the broader market. The final factor included in the Fama and French model is the relative value of the individual asset. Fama and French measure the relative value of the asset using the book-to-market ratio. Fama and French demonstrate that firms with higher relative book-to-market ratios can outperform the broader market. They also demonstrate that by incorporating all three factors appropriate returns are most accurately predicted.

Acharya and Pedersen (2005) conclude that CAPM could be improved if estimated returns consider the liquidity of the underlying asset. Moreover, Acharya and Pedersen's liquidity-adjusted CAPM consider the underlying asset's liquidity as well as the liquidity of the broader market. Additionally, Acharya and Pedersen identify three scenarios of liquidity risk: (1) commonality in liquidity with the market liquidity (i.e., both market and asset are illiquid); (2) return sensitivity to market liquidity (i.e., investors demonstrate a preference for high return securities when the broader market is illiquid); and (3) liquidity sensitivity to market returns (i.e., investors will pay a premium for liquid stocks when the broader market returns are low) (Acharya & Pedersen, 2005, p. 376). Acharya and Pedersen conclude that, in scenario one, the required return of an individual security increases as the gap between the securities liquidity and the broader markets liquidity increases. Under scenario two, Acharya and Pedersen show that investors will move toward high return securities (dividend yielding equities) when the broader market is illiquid. Finally, Acharya and Pedersen establish in scenario three, the premium for liquid stocks decreases as the broader market returns are decreased (2005, p. 405).

Originally put forth in 2003, and then revised in 2007, Estrada postulates that β , as a measure of risk, may be inappropriate and inaccurate for a variety of reasons. Estrada argues that β , as calculated by Sharpe and Markowitz, is only an appropriate measure of risk when the distributions of the underlying returns are both symmetric (i.e., up days are

likely to be “*as up*” as down days are likely to be “*as down*”), and normally distributed. Estrada questions whether these assumptions hold for empirical evidence and puts forth his own alternative approach to measure risk through an alternative definition of β . While Sharpe’s β measurement relies on the variance between the underlying assets and the broader market, Estrada believes a better measurement would be to rely on the semi-variance between the asset and the market, a slightly modification of β , he deems *downside β* . Without getting into the specifics of Estrada’s modified downside β , he believes a reliance on semi-variance will address and mitigate the flaws in Sharpe’s β , namely the assumption of symmetrical and normal distribution of returns. To test his hypothesis, Estrada examines both developed markets (DM) and emerging markets (EM) together and then independently. In his commingled analysis, Estrada finds that his downside β explains more of the variations in commingled returns than the original β , 69% versus 54%. In his independent DM analysis, Estrada finds that although the downside β better explains variations in returns (8%), neither Sharpe’s original β , nor his proposed downside β explains a statistically significant amount of variation in returns. Conversely, in EMs, Estrada finds that the downside β explains 55% of the mean variation in the returns examined. Estrada goes on to explain much of the variation between the original β and downside β displayed in EMs can be credited to a less normal distribution among emerging market returns (2007, pp. 179–181). As a final conclusion, although Estrada’s downside β is more accurate in both DMs and EMs, he recommends the original β calculation for DMs due to its ease of calculation and similar result in normally distributed returns. With respect to EMs, Estrada concludes the downside β calculation can go further to explain individual asset and market returns due to their more erratic and unsymmetrical, non-normal returns (2007, p. 183).

The relatively recent Dual β theory proposed by Chong, Pfeiffer, and Phillips (2010) in the *Journal of Personal Finance* tests the hypothesis that CAPM accuracy could be improved by calculating two historical β_i , one for broader market up days, and one for broader market down days. The Dual β model defines β_i in much the same way that Sharpe defines the original β_i , except that variation is segregated based on the up or

down nature of the broader market on the particular day examined. Therefore the Dual β adjusted CAPM is defined such that

$$(r_j - r_f)_t = \alpha_j^+ D + \beta_j^+ (r_m^+ - r_f) D + \alpha_j^- (1 - D) + \beta_j^- (r_m^- - r_f) (1 - D) + \varepsilon_t \quad (3)$$

“where α_j^+ , β_j^+ , α_j^- , and β_j^- are the estimated parameters for up-market and down-market days respectively; $r_m^+ = r_m$ on days the market index did not decline and $r_m^- = r_m$ on days it did; D is a dummy variable, which takes the value of 1 when the market index daily return is non-negative, and zero otherwise” (Chong, Pfeiffer, & Phillips, 2010, p. 73). Chong, Pfeiffer, and Phillips conclude that using only the down-market day β provides a statistically significant improvement over Sharpe’s original β , without considerable difficulties in calculation. Nevertheless, the authors also concede that using both the up-days β and down-days β offer a marginal addition of accuracy, and that the cost in additional computation may negate the added benefit over the single down-day β (2010, p. 83).

Roodposhti and Amirhosseini (2010) of Islamic Azad University examined 70 firms listed on the Tehran stock exchange in order to determine whether there was a correlation between a firm’s returns and three macroeconomic variables; interest rates, exchange rates and inflation rates. While Roodposhti and Amirhosseini ultimately reject all three hypotheses, because they found no correlation between the return of individual firms and larger macroeconomic variables, they did proposed and accept an alternate CAPM, referred to as Revised-CAPM or R-CAPM defined as

$$K_j = R_F + \beta^R (R_M - R_F) \quad (4)$$

where

$$\beta^R = (DEL)(DFL)(DOL)\beta_j^o \quad (5)$$

and

- β^R is the revised β^o .
- β^o is the original CAPM defined β .
- DOL (Degree of Operational Leverage) is a measure of the unique *operational risk* calculated as a ratio of the firm’s change in earnings

before interest and corporate taxes relative to the larger market index's change in earnings before interest and taxes.

- DFL (Degree of Financial Leverage) is a measure of the unique *financial risk* calculated as a ratio of the firm's change in earnings after interest and corporate taxes relative to the larger market index's change in earnings after interest and taxes.
- DEL (Degree of Economic Leverage) is a measure of the unique *economic risk* calculated as "a percentage change in the firm's sales resulting from a percentage change attribute to an exogenous disturbance" in the broader economy (Roodposhti and Amirhosseini, 2010, p. 5).
- For more specific details on the calculations of DOL, DEL, and DFL see Roodposhti and Amirhosseini's published findings in the *Journal of Finance and Accountancy*.

When compared against Sharpe's original CAPM, Estrada's Downside-Adjusted CAPM (2007), and Acharya and Pedersen's Liquidity Adjusted CAPM (2004), the R-CAPM are all found to be better predictors of the actual returns of individual assets. By incorporating not only systematic risk, but also unique or unsystematic risk both before taxes and interest (DOL), after taxes and interest (DFL), and the firm's relative exposure to broader economic disturbances (DEL), Roodposhti and Amirhosseini (2010) demonstrate that a narrow view of market compensation for systemic risk alone, while rational, may not tell the whole story.

Much of the discussion involved in this research will revolve around the difficult assumption that the actors involved in price discovery are rational and have perfect information. Many works of past research examine and evaluate the suitability of these assumptions, including Robert Merton's (1987) article "A Simple Model of Capital Market Equilibrium with Incomplete Information". Although at the cusp of the information age, Merton postulates that information digestion into capital asset pricing is not instantaneous, but rather requires time for the investor to evaluate whether the potential gains of acting on the new information outweigh the potential costs of changing strategies. A quarter century later, while many of these cost/benefit analyses are executed algorithmically through HFT machines, the original proposal, that *some amount of time exists between information received and information acted*, however shortening, still holds true. Additionally, Merton infers that market capitalization can be used as a proxy

for perfect information as larger companies attract more investors, relative and nominal, than smaller firms. Furthermore, those firms with a large number of investors will garner more market scrutiny from the media, governmental regulatory agencies, and rating agencies. This increased scrutiny is the reason that Merton believes the firm's value can be used as a proxy for relatively perfect information; the larger the firm the more perfect investor knowledge will be relative to the size of the broader market. Merton uses this proxy in his model for firm returns; postulating that investment returns will increase with systematic risk, unique (firm-specific risk) and relative market value (information proxy).

The last piece of relevant prior work on capital asset pricing is from Berrada and Hugonnier (2012) titled "Incomplete Information, Idiosyncratic Volatility and Stock Returns." Like Merton, Berrada and Hugonnier also challenge the view that systematic risk should be the only determinant in return calculations. Berrada and Hugonnier argue that idiosyncratic volatility must contribute to the individual returns of assets. Using a dataset of 2800 firms, Berrada and Hugonnier use "forecast errors" as a proxy for idiosyncratic volatility, concluding that, in fact, "incomplete information explains a significant part of the relationship between idiosyncratic volatility and stock returns" (Berrada and Hugonnier, 2012, p. 460).

C. HIGH-FREQUENCY TRADING AND ECONOMIC INDICATORS

Although high-frequency trading (HFT) and algorithmic trading (AT) are separate disciplines and activities, significant overlap exists in their implementation. If HFT is a description of the speed at which order decisions are made and executed, then AT is a set of rules governing those decisions (Gehm, 2010, pp. 58–60). Due to the interdependencies between their implementation, much of modern research data sets and analyses consider both trading tools together, because separating the two practices is difficult, if not impossible. Significant academic research has recently been conducted as a consequence of the impressive growth of HFT/AT across global financial markets. Much of this research has been difficult to conduct because of both the vast amount of storage required to analyze HFT data, and the proprietary nature of data itself. For example, data storage estimates for quotes and trades from 2011 are more than 750 times

larger than from 1993, and more than 15 times larger than 2004 (Nexa Technologies, 2012).

Champions of HFT growth often claim it reduces volatility and aides in price discovery, both which are universally accepted as positive contributions to healthy financial markets. Zhang (2010) of Yale University’s School of Management examines these claims and others in his published work, “The Effect of High-Frequency Trading on Stock Volatility and Price Discovery”. To test these hypothesizes, Zhang runs statistical models on historical databases provided by Thomson Reuters of individual firms trading above \$1 per share from 1985–2009 (11). Zhang breaks out the data into institutional investors, individual (retail) investors, and HFT firms to calculate total stock turnover on a quarterly basis

$$TO = \frac{VOL_{TOTAL}}{SHROUT} = \frac{VOL_{INST} + VOL_{IND} + VOL_{HFT}}{SHROUT} \quad (6)$$

$$TO = \frac{VOL_{INST}}{HLD_{INST}} * \frac{HLD_{INST}}{SHROUT} + \frac{VOL_{IND}}{HLD_{IND}} * \frac{HLD_{IND}}{SHROUT} + \frac{VOL_{HFT}}{SHROUT} \quad (7)$$

$$TO = TO_{INST} * HLD_{INST} + TO_{IND} * HLD_{IND} + VOL_{HFT} \quad (8)$$

where TO_X is stock turnover contributed by market participant X, VOL_X is the quarterly volume traded of X market participant, $SHROUT$ is the total number of outstanding shares, and HLD_X is the number of shares held by market participant X during the quarter (14). Using regression, while controlling for the underlying business fundamentals and macroeconomic volatility, Zhang finds that, in fact, HFT is positively correlated with volatility. Additionally, HFT hinders markets ability to price in both positive and negative news, leading to overreactions on both up and down days. As a final note, Zhang fortuitously finds that while HFT does contribute significantly to liquidity levels, he find the contributions on a daily basis “excessive” at nearly 78% of all executed orders (2010, p. 33).

Also in 2010, Smith finds that HFT from 2002-2009 has significantly contributed to levels of “Gaussian noise” in the broader market as a result of the 2005 Regulation National Market Systems (Reg NMS) reforms that permit the expansive growth of HFT

Wall Street firms. These revisions, specifically Rule 611, required that automatic trades be executed only at the national best bid offer, with no regard for reliability or transaction speed of the counter-party (Smith, 2010, p. 3). Furthermore, Smith finds the SEC's decision to eliminate decimalization, the listing of stock prices in 10¢ increments, also contributes to the rise of arbitrage pricing, as firms could chase smaller bid-ask spreads (Smith, 2010, p. 3). Smith finds that, with the introduction of these two changes, and using Hurst exponent calculations on 14 different publically traded companies (e.g., aapl, gild, bac), Gaussian white noise has increased from a long term average of $H = .5$ to well above $H > .6$ in recent years (Smith, 2010, p. 12). Finally, Smith concludes that while his analysis is of a limited time scale, and that the liquidity benefits of HFT may outweigh his findings of increased volatility, HFT firms are having a measurable impact on the microstructure and trading dynamics in the markets they operate (Smith, 2010, p. 13).

Tabb, of the research and strategic capital advisory firm TABB Group, has made significant contributions to the understanding and awareness of both HFT and ATS effects on the broader market. TABB Group's Director of Research, Sussman's prepared and oral testimony before the Senate *SUBCOMMITTEE ON SECURITIES, INSURANCE, AND INVESTMENT* in 2009, as well as Tabb's personal testimony before the same subcommittee three years later, provide a useful industry perspective on the wide array of costs and benefits of HFT. When speaking to the issue of cancelation rates (i.e., the percentage of orders that are canceled before they are executed either by the order originator and the order's own internal expiration), Tabb believed the rate was around 30-40% for the broader market, and 96% for HFT firms. More simply put, according to Tabb, 96% of all HFT orders placed go unexecuted. For additional perspective, it will be helpful to reiterate that, according to Zhang, of all executed orders, 78% originate from HFT firms, meaning that just 4% of HFT orders represent 78% of the total market traded. The body of this research relies on many of the statements and convictions of Sussman's, Tabb's, and the other witnesses' oral and written testimonials from these two congressional hearings.

In 2012, Baron, Brogaard, and Kirilenko of Princeton, University of Washington, and the Commodity Futures Trading Commission (CFTC), respectively, examine the

profitability of HFT firms to determine whether operating margins justify the explosive growth of such firms. Using non-anonymized transactional data gathered from August 2010 to August 2012, Baron et al. conclude that HFT firms are highly profitable, especially those firms acting as liquidity takers and not market makers. Furthermore, most HFT profits are accumulated in the short to medium run (seconds to minutes). Additionally, adding HFT firms on the aggregate does not reduce the profitability of individual firms. This is likely because those additional firms underperform in relative terms and exit the market quickly (2012, p. 3). Finally, Baron et al. demonstrated that, while quite profitable on the average, \$45,267 per day, the risk is considerable with a standard deviation of \$167,411 per day, almost four times the average (2012, p. 15). Nevertheless, even with the sizeable standard deviation, Baron et al. models the probability of default to be a rounding error away from zero, where $P(\text{default}) < .0001$ and the probability of doubling of initial capital after one year is 69.0% (2012, p. 16). Finally, and least surprising, the authors find a significant negative correlation between latency and profit (2012, p. 34).

Originally published in 2010 and revised in 2013, Menkveld examines HFT firm's sensitivity to the cost of capital and the effects of other market frictions on performance in his work, "High Frequency Trading and the New Market Makers". Drawing on one year of anonymized trading data from a European low fee, low latency exchange Chi-X, Menkveld first broke down HFT orders as either liquidity producers, that is those orders that were not executed immediately, but waited for an appropriate bid/ask, or liquidity consumers, those orders that were executed immediately (2013, p. 8). Menkveld observed a relatively low cancellation-to-trade ratio of approximately 5, with a fee or rebate only imposed on executed orders (2013, p. 9). Using statistical analysis, Menkveld identified a particular HFT firm and determined the firm placed on average 1,397 trades per stock per day and is more active on equities with larger than smaller market capitalization (1,582 versus 315, on average). Finally, Menkveld finds that HFT firms are particularly sensitive to market fee structures thusly gravitating toward exchanges with the lowest costs and associated latencies, valuing speed as well as reduced friction over volume and liquidity (2013, p. 30).

Kishore (2012) of the Wharton School examined the success of a specific trading strategy commonly known as trading pairs in which a trader “takes opposing long and short positions in two assets when the difference their prices hits a certain opening threshold” (2012, p. 1). The strategy relies on the underlying assumption that the two assets trade together over the long run and exploits a temporary mispricing in the market until a correction brings the assets back in line with each other’s valuation (2012, p. 2). Using tick-by-tick quote data on XOM and CVX, Kishore determined that trading pairs strategy is not useful to HFT because corrections do not occur frequently enough on an intra-day basis. Intra-day corrections are required in large part because HFT firms make every effort to close out all positions each trading day, without holding any positions overnight (2012, p. 12). Additionally, like Menkveld, Kishore found that HFT profits are highly sensitive to market friction, namely transaction fees. For example, Kishore found that “imposing transaction cost of 5bp and 15bp decreased returns by 11% and 25%, respectively” (2012, p. 13).

Perhaps most appropriate for this research, Ki (2011) of the University of Kansas analyzed whether the Capital Asset Pricing Model could be considered effective under current market conditions dominated by HFT activities, in “The CAPM and the High Frequency Trading; Will CAPM Hold Good Under the Impact of High-Frequency Trading?” Using monthly closing prices in 27 different equities over a 20-year period, Ki broke down his dataset into three periods of market evolution: before HFT 1994-2000, after HFT’s introduction 2001-2005, and after HFT’s deregulation 2005-2010. Ki concludes that both the original unconditional CAPM and modern conditional CAPM’s, previously reviewed, cannot generate accurate results. Moreover, inaccuracies in results have only grown since HFT deregulation in 2005 (2011, p. 14). Ki does not offer his own modifications to CAPM for a more accurate model under current HFT market conditions, but does advocate for the development of a “good representation for HFT in the capital asset pricing model to regain its power to predict the expected return” (2011, p. 14).

Although not directly related to high-frequency trading, Kubis and Cicarelli’s (2012) examination of leading economic indicators as a tool of anticipating turning points in business cycles offers some useful insights. Although focused on macro-level

economics, Kubis and Cicarelli evaluated 11 widely accepted economic indicators (e.g., jobless claims, building permits, money supply, consumer sentiment, etc.) to determine whether each could, with any degree of accuracy, predict future economic conditions in the broader economy (2012, p. 5). As expected, with the exception of money supply, none of the individual indicators had a probability greater than .5 or 50% of accurately forecasting recessions (2012, p. 8). Furthermore, over the 20-year period analyzed, more than 120 times indicators signaled false positives, either an expanding economy, when in reality a recession was on the horizon, or vice versa (2012, p. 8). Although Kubis and Cicarelli found sufficient evidence to demonstrate indicators were able to predict peak economic environments with some regularity, they conclude that predicting the future remains an “innately difficult task” (2012, p. 8).

D. ALTERNATIVE TRADING SYSTEMS

Just as academic literature on high-frequency trading is both sparse and recent, so too is much of what has been written on alternative trading systems (ATS) commonly referred to as dark pools. Started in 1998 as a response to the growing concern that large institutional investors were being taken advantage of in the open market, dark pools represent an increasing share of trading activity (Young, Pettifer, & Fournier, 2009, p. 30). Author Erik Banks (2010) studies dark pools extensively in his authoritative text, *Dark Pools: The Structure and Future of Off-Exchange Trading and Liquidity*. Banks estimates that approximately 10% to 15% of all U.S. equity trading is conducted in dark pools, with some months, depending on market liquidity and volatility, running as high as 20% (2010, p. 6). These estimates, published only three years ago, are most likely considerably higher today, as dark pools trading has been growing at estimates of up to 40%, annualized (Mittal, 2008, p. 20). Thus dark pools represent a sizeable portion of U.S. equity trading and, as such, merit discussion on their historical origins, rise to prominence, and useful functions moving forward.

Markham and Harty (2008) offer a colorful history of the rise of U.S. exchanges, focusing on the rise of computerized trading systems known as electronic communication networks (ECN), an alternative to the bellowing trading floor of brokers, market makers,

and investors of the early 20th century. Of special importance for this discussion was the intermarket trading system (ITS) implemented by the SEC. The ITS created an electronic link between exchanges listing the same equity. In 1981, the ITS and the SEC implemented the “trade through” rule that required market makers on other exchanges to only execute trades at the best available price, which would come to be known as the national best bid offer (NBBO) (Markham & Harty, 2010, p. 878–879). Nevertheless, just requiring exchanges to be electronically connected and offer the NBBO, does not explain the need for, or rise of dark pools. For that, first it will be necessary to examine the role of institutional investors, iceberg orders, and gamblers.

There exists a pervasive belief among large institutional investors that large market orders to buy (sell) shares publicly will place increased pressure on underlying equity and the share price will rise (fall) as a result of just the public disclosure of interest by the institution (Banks, 2010, p. 6). An early solution to the problem institutional investors faced is the iceberg order. While a derivative of the limit order, the iceberg order only displays the peak of the iceberg to the open exchange. For instance, if an institutional buyer A wants to purchase 10,000 shares of ABC Corp at a limit of \$5.00 and places an iceberg order divided into 50 tranches, only one 200 share limit order at \$5.00 (the peak) would be visible on the open order book. Once that peak is filled, taken out of liquidity, the new peak would appear on the open order book for 200 shares at \$5.00. This continues until the entire order is filled, the order is canceled, or the order expires. Esser and Monch (2005) examine iceberg orders to determine the optimal limit price and optimal peak size for a required probability of complete order execution. Of note, Esser and Monch see an inherent tradeoff between peak size and time priority, as many exchanges force each additional tranche to the “back of the line” for a given limit price (2005, p. 3). In the example above, even if a retail investor B places a separate limit order for 100 shares of ABC Corp at \$5.00, after institutional investor A places her order, B will move ahead of A once the first peak of A is executed. This simplified example shows the time tradeoff with peak size that Esser and Monch discuss. The larger the peak, the faster the entire order is executed. For their calculations, Esser and Monch used the order book data from 61 trading days on a German automated trading System, XETRA

(2005, pp. 8–10). Although not necessarily relevant to their conclusions or the establishment of iceberg orders, XETRA is an anonymous exchange, displaying limit orders, but not market participant identifiers. As seen in Figure 6, Esser and Monch find that a full 293 of out the 786 (nearly 40%) of examined icebergs were divided into 10 equal parts before being openly displayed as limit orders. Seemingly more a consequence of our base 10 numerical education that rational examination of the optimal peak size, the second most common divisor without surprise is five (Esser and Monch, 2005, p. 10).

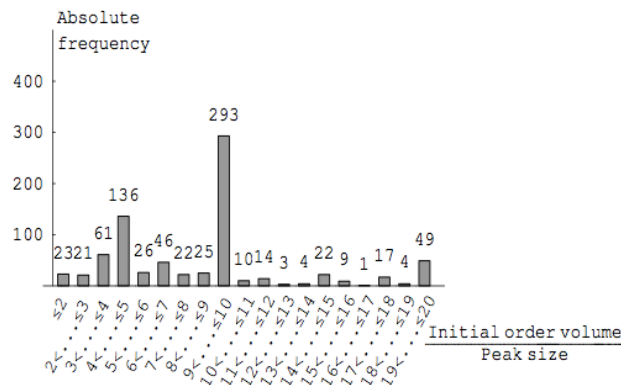


Figure 6. Ratio of Initial Order Volume to Peak Size of All Different Iceberg Sell Orders in the Sample (from Esser & Monch, 2005, p.10).

Also of interest, are findings that showed less than 18% of all iceberg orders examined were executed in full and a majority (52%) were not executed at all, partially or completely (Esser and Monch, 2005, p. 11). Esser and Monch consider order size, limit price, time before expiration, and probability of order completion when determining the optimal peak size. Throughout many their computations, some variables are held constant so as to graphically demonstrate the relationships and trade-offs. Figure 7 shows one step-function of these relationships, optimal peak (φ_p), for a given total order size (φ_0). This example is selected to contrast to the prior market finding preference for

$$\varphi_0 = 10 * \varphi_p \tag{9}$$

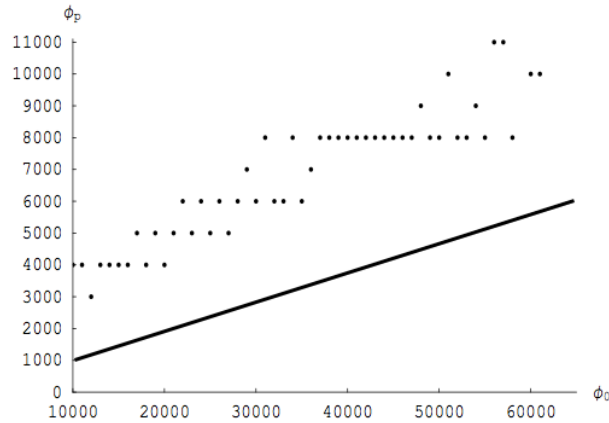


Figure 7. Optimal Peak Size ϕ_p as a Step Function of ϕ_0 (Other parameters: $P^* = 25\%$, $T = 100$ hours) with Equation 9 Imposed (after Esser & Monch, 2005, p. 30).

Esser and Monch conclude that their modeled optimal peak sizes are considerably larger than the observed market data, as demonstrated in Figure 7. Additionally, the authors believe two reasons may aid in explaining this disparity. First, they concede that their model may underestimate the negative price-impact that information leakage could have on large institutional investors by displaying large limit orders on the open book. Secondly, and without significantly more insight, the authors offer that it could be the market that is over-estimating the negative price-impact on information leakage (Esser and Monch, 2005, p. 27).

One facet of what makes dark pools efficient lies in the anonymity they provide and what, if any, this trait has on liquidity and volatility? These questions and others related to anonymity are examined by Foucault, Moinas, and Theissen (2007) in a throughout examination of the natural experiment created by the French Stock Exchange, Euronext. Foucault et al. analyze Euronext market data from both before and after Euronext switched from open identities to anonymous quotes in April, 2001 to confirm their hypothesis that average quoted spreads are smaller in anonymous markets. This finding suggests to Foucault et al. that an open limit order book is a source of volatility resulting from information asymmetry (Foucault, Moinas, & Theissen, 2007, pp. 1708–1709). Unlike much of the research conducted on anonymity, Foucault et al.’s study focuses on *liquidity suppliers*, (i.e., pre-trade limit orders anonymity) versa *liquidity*

takers (i.e., pre-trade block market order anonymity). While research shows that concealing identities of *liquidity takers* exacerbates the reduction of overall liquidity (Seppi, 1990), Foucault et al. show that concealing identities of *liquidity suppliers* improves overall liquidity. Much of Foucault et al.'s model rest on information asymmetry between *informed* and *uninformed* limit orders about pending *information events* (2007, pp. 1710-1711). The authors propose a model to quantify the final value of a security \tilde{V} at time 2, \tilde{V}_2 , such that

$$\tilde{V}_2 = V_0 + \tilde{I} * \tilde{\epsilon}_1 \quad (10)$$

where V_0 is the value of security V at time 0; \tilde{I} is equal to 1 if the *information event* occurs, otherwise 0; and $\tilde{\epsilon}_1$ is equal to $+\sigma$ if the information event has a positive event on security V , or $-\sigma$ if the information event has a negative price effect (2007, pp. 1711–1712). Foucault et al. ultimately forecast their model against the natural experiment listed above to determine what effect, if any, adding anonymity has on future volatility of bid-ask spreads and by extension market liquidity. The authors' findings include smaller bid-ask spreads post anonymity introduction, implying unsurprisingly that *informed* traders are more inclined to expose their information advantage in an anonymous environment, consequently leading to more market liquidity. Additionally, Foucault et al.'s findings support the notion that asymmetrical information contributed to volatility and that limit order books contain such information beyond that which is publically available. (Foucault, Moinas, & Theissen, 2007, p. 1740).

Anand and Weaver (2004) examine a similar natural experiment when in 1996 the Toronto Stock Exchange first prohibited hidden orders, only to reintroduce them 8 years later in 2002 (2004, p. 405). While similar, this dataset has some differences, namely that while only identities were hidden for Foucault et al., Anand and Weaver's hidden details were comprehensive, (i.e., ID, price, volume, etc.) until the limit orders were executed. After reviewing 272 Canadian stocks traded over the time periods described, Anand and Weaver conclude, surprisingly, that market liquidity is not reduced by the removal of anonymity from the system. Anand and Weaver make this conclusion while admitting those traders that would have placed hidden limit orders (*liquidity suppliers*) instead

placed market orders (*liquidity takers*) (Anand & Weaver, 2004, p. 425). While unchanged volume is not surprising, Anand and Weaver do not address the unresolved discrepancy that an increase in liquidity takers does not result in a decrease to overall liquidity. Additionally, while this switch (limit to market) allows traders in effect to hide their order, Anand and Weaver do not evaluate the price impact or adverse selection this change has on those traders. Lastly, Anand and Weaver reinforce their view that regulators seeking to increase liquidity, as many do, should not expect that mandated order exposure will result in additional limit orders (*liquidity suppliers*) and, in turn, liquidity, but rather, traders will use market order mechanisms to implement strategies (Anand & Weaver, 2004, p. 425).

Winne and D'Hondt (2007) model hidden orders in order to discern why traders use such tactics and what risks are avoided by so doing. Using a public dataset from Euronext of 40 large capitalization stocks from a three month period, Winne and D'Hondt show that traders employ hidden orders to overcome two visible limit order risks: exposure and pick off (2007, p. 5). Exposure risk, as previously discussed, is the risk that a visible limit order may adversely affect the price by exposing the trader's motives. Specifically, Winne and D'Hondt hypothesize that, while order size is a factor for traders in determining whether to employ hidden orders, relative liquidity will provide a better determinant for the trader's decision. Specifically, "traders are more likely to hide part of their limit orders when the prevailing displayed depth is small relative to their order size" (Winne & D'Hondt, 2007, p. 7). The second danger, pick off risk, is the chance of a second trader undercutting the visible limit order within the existing bid-ask spread. Furthermore, Winne and D'Hondt hypothesize that proof of traders trying to mitigate this risk is shown by more hidden buy (sell) orders when the buy (sell) side of the limit book is heavier, i.e., more bids (asks). Specifically, "buyers (sellers) are more likely to hide part of their limit orders when the visible ask (bid) depth is larger than the visible bid (ask) depth" (Winne & D'Hondt, 2007, p. 7). When Winne and D'Hondt present and model their data, both theories are accepted. Furthermore, the authors find that not only are the above market conditions predictors in hidden orders a likelihood, but the presence of hidden orders themselves also affect trader behavior, and that focusing

solely on displayed market information without hidden inference may result in misleading or incorrect conclusions (Winne & D'Hondt, 2007, p. 13).

Ganchev, Nevmyvaka, Kearns, and Vaughan (2010) examine the appropriate allocation of large orders over multiple competing dark pools. While dark pools are designed to handle large institutional orders, placing too large an order can have a negative price impact for the buyer and can run the risk of removing all liquidity of a particular pool (Ganchev, Nevmyvaka, Kearns, and Vaughan, 2010, pp. 99–100). Ganchev et al.'s uncharacteristically comprehensive dataset includes both submissions and executed orders from four dark pools: BIDS Trading, Automated Trading Desk, D.E. Shaw, and NYFIX with individual order sizes ranging from 100 to 50,000 shares. Ganchev et al.'s conclude that their proposed *learning algorithm* for determining how many dark pools to target is more effective than targeting a single pool (2010, p. 106). Also, while examining their dataset, Ganchev et al. discover that a full 84% of submitted orders go entirely unexecuted with neither partial nor complete order fills (2010, p. 104).

Now discussing ATS, Tabb (2008) categorizes dark pools based on inherent characteristics of their design. According to Tabb, “ownership, matching frequency, price formulation, access, and liquidity indicators” are natural segmentations of dark pools (Tabb, 2008, p. 1). Ownership, the most straightforward of the classifications, is broken down into four categories: independent, exchange-owned, broker-owned, and consortium-owned. While Tabb briefly discusses matching frequency, he quickly dismisses it as “less critical [in recent years]” (Tabb, 2008, p. 1). Conversely, a solid understanding of the pricing formulation techniques of individual dark pools is critical to order success, as pricing algorithms can differ significantly from one pool to another. According to Tabb, dark pools “do not have equal or fair access—not everyone can play and not everyone is equal” (Tabb, 2008, p. 1). Understanding where the lines are drawn on access defines the target population and the sophistication of that population. Tabb's final segmentation, liquidity, is a vital component of dark pools. Without liquidity, dark pools lose viability as a trading alternative to public exchanges. According to Tabb, to facilitate this liquidity some “algorithmic providers are increasingly using liquidity alerts or indicators of interest (IOI) to notify liquidity providers of a trading opportunity”

(Tabb, 2008, p. 1). Tabb goes on to point out that these IOI's run counter to the original intent of dark pools, namely to provide liquidity for large trades without information leakage (Tabb, 2008 p. 1). Four years later, in Tabb's (2012) written testimony to the House Committee on Banking, Housing, and Urban Affairs, Tabb clarifies his prior comments on segmentation challenges when he writes, "ATSS do not need to publish their matching rules, order types, or even their volumes, in fact, ATS anonymity is protected by SEC under Reg ATS, so there isn't a single consolidated list of ATSS and the SEC will only provide the information under a Freedom of Information Act filing" (Tabb, 2012, p. 10).

E. INFORMATION OPERATIONS

While information operations (IO) is a relatively new military discipline by name, in many ways as old as warfare itself by characteristic and definitions. With its present-day origins in the electronic warfare community of the late 1980s, information warfare, now information operations, doctrine has been through many reorganizations and repositioning over the past three decades. Before the current iteration IO was organized under five pillars: 1) psychological operations; 2) military deception; 3) operations security; 4) electronic warfare; and 5) computer network operations (Joint Chiefs of Staff, 2006, p. I-1). Nevertheless, joint doctrine has recently, yet again, refined the scope and principles associated with IO. Currently accepted, though increasingly nebulous, doctrine defines IO as is "*the integrated employment, during military operations, of information-related capabilities in concert with other lines of operation to influence, disrupt, corrupt, or usurp the decision-making of adversaries and potential adversaries while protecting our own*" (Joint Chiefs of Staff, 2012, p. vii). The new Joint Publication, 3-13, continues to incorporate both operations security and military deception as two critical information related capabilities (IRCs). These two IRCs, along with their tenants, principles, and components will serve as substantial elements in this research (Joint Chiefs of Staff, 2012, p. II-6).

A comprehensive review of information operations literature and research more broadly will be of considerable value, before operations security and deception academic

and practitioner literature is considered. First off, a quick note on the distinction between information warfare and information operations may explain one particular element of nuance in the discussion. According to many academics and practitioners information warfare, notably absent from Joint Publications since 2006, is the application of information operations during a time of conflict or crisis. This is largely a consequence of the broader understanding that information warfare contains an element of coercion and inherent hostility to achieve specific objectives (Allen, 2007, p. 5). With this distinction in mind, and given the area of study in this research, information operations will be the focus of review and analysis over information warfare, although both are considered and each for their own merit.

The most overwhelming facet of IO is the blend of complexity, coupled with the expansive definitions integral to the successful employment of the art and science of information operations planning. From the electromagnetic spectrum, to influence operations rooted in the human psyche, operating in the information domain represents an enormous challenge to military commanders even with a nuanced understanding of today's information landscape. Allen, author and project manager with General Dynamics Advance Information System, writes in his 2007 textbook on IO planning, "the IO planning space is much larger than the tradition military planning space ... both in terms of the types of desired effects ... and in terms of the number of capabilities potentially available" (Allen, 2007, p. 38).

In agreement with Allen is Armistead, editor of *Information Operations: Warfare and the Hard Reality of Soft Power* when he writes, "a common complaint about IO is that because its definition is so broad, IO is at once everything and it is nothing" (Armistead, 2004, p. 19). Armistead goes on to draw attention to a list of IO related capabilities that would be considered to be quaint by today's standards in regard to size and scope, including CA, CAN, deception, destruction, EW, OPSEC, PA, and PSYOPs (Armistead, 2004, p. 20). From there Armistead continues to examine IO from an organizational perspective, identifying roles and responsibilities across U.S. government agencies and departments. While critical to understanding how the U.S. conducts information operations, this organizational perspective of IO offers little marginal value

to this research and the theoretical conduct of IO in the U.S. or global financial landscape (Armistead, 2004, pp. 25–63, 163–166). Furthermore, a large part of Armistead’s research focuses on computer network operations (CNO), both in the attack (CNA) and in the defense (CND) (Armistead, 2004, pp. 65–89, 111–122). This is a recurring theme in IO related publications. Many times one facet or element of IO dominates the research, such that other capabilities are neglected, not out of carelessness, but out of necessity, lest the publications grow unwieldy in scope, weight, and undertaking. This again highlights the need for simple paradigms and analogies when discussing a topic as broad as integrating more than 20 different military and non-military capabilities (Department of Defense, 2013, pp. 41–44).

One such model published in 1998 by Waltz of Environmental Research Institute of Michigan (ERIM) International shows the information processes involved in conflict between two sides and is shown in Figure 8. This model is of particular value because it does not rely on any one information related capability while tracing the actions of one party through the physical domain, to the enemy’s perception, will, and ultimately actions. This action is the proverbial forest of which some IO researchers and academics lose sight, while focusing on the individual aspects of particular information related capabilities.

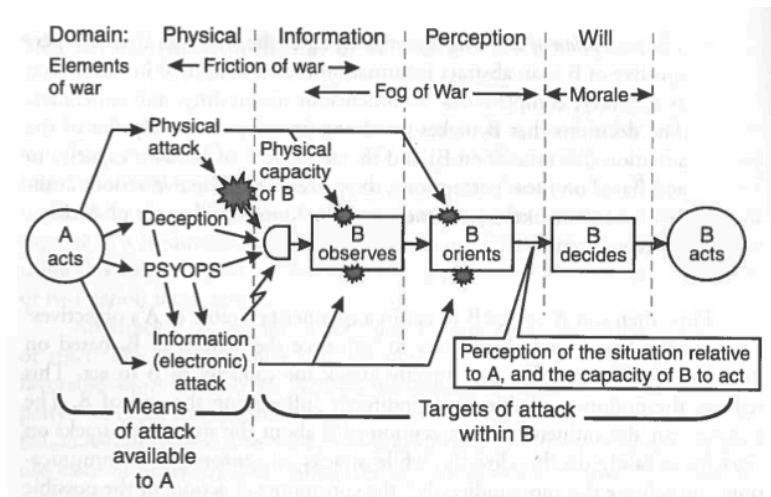


Figure 8. Waltz’s Basic Model of Information Process in Conflict (from Waltz, 1998, p. 6)

Also of note is Waltz's elegant description of information theory first addressed by Shannon in 1991. In Shannon's model an inverse relationship exists between the value of a piece of information and the probability that the particular piece of information is true or has occurred. Waltz's gives the example of a battlefield sensor where the most valuable information (i.e., nuclear weapons' deployment, enemy surrender, etc.) is also the least likely and the least valuable information (i.e., truck movement, satisfactory readiness level reports, etc.) are the most likely to occur frequently (Waltz, 1998, p. 58). Shannon's model is shown such that $M = (x_1, x_2, x_3, \dots x_n)$ and is defined as a set of all possible "messages" from the system X that can exist in any one of n states. Shannon derives the value of information as a measurement of the information entropy, a metric of disorder or uncertainty. Therefore, the higher the entropy of the information, the more valuable the underlying information is reasoned to be (Waltz, 1998, p. 60). With this in mind Shannon defines the entropy to be H :

$$H = \sum_{i=1}^n P_i \log_2 P_i \quad (11)$$

where H is the entropy; P_i is the probability that the information is in the i^{th} state; and n is the number of possible states in which the information could exist. \log_2 puts the entropy's units in base 2 or bits (Waltz, 1998, p. 60). From this model, Waltz draws three useful and essential conclusions. First, if there is only one possible message that can be reported by the system, X (i.e., $n=1$), then the entropy of the information is 0, $H = 0$. This also means that the information is of no value, which is of course true as the outcome was predictable and self-determined. Second, if the probability of all messages is the same (i.e., $p_1=p_2=p_3=\dots p_n$), then the entropy of the system is non-zero and increases as n increases. Finally, if the probability of each message is not the same, then the entropy of the information will decrease as the variance in probabilities increase until the extreme example of the first inference is reached and the entropy is 0 (Waltz, 1998, p. 60). This model is shown in Figure 9.

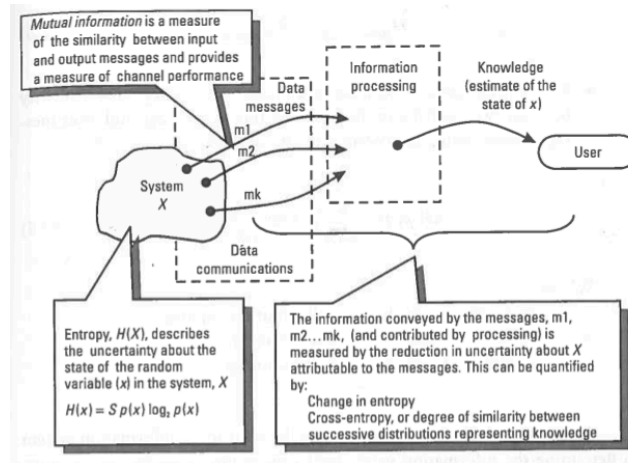


Figure 9. Entropy Measurement of Information (from Waltz, 1998, p. 61)

While many of the general information operations' models and theories discussed previously are drawn upon in follow-on chapters, before new materials are presented, a thorough discussion of operations security and deception will be of significant value.

F. OPERATIONS SECURITY: IDENTIFYING AND KEEPING SECRETS

The purpose of operations security or OPSEC as defined in Joint Publication, JP, 3-13.3 is "to reduce the vulnerability of US, coalition, and combined forces from successful adversary exploitation of critical information" (Joint Chiefs of Staff, 2006, I-2). Furthermore the JP defines the OPSEC process in three steps:

- 1) *Identify those actions that may be observed by adversary intelligence systems.*
- 2) *Determine what specific indications could be collected, analyzed, and interpreted to derive critical information in time to be useful to adversaries. The commander must know the model or profile of his or her organization.*
- 3) *Select and execute measures that eliminate or reduce to the visibility of joint forces to observation and exploitation. (Joint Chiefs of Staff, 2006, p. I-2)*

Aside from joint publications and other doctrinal sources, surprisingly little academic material concerning operations security has been published. Nevertheless, from corporate espionage to computer security models, a considerable amount of research has

been conducted around the periphery of OPSEC. These topics and others are examined herein to offer additional background on the matter of military information leakage and how it relates to the forthcoming discussion on financial information leakage.

The best known security model, and the one most militaries model their own information classification schemes on, including the U.S., is the Bell and LaPadula model of 1973. Originally published for the MITRE Corporation, the elegant Bell and LaPadula model defines two entity types and two simple rules. The first entity, a piece of data, always has a level of classification (i.e., unclassified, confidential, secret, or top secret) for which the data is associated. The classification level is a consequence of how damaging the information contained in the data would be if released (Ferson, 2004, p. 23). The second entity, a subject, always has a clearance level (i.e., unclassified, confidential, etc.) for which the subject is permitted to read and write new data. The two simple rules, which, when followed, would ensure classified data was not compromised are 1) A subject may only read at his/her classification level or lower and 2) A subject may only write at his/her classification level or higher. Nevertheless, while keeping the information secure one unfortunate side effect is communication difficulties to subjects down the classification ladder (Ferson, 2004, pp. 23–24). This considerable misgiving means that ultimately the utopian implementation of the Bell and LaPadula model is unfortunately untenable.

Another disadvantage of the Bell and LaPadula model is the lack of attention the model gives to the integrity of the underlying data. Specifically, the model de facto encourages lower level cleared subjects to write to higher clearance levels. This neglected integrity is of great concern, because just as a loss of confidentiality, the focus of Bell and LaPadula model, poor integrity control measures can also have devastating consequences for decision makers and analysts. The Clark and Wilson model offers some relief over the Bell and LaPadula model by adding a third entity over subjects and objects called transformation procedures or TPs (Ferson, 2004, p. 24). These TPs act on behalf of the user, restricting the subject from directly creating or modifying the underlying data. Additionally, these TPs flag any changes or additions the subjects make to the data as “unconstrained data items.” An independent third party must review these “unconstrained

data items” before they can be converted into “constrained data items.” The integrity of the data is then maintained, as the “constrained data items” are verified before re-integration with the larger dataset (Ferson, 2004, p. 24). Also important to note, the original Clark and Wilson model offers some confidentiality controls in addition to the integrity measures above. The TPs can also act as authentication systems, barring users from interacting (i.e., reading, writing, or executing) with datasets without appropriate clearance levels (Ferson, 2004, p. 25).

Outside of doctrine and academic models for safeguarding integrity and confidentiality, many operations security practitioners, both military and civilian, have examined real-world features and characteristics of OPSEC. One such practitioner, LtCol Michnowicz of the U.S. Army War College, Strategic Research Project, examines the roles of protecting information, specifically confidentiality, in his 2006 paper entitled, *OPSEC in the Information Age*. Michnowicz succinctly describes OPSEC as “the attempt to prevent information leakage that [could be used] to derive intelligence from information” (Michnowicz, 2006, p. 2). Beyond the classification systems described above, Michnowicz finds that according to al Qaeda training manuals, near 80% of “their required information about US forces could be obtained from open [unclassified] source material” (Michnowicz, 2006, p. 5). Michnowicz’s understandably concludes “the information age brings with it increased capabilities in ... telecommunications and the Internet with world wide access,” and that unless the DoD “can manage its internal information properly, adversaries can effectively glean *intent*, capabilities, and vulnerabilities [emphasis added]” (Michnowicz, 2006, p. 8).

Although Michnowicz’s and, in general, OPSEC primary concern lies with the piecing together publically available information gaining a competitive advantage, also of concerns is the active gathering of private information, known as espionage. An annual report produced by the DoD’s Defense Security Services compiles and analyses defense industry reports of foreign espionage. While taken in full the report is fascinating, for the purposes of this research, *how* the espionage is conducted is of more value than *where* or on *what* targets. Of specific note, the 2013 report finds 657 cases of foreign espionage conducted mostly by commercial enterprises, 34%, through what they refer to as

suspicious network activity (SNA). SNA replaced the 2012 most common method of operation (MO), attempted acquisition of technology (AAT), and request for information (RFI) (Defense Security Service, 2013, p. 6). Shockingly, this means that up until the most recent reporting period the most common technique for gathering sensitive or classified information, according to DSS, was simply to ask for it. Characterized by cyber intrusions, viruses, worms, spear phishing, along with other malware, SNA has risen considerably faster than any other MO in the past 12 months, rising globally 19% with a staggering 240% rise in the “East Asia and the Pacific” region alone (Defense Security Service, 2013, pp. 11, 25–26). Figure 10 shows the top five MOs from both FY11 and FY12 for comparison purposes.

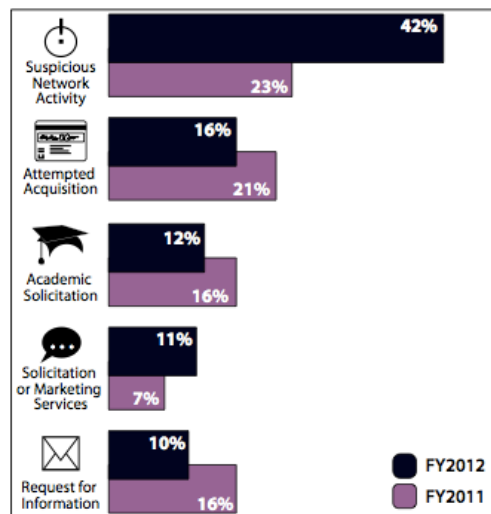


Figure 10. Top 5 Methods of Operations for Foreign Espionage (from Defense Security Service, 2013, p. 26)

Allen, of GD AIS, proposes a more comprehensive seven-step process to operations security. Allen’s OPSEC process parallels his military deception planning steps, outlined in later chapters. Allen elegantly concludes his steps when he writes, “The execution of the OSPEC plan does not have to be perfect; it just has to have fewer leaks than the features of the deception plan accepted by the enemy” (Allen, 2007, p. 144).

- 1) Select a COA using the joint operation planning process (JOPP)

- 2) Establish which characteristics of the selected COA differ from the corollary deception plan and would cause damage if exposed to enemy intelligence collections.
- 3) Outline the signatures and indicators of the operations plan that are to be kept hidden from enemy collections.
- 4) Outline the tactics, techniques, and procedures enemy intelligence collectors will use to detect the outlined signatures and indicators. Specifically what sensors will enemy intelligence gathers employ for their collection efforts.
- 5) Establish metrics for determining if enemy detection efforts are successful in targeting the outlined signatures and indicators.
- 6) During the conduct of operations confirm via friendly intelligence channels whether enemy sensors have detected the established signatures and indicators, and furthermore, whether intelligence analysts and decision-makers have accepted those collections as true.
- 7) Finally, compare the results of Step 6 to the results of the military deception plan to determine if the OPSEC plan was as or more effective at hiding signatures and indicators than the MILDEC plan was at portraying false signatures and indicators. (Allen, 2007, pp. 143–144)

This seven-step, and the three-step, OPSEC process outlined in the Joint Publication will offer considerable value in the context of leaking financial information to opportunistic third-parties. Of particular interest is how signatures and indicators factor into trading strategies and investment decisions. Furthermore, how can the BLP and CW models be implemented in financial market mechanisms to prevent information leakage and, barring prevention, successfully detect the leakage has occurred? While not exhaustive, this comprehensive review of academic, industry, and government literature on operations security, and other information guarding activities, provides a solid baseline from which to discuss information leakage in a financial context. Nevertheless, before this discussion it will be of significant value to examine the topic of military deception and its role in both the financial and military information landscape.

G. DECEPTION: APPEARING WHERE YOU ARE NOT

There is no shortage of academic and practitioner writings on military deception, colloquially referred to as MILDEC. First, it will be useful, however, to first examine the

broader academic topic of deception before delving into the differences between interpersonal, political, and military deception.

Bell and Whaley’s published work, *Cheating and Deception*, traces the origins and evolution of contemporary academic work concerning deception from Plutarch of ancient Greece, to Machiavelli of Renaissance Italy. Bell and Whaley found the philosophers in agreement that “the question is one of brute force versus disassembling, cunning, guile, fraud, in short, force versus deception” (Bell & Whaley, 1982, pp. 3–4, 36–37). Later the authors add a caveat to this conclusion when they write, “[deception] need not even be the weapon of the weak ... It can be, rather, a means toward an end not easily achieved by brute force” (Bell & Whaley, 1982, p. 9). Bell & Whaley propose the most succinct of definitions when they advocate that deception is “advantageous distortion of perceived reality” (Bell & Whaley, 1982, p. 47). The authors organize deception into two broad categories, both derived from natural occurring deception found in the environment. Those broad categories, showing and hiding, provide a framework for examining deception. Bell and Whaley define three subcategories in each, with showing’s components of *mimicking*, *inventing*, and *decoying*, and hiding’s component of *masking*, *repackaging*, and *dazzling* (Bell & Whaley, 1982, pp. 48–61). Later in the text, the authors depict and describe a proposed planning loop for deception.

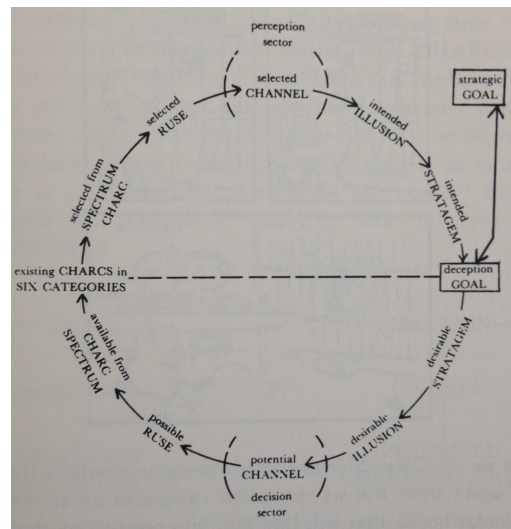


Figure 11. The Bell & Whaley Deception Planning Loop (from Bell & Whaley, 1982, p. 71)

Shown in Figure 11, the Bell and Whaley deception planning loop is a multi-step process to successful deception. The loop begins with a selected channel, to deliver an intended illusion, to achieve an intended stratagem, to contribute to a deception goal, and ultimately accomplish a strategic goal. After the ruse is composed and projected, the success of the plan is out of the hands of the deception practitioner and into the perceived reality of the intended victim (Bell & Whaley, 1982, pp. 71–74).

One authoritative text, required for any comprehensive review of Military Deception is the 1981 compilation of papers included in the book, *Strategic Military Deception*, edited by Daniel and Herbig. Originally commissioned by the Central Intelligence Agency’s Office of Research and Development in 1978, this collection brings a wide range of academic perspectives to the discipline of military deception including two political scientists, an historian, a physicist, a psychologist, and an electrical engineer (Daniel & Herbig, 1981, p. xi). While each author conducts the majority of their research and findings independently of the group, a wide range of views helps the reader appreciate the spectrum of inquiry, from the psychologist’s qualitative perspectives on analyst bias, to the electrical engineer’s system’s approach to deception. The joint introduction concisely defines deception as “the deliberate misrepresentation of reality done to gain a competitive advantage” (Daniel & Herbig, 1981, p. 3). A close derivative of Bell and Whaley, the Daniel and Herbig definition includes many of the same elements such as the non-arbitrary origination and the deceiver’s purpose to gain an advantage over the deceived. The authors also identify three goals of deception: condition the target’s belief; influence the target’s actions; and benefit from the target’s actions (Daniel & Herbig, 1981, p. 5). Daniel and Herbig’s deception process is shown in Figure 12. Though similar to Bell and Whaley’s deception planning loop, in the distinct deception process the deceiver must transmit multiple signals through multiple channels in hope the target will rebuild the “deception puzzle.” Only if the deception puzzle is rebuilt by the state intelligence apparatus, forwarded through the decision maker’s gatekeeper, and acted upon by the decision maker in a favorable manor is the deception ruse considered a success (Daniel & Herbig, 1981, pp. 7–11).

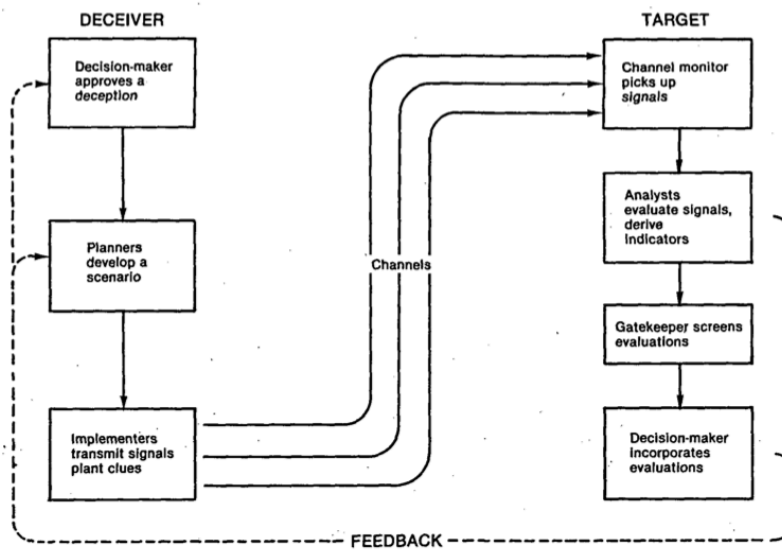


Figure 12. Daniel and Herbig Process of Deception (from Daniel & Herbig, 1981, p. 8)

Defense technology expert, Reese's contribution to the strategic deception compilation approaches deception from the classic communication's paradigm depicted in Figure 13. Reese begins by simply describing each component of the paradigm and how each stage's output serves as the follow-on stage's input (Daniel & Herbig, 1981, pp. 100-105). Of special note, is Reese's discussion of signal-to-noise ratios. Originally defined in communication theory, the signal-to-noise ratio describes the power output of the system over the Gaussian random white noise injected by the nature of the encoder/decoder and the selected channel. Nevertheless, Reese astutely observes that the phrase "signal-to-noise" in an intelligence setting has been widely used to identify relevant indicators of enemy intentions, from either false indicators or indicators of little importance. This intelligence adoption of the phrase "signal-to-noise" is therefore somewhat inappropriate as the denominator. Noise lacks any element of randomness and is not inherent to the encoder/decoder and environment, but rather inherent to the fog of intelligence gathering (Daniel & Herbig, 1981, p. 101).

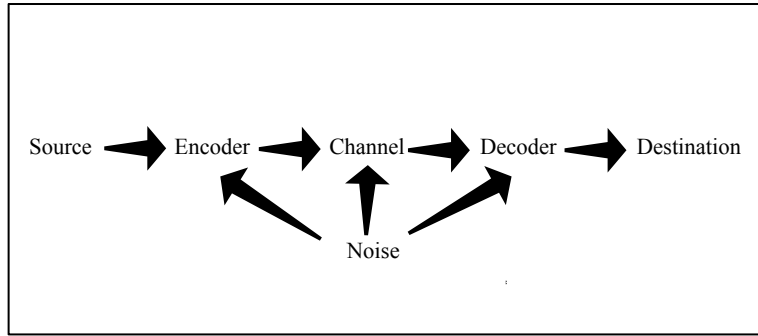


Figure 13. Classic Communication's Paradigm (from Daniel & Herbig, 1981, p. 99)

After addressing the classic communication's paradigm, Reese breaks down the message concept illustrated in the classic paradigm into the summation of micro-messages. These micro-messages or indicators are designed by the deceiver and sent over a predetermined channel for reception by the intended victim. As shown in Figure 14, each indicator, I_x , must first pass through channel, C_x , before being decoded by the receiver into I'_x . According to Reese, the deception plan has its best bid for success if, but not only if, the summation of I'_x is a reasonable approximation of the summation of the original indicators I_x . Reese asserts that the deception plan may still succeed regardless of whether the indicators are decoded incorrectly, as ambiguity-increasing deception does not require the deception puzzle advanced by Bell and Whaley (Daniel & Herbig, 1981, pp. 109–110).

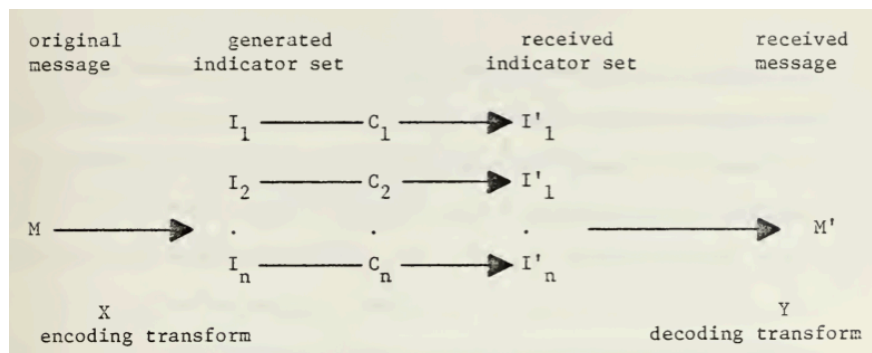


Figure 14. Level 1 and 2 Transaction Depiction (from Daniel & Herbig, 1981, p. 110)

Electrical engineer and system's theorist Moose's contribution to the aforementioned anthology, "A System's View of Deception" (1981) refines Reese's writings of the communication's paradigm from a system's perspective. Moose's model, depicted in Figure 15 includes more realistic variables than Reese's, including unintentional leaks, delays in transmission and relays, and human errors throughout. Moose also describes a tactic he calls, "probing the channel," when a deceiver will send signals to the victim for the sole intention of gauging the response of the victim. This gives the deceiver two advantages. First, it demonstrates the channel is active and the victim is decoding messages. Second, it allows the deceiver to better craft future messages to elicit the intended response from the victim, now aware of how the victim will react to certain stimuli (Daniel & Herbig, 1981, pp. 140–142). One final note on Moose's work is the distinction he draws between static or stable system's operations and dynamic or transitional system's operations. Moose cautions that stable decision systems are more predictable, and, as such, success of deception plans may be more easily assessed. Furthermore, transitional systems tend to produce unpredictable outputs that may not only have an effect on the success of deception, but will undoubtedly have an effect on the detection of said success (Daniel & Herbig, 1981, pp. 142–143).

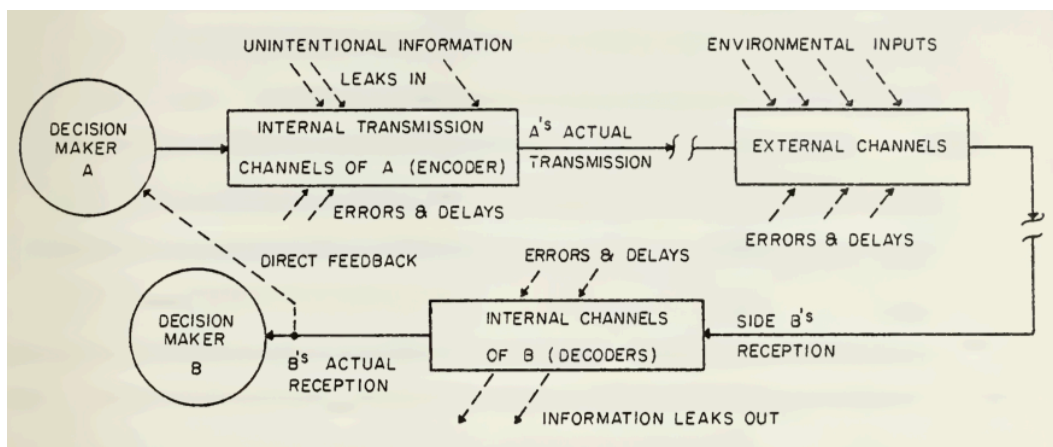


Figure 15. Modified Classic Communication's Paradigm
(from Daniel & Herbig, 1981, p. 141)

At this juncture, it's imperative to revisit the impressive collection of academic work by the late deception philosopher, once Tuft's University and Naval Postgraduate

School professor, Whaley. Whaley's 1969 MIT dissertation, "Stratagem: Deception and Surprise in War," provides the authoritative text on deception successes and failures from 1914–1968, categorizing and analyzing more than 165 battles from 16 separate wars (Whaley, 1969, p. v). Claiming first analytical approach to military deception, Whaley finds that deception is an effective means of aiding strategic surprise in 41 out of 53 cases (Whaley, 1969, pp. 3–5). Whaley goes on to define, discuss, and digest the practitioners of deception from the West, such as Hitler and Churchill, as well as from the East, such as Mao and Giap (Whaley, 1969, p. 6). After this recap, Whaley begins the more practical discussion of both strategic and tactical deception such as feints, demonstrations, disinformation, and ruses as well as channels such as word-of-mouth, newspapers, radio diplomacy, and espionage (Whaley, 1969, pp. 18–23). Much of Whaley's research is most useful in a military context. For instance, Whaley examines the dataset to detect patterns in victory rates and casualty rates resulting from surprise and deception. Additionally, Whaley examines his dataset to determine under what operations is deception most likely employed, such as 40% for land based operations and 85% of amphibious operations (Whaley, 1969, pp. 189–223).

Whaley, like many others, makes the observation that successful deception essentially boils down to a question of choice for the victim. Building on the philosophical discussions of English military theorist Liddell Hart and American civil war general Tecumseh Sherman, Whaley describes the deception plan as aiming to put the victim in the "horns of a dilemma and then impale him on the one of your choosing" (Whaley, 1969, p. 129). Distinct in Whaley's discussion is the concept of victim choice. According the Whaley, the victim has the illusion of choice, and the deceiver, if successful, chooses from the set of alternatives for the victim, aptly put, "the ultimate goal of [deception] is to make the enemy quite certain, very decisive, and wrong. [emphasis in the original]" (Whaley, 1969, p. 135).

Also of note is Whaley's discussion on ethics, which for obvious reasons, may be of considerable value to this research. In Chapter III, Whaley asks whether deception in warfare is ethical. Whaley finds that while almost universally, "occidental and oriental military cultures find [deception] ... to be immoral," in practice "sheer expediency has

proven sufficient justification” and with two exceptions, no culture has “unilaterally forsworn [deception]” (Whaley, 1969, p. 100). Whaley argues his two exceptions, the Vedic age in India and the Middle Ages in Europe, stem from underlying cultural circumstances of the periods, and are most notable for their rarity in history. Additionally, these unique examples do suggest that, given an appropriate cultural environment, deception has been completely removed from warfare (Whaley, 1969, p. 103). Understandably, Whaley’s justification of deception in a military context does not fully justify deception used for financial gains. For this reason and others discussed later on, the topic of ethical deception in financial matters is left very much open for debate.

Whaley concludes with three economic maxims he has found true throughout his research. First, deception is cheap. Whaley advocates that deception plans require small investments in personnel, materials and monies to be effective. As an example, Whaley estimates that the entire allied invasion deception plan of 1944 required no more than 2,000 soldiers and greatly hastened their victory (Whaley, 1969, pp. 232–232). Second, deception presents a solid return on investment. According to Whaley’s research, the deceiver surprised the victim 80% of the time when a deception tactic was implemented. Given the aforementioned minimal costs, and the overwhelming evidence of resulting surprise, Whaley concludes “[deception] is certainly the cheapest and often the most effective means of manipulating an opponent’s military economy” (Whaley, 1969, pp. 233–238). Finally, while deception and security can be mutually supporting, deception, not security is the best guarantor of surprise. Specifically the author views security systems, such as operations security, as requiring greater investments in personnel and resources than deception, as well as, having a smaller overall chance of success than deception. Whaley’s opinion on this matter extends to both strategic and tactical operations (Whaley, 1969, pp. 240-243). Perhaps most surprising of all, in Whaley’s summary, he concedes that while it is possible for deception to backfire on the deceiver, he has found no historical evidence of such an incident (Whaley, 1969, p. 262). Also of note is Whaley’s reiteration of his previous points on the economics of deception in 2007. Whaley’s theories on the cost effectiveness of deception are demonstrated with both new

and old evidence in the text *Information Strategy and Warfare*, edited by Arquilla and Borer of the Naval Postgraduate School (Arquilla & Borer, 2007, pp. 127–155).

More than 30 years after his dissertation, Whaley revisits the topic of deception as an editor in his self-published compilation, *A Reader in Deception and Counterdeception* (2003). Although many of the articles are reprints from both earlier unpublished and published work, Whaley again offers an insightful academic perspective on the value of deception in military affairs. For instance, in Whaley's quantitative research he discovers that the "probability of achieving surprise by using two deception ruses is quite high (.88), and the probability of achieving surprise given three or more deception ruses is [1.0]" (Whaley, 2003, p. 76). Furthermore, once surprise is achieved, through deception of security, then the probably of victory associated with that operation is also quite high, .87 (Whaley, 2003, p. 76). Whaley cautions the reader, and correctly so, not to inappropriately concluded causations from his derived correlated statistics. Although Whaley does not identify by name any possible hidden variables that could explain causation between deception, surprise, and victory, even the most unimaginative reader could propose alternative causation for Whaley's correlation (Whaley, 2003, p. 76–78).

Over the course of his 2003 composition, Whaley discusses deception in a multitude of settings including games of chance, cheating spouses, magician's illusions, military affairs, politics, and crime solving. Inordinately well versed in these fields, Whaley concludes (2003, p. 82)

I ... assert that deception is the same regardless of whatever field it appears in. It is not a function of technology. All deceptions are applied psychology – the psychology of misperception. Consequently, along psychological lines it must be logically possible to develop a general theory of deception.

In a separate Whaley article of the same anthology, the author revisits his topology of deception as outlined earlier in his book, *Cheating and Deception* with co-author Bell. Though at first mostly semantic, Whaley renames the *showing* category as *simulation*, and the *hiding* category as *dissimulation* (Whaley, 2003, p. 86). Nevertheless, later Whaley makes the elegant conclusion that each subcategory in *simulation* (e.g., mimicking, inventing, decoying) has a counterpart or antonym in *dissimulation* (e.g.,

masking, repackaging, dazzling). Whaley theorizes that these three pairs of subcategories, masking/mimicking, repackaging/inventing, and dazzling/decoying, are most effective when used in conjunction. To test his hypothesis, Whaley examines 60 magic tricks to see which tactics are used most often, logically inferring that the most often used tactics are also the most effective. Whaley goes on to show not only his hypothesis is true, but also that certain subcategory pairs are most effective than others, with *masking/mimicking* as the most effective (Whaley, 2003, pp. 87–90).

Deception (Distorting Reality)	
Dissimulation (hiding the real)	Simulation (showing the false)
<i>Masking</i> Concealing one's own or matching another's charcs to eliminate an old pattern or blend it with a background pattern	<i>Mimicking</i> Copying another's charcs to create an old pattern, imitating it
<i>Repackaging</i> Adding new or subtracting old charcs to modify an old pattern by matching another	<i>Inventing</i> Creating new charcs to create a new pattern
<i>Dazzling</i> Obscure old or add alternative charcs to blur an old pattern, reducing its certainty.	<i>Decoying</i> Create alternative charcs to give an additional, alternative pattern, increasing its certainty.

Decreasing effectiveness

Figure 16. Whaley's Deception Subcategories (from Bennett & Waltz, 2007, p. 26)

In Whaley's final work, he discusses military deception successes and failures in the work *When Deception Fails: The Theory of Outs*. Whaley postulates that rarely does military deception actually fail, in fact, total failure and total success almost never occur. Even implemented poorly, some deception is better than no deception, because of the preponderance of evidence that total failure is unlikely (Whaley, 2010, pp. 6–8). Nevertheless, Whaley does concede that failure can occur in military deception, and when it does, it is a result of one or more of five causes: 1) design failure; 2) initiation failure; 3) transmission failure; 4) inept implementation; or 5) target detects the deception (Whaley, 2010, p. 7). In addition to these most common errors, Whaley enumerates 14 lessons learned from his years of research. Although, it is not useful to detail all of his learned lessons here, three that may be particular useful for this research and context are

1) know the tools of your craft, 2) notify HQ in advance if friendly units may be adversely affected, and 3) keep the plan simple, short and flexible (Whaley, 2010, pp. 10-12). While the application of these principles in the context of this research may not be obvious yet, more parallels will be drawn in follow-on chapters.

In more recent years, a near constant source for Whaley, Greenberg, attempts to further quantify the economies and payoffs of deception in his 1982 article “The Role of Deception in Decision Theory.” Greenberg begins by laying out a simple two-dimensional model for decision-making, shown in Figure 17. According to Greenberg, the decider must first assess the “State of Nature” (S_N), and then choose from a list of alternative decisions (A_M), in accordance with the greatest payoff (P_{MN}) (Greenberg, 1982, pp. 141–142).

		STATE OF NATURE			
		S_1	S_2	. . .	S_N
ALTERNATIVE	A_1	P_{11}	P_{12}	. . .	P_{1N}
	A_2	P_{21}	P_{22}	. . .	P_{2N}

	A_M	P_{M1}	P_{M2}	. . .	P_{MN}

Figure 17. Greenberg’s General Decision Problem (from Greenberg, 1982, p. 142)

Unfortunately, rarely is the state of nature definitive so the decider must consider the probability of each state of nature and calculate the expected payoff in accordance with that probability. The empirical value of this expected return is shown in Equation 12. E_i^j is the summation of each payoff (P_{ij}) from all the possible states of nature (from one to j), in the selected alternative row (i) crossed with the probability (q_j) of that particular state of nature (Greenberg, 1982, pp. 141–143).

$$E_i' = \sum_{j=1}^N q_j P_{ij} \quad (12)$$

When the decider is deceived, the perceived probabilities of each state of nature are altered so as to encourage the decider to unknowingly pick a less than optimal expected return. In Figure 18, Greenberg shows an abbreviated example of this approach to calculating the cost of deception to the victim. The figure shows the optimal alternative for the victim based on the true probabilities of each state of nature to be A_2 , for a return of 2.3. Nevertheless, the deceiver has been successful at manipulating the victim's probability perception into believing A_4 is the optimal alternative. As such, the cost to the victim is the difference between the highest expected value (2.3) and the chosen expected value (1.5) or .8 (Greenberg, 1982, p. 144–145). From the perpetrator's perspective, a more valuable approach, a therefore more costly for the victim, would have been to raise the target's perceived probabilities such that alternative one was selected. This would have given the victim the smallest expected value (0) from the list of alternatives. The reader is left with only conjecture (e.g., costs, miscalculations, unintended consequences) to explain this oversight by the perpetrator.

STATE OF NATURE		S ₁	S ₂	S ₃	EXPECTED		
		0.5	0.3	0.2	VALUE		
TRUE PROBABILITY (q ₁)					E ₁	E _i '	
PERCEIVED PROBABILITY (q ₁ ')		0.2	0.3	0.5			
ALTERNATIVE	A ₁	0	2	-3	0	-0.9	
	A ₂	4	1	0	2.3	1.1	
	A ₃	5	-6	2	1.1	0.2	
	A ₄	2	-1	4	1.5	2.1	
OPTIMUM STRATEGY		- CHOOSE A ₂ ;				EXPECTED PAYOFF = 2.3	
MISPERCEIVED OPTIMUM		- CHOOSE A ₄ ;				EXPECTED PAYOFF = 2.1	
DECISION MAKER CHOOSES A ₄ ;						ACTUAL EXPECTED PAYOFF = 1.5	
		LOSS DUE TO DECEPTION = 2.3 - 1.5 = 0.8					

Figure 18. Greenberg's Cost (Value) of Deception to the Victim (Perpetrator) (from Greenberg, 1982, p. 144)

No discussion on military deception would be complete without at least a brief mention of another monolith of the discipline, Handel. Much of Handel's work focuses on the study and exploitation of intelligence; offering analysis on historical case studies from the U.S. Civil War to cold war operations, that dominated the second half of the 21st century. Interestingly, Handel's definition of deception lacks the competitive advantage element so consistent in others work (see Whaley, Daniel, Herbig, etc.). Handel defines deception as "the process of influencing the enemy to make decisions disadvantageous to himself by supplying or denying information" (Handel, 1987 p. 1). Although pure speculation, perhaps implicit in Handel's definition is the zero-sum game of warfare, whereby if the enemy is disadvantaged, then friendly forces are naturally advantaged. Handel goes on to mildly endorse the notion that at the root of all deception plans is the intent to surprise when he writes "deception *per se* has no value; it assumes significance only when used as a *means* of achieving surprise [emphasis in the original]" (Handel, 1987, p. 2). Today this claim, one worth revisiting, appears, at best, extremely limiting for deception planners and, at worst, dangerously naïve for counterdeception practitioners. Handel writes extensively about the significance of feedback during deception execution. For instance, Handel writes specifically about the role of the *Ultra* program during the Second World War (i.e., a covert signals intelligence program to break German cypher codes and monitor German communications), "Ultra was the single most important means of facilitating deception available to the Allies ... the deceivers could rely on Ultra to monitor the degree to which it had been accepted by the Germans, then follow this up by fine-tuning continue deception cover plans" (Handel, 1987, p. 22).

Also of value is Handel's observation that "an inverse correlation exists between strength and the resort to deception" (Handel, 1987, pp. 30-31) This is to say that stronger states will shy away from deception plans, as their own hubris reassures them that no such plan is necessary, often with devastating consequences. Handel points to the Soviet Union's attack on Finland in 1939, Germany's attack on the Soviet Union in 1941, and the Arab attack on Israel in 1948, as just three examples where deception was not attempted, with demoralizing defeats for the aggressing belligerents (Handel, 1987, p. 31). Handel concludes this point when he emphatically states, "Although the tendency of power states to rely on 'brute force' can be understood, it certainly cannot be justified:

the strong and powerful need not waste their strength ... simply because they are confident of victory” (Handel, 1987, p. 41). These points and others Handel makes throughout his collection of works are as useful as they are prolific. While focusing on case studies Handel makes many appreciated observations about the role of deception throughout history.

Building on their earlier work, Daniel and Herbig revisit deception in their 1982 paper, *Propositions in Military Deception*. Taking cues from two World War II deception planners, one allied, one axis, Daniel and Herbig advocate five factors of successful deception schemes: 1) secrecy, organization, and coordination; 2) plausibility and confirmation; 3) adaptability; 4) predisposition of the target; 5) strategic situation (Daniel & Herbig, 1982, p. 167). The authors identify the minimum two levels of secrecy required for deception. The first protects the facts and circumstances of the intended operations, while the second protects the existence of the deception plan itself (Daniel, Daniel & Herbig, 1982, p. 168). The second factor is the plausibility of the deception scheme. Though it seems intuitive, at least as recently as WWII, enemy intelligence analysts, based solely on the improbable nature of the implied operation, have dismissed deception indicators (Daniel & Herbig, 1982, p. 169). Additionally, Daniel and Herbig’s axis deception planner, Von Grieffenberg, suggests, “deception is enhanced if the deceiver adapts to changing circumstances and unplanned events” (Daniel & Herbig, 1982, p. 170). Surprisingly, the final two factors, predisposition and strategic situation, were not addressed by Daniel and Herbig’s sources, but were added after the fact. While admittedly not impossible, changing the victim’s preconceived notions, according to the authors, is certainly psychologically more difficult than reinforcing those beliefs (Daniel & Herbig, 1982, p. 173). Also of note is the tendency of victims to follow predispositions when in an extreme mental state of hyper-vigilance or indifference. Conversely, therefore, biases are most easily altered when the victim’s mental state is one of moderate tension (Daniel & Herbig, 1982, p. 173). Daniel and Herbig’s final factor deals with the initiative advantage the deceiver has over the victim. The authors consider this time advantage of the deceiver to be a critical factor in the success of the overall plan. In their view, a rushed deception plan will be risky, unadvisable, and ultimately ineffective (Daniel & Herbig, 1982, pp. 174–175).

Bennett and Waltz’s 2007 text, *Counterdeception: Principles and Applications for National Security* offers a compressive contemporary and historical overview of the development of both deception and counterdeception. Modeled after Whaley’s deception paradigm, but semantically divergent, the authors separate hiding from showing, or simulation from dissimulation, by renaming the breakdown *denial* and *deception* (Bennett & Waltz, 2007, p. 5). Bennett and Waltz offer a worthwhile illustrative example of a generic deception information flow, shown in Figure 19. Beginning with objectives, the deception indicators flow from methods, through channels, to targets, and ultimately for effects (Bennett & Waltz, 2007, p. 6).

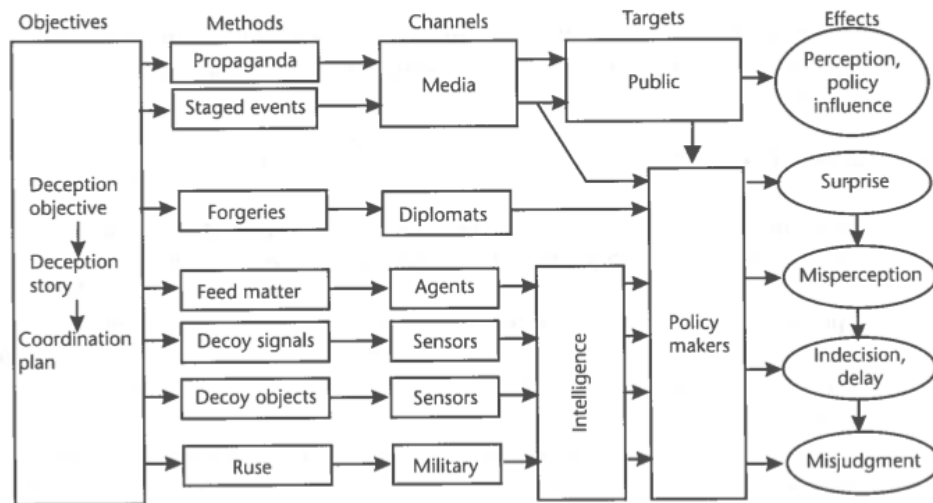


Figure 19. Bennett and Waltz’s Generic Deception Information Flow (from Bennett & Waltz, 2007, p. 6)

Perhaps most valuable in Bennett and Waltz writings are their four fundamental principles of deception, first outlined in Chapter Two: “1) *Truth* – All deception works within the context of what is true; 2) *Denials* – Denying the target access to the truth is the prerequisite to all deception; 3) *Deceit* – All deception requires deceit; 4) *Misdirection* – Deception depends on manipulating what the target registers” (Bennett & Waltz, 2007, p. 59). While some of these fundamental principles seem more obvious than helpful, a few points of nuance will help clarify the discussion. Bennett and Waltz’s first principle, on *truth*, astutely identifies the condition that when no secrets require

protecting, then no deception plan is necessary. Furthermore, if the target audience gains access to the aforementioned valuable secrets and accepts those secrets as truth, a frequently underestimated condition, then the deception plan is also moot. This notion is encapsulated in Bennett and Waltz's second and fourth principle. Perhaps most useful is Bennett and Waltz's last principle which, stated differently, is that projection is irrelevant, that perception and action is where the focus of deception metrics as well as methods must be defined. (Bennett & Waltz, 2007, pp. 58–60)

Beyond the academics, many practitioners of military deception have matriculated through the halls of the Naval Postgraduate School. One such practitioner from the Defense Analysis program, Martin, under the tutelage of academic John Arquilla, tackled Military Deception in her work, *Military Deception Reconsidered*. Martin does an excellent job recapping the academic theories of military deception from the past fifty years and makes many compelling conclusions. Martin began by identifying the two commonly accepted types of deception, Misleading (M-Type) and Ambiguity Increasing (A-type) (Martin, 2008, p. 11). These two types of deception will play a critical role in this research, as each will have a different effect on the decision making environment for the actors involved. Martin goes on to categorize and classify different academic theories on what factors contribute to a successful military deception campaign. Martin concludes that six different elements recur in most, but not all, literature, as required factors for successful deception. These elements include: 1) focus; 2) objective; 3) centralized control; 4) security; 5) timelines; and 6) integration (Martin, 2008, p. 35). Although not all of these factors were present in all the case studies Martin examined, most contained four or more characteristics, demonstrating a clear association, if not causation, between these factors and the success of the deception (Martin, 2008, pp. 21–34).

A second practitioner of military deception, MacKrell, also wrote on the principles involved in successful deception campaigns. Although MacKrell describes the same two types of deception, A-type and M-type, she refers to M-type as misdirection instead of misleading (MacKrell, 1996, p. 2). While this is again mostly a semantic difference between the two academics, it shows that much of the jargon associated with

deception and more broadly, information warfare, has still not been solidified nearly two and a half millennia after Sun Tzu. Understandably, this reoccurring theme makes clear definitions vitally important to conveying complex topic and relationships. Written nearly two decades ago, MacKrell believes that an age of “perfect information” would make deception exceedingly difficult, but not impossible (MacKrell, 1996, p. 4). Furthermore, MacKrell advocates that successful deception campaigns contain four required elements: 1) reinforcing preconceptions, 2) plausibility, 3) multi-channel deception, and 4) “The administrative side: secrecy, control coordination” (MacKrell 1996, pp. 4–16). Many of the topics and conclusions in MacKrell’s research are ripe for reexaminations in the age of information overload.

The topics of denial and deception are not unique to military operations or disciplines. Though some people may be uncomfortable in applying the paradigms and constructs above, especially misinformation campaigns, to financial decisions and calculations, to ignore the existence of such constructs already in place is both naïve and would fail to adequately address current financial landscapes. To that end, from here the research and follow-up discussion revolves around the ideal environment for reevaluating the capital asset pricing model. After the revision is presented and dissected, the discussion shifts to underlying assumptions and complications presented in real world implementation of such calculations. Finally, dark pools and HFT implications are addressed as additional obstacles to implementation, while Chapter V concludes and offers a number of topics for future work.

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III. ADJUSTING CAPM, THE MODEL, THE PROXY, AND DECEPTION

Even minutiae should have a place in our collection, for things of a seemingly trifling nature, when enjoined with others of a more serious cast, may lead to valuable conclusion.

—President George Washington (1732–1799)

A. LONG-TERM BETA

The vast majority of the critics of the capital asset pricing model accept many of the underlying premises of Sharpe’s argument. Instead these critics, including Acharya and Pedersen (2005); Estrada (2007); Chong, Pfeiffer and Phillips (2010); and Roodposhti and Amirhosseini (2012) target the sensitivity index, β , for improvement and refinement. While accurately forecasting β has proved difficult, the classic approach is to use past results as a proxy to measure and forecast β through historical regression. Specifically, the β is forecasted as the slope of the underlying assets historical returns, as they relate to the historical returns of the overall market for a given period of time (Chong & Phillips, 2011, pp. 68). Nevertheless, even this relatively straight-forward calculation can vary greatly depending on assumptions of the estimating statistician, such as the “look-back period” or whichever index is selected as the reference benchmark for the broader market (Chong & Phillips, 2011, pp. 67). While standard industry practices recommend a minimum of a one-year look-back period and the S&P 500 as the broader market for U.S. equities, these estimating parameters do little to estimate the most current market conditions; a great concern for high-frequency trading firms and other short-term investors who open and close positions quickly and rarely hold sizeable positions overnight (Chong & Phillips, 2011, pp. 69).

This thesis proposes that incorporating short-term sensitivity indicators into β forecasting, along with the classic long-term historical correlation between market return and asset return, could improve β forecasting resulting in a more accurate prediction for

an assets return given an anticipated market return. This slight modification is illustrated in equations 13, 14, and 15. Equation 13 is the original CAPM as described in the literature review; Equation 14 is the slightly modified CAPM with β' ; and Equation 15 defines β' as the un-weighted average of the historical β for the short-term, current market correcting factor, ϕ . For simplicity, the short-term correcting factor ϕ is given equal weight as the long-term classic proxy, historically regressed β . Nevertheless, it could be true that an equal weight is inappropriate and a more accurate β' could be forecasted by placing more emphasis on either the short-term correcting factor or the long-term one. This possibility and other data-driven areas of recommended research are addressed in Chapter V, Conclusion.

$$E[r_i] = r_f + \beta_i(E[r_m] - r_f) \quad (13)$$

$$E'[r_i] = r_f + \beta'_i(E[r_m] - r_f) \quad (14)$$

$$\beta'_i = \frac{\phi_i + \beta_i}{2} \quad (15)$$

B. SHORT-TERM PHI, BETA PRIME, AND THE LOB

Estimating ϕ presents many of the same difficult assumptions that accompany measuring β , the long-term sensitivity of an asset's return. Ultimately, historical regression was selected as a proxy to estimate future asset returns based on projected returns of the broader market. Because ϕ is defined as a measurement of current to short-term sensitivity, historical regression is ill-suited, and a more dynamic metric should substitute for the short-term sensitivity of an asset. For simplicity of comparison to original β , the S&P 500 index will continue to be used as a comparison baseline when defining the broader market. As a proxy for short-term sensitivity of an asset to the broader market, this research will turn to the information and market interest expressed in the limit order book.

Last Traded Price: \$10.00

<u>Buy-Side</u>				<u>Sell-Side</u>			
<u>Date/Time</u>	<u>Unique ID</u>	<u>Order Quantity</u>	<u>Bid Price</u>	<u>Date/Time</u>	<u>Unique ID</u>	<u>Order Quantity</u>	<u>Ask Price</u>
5/12/2013 09:54:23	132215	300	\$9.98	5/12/2013 09:54:21	390043	200	\$10.02
5/12/2013 09:54:69	351969	100	\$9.97	5/12/2013 09:53:94	213676	300	\$10.03
5/12/2013 09:54:01	275666	700	\$9.97	5/12/2013 09:54:10	390092	800	\$10.03
5/12/2013 09:54:99	495482	900	\$9.95	5/12/2013 09:54:03	163882	300	\$10.05
5/12/2013 09:53:13	266820	300	\$9.94	5/12/2013 09:53:83	66618	500	\$10.06
5/12/2013 09:53:98	135559	700	\$9.92	5/12/2013 09:54:13	178274	450	\$10.06
5/12/2013 09:53:93	442929	300	\$9.92	5/12/2013 09:53:23	440217	500	\$10.08

Figure 20. Sample Simplified Limit Order Book at Time t

Although the information contained can vary, the most basic limit order book (LOB) contains, at a minimum, unique order identifiers, bid/ask prices, order sizes, and the date/time the orders arrived at the exchange. When taken in total, the LOB can offer significant insight into the short-term volatility of the underlying asset, offering substantial economic value of LOB analysis, such as order depth, order flow, and book balance (Kozhan & Salmon, 2010, pp. 2–4). Although these terms are used liberally throughout limit order book academic research, a common definition remains elusive in many cases. Broadly speaking, order depth refers to the quantitative number of unique price levels contained on both the buy and sell side of the order book. For example, Figure 20 shows five distinct price levels are present on both the buy and the sell side of the LOB. Less quantifiable, though certainly related, is a variation on this definition for *market depth*, defined as the market’s ability to sustain relatively large market orders without impacting the price of the security (Banks, 2010, pp. 17, 54). This definition is more versatile than merely counting the various price levels because it incorporates all the various price levels, as well as the breath of the LOB (i.e., how many shares per order).

The order flow is commonly defined by the rules and fees that dictate how, and in what order, trades execute. Discussed briefly earlier, the fees and rebates associated with liquidity takers and suppliers, as well as rules governing first-come-first-fill execution, are just some of the elements included in order flow and visible in the LOB. Finally, the book balance is defined as the intensity of the buying liquidity present in relation to the intensity of the selling liquidity in the limit order book (Foucault & Menkveld, 2008, p. 152). More simply put, the balance of the book merely refers to the buy side versus the sell side of the limit order book.

C. THE RATIONALE BEHIND THE MODEL

As was discussed previously, in addition to contributing depth, limit orders also provide liquidity to the market. Various calculations on book balance and this liquidity may provide an excellent proxy for measuring short-term sensitivity, just as historical regression serves as the long-term alternative. Before specific calculations are discussed, it will be of considerable value to discuss the rationale behind turning to the limit order book and the book's balance as a short-term proxy for sensitivity. Much of the rationale is drawn from the logical inference that, when the LOB balance weighs heavily toward buying liquidity, then a heavier propensity of price support for the underlying asset would follow, as the buying liquidity would more easily absorb market sell orders than the selling liquidity could absorb corresponding buy orders (Fong & Liu, 2010). Price support refers to a price level, which a stock has difficulty falling below. Consider Figure 21, little imagination is required to accept that, given a moderately equal number of market buy/sell orders, the price of the underlying asset would rise, or barring a rise at least not fall, due to the lop-sided nature of the LOB (Gomes & Waelbroeck, 2010, pp. 1099–1100). While not difficult to imagine, this proposition, and the forthcoming converse, requires a number of assumptions that have yet to be addressed.

<u>Last Traded Price: \$10.00</u>							
<u>Buy-Side</u>				<u>Sell-Side</u>			
<u>Date/Time</u>	<u>Unique ID</u>	<u>Order Quantity</u>	<u>Bid Price</u>	<u>Date/Time</u>	<u>Unique ID</u>	<u>Order Quantity</u>	<u>Ask Price</u>
5/12/2013 09:54:23	411151	300	\$9.98	5/12/2013 09:54:21	424634	200	\$10.02
5/12/2013 09:54:69	473739	100	\$9.97	5/12/2013 09:53:94	176515	300	\$10.03
5/12/2013 09:54:01	146283	700	\$9.97				
5/12/2013 09:54:99	9950	900	\$9.95				
5/12/2013 09:53:13	95397	300	\$9.94				
5/12/2013 09:53:98	450026	700	\$9.92				
5/12/2013 09:53:93	333607	300	\$9.92				

Figure 21. LOB Weighted Toward Buying Liquidity

Conversely, when the LOB balance weighs heavily towards selling liquidity, this would imply a similarly heavy propensity of price resistance for the underlying asset as the selling liquidity would more easily absorb market buy orders and marketable buy limit orders than the buying liquidity could absorb corresponding sell orders (Fong & Liu, 2010). The opposite side of the previous example is depicted in Figure 22, where

given a moderately balanced number of market buy/sell orders, the price of the underlying security would fall, or barring a fall, at least not rise, due to the heavily weighted sell side of the LOB (Gomes & Waelbroeck, 2010, p. 1099).

<u>Last Traded Price: \$10.00</u>							
<u>Buy-Side</u>				<u>Sell-Side</u>			
<u>Date/Time</u>	<u>Unique ID</u>	<u>Order Quantity</u>	<u>Bid Price</u>	<u>Date/Time</u>	<u>Unique ID</u>	<u>Order Quantity</u>	<u>Ask Price</u>
5/12/2013 09:54:23	56633	300	\$9.98	5/12/2013 09:54:21	329846	200	\$10.02
5/12/2013 09:54:69	19067	100	\$9.97	5/12/2013 09:53:94	250723	300	\$10.03
				5/12/2013 09:54:10	86791	800	\$10.03
				5/12/2013 09:54:03	20036	300	\$10.05
				5/12/2013 09:53:83	262808	500	\$10.06
				5/12/2013 09:54:13	282516	450	\$10.06
				5/12/2013 09:53:23	117024	500	\$10.08

Figure 22. LOB Weighted Toward Selling Liquidity

D. DERIVING THE PROXY

Carrying these two suppositions, that a book weighted toward buy limit orders leads to price support and that a book weighted toward sell limit orders leads to price resistance, to their logical conclusions suggests that a balanced limit order book, as roughly depicted in Figure 20, would likely experience both price support and resistance. Put another way, given a few forthcoming assumptions, this balanced limited order book would likely lead to a reduction in volatility and a more stable price level of the underlying security. Nevertheless, these generalities remain unquantifiable until thorough definitions and metrics are established to establish how balanced a LOB is along with the weight of each side of the LOB. In order to determine the balance of the overall book, the first step is to establish the weight of each side. The most primitive approach to measuring this weight is shown in Equation 16 where the weight of each side is simply defined as the summations of the orders from the corresponding side, referred to, moving forward, as the simple liquidity for its respective side.

$$SL = \sum_{i=0}^n q_i \quad (16)$$

Given the state of the LOB is as depicted in Figure 22, then the simple liquidity of the buy side of the LOB would be 400 shares (e.g., 300 shares from 56633 plus 100 shares

from 19067). Conversely, the simple liquidity of the sell side of the LOB would be the simple sum of quantity of shares at each price point, or 3050 shares.

However, because the aim is to measure the support or resistance of the current price level, this simple liquidity metric could be improved upon to measure not only the total quantity of shares ordered per side, but also the distance from the most recent price point of the security. Therefore, a more accurate representation of implied support and resistance could be estimated by more heavily valuing liquidity near the last traded price – which will typically, though not always, be near the midpoint between the highest ask and the lowest bid. Just as in the case of simple liquidity, complex liquidity is measured for each side and defined in Equation 17 where q is the order quantity, QP is the most recent quoted price, and Bid/Ask is the ordered price at each of the various price levels from 0 to n .

$$CL = \sum_{i=0}^n \frac{q_i}{|QP - (Bid / Ask)_i|} \quad (17)$$

Continuing the simple example in Figure 22, in this case the complex liquidity of the buy side of the LOB would be 18,333.34 (e.g., $300 \div .02 + 100 \div .03$). The lengthier, though trivial, computation of the sell side Complex Liquidity is 74,750 and is outline in Figure 23. Although multiple orders at the same price level have not been collapsed, the unique identifiers have been removed for this example for ease of presentation.

<u>Last Traded Price: \$10.00</u>							
<u>Buy-Side</u>				<u>Sell-Side</u>			
<u>Date/Time</u>	<u>Order Quantity</u>	<u>Bid Price</u>	<u>Complex Liquidity</u>	<u>Date/Time</u>	<u>Order Quantity</u>	<u>Ask Price</u>	<u>Complex Liquidity</u>
5/12/2013 09:54:23	300	\$9.98	15000.00	5/12/2013 09:54:21	200	\$10.02	10000.00
5/12/2013 09:54:69	100	\$9.97	<u>3333.33</u>	5/12/2013 09:53:94	300	\$10.03	10000.00
			<u>Buy-Side Complex Liquidity</u>	5/12/2013 09:54:10	800	\$10.03	26666.67
			18333.33	5/12/2013 09:54:03	300	\$10.05	6000.00
				5/12/2013 09:53:83	500	\$10.06	8333.33
				5/12/2013 09:54:13	450	\$10.06	7500.00
				5/12/2013 09:53:23	500	\$10.08	<u>6250.00</u>
						<u>Sell-Side Complex Liquidity</u>	74750.00

Figure 23. LOB with calculated Complex Liquidity

If the total complex liquidity, TCL, is defined as the sum of the buy side and sell side complex liquidity, then these quantitative metrics now allow for easy comparison of

book balance by comparing the complex liquidity ratio of each side of the LOB. The buy side complex liquidity ratio, BCLR, is defined in Equation 18, with the sell side complex liquidity ratio, SCLR, defined in Equation 19 – both equations include example metrics from Figure 23.

$$BCLR = \frac{BCL}{TCL} = \frac{18333.33}{93083.33} = .197 \quad (18)$$

$$SCLR = \frac{SCL}{TCL} = 1 - BCLR = \frac{74750}{93083.33} = .803 \quad (19)$$

Immediately apparent is that as the SCLR converges to the BCLR, or vice versa, volatility is reduced as the implied support approaches resistance. Additionally, as the SCLR diverges from the BCLR volatility, is increased and stability is reduced, as the implied support digresses from resistance. Nevertheless, the liquidity ratios alone are an insufficient metric in isolation and must be compared relative to the liquidity ratios of the broader market. Additionally, and in keeping with the 2003 Dual β proposal of Estrada, it will be helpful to approach up market β slightly differently than down market β . Specifically, the aforementioned ϕ will be defined in an up market as the ratio of the buy side CLR of the asset to the buy side CLR of the broader market, while in a down market ϕ will be defined as the sell side CLR of the asset to the sell side CLR of the broader market.

Continuing with example in Figure 22, let us assume that the broader market is down and has a composite sell side CLR of .75. This composite sell side CLR of the broader market is defined as the ratio of the summation of weighted sell liquidity over the total liquidity. Just as in the case of the original β , a large basket of equities, such as the S&P 500 would be an appropriate proxy for the total market. Therefore in this instance (e.g., a down market) ϕ , or short-term sensitivity, as measured through relative liquidity from the LOB, is estimated to be about 1.25 and is shown in equation 20.

$$\phi = \frac{SCLR_a}{SCLR_m} = \frac{.803}{.64} = 1.25 \quad (20)$$

Carrying the example to its conclusion, and when a long-term historical β of 1.5 is given, then the adjusted β' , outlined in Equation 15, is a simple non-weighted average of 1.38, ultimately reducing the expected losses in this instance by about 8%. This is in line with expectations, as a smaller than anticipated increase in selling liquidity from asset a , in relative terms to the selling liquidity of the overall market, would slightly depress the downward pressure on the losses of asset a . When instead, a long-term historical β of 1.0 is given, then the adjusted β' , outlined in Equation 15, is a simple non-weighted average of 1.13, ultimately increasing the expected losses in this instance by 11%. This is also in line with expectations, as a larger than anticipated increase in selling liquidity from asset a , in relative terms to the selling liquidity of the overall market would slightly exacerbate the downward pressure on the losses of asset a . These findings are also consistent with Cao, Hansch, and Wang's research suggesting that as much as 22% of price discovery can be explained based on step increments below and above the best bid and ask listings in the limit order book (Cao, Hansch, & Wang, 2009, p. 18).

E. THE PROXY OVER TIME

The LOB depicted in Figures 21, 22, and 23 are snapshots in time and drastic changes in the composition of the book, both in terms of liquidity and balance, just before and after the snapshot, is both expected and not trivial. As such, the derived β is also likely to change, perhaps considerably, over time. This is again, not unexpected, and not unlike the classic calculation of historical regression. Just as each day adds another data point to determine the long-term sensitivity of the asset to volatility of the broader market, running snapshots of the LOB over time are expected to reveal a shorter-run sensitivity. Further research in this area is recommended to determine the usefulness of tracking "historical" (measured in micro-seconds) short-run sensitivity metrics from the LOB for forecasting purposes using models such as weighted moving averages or exponential smoothing.

F. JUSTIFYING ECONOMIC VALUE DERIVED FROM THE LOB

Using the limit order book information and arithmetic derivations thereof as a proxy is a feasible proposition. The New York Stock Exchange began publishing both

sides of the book under the OpenBook program in 2002, while the NASDAQ has a more restricting policy of only publishing the top five price levels from either side (Kozhan & Salmon, 2010, p. 4). Furthermore, many non-public limit order books are accessible by industry professionals through internalizers and wholesale broker/dealers. A controversial practice, using information from non-public limit order books and internalizing less informed retail investors, is known as ‘skimming the cream’, and has been shown to reduce the probability of adverse selection for the internalizing institution. Internalizing smaller retail orders and forwarding larger institutional order to the broader market reduces the probability of adverse selection. Evidence suggests that this reduction in adverse selection (i.e., trading with a more informed agent) occurs because smaller orders are unlikely to have private information relating to the value of the traded asset. Furthermore, this increases the risk of adverse selection on the open exchanges, as a larger proportion of informed orders are forwarded and not internalized (Grammig & Theissen, 2012, pp. 82–83). Grammig and Theissen find evidence to support the hypothesis that internalizers lead to “cream-skimming” and the exploitation of less informed retail investors. They also found that the retail investor enjoys a price improvement over the institutional investor because regulation requires the internalizers to offer securities at, or better, than the best open market bid/offer. Because Grammig and Theissen do not measure the economic value of the price improvement for the retail investor, in relative terms, to the economic value for the internalizers because of their reduced adverse selection risk, it is difficult to know which party enjoys more benefits of internalizers (Grammig & Theissen, 2012, pp. 99–100).

Using the limit order book to derive economic value is not new and has been used to improve profitability as well as predict short-term asset returns in the past (Kozhan & Salmon, 2010, p. 1–2). Nevertheless, some research has suggested that profitability derived from LOB information has been reduced over the past five years as these methods have become more widely exploited (Kozhan & Salmon, 2010, p. 20). For instance, in 2010, Kozhan and Salmon back-tested a series of algorithmic trading strategies based on information contained in the limit order book and determined that, as recently as 2003, a “high level of profitability” was achievable based on such

information. Nevertheless, when Kozhan and Salmon tested the same strategies against a dataset from 2008, the level of profitability was significantly reduced, though not eliminated. Kozhan and Salmon concluded that this finding was in line with Lo's 2004 proposed adaptive market hypothesis, AMH, which is a revisited modification to the longstanding economic principles of efficient market hypothesis, EMH (Kozhan & Salmon, 2010, p. 23). Professor of Economics at MIT's Sloan School of Management, Andrew Lo, first reminds the reader that EMH claims that investors will never profit from information-based trading because all information in efficient frictionless markets is instantaneously incorporated into the price as the information is released and all other price movements are random (Lo, 2004, p. 16). Lo goes on to proposed an evolutionary twist on the classic EMH called adaptive market hypothesis where "prices reflect as much information as dictated by the combination of environmental conditions and the number and nature of 'species' in the economy or, to use a more appropriate biological term, the ecology" (Lo, 2004, p. 23).

What Lo meant by this rather odd biological/economic principle is that when different groups of market participants (i.e., differing species of market segments such as pension funds, retail investors, educational endowment managers, etc.) compete for one particular single market, such as treasury bonds, then that market will be more efficient. Furthermore, as the efficiency is increased the market becomes less profitable. Conversely, when efficiency is low or decreased because various market participants are less interested in competing for a particular market, such as Italian renaissance oil paintings, then profitability is expected to increase (Lo, 2004, p. 23). Lo goes on to explain that as cultural biases inherent in the various market participants or species shift, specific markets efficiencies rise and fall, depending on the focus of the participants' biases. As the efficiencies rise and fall, Lo predicts profitability, in accordance with EMH, is reduced and increased, respectively (Lo, 2004, p. 24). Kozhan and Salmon tie this principle to their findings that as different investor segments increase their focus on the information contained in the limit order book from 2003 to 2008, profitability of that information has been reduced in accordance with the increase in efficiency (Kozhan & Salmon, 2010, p. 23).

G. ASSUMPTIONS

This model, which is based on the limit order book as a proxy for short-term sensitivity, has a number of required assumptions that, when invalid, would invalidate the model put forth. These assumptions, including the distribution of informed traders along with the probability of the presence of false liquidity, are described, defended, and supported in the face of invalidation below.

1. Distribution of Informed Traders

As discussed previously, an informed trader is a market participant acting on non-public information to gain a competitive advantage in the open market. This is closely related to the already outlined problem of adverse selection, as the uninformed trader unknowingly exchanges with a more informed trader. Some research has found evidence to support the idea that informed traders favor market orders to reduce information leakage and ensure execution before their information's value expires. Gilles Daniel's 2006 PhD dissertation, "Asynchronous Simulations of a Limit Order Book", found evidence to support this claim, and concludes, after running a variety of simulations on how price level stability is affected by liquidity, that price changes are the result of uninformed, liquidity supplying traders [e.g., limit orders] rather than informed traders that by in large demand liquidity [e.g., market orders] (Daniel, 2006, p. 173).

While many agree with Daniel that informed traders will invariably use market orders so as to limit information leakage and improve execution times, some research has been found to support the theory that "if the cost of being picked-off by an informed trader is lower than the expected gain to limit order execution then a limit order strategy can be profitable" (Kozhan & Salmon, 2010, pp. 4). Put differently, limit order trading by informed traders can be profitable, when the cost of information leakage and reduced execution times is low. Still others have found that informed traders actually *prefer* limit orders and that "informed traders may act strategically ... using passive limit order to *hide* information [emphasis added]" (Pascual & Veredas, 2009, p. 530). Others claim that market order traders are the most "uninformed," not because of information leakage or the trade-offs involved in execution time, but because market order traders are willing to

pay (accept) any price the market offers with no regard for the value of the underlying equity (Dick, 2012). Finally some research has found that informed traders are indifferent to order types, instead impatient traders, regardless of how informed, favor market orders, and patient traders, also regardless of how informed, favor limit orders (Pascual & Veredas, 2009, p. 528).

To summarize, the three perspectives on the distribution of traders asserts that informed traders favor either limit or market orders, or neither, and instead order choice type is dictated by other factors, including the patience level of the trader at the time the order was placed. While not necessarily invalidated under the first position, informed traders favor market over limit orders, the face-validity of the model put forth in this chapter would be strengthened considerably under either the second or third position; informed traders favor limit orders; or no correlation exists between private information and the type of order preferred. If, in fact, informed traders favor market orders, then due to the short-term value of the trader's private information, short-term return models, such as this one, should focus on the behavior of those investors compared to those of the uninformed traders in the limit order book. Nevertheless, when the contrary is true, then placing the model's focus, or proxy, on the contents of the limit order book seems appropriate and reasonable. Lastly, if the final supposition is correct, and an even distribution of informed traders exists between market and limit orders, then the selection of the LOB as the acting proxy for short-term sensitivity would appear to be no better or worse than any other indicator to adjust the capital asset pricing model using short-term metrics.

2. The Probability of Presented False Liquidity

Of great concern and more problematic than the distribution of informed traders is the presence of false liquidity in the limit order book. False liquidity is a very different matter from hidden liquidity previously discussed in the literature review. Where hidden liquidity consists of orders not visible to the trading public, false liquidity is comprised of orders visible to the trading public, but that will never be executed. Moreover, the orders, while placed for a variety of purposes, are never intended to be executed and are canceled

before a market order can withdraw the limit order's liquidity. Unfortunately, as was also discussed in the review of literature, increasing cancellation rates can be alarmingly high, 35% for non-HFT and 96% for HFT (Tabb, 2012). Additionally on some international exchanges, nearly 37% of all limit orders are not only cancelled, but also cancelled within 2 seconds of submission (Fong & Liu, 2010, pp. 1873–1874). These statistics suggest a great deal of false liquidity is present in current market conditions, and warrants further examination to determine what, if any, effect this false liquidity may have on the model.

Fong and Liu, of The University of South Wales and the Australian National University, respectively, examined this issue in their published work, "Limit Order Revisions". Fong and Liu find that order revisions, either a cancellation or a cancel and replace, occur for two reasons. The first reason to cancel, or cancel and replace, is when the trader decides the non-execution (NE) risk is unacceptably high – that is the limit bid (ask) price falls (rises) unacceptability far from the last executed trade. The contra-risk to NE and the second major reason for order cancellation is the free option (FO) risk. FO risk arises because the nature of a limit order provides what is essentially an options contract for the order size with no required premium. While with rising NE risk, the trade is increasingly unlikely to execute, conversely as FO risk rises, the trade is increasingly likely to execute (Fong & Liu, 2010, p. 1873). Unfortunately, Fong and Liu find that the probability of cancellation, or ultimately false liquidity, increases with both the size of the order and the proximity of the order price to the price of the last trade (Fong & Liu, 2010, pp. 1873–1877, 1881). In other words, as both the order size increases and the bid/ask price becomes more competitive, the risk of cancellation also increases. In fact, Fong and Liu find that 90% of the revisions and cancellations occur within the first two price steps down the buy side and up the sell side of the entire limit order book (Fong & Liu, 2010, p. 1879). This is unfortunate because those are the very same order for which the model gives the most weight when measuring the short-term sensitivity of the asset against the short-term sensitivity of the broader market. Also important to note, because it may affect the accuracy of the model depending upon when the calculation are made, Fong and Liu find that cancellation and revision "activity intensifies near the end of trading hours" (Fong & Liu, 2010, pp. 1878–1881).

While the simple first question is what undermining effect will invalidating the assumed liquidity in the limit order book have on the presented model, the second more complex question is when an undermining effect is suspected, how can the model be adjusted to compensate for this incorrect assumption? Fortunately, it may be that the false liquidity detected by Fong and Liu will not affect the accuracy of the limit order book balance proxy for short-term sensitivity, because NE and FO risk exist in both the broader market and the individually assessed security, essentially canceling out when the ratio is computed. This assumes the false liquidity in both the broader market and the individual security exists in the same proportion (i.e., particular securities are more or less prone to false liquidity); an assumption for which unfortunately none of which the reviewed literature has explored or concluded on in either the affirmative or negative. Furthermore, and contributing to the validity of the model, nothing in Fong and Liu's research suggests that one particular side of the limit order book is more likely to be filled with revised or canceled orders. If one side of the limit order book was more likely to contain false liquidity the liquidity ratios calculated would be less likely to truly represent the liquidity, in the marketplace or the particular security. Fortunately, no research has suggested such an imbalance exists.

H. DECEIVING THE PROXY

While Fong and Liu identify two reasons for false liquidity, NE and FO, other more probing and algorithmic, less risk-oriented, motives exist, and may represent a not insignificant portion of the limit order book. Accordingly, the proxy and model presented, and in fact, any system employing the limit order book as a source for estimating security returns or trading strategies, may have reduced accuracy and value from the incentive to expose false liquidity. Dark pool liquidity detection techniques and manipulative algorithms are two examples when order may present false liquidity in addition to the more innocuous risk motives described by Fong and Liu. These two cases bear addressing for probability and, when probable, mitigation techniques for identifying and dismissing such liquidity.

1. Liquidity Detection

One of the most popular trading algorithms aims to detect hidden liquidity, and in so doing, may place false liquidity, very briefly, on the LOB inadvertently (Banks, 2010, p. 125). A general example of this will help illustrate the phenomenon. To begin, assume that an institutional investor has to make a large buy order, perhaps 10,000 shares of ABC Corporation by the close of daily trading. In order to avoid market impact, that is, a rise in purchase price from the large buy order, the investor lists his 10,000-share limit order as a hidden order in a dark pool with a bid midway between the national best bid and offer. Unaware of the hidden order, a second actor, the fisher, attempting to locate large hidden orders like this one (ultimately for front-running purposes—though this is a separate discussion), sends a series of small, no more than 100 shares, limit immediate-or-cancel (IOC) orders to dark pools with offer prices also midway between the advertised best bid and offer. If the fisher's 100-share order is submitted to the dark pool with the hidden order, then the order executes, leaving the remaining 9,900 shares still hidden. Otherwise the fisher's 100-share order is canceled after a specified period of time elapses from less than a second to a few minutes. During the interval between the reception of the order and its cancelation, the limit order will be displayed on the LOB unless it has been given clear instructions not to forward the order beyond the targeted dark pool (Banks, 2010, p. 134). This liquidity, however brief, is clearly unintentional and including it in either complex or simple liquidity metrics may degrade the accuracy of the model. This is especially true in the complex model because more value is placed on liquidity near the NBBO, the very place the false liquidity in this example is likely to appear, though this is may not always be the case and where false liquidity appears in the pursuit of liquidity detection.

2. Manipulative Algorithms

Some algorithms meant to manipulate market prices in the short-run may present false liquidity. One such example is the technique of 'quote stuffing', as addressed by both the Norges Bank Investment Management group in 2013 and the 112th U.S. Congressional hearing on *Examining Computerized Trading* in 2012. The practice of

‘quote stuffing’ by sophisticated HFT firms and others, relies on submitting a large number of orders and cancellations on both sides of a trade in rapid succession, with the intent to slow down the release of market data to the broader public. Once the release of market data has been sufficiently slowed, the trading firm exploits their speed to make riskless trades based on their now proprietary knowledge of where the market price will return once the firm stops the stuffing orders. Additionally, these rapid trades create, however briefly, false midpoints (i.e., half the difference from the highest bid and the lowest offer). Dark pool operators then go on to use these false midpoints as reference points in their own algorithms for determining protocols such as execution precedence (NBIM, 2013, pp. 10, 13).

Not only are these manipulative behaviors iniquitous, they are frequent enough to merit discussion as to how they might affect the accuracy of a limit order book based model, such as the one proposed. Market research has found that quote stuffing “is pervasive with several hundred events occurring each trading day and that over 74 percent of U.S. listed equity securities experience at least one episode during 2010” (Reed & Crapo, 2012, p. 36). Although certainly troubling, the characterization of “pervasive” may be a slight exaggeration. Nevertheless, with these techniques affecting less than 8% of the market on a daily basis, the trend is still sufficiently widespread to warrant further discussions on the affect it may have on the model (Santoli, 2013). The quantity of false liquidity could be prevalent on either side of the LOB, depending on the side of the trade the stuffer targets. Proposed regulations to eliminate ‘quote stuffing’ and other malicious trading practices designed to manipulate market prices in the short-term include requiring substantial price improvement, more than \$0.001, before internalizers, such as dark pools change execution precedence; mandating unique identifiers for all trades to eliminate the veil of anonymity in market actions; and requiring a 50 ms minimum quote life to discourage the processing/speed arms race in the high-frequency trading industry (Reed & Crapo, 2012, pp. 36–39). If enacted, these reforms would not only level the playing field for investors of all classes, but it would go a long way toward reducing the false liquidity levels across the limit order books and thus improve the accuracy of the proposed model.

IV. DARK POOL DENIALS: ALTERNATIVE PROXIES AND APPROACHES

Prediction is very difficult, especially about the future.

—Physicist Niels Bohr (1885–1962)

Alternative trading systems (dark pools) pose significant problems for the model outlined in the previous chapter. Before those problems are examined and solutions discussed, a brief review of the rise of dark pools provides needed context regarding the equity market landscape as it stands today. This chapter begins by discussing what solutions dark pools provide to markets and market participants. The chapter then addresses the unintended consequences these dark pools have in general and on macro-level liquidity models, such as the one proposed. The chapter then addresses and proposes alternative macro and micro-level liquidity proxies, other than the LOB. From there, the chapter looks beyond liquidity, and discusses several other metrics of short-term sensitivity, both proposed and tested in outside research including social network trends, “expert” forums contributions, and a specific web query statistic known as the search volume index (SVI). Finally, the chapter concludes by revisiting both the efficient market hypothesis (EMH) and the adaptive market hypothesis (AMH), briefly addressed in Chapter III. These theories are examined in light of the various proxies, answering the question of how EMH and AMH theorists would expect the market to respond to widespread employment of these metrics in return analysis.

A. SOLUTIONS DARK POOLS PROVIDE

As was first addressed in Chapter I, dark pools offer a number of significant advantages over their lit counterparts including confidentiality, reduced market impact, cost savings, and even price improvement. The nature of dark pools offers participants confidentiality by not openly publishing the contents of the limit order book to market actors. A side effect of this confidentiality is a reduction in market impact of large trades. For example, it is not unreasonable to expect that when a large institutional block buy

trade was made public, as it would be in a lit exchange, smaller market participants would try to jump ahead of the block order, effectively pushing up the purchase price for the institutional investor. This effect, known as market impact, is reduced in dark pools because anticipating the removal of that liquidity by the institutional investor is more difficult, though not impossible (Banks, 2010, pp. 5–6, 125).

Dark pools also offer long-term transactional cost savings through increased competition in the exchange landscape. In March of 1792, the “Buttonwood Agreements” established a central monopoly exchange in New York, which was the precursor to the New York Stock Exchange (Markham & Harty, 2010, pp. 868–869). In 1861, and in the face of rising competition, the NYSE board made changes to the exchange’s constitution, prohibiting exchange members from trading securities outside of the NYSE (Markham & Harty, 2010, p. 869). This exchange monopoly would continue relatively unrivaled for nearly a century until the National Association of Security Dealers (NASD), formed a rival exchange in 1968, the Nasdaq. Even with increased competition from the Nasdaq and other in house broker/dealer exchanges, the NYSE continued to execute nearly 70% of all trading volume and 80% of all listed company trading volume as recently as 1993 (Markham & Harty, 2010, p. 877). Against strong objections on market fragmentation and reduced liquidity concerns from the NYSE, central market regulatory changes in the 1990s allowed the Nasdaq and other electronic exchanges (ECNs) to grow both in popularity and volumes. By 2000, the NYSE was faced with a full-fledged competitor for the first time as Nasdaq volume began to eclipse the New York Stock Exchange by nearly a billion shares a day (Markham & Harty, 2010, pp. 880, 899). While Nasdaq was gaining ground on the NYSE, the SEC put in place another regulation in 1998, Reg ATS, which would govern the rules for creating and operating alternative trading systems. Rule 301 of Reg ATS defines ATSS as registered, self-governed, public quote systems operated as broker/dealer exchanges with 5% or more of the total daily trading volume (Banks, 2010, p. 8). With volumes as a proxy for exchange profit and with the rise in trading volumes on ATSS (dark pools) to nearly 20% of total trading volume by 2010, both market fragmentation and competition have substantially increased over the past century (Bank, 2010, p. 6). All of this is to say, competition in the exchange landscape

has led to a significant reduction in fees, to the lowest levels since the modern markets' inception, as exchanges vie for liquidity and volume (Hau, 2006, p. 863). These lower fees can, at least in part, be attributed to the rise and dominance of ECNs along with ATSS over the past 100 years broadly, compounded by substantial market fragmentation over the past twenty years (Lee, 2007, pp. 2–3, 20). A visual breakdown, by volume of market fragmentation, as of 2007, is shown in Figure 24. While at the time of publication Direct Edge, BATS were the leading third-party dark pools, since publication, still others have grown in volume, such as Instinet and LevelL ATS (Banks, 2010, p. 199). The broker/dealer dark pools are also known as internalizers, as discussed in previous chapters.

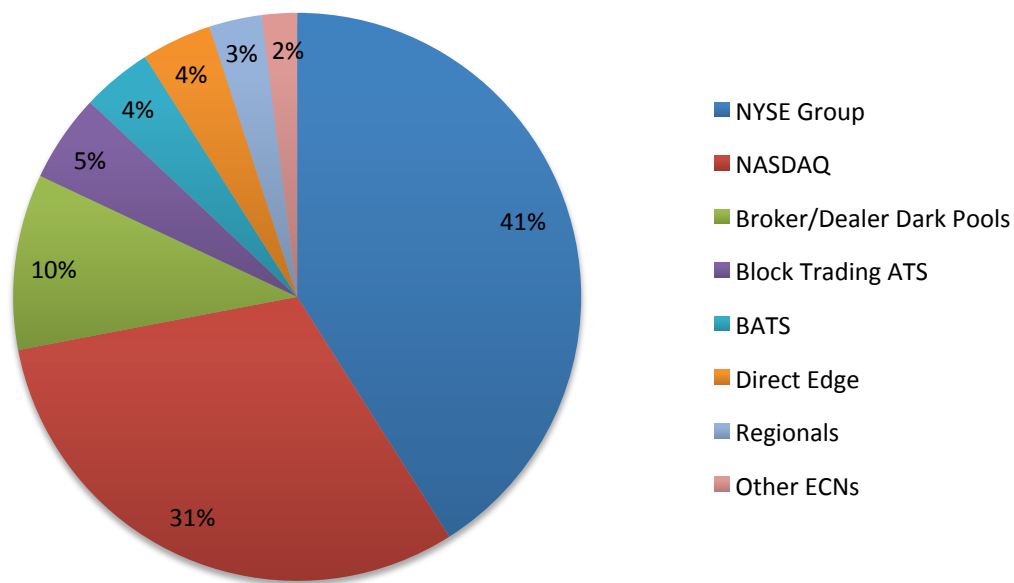


Figure 24. Market Fragmentation of as Q3 2007 (from Lee, 2007, p. 2)

As an aside, some research has suggested that the unfortunate consequence of this cost reduction or loss of trading friction is an increase in volatility, as barriers to trade have been removed. This research has led some prominent economists to suggest a transaction tax to raise trading costs, which would discourage speculations and reduce

volatility, including John Maynard Keynes and former Secretary of the Treasury, Lawrence Summers (Summers & Summers, 1989 pp. 262–263).

The last great advantage dark pools provide is price improvement. While operating under the U.S. paradigm of a national best bid offer system, at first, price improvement over the market price appears superficially impossible, however, in light of the reduced market impact described above, price improvement is possible and achievable. Considering the institutional buyer example above, any achieved reduction in market impact is going to have a direct relationship to a lower cost basis of the share purchases by the institutional investor. This lowered cost basis is the final advantage, and driving factor “a venue that can interact with dark liquidity to routinely deliver price improvement will attract interest” (Bank, 2010, pp. 6–7).

B. PROBLEMS DARK POOLS CREATE

While the rise of ATSS and internalizers provide significant benefits as described, dark pool detractors offer a number of legitimate critiques stemming from a lack of transparency and excessive market fragmentation. Additionally, dark pool hidden liquidity make calculating aggregate cross exchange liquidity levels difficult.

1. Lack of Transparency

Apprehensions stemming from dark pools and an absence of transparency are both growing and considerable. The most vocal of critics are concerned about unintended consequences of the anonymity, the difficulty in auditing problematic algorithms, as well as incomprehensible order flow and matching procedures. Since 2012, regulators and industry insiders have recommended supervisory changes to dark pools that would require unique identifiers, tied to market participants, to be attached to successfully matched orders. This would remove “the cloak of anonymity that has allowed for manipulative behavior” and provide for emergency contact information (Reed & Crapo, 2012, p. 5). These unique identifiers would provide market participants and regulators the security construct of non-repudiation, principally the prohibition of actors to deny actions taken. Not only does such a list of authorized dark pool actors not exist, today the converse is true; thus “anonymity is protected by SEC under Reg ATS, so there isn’t a

single consolidated list of ATSS and the SEC will only provide the information under a Freedom of Information Act filing” (Tabb, 2012, pp. 10-11).

Closely related to the manipulative market behavior allowed by anonymity is the discussion of audit trails. Audit trails, that is a detailed record of trades executed, by whom, at what price and time, is neither required nor exists in most dark pools. Just as in the case of non-repudiation above, comprehensive audit trails would also have a “chilling effect” on manipulative behavior, allowing regulators to quickly and easily “reconstruct what happened within the market” (Reed & Crapo, 2012, p. 21). Additionally, comprehensive audit trails would provide market participants greater ability to evaluate trading algorithms for effectiveness, identifying bugs early and often to reduce mishaps, such as the flash crash in May 2010. Although anomalies in algorithms will never be eliminated, comprehensive audit trails, currently not implemented in dark pools, would provide developers an outlet to recreate market actions to better respond in the future (Reed & Crapo, 2012, pp. 1, 20).

The last major concern stemming from a lack of transparency is the unpublished matching priorities of individual dark pools. While matching priorities in lit exchanges are open and defined, based on price discrimination as well as order arrival time, dark pools matching protocols and order routing methodologies are private and considered by many dark pool operators to be proprietary (Tabb, 2012, pp. 10-11). One such example of proprietary matching protocol gone awry comes from an SEC investigation into Pipeline Trading Systems, a now shuttered dark pool operator. Although Pipeline was assumed to be matching buyers and sellers with dark liquidity, in fact, the operators were secretly trading against clients, often for a profit (Reed & Crapo, 2012, p. 82). Pipeline ultimately settled with the SEC for deliberately taking advantage of their matchmaker role in marketplace and reopened under a different name, Aritas (Patterson & Strasburg, 2012). While Pipeline’s procedures may not be indicative of how most dark pools operate, critics maintain that the industry-wide opaque matching protocols contribute to a deterioration of investor confidence (Reed & Crapo, 2012, p. 81) Additionally, difficulties measuring aggregate liquidity stem from a lack of transparency. This issue is discussed separately because of the effect this concern has on the model put forth in Chapter III.

2. Market Fragmentation

While exchange competition has decreased transaction costs, there are a number of less tangible costs incurred from decentralizing the exchange market structure. With stocks trading electronically on 13 national securities exchanges and more than 50 dark pools, many believe the market is overly fragmented and in turn overly complex (Reed & Crapo, 2012, pp. 8). The critics endorse the idea that the overly fragmented state of the markets has led to trends, such as adverse selection and widening price spreads to rise. Additionally, critics point to the differences in regulations governing lit and dark exchanges as contributing only to the complexity of the landscape, and that a unified regulatory approach would “level the playing field” for both exchanges (Reed & Crapo, 2012, pp. 17, 46).

As was already briefly discussed in Chapter III, adverse selection, trading with a more informed actor to the detriment of the less informed, poses considerable obstacles to investor confidence. Some believe market fragmentation, and specifically dark pool growth in volume and quantity, increases the probability of adverse selection. Again speaking before Congress, Lauer of Better Markets, a market structure and high-frequency trading consultant firm, describes the state of adverse selection when he claims, “As order flow goes from place to place ... before it gets to the lit exchange, it is picked off at every step of the way by internalizers, by dark pools, by high-frequency traders, proprietary trading desks” (Reed & Crapo, 2012, p. 17). Lauer goes on to address the remaining order, finally hitting the common exchanges, when he says, “the flow that eventually gets to the lit exchanges is what we refer to in the industry as toxic flow that nobody wants to trade with” (Reed & Crapo, 2012, p. 17). Lauer and others believe the overly complex order routing procedures, starting with internalizers, then internal and external dark pools, then ultimately lit exchanges, as depicted in Figure 5, significantly affects the quality of the liquidity in the conventional exchanges. This also provides a challenge to the model presented in the previous chapter, as this is the very liquidity against which short-term sensitivity is measured. If Lauer is correct, and this liquidity represents the remains of uninformed investors, so-called ‘toxic flow’, then the validity of the model is uncertain, at best, and possibly misleading, at worst.

Some research has shown that bid/ask spreads are widening as a result of fragmented liquidity spread between the dozen national exchanges and 50 dark pools. Specifically, one such study out of Rutgers University finds that since the rise in popularity of alternative trading venues, bid/ask spreads at the NYSE have increased by an average of \$1.28. While a \$1.28 may seem superficially insignificant, over the long-term this dramatically increases transaction costs, volatility, and market friction (Reed & Crapo, 2012, pp. 17, 37). While causality has proved difficult to assess, research has shown a positive correlation between bid-ask spreads and volatility (Frank & Garcia, 2010, p. 222). Additionally, transaction costs are indirectly raised proportionally to the increases in the spread as market orders are forced to accept the lower (higher) bid (ask) price. Finally, although not synonymous with transactions costs, market friction (i.e., the ease at which investor can move between investments and cash) is increased with transaction costs (Langlois, 2005, p. 2). Although a solution outside of some degree of consolidation is unclear, for these reasons and others, widening spreads as a result of market fragmentation, are of great concern to industry experts, regulators, and governing bodies (Reed & Crapo, 2012, p. 17).

The last concern stemming from market fragmentation is that different regulations governing lit and dark exchanges have led to an overly complex rule set, which is, though unintentionally, negatively affecting investor confidence and their command of the exchange landscape. Advocates of unified rule sets governing lit and dark pools believe that incorporating Reg ATS within Reg NMS will provide investors, financial professionals, regulators, and the broader public a clearer understand of market mechanism. Although some regulations will continue to be separate out of necessity (i.e., hiding large block liquidity is the point of dark pools and will need to be preserved), some rules could be more broadly applied without undue burden to the exchanges, such as requiring more substantial price improvement, more than \$0.001 for example, for execution priority to discourage front-running (Reed & Crapo, 2012, p. 37). Critics of this approach believe that subjecting dark pools to similar regulatory requirements, as their lit counterparts, will dampen the innovation they provide, marking a return to a market landscape where large institutional investors are easily identified and exploited (Reed & Crapo, 2012, p. 22).

3. Measuring Aggregate Liquidity

The final cost from the rise in dark pools is the considerable difficulty in measuring aggregate liquidity in the marketplace. As was mentioned previously, this cost stems from the lack of transparency inherent in a design principle of dark pools. That design principle, to protect large block order liquidity from exploitation, necessitates the unfortunate side effect of hiding, not only single large block orders, but aggregate liquidity, and so there is no publically displayed limit order book. Again speaking to Congress on the topic of detecting aggregate market liquidity supply, Andrew Brooks, Vice President of US Equity Trading at T. Rowe Price Associates said, “it is awfully hard to figure out the supply demand equation in the stock today when there are so many different places that trading interests reside” (Reed & Crapo, 2012, p. 17). This is a considerable obstacle for implementing the model outlined in the previous chapter. The remainder of this chapter will look at overcoming this obstacle through alternative methods of measuring aggregate liquidity using both what LOB data is available, beyond the LOB, and, more broadly, alternatives to liquidity for measuring short-term sensitivity.

C. VISIBLE LOB AS A SAMPLE FROM THE LARGER LIQUIDITY POPULATION

Measuring both sides (buy/sell) of aggregate liquidity of a single security across 13 national exchanges, more than 50 dark pools, not to mention dozens of internalized exchanges collocated with broker/dealers, then comparing that against the aggregate liquidity of both sides of the entire market is not feasible because of the design principles involved in the operations of those exchanges, specifically internalizers and dark pools. Unfortunately, information gleaned from the few exchanges with open limit order books cannot be considered a sample taken from a larger population of liquidity because the population distribution is unknown and the sample taken from the population cannot be randomized. Any sample taken from the open limit order book would fail the randomization test because not all orders are equally likely of selection. In fact, a large portion of the population, those orders placed or executed in dark pools and internalizers, are specifically excluded from the population (Plackett, 1971, pp. 91–94). Although a different context, this selection problem is what Lauer references when explaining how

only liquidity is “picked off” before arriving at the lit exchanges. The “picking off” process at various non-public exchanges along the way depicted in Figure 5 leaves the remaining data set sample non-random, and therefore difficult to make inference conclusions on the larger population’s sensitivity to short-run metrics such as liquidity.

D. MICRO-LEVEL (SINGLE ORDER) LIQUIDITY, NO PROXY REQUIRED

While measuring market-wide, aggregate liquidity may not be feasible because of the growth in dark pools and internalizers, observing micro liquidity, that is single orders, was feasible until recently through so-called “flash orders”. First introduced in the options market in 2004, flash orders are limit orders originating in either dark pools or internalizers that are not marketable, that is, not immediately executed (DeCovny, 2010, p. 28). After the order is placed and not executed, but before it is routed to lit and open exchanges, the details of the order, size, bid/ask price, et cetera, are flashed for other broker/dealers participating in the market as a “second chance” for the order to execute. If after the flash, the order still is not executed, it is then forwarded to the lit exchanges. Some exchanges, such as the Nasdaq’s Dark Pool, INET, will, by default, flash orders even if the order instructions detail the order as non-routable. Many have criticized this practice as antithetical to the *raison d’être* of dark pools; protect large single order from information leakage (Schmerken, 2009, p. 5). Supporters of flash orders have countered by insisting orders are not required to flash regardless of routing instructions, and decisions on whether orders are flashed should be left up to market participants not regulators.

In 2009, the Securities and Exchange Commission, along with its chairperson Mary Schapiro, first proposed a ban on flash order. According to Schapiro, “flash orders have the potential to discourage publically displayed trading interest and harm quote competition among market” (Mehta, 2009, p. 20). Schapiro and other critics believe, correctly, that publically displayed trading interests, namely from open limit order books, are reduced as flashed orders are taken out of liquidity before they are routed to public exchanges. Additionally, Schapiro criticizes the two-tiered design where only a small portion of the overall market pays to receive flash orders from proprietary feeds operated

by the dark exchanges. In the wake of the SEC proposal, many, but not all, dark pools have shut down their flash order mechanisms. Since 2009, however, the SEC has made no statements about plans to implement the ban.

Unfortunately, these micro-liquidity single flash orders provide little context for extrapolating to aggregate liquidity metrics as described in Chapter III. Again, as was the case with the visible LOB previously addressed, selection bias proves to be a limiting factor, as those orders that either unknowingly or intentionally choose to display otherwise hidden liquidity cannot be inferred to be a representative sample of the broader liquidity population. Beyond the controversial practice of front running, these orders may offer limited economic value. Perhaps, aside from political pressure, this is why many dark exchanges are no longer publishing such orders and/or never began the practice.

E. BEYOND LIQUIDITY: OTHER PROPOSALS FOR ADJUSTING RETURN ESTIMATES IN THE SHORT-RUN

It will now be of some value to expand the proxy search beyond liquidity, because of the previously outlined limitations in its observations, both in the aggregate and at the single order level. The theory and practice of economic forecasting is not new and the topic has intrigued economists for decades. For example, in 1990, recently retired Federal Reserve chairman Ben Bernanke advocated that interest rate spreads, defined as the difference in rates between various financial assets, could serve as a viable predictor of future economic activity and growth (Bernanke, 1990, pp. 51–52). Specifically, Bernanke investigated the forecasting reliability derived from the difference between commercial bond interest rates and the Treasury bill rate. Bernanke postulates that the economic activity is negatively correlated with the interest rate spread, because either a) the interest rate on commercial paper will rise, faster than Treasury bills, as investors observe an economic downturn, or b) the interest rate spread is a derivative of monetary policy, and that future decreases (increases) in economic activity will force the federal reserve to lower (raise) the target rate, ultimately widening (narrowing) the interest rate spread (Bernanke, 1990, p. 52). While Bernanke does not conclude with either hypothesis, he rather outlines specific predictions that, if true, in the coming decades will confirm which hypothesis is the more likely, and what value can be gleaned from the interest rate spread

moving forward. As a perfect transition to a discussion on the lessons of both the efficient and adaptive market hypothesis, these predictions are revisited at the conclusion of this segment. Firstly, however, this section examines various other predictive proxies in current research, including social network activity, search activity on two different engines, and Internet forum posts, also on two different forums.

Stemming from the open nature of the network and protocol, Twitter has served, with varying levels of success, as the focus for many studies in prediction. Though only peripherally related to financial markets and prediction, one of the clearest, thorough, and well-reasoned studies examines both the truthfulness along with the newsworthiness of Twitter feeds as an “automatic discovery process” (Castillo, Mendoza, & Poblete, 2012, p. 560). Although not related directly to prediction, research of this nature is included in the discussion based upon the assumption that any predictive protocol’s success would, at least in part, be a function of the protocol’s ability to distinguish between true/false and varying degrees of relevance to the prediction at hand. The authors examine, both on aggregate and single tweet levels, the micro blogging service during natural disasters and emergencies. Additionally, in section five, the authors outline a classifier protocol for first determining the truthfulness of tweet, then, after false tweets have been discarded, determines the tweet’s newsworthiness using historically observed correlative relationships. Some of the most useful relationships include a positive correlation between credible tweets with URL sourcing, follower counts of the author, and length of the tweet. Furthermore, the study found a negative correlation relationship between credible tweets and excessive punctuations, specifically question marks, exclamations, as well as the frequency of first and third person pronouns (Castillo, Mendoza, & Poblete, 2012, pp. 574–576). On the evaluations of newsworthiness, which could be aptly refined and re-designated market newsworthiness, the authors find a negative correlation between relevance and frequency of hashtags, emoticons, as well as a positive correlation with respect to tweet length and “fraction of URLs pointing to domains in the top 100 most visited” (Castillo, Mendoza, & Poblete, 2012, pp. 572–574). Using those correlative relationships the authors built a cascading protocol to first automatically evaluate the newsworthiness in addition to the credibility of tweets. While the author’s protocol failed

to improve on evaluating newsworthiness levels in tweets when compared to human evaluation, it did succeed when evaluating credibility levels (Castillo, Mendoza, & Poblete, 2012, p. 579). Protocols such as this, and others like it, may become increasingly valuable to financial professionals or investors for use in both predictive algorithms, as is discussed next, and high-frequency trading algorithms that respond dynamically to breaking news, as is discussed briefly in Chapter V.

1. Aggregate Twitter Activity Forecasts Broader Economy and Industry

Three studies, two in 2011 and one in 2012, examine the relationship between aggregate Twitter feeds and the broader equity market in the U.S. While Bollen, Mao, and Zeng (2011) examine a predicative correlation between the “mood” on Twitter and the closing price of the Dow Jones Industrial Average (DJIA), Zhang, Fuehres, and Gloor (2011) examine a predictive positive correlation between a fear/hope index with the DJIA, and a negative correlation to the volatility index, VIX. Zhang, Fuehres, and Gloor’s follow-up work in 2012, continues to focus on Twitter feeds, while broadening the predictive realm to currencies, commodities, and employment outlook. Returning to the 2011 studies, Bollen et al. find that on Twitter, when quantified, only expressions of calmness have a “causality relationship with DJIA for lags ranging 2-6 days.” Ultimately without predicative qualities, Bollen et al. examine quantified expressions of alertness, sureness, vitality, kindness and happiness, drawing on data set collected from February to December 2008 (Bollen, Mao, & Zeng, 2011, pp. 2, 5). Graphical representation of the predictive relationship, normalized, between calmness and the DJIA is depicted in Figure 25.

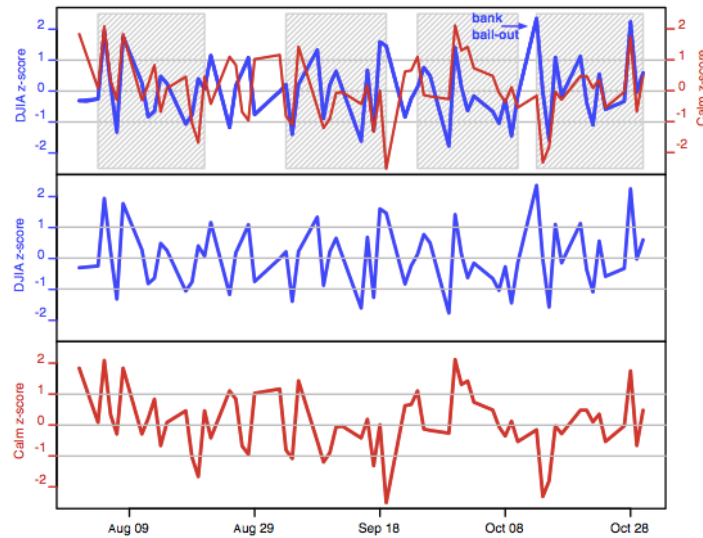


Figure 25. Normalized: Day-to-Day Differences of DJIA with Twitter Calm Index Overlaid (Top), Day-to-Day Differences of DJIA (Middle), and Twitter Calm Index (Bottom) (from Bollen, Mao, & Zeng, 2011, p. 5)

Zhang, Fuehres, and Gloor’s 2011 study finds somewhat contradictory results when examining a dataset of roughly 40,000 tweets per day from 30 March to 7 September 2009 (Zhang, Fuehres, & Gloor, 2011, p. 56). Zhang et al. examine the predictive relationship between emotion levels expressed in tweets with the direction of the DJIA, S&P 500, and Nasdaq on the following trading day, finding a negative correlation between the level of emotion and those indexes. This negative correlation existed regardless of whether the emotional level stemmed from positive or negative sentiment. In the words of the authors, and with mild exaggeration, “when the emotions on Twitter fly high, that is when people express a lot of hope, fear, and worry, the [index] goes down the next day” (Zhang, Fuehres, & Gloor, 2011, pp. 60-61).

The authors’ more compressive 2012 follow-on work examines a broader set of keywords including “gold”, “dollar”, “\$”, “oil”, “economy”, and “job” with their relationship to market movement across equities, currencies, and commodities. Zhang et al.’s dataset, a collection of five months of tweet from the first half of 2011, contains nearly 4M re-tweets from more than 961k users (Zhang, Fuehres, & Gloor, 2012, pp. 1, 3). The authors find that, of the keywords examined, “dollar” is the most predictive variable with a correlation coefficient of more than .3 at $t+1$, decreasing coefficients at

$t+2$ and $t+3$. Conversely, only “\$” and “job” contain a no more than chance correlation to the targeted markets as a predictive variable (Zhang, Fuehres, & Gloor, 2012, pp. 7, 10). Finally, the authors concede that their simple algorithms for re-tweet collection could possibly be made more effective by constraining their dataset with hashtags relevant to financial market sentiment, as well as considering non-linear relationships between Twitter sentiments at t and market movements in $t+x$ (Zhang, Fuehres, & Gloor, 2012, p. 11).

2. Aggregate Twitter Activity Forecasts Individual Firm Values

Moving away from macro-economic predictions, a number of studies have been conducted to examine the relationship between Twitter mentions as a forecasting variable for individual asset values and short-term returns. One such study examines stock prices and returns of 18 Fortune 500 publically trading companies and the tweets associated with those companies. The authors find that, beyond what can be explained by fluctuations in the broader market, 8.3% of the variability in the companies’ share price can be explained through Twitter macro analysis (Evangelopoulos, Magro, & Sidorova, 2012, p. 247). The authors’ dataset included approximately 3.85M tweets, filtered for relevancy, collected from 1 November 2010 to 15 January 2011 (Evangelopoulos, Magro, & Sidorova, 2012, p. 252). Furthermore, and particularly relevant to this thesis, the authors examine what inferences, gleaned through macro evaluations of tweets, can be applied to the capital asset pricing model. After analyzing the findings from the dataset, the authors modified the CAPM such that

$$RA_i = r_i - \hat{r}_i = r_i - (\hat{\alpha}_{ii} + \hat{\beta}_{ii}r_I) \quad (21)$$

where RA is the return anomalies for asset i , r_i is the actual return of asset i , \hat{r}_i is the expected return of asset i , and $\hat{\alpha}_{ii} + \hat{\beta}_{ii}r_I$ is the classically defined CAPM formula and best estimated using historical regression (Evangelopoulos, Magro, & Sidorova, 2012, pp. 254–255). Evangelopoulos et al. go on to discuss the return anomalies as variations in returns unexplained by returns in the broader market, I , and apply those return anomalies

to the 53 observed trading days and 18 observed companies, for a total of 954 data points, depicted in Equation 22.

$$RA_{ij} = \beta_o + \theta TV_{ij} + \sum_{k=0}^6 \sum_{d=1}^{20} \beta_{dk} T_{ijd,t-k} + \varepsilon_{ij}, \quad 1 \leq i \leq 53, \quad 1 \leq j \leq 18 \quad (22)$$

where TV is the tweet volume associate with asset j on day i , T is the “tweet topic factor” strength, also of asset j on day i , with a lag window of 6 days, and with 20 different “tweet topic factors” (Evangelopoulos, Magro, & Sidorova, 2012, pp. 254–255). The authors’ definitions of the 20 tweet topic factors vary from the product specific (e.g., Xbox or Android) to generic shopping terms such as *buy*, *deal*, or *get*. By breaking the data down by tweet topics, the authors’ teased out inferences that otherwise may have gone unnoticed, such as a slight negative correlation between individual firm stock performance in the day immediately following a spike in references to *deals*, *gift cards*, and *sales*. More broadly, the authors find a negative correlation between the sheer number of tweets about a firm and the firm’s stock performance on that trading day. Conversely, the authors find that “tweeting about ‘*buying*’ or ‘*getting*’ something is positively reflected in the future stock performance of the companies mentioned in those tweets, even though some of the effects are delayed by several days [emphasis added]” (Evangelopoulos, Magro, & Sidorova, 2012, pp. 255–258, 262–263).

A different study, peripherally also related to Twitter, takes an unusual twist on the approaches and theories of the research already discussed. The authors’ postulate that instead of *predicting* future market forces determined firm values, social network aggregate buzz can instead *influence* future firm values. Luo and Zhang, of no relation to past-referenced work, focus on user-generated reviews from the online consumer report website CNET.com. Luo and Zhang find a positive correlation between buzz level (i.e., the level of advocacy for a particular brand), buzz volume (i.e., the sheer quantity of mentions for a particular brand) and the individual firm value (Luo & Zhang, 2013, pp. 213, 220). When quantified, the authors find that firm buzz can explain as much as 10.75% of individual firm value beyond what can be explained by fluctuations in the broader market, and as much as 11.49% of the variation in the idiosyncratic risk of the individual firm (Luo & Zhang, 2013, p. 227). This is not entirely unexpected. The authors

make clear no causal link can be established directly between the buzz and the individual firm’s stock price. More likely a hidden variable, such as well-received product lines and customer service, explain both the variations in individual return and the buzz surrounding a particular company or product (Luo & Zhang, 2013, pp. 226, 234–235).

3. SVI Forecasts Individual Firm Values

Two studies, one from 2011 and one from 2012, examine aggregate search histories in an aim to detect correlations between volume and firm value. Da, Engelberg, and Gao find that an increasing search volume index (SVI) may predict higher individual firm share prices with an ultimate price reversal within one year (Da, Engelberg, & Gao, 2011, p. 1461). Google provides and defines weekly SVI for a term as the “number of searches for that term, scaled by its time-series average” (Da, Engelberg, & Gao, 2011, p. 1463). A useful example of SVI is depicted in Figure 26 as a graph for the terms “*diet*”, and “*cranberry*”.

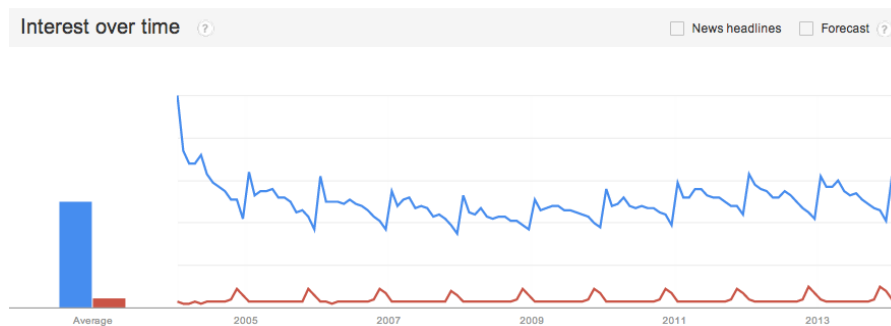


Figure 26. SVI Graph for “Diet” (blue) and “Cranberry” (red) (from Da, Engelberg, & Gao, 2011, p. 1464)

As expected the SVI for “diet” jumps after the New Year, slowly declines throughout the year and then jumps again as New Year’s “resoluters” the world over flock to loose holiday weight. Similarly, “cranberry” SVI jumps just before Thanksgiving and then tapers throughout the holiday season (Da, Engelberg, & Gao, 2011, p. 1464). Interestingly, Da et al. finds that among stocks experiencing an increase in the average SVI during week t , will also experience an increase in share price by an average of 30 basis points in weeks $t+1$ and $t+2$. The increase, however, is short-lived with a near

complete reversal, on average, within one year (Da, Engelberg, & Gao, 2011, p. 1465). Da et al. sample stocks from one of the most comprehensive U.S. indexes, the Russell 3000, which contains the 3,000 largest firms and comprises more than 90% of the total U.S. public market (Da, Engelberg, & Gao, 2011, p. 1466). Da et al. conclude that their findings show that Google’s SVI is one of the few metrics capable of directly assessing investor interest outside of trading volume and returns (Da, Engelberg, & Gao, 2011, p. 1476). While the authors make no mention of liquidity as a metric, it remains a logical extension of both volume and returns as a quantifiable method of assessing investor interest, as was described in Chapter III.

In 2012, a second study, with a similar scope and aim, using Yahoo! search queries and a more limited dataset of the Nasdaq 100, Bordino et al. find a strong correlation between the volume of queries and the volumes of traded equities (Bordino et al., 2012, p. 2). Of interest, Bordino et al. find both predictive forecasting qualities inherent in their data, and “nowcasting” traits that show peaks in volume of search queries overlapping with trading volumes having a lag of up to 3 days after the search queries (Bordino et al., 2012, p. 2–4). A graphic example of this result, normalized peaks in time-series near overlapping in trading and search volume, is depicted in Figure 27.

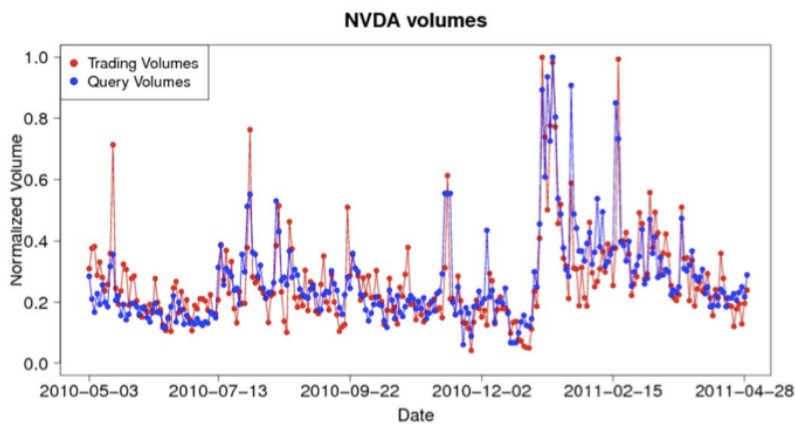


Figure 27. NVDA’s Overlaid Normalized Trading and Query Volumes (from Bordino, 2012, p. 4)

Bordino et al. believe that this relationship, frequently referred to as the “wisdom of the crowds”, could be used, in addition to volatility forecasting, as a short-term stress test to “detect early signs of financial distress” (Bordino et al., 2012, pp. 7–8).

4. Expert and Novice Forums Forecast Individual Firm Value

In addition to search queries, Twitter feeds, and user-generated reviews, various studies have examined forums in aggregate for economic value. One of the first studies to examine this take on the ‘wisdom of the crowds’ effect was conducted in 2004, by two Canadians, Antweiler and Frank. They examine Yahoo! Finance forum boards for bullish/bearish sentiment, its effects on returns, the level of disagreement on boards, and the volume associated with those equities at the time. Additionally, the authors examined volatility and what information, if any, can be gleaned from the forums in advance of that volatility (Antweiler & Frank, 2004, p. 1259). The dataset, approximately 1.5M forum posts, was examined in aggregate for bullish/bearish predictions as well as the level of disagreement between forum users. Antweiler and Frank find that regardless of sentiment, while an increase level of activity predicts statistically significant negative returns the following day, the short-term negative returns are most likely economically useless compared to the required transaction costs. Additionally, the researchers find that disagreement levels and forum volumes on day t have a positive correlation with trading volumes and volatility on day t . Finally, the authors also find increased disagreement levels have an unexpected negative correlation with trading volumes on day $t+1$ (Antweiler & Frank, 2004, p. 1264, 1292).

A second, more recent and filtered study, from 2011, concerning forum postings in aggregate, targeted the Motley Fool CAPS message boards (a search internal and external to the boards reveal CAPS is not an acronym and is instead merely the name of the board). The authors, Hill and Ready-Campbell, weighted the contributions of users based on their historical returns. This allowed the researchers to “take better advantage of the ‘wisdom of the crowds’ by restricting the crowd to a set of experts” (Hill & Ready-Campbell, 2011, p. 74). The dataset, upon which the conclusions were drawn was collected from January 2007 to December 2009 and contained more than 2M stock picks

from more than 770,000 users (Hill & Ready-Campbell, 2011, p. 76–77). From this dataset, the authors find that, when the overall crowd was relied upon equally, the portfolio of recommendations outperformed the S&P 500 with a -23.2% returned from the crowd and a -35.5% returned from the S&P 500. Additionally, Hill and Ready-Campbell find that when the crowd is thinned to those users with historically better averages, the expert crowd outperforms, moving forward in the future, both the larger population and the S&P500, although no metrics were provided (Hill & Ready-Campbell, 2011, p. 95).

While intriguing, what lasting value do these studies on forums, searches, and tweets provide? Because all of the studies used historical relationships to predict historical results it is difficult to assess what predictive powers the studies have on the days after their publication. As was briefly discussed in Chapter III, some evidence suggests that predictive economic characteristics degrade overtime. This was the case with both Bernanke’s interest-rate spread indicator for broader economic growth as well as Kozhan and Salmon’s Limit Order Book model for economic value (Bernanke, 1990, p. 52) (Kozhan & Salmon, 2010, p. 20). These studies reinforce the notion, integral to both the efficient market hypothesis and the adaptive market hypothesis, that information expires and it generally expires quickly. One vivid illustration of this point is demonstrated in a 2011 paper, “Event-Driven Trading and the ‘New News’”. In it, the authors find that considerable pre-event information leak significantly degrading short-term returns of those looking to capitalize on news as it happens. The research shows that near “90% of the return [occurs] prior to, or to the left of, the event line” with the phenomenon depicted graphically in Figure 28 (Leinweber & Sisk, 2011, p. 113). The graph shows short-term positive and negative returns, measured in seconds, immediately preceding and after the news is released, denoted by the vertical bar midway through the chart. As observed, the majority of the returns, 90% by the authors’ estimates, have already occurred in the seconds leading up to the release.

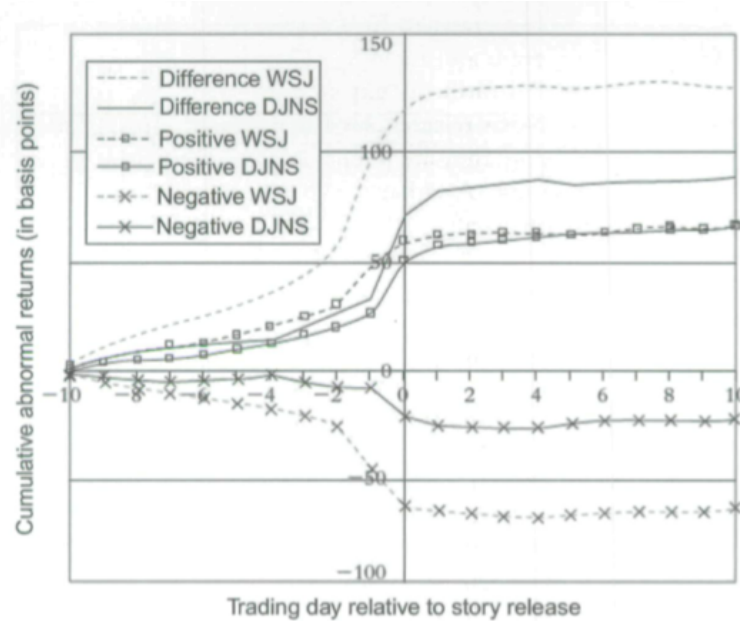


Figure 28. Twenty-Year News Event Studies for the S&P 500, 1984-2004 (from Leinweber and Sisk, 2011, p. 113)

This seeming validation of the efficient market hypothesis and its derivative, adaptive market hypothesis may provide some clarity as to how the market may respond to the predictive indicators described above, from liquidity to social media, search metrics and beyond.

F. ADAPTIVE MARKET HYPOTHESIS AND A RETURN TO EFFICIENT MARKETS

In 1970, two decades before his three factor CAPM contributions, economist Eugene Fama postulated the efficient market hypothesis (EMH) in the paper “Efficient Capital Markets: A Review of Theory and Empirical Work.” EMH postulates that prices in markets, be the asset, bond, stock, options or any other class, reflect varying levels of information, depending on the form of EMH to which the investor subscribes (Brown, 2010, p. 2). The lowest threshold form of EMH, the so-called “weak” form EMH, states that the price of the asset will reflect only all historical information. The “semi-strong” form states that the price reflects all historical information and current publically available information. The “strong” form of EMH claims the price of the asset will always reflect all information, both public and private (Fama, 1970, p. 383). Fama

outlined three market conditions sufficient to support the “strong” form of EMH: i) Zero transactions costs, ii) All available information is free to all market participants, and iii) All market participants agree on the implications of the available information (Fama, 1970, p. 387). Fama is quick to admit that no such market operates under these conditions in reality, and counters that these conditions are not necessary for market efficiency. Specially, Fama claims a market may be efficient when a “sufficient number of investors have ready access to available information” and “disagreements among investors about the implications ... does not in itself imply market inefficiency” (Fama, 1970, p. 388). From the outset, Fama is apprehensive of “strong” form EMH and does “not expect it to be literally true”. He “[contends] that there is no important evidence against ... the weak and semi-strong form tests ... and limited evidence against the hypothesis in the strong form” (Fama, 1970, p. 388). Through various academic studies and research, the semi-strong form of EMH has shown to be the most accurate (or least inaccurate) model for predicting asset pricing. While semi-strong EMH is mostly accepted by the academic community, the community of investment professions has been hesitant to endorse the theory, namely because of the theory’s ultimate conclusions – that financial advisors, as well as mutual fund and wealth managers, will not be able to consistently outperform the broader market using only publically available information (Sorensen, 1983, p. 29). It is fortunate for Fama that this skepticism permeates the investor landscape. As pointed out by James Lorie and Mary Hamilton three years after EMH’s publication in 1970:

This is a curious paradox. In order for the hypothesis to be true, it is necessary for many investors to disbelieve it. That is, market prices will promptly and fully reflect what is knowable about the companies whose shares are traded only if investors seek to earn superior returns, make conscientious and competent efforts to learn about the companies whose securities are traded, and analyze relevant information promptly and perceptively. If that effort were abandoned, the efficiency of the market would diminish rapidly. (Lorie & Hamilton, 1973, p. 98)

All three forms of EMH are predicated, to varying degrees, on both the disbelief in EMH as being accurate and on maintaining investor attention to the information from which that particular form draws its pricings (e.g., historical, all publically available, or all information). Nevertheless, given the overload of the global information age, these

suppositions, particularly the latter, seems increasingly difficult to accept. As the late economist Herbert Simon so aptly said, “A wealth of information, creates a poverty of attention” (Simon, 1971, pp. 40-41).

This poverty of attention has unavoidably led to the treatment of focus as a scarce commodity rather than a limitless lubricant greasing the wheels of all markets to efficiency. The behaviorally-adjusted, adaptive market hypothesis accommodates this deficit of attention by, instead of a rigid faith that capital prices reflect all information, past and present, advocating that “prices reflect as much information as dictated by the combination of environmental conditions and the number and nature of ‘species’ in the economy or, to use a more appropriate biological term, the ecology” (Lo, 2004, p. 23). In other words, evolutionary forces may shape the market more than EMH would suggest. Specifically in AMH, as information or derivations of information relate to short-term returns, as profitable ventures are exploited, they disappear. Nevertheless, “new opportunities are also constantly being created as certain species die out, as others are born, and as institutions and business conditions change” (Lo, 2004, p. 24). Furthermore, these new opportunities are destined to arise because new and surviving species will have varied evolutionary background, which will lend the market participants to differing investing focuses (Lo, 2004, p. 25–26).

In fact, under the premises of both the semi-strong and strong form of the EMH framework, none of the information discussed and derived above, be it liquidity, interest-rate spreads, tweets, search queries, or forum posts, would effectively predict future price movements for the target securities. Yet the success of these indicators and others are not a contradiction under the AMH. AMH would stipulate that these indicators may be successful in the short-run, until mass attentions shift to these practices, thus eliminating any would-be gains from information derived from aggregating liquidity, SVI, et cetera. Encouraging for AMH, this has been observed as the case for both Bernanke and Kozhan and Salmon’s research.

To summarize this chapter began by addressing the rise of dark pools, firstly focusing on the significant advantages they provide large market participants (i.e., reduction in information leakage) and more broadly retail investors (i.e., market

competition driving down transaction costs). From there the chapter addressed a variety of unintended consequences of dark pools ranging from market fragmentation, to regulation complexity, and to a lack of transparency. This opaque nature presents considerable real world implementation challenges for the proposed liquidity-based model, both in macro and micro levels, and, as such, the chapter concluded by examining a variety of alternative current research topics on pricing models.

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V. CONCLUSION AND FURTHER RESEARCH

That mysterious fragile flower where price is part perception, part valuation, and part hope or lack thereof.

—Financial Manager Bill Gross (1944–)

While dark pools represent a clear denial of much of the information required to perform an algorithmic-based liquidity assessment, such as the one outlined in Chapter III, they are not the only condition and concern for algorithmic trading. Deception, that is “the deliberate misrepresentation of reality done to gain a competitive advantage,” poses a considerable risk, as many of the programmers of such algorithms discovered on April 23, 2013 (Daniel & Herbig, 1981, p. 3). On the 23rd, at 1:07 in the afternoon, a news tweet broadcasted via the Associated Presses (AP) to nearly 2 million followers, announced that “Breaking: Two Explosions in the White House and Barack Obama is injured” (Fisher, 2013). The broader market immediately reacted with the DJIA shedding nearly 150 points, or \$136 billion in market value (Fisher, 2013). News spread quickly that the tweet had been a fake; the result of a phishing scheme orchestrated by cyber vandals, the Syrian Electronic Army, a grouping of advocates and possibly surrogates of the Assad regime (Fisher, 2013). By 1:10 PM, the market had fully recovered and the associated press had regained control of their quite influential Twitter feed. While the Syrian Electronic Army offered neither proof nor motive for the hacking, the incident represented a clear financial opportunity for those with advance warning.

Had the algorithms designed to make buy and sell decisions that led to the temporary collapse been more complex, the credibility of the tweet could have been significantly discounted as demonstrated in the aforementioned work of Castillo et al (2012). Many journalists were immediately wary of the tweet for two reasons, 1) the tweet led with “Breaking:” whereas standard AP tweet format dictated such a tweet would have led with BREAKING in all capitals, and 2) standard AP protocol always referred to the President by his title (Jackson, 2013). These intuitive suspicions echo the

words of military deception academic Bart Whaley when, in his 2002 compilation on the topic, he writes, “deceptions can be detected regardless of the field in which they occur” (Godson & Wirtz, 2002, p. 182). Whaley continues, concluding that of his 46 case studies of successful counterdeception all, save one, “used standard logical systems (both deductive and inductive) in combination with intuitive methods” (Godson & Wirtz, 2002, p. 218–219). No great leap of faith is required to conclude that, with adequate pattern recognition algorithms, these two deviations from standard AP tweet format “fingerprints” could have been detected, and it could have been estimated that the tweet was most likely not credible. Even without prior knowledge of the hack, had such a credibly discount determination been made, an algorithm would have stood to make considerable short-term returns by taking the opposite side of the prevailing wisdom, showing that counterdeception is critical to not only avoiding a disadvantage, but gaining a competitive advantage, both on the battlefield and in the marketplace.



Figure 29. AP’s Hacked Tweet: Immediate Aftermath and Recovery (from Farrell, 2013)

This is just one example of how important credibility and deception detection (i.e., counterdeception) should be to algorithmic and high-frequency trading systems. This final chapter will first provide a brief discussion tying military deception and counterdeception paradigms to automated financial decision models in order to ferret out misinformation for more effective assessments. From there, policy recommendations, for both regulators and market participants, are considered, key thesis points are reiterated, and broader implications of these ideas are addressed. Finally, the chapter concludes with future research suggestions and a closing case study.

A. GUNS AND BUTTER: SPEED OR CREDIBILITY?

While orchestrating the deception campaign outlined in the Twitter example would be a clear violation of U.S. securities laws, and classified as securities fraud – not to mention the associated cyber crime and identity theft – profiting from such a campaign without prior knowledge of the deception is a decidedly foggier area of SEC regulation (FBI, 2005). The Twitter example also exposes a major tradeoff, the sacrifice of credibility for speed. High-frequency traders scrapping Twitter feed for pricing decisions did not accurately evaluate the credibility of the specific tweet, choosing instead to base credibility, and by extension pricing decisions, on the credibility of the Twitter user, AP. While this approach, assessing credibility of information on the historical credibility of the source, is not unreasonable and, in fact, is standard practice for intelligence agencies, anomaly detection protocols should still play a role, if only supporting, in assessments (Green, 2003, p. 3). When high-frequency pricing algorithms focus, not just the newsworthiness of the information, but also the inverse relationship between the probability of the specific event (e.g., an explosion at the White House), and the credibility of that information, as advocated by Shannon, increased scrutiny may have detected the outlined inconsistencies (Waltz, 1998, p. 58). Nevertheless, this increased scrutiny would have consumed precious clock cycles associated with the additional algorithmic complexity.

To demonstrate just how valuable those clock cycles can be, consider the case of the two-second advanced copy of the twice-monthly consumer sentiment report. It was reported in the Wall Street Journal that, until recently, the news and business-reporting agency, Thompson Reuters, sold early access to the widely read report on consumer sentiment compiled by the University of Michigan. For an annual fee, Thompson Reuters sold the report to institutional investors and news agencies at 9:55 AM, five minutes before the university publishes the findings to the Internet at 10:00 AM. Moreover, for an additional fee, Reuters distributed the report an additional two seconds earlier, at 9:54:58. While two seconds may sound inconsequential, it provided high-frequency trading firms ample time to make trades in anticipation of the broader market reaction that followed at 9:55. On March 15th, 2013, one such HFT firm, Infinium Capital Management, bet

nearly 7 million shares that the broader market would fall in the two seconds prior to wide spread distribution of the report. Just as Infinium had predicted, the market did, in fact, decline in the wake of the weaker-than-expected report, netting the firm hundreds of thousands in profit in two seconds of trading (Mullins, 2013). Important to note, neither the University of Michigan, Thompson Reuters, nor Infinium broke any state law, federal regulation, or SEC regulation. Only reports released by the government are required by law to be available to all interested parties simultaneously.

In July 2013, Thompson Reuters suspended their practice of releasing the report two seconds in advance to high-frequency clients, which had dramatic effects on market activity. To illustrate these effects, consider the volume of a broader market exchange traded fund tracking the S&P 500. In the 10-millisecond period immediately following the two-second-advanced copy's release a year prior, July, 2012, an estimated 200,000 shares were purchased and sold. Contrasting those 200,000 shares with the 500 that were traded in the 10-millisecond period after the suspension was enacted, the value of advance warning is both apparent and striking (Stewart, 2013, p. B1). Just as reasonable, though not without risk, university and government published reports are assumed as credible as Twitter feeds are of reputable organizations of the fourth estate.

This tradeoff, time spent in credibility verification versus time spent executing trades based on the information, is unavoidable as every clock cycle spent verifying is one less cycle spent executing. Considering that the information landscape, and by extension financial decision inputs, are only likely to continue their expansion, striking the balance between the two activities, verification along with execution, will grow in importance for high-frequency and algorithmic traders moving forward. In addition to the execution opportunity cost, algorithmic credibility assessments, such as the pattern recognition approach described above, are also expected to have considerable real costs, both in IT infrastructure and human resources to build and test the tools necessary to detect anomalies and trade accordingly. Likely, however, the most costly approach would be to neglect credibility entirely, trade exclusively on rumor and hearsay, thus categorically forsaking verification in favor of execution speed. To reiterate, as the business model develops, the most successful algorithmic trading is likely a consequence

of striking the right balance between verification and speed, while where that balance lies is best left for future research and thoughtful consideration.

B. RECOMMENDATIONS AND POLICY CHOICES

Through the sources reviewed for this research, including working papers, journal articles, full-length texts, congressional testimony, newspaper, and industry publications, many dedicate at least of portion of their effort to the topic of policy recommendations and considerations in light of the evolving equity market landscape over the past decades. In that spirit, it will be of value to highlight here recurring and notable recommendations most appropriate for policy makers and industry leaders, given the topics addressed throughout this work. One recommendation, perhaps the wisest, that persisted across topics and advocates was “do no harm”. Tabb most elegantly addressed this advice in his congressional testimony when he read, “the U.S. markets are the deepest and most liquid on the globe. The markets are also complex and interrelated. Small changes can cause significant impact. So, first, do nothing radical. A radical shift of market structure will unquestionably hurt investors” (Reed & Crapo, 2012, p. 10). With that caution in mind, various policy considerations and recommendations are most easily segregated by separating those targeting dark pools from those addressing algorithmic and high-frequency trading.

1. Dark Pools: Audits, Matching, and Licenses

Three recurring policy recommendations address the two primary concerns of the current exchange and dark pool landscape previously outlined in Chapter IV. The first concern, a lack of transparency, is, in no small measure, a balancing act between the need for a fair and level playing field, while maintaining the *raison d'être* of dark pools, which is to protect institutional investors from exploitation of information leakage. This concern could be addressed with comprehensive, confidential, ‘after the fact’ audit trails delivered only to regulatory agencies and more transparency in dark pool matching procedures. The second concern, market fragmentation, can be addressed by limiting the expansion of dark pool licenses, a limiting constraint well within the SEC’s purview (Reed & Crapo, 2012, p. 11).

Two encouraged regulatory changes that, if enacted, kept confidential, and only forwarded to monitoring agencies, would have a “dramatic chilling effect on malicious behavior” in dark pools include audit trails (i.e., a comprehensive trade history) and unique identifiers (i.e., so as to easily identify market actors) (Reed & Crapo, 2012, pp. 21, 37). These changes would preserve the protective role of the pools, while providing regulators recourse to hold manipulative and opportunistic participants accountable, by recreating market interactions in the days and weeks after the trades occurred. While no such requirement currently exists, if enacted, audit trails would also be useful in reconstructing trades in the wakes of extreme volatility and emergencies such as the flash crash in May 2010 (Reed & Crapo, 2012, pp. 21). Important to note, however, multiple authorities from academia to industry suggest that keeping the reporting contents, though not requirements, confidential is crucial to ensuring institutional investor confidence in such pools, as reliable sources of anonymous liquidity (Banks, 2010, p. 181).

Many also agree that matching protocols need to be more transparent for dark pools and that substantial price improvements should also be required for internalized flow in order to circumvent those protocols prioritizing time arrival of limit orders (Banks, 2010, p. 179). For example, Lauer suggests a minimum price improvement of \$.001 for new limit order to skip the queue of those orders already in the stack at that price point (Reed & Crapo, 2012, p. 37). Furthermore, others have suggested that the one-size-fits-all model currently applied to most tick-sizes and minimum price improvements, both in dark as with lit venues, is inappropriate. They believe instead a percentage of the trading price per share would be a better approach to minimizing unnecessary volatility and discourage liquidity detections algorithms (Reed & Crapo, 2012, p. 9) (Tabb, 2012, p. 21). Conversely, minimum tick sizes and price improvements will widen bid/ask spreads, “[reducing] the probability of price improvement”, and “unintentionally force liquidity consumers [i.e., market orders]” to unregulated venues such as broker/dealer internalizers (NBIM, 2013, p. 17).

Consequences stemming for market fragmentation, ultimately from the explosion of dark pools in the exchange landscape, also rank among the most pressing of concerns.

While rolling back those dark pools already licensed under Reg ATS is unrealistic, most recognize that limiting the fragmentation moving forward will not impede innovation or cause an unintended rise in recently reduced transaction costs. Furthermore, additional research is recommended to evaluate the optimal number of lit and dark exchanges, most likely as a function of the size of the equity market. Such research would be vital to calculating how many licenses should be issued, at what rate in order to maintain a balance for competitive forces, and an acceptable level of complexity between the investor and where the order is ultimately executed (Reed & Crapo, 2012, p. 11).

2. HFT: Transaction Taxes, Resting Periods, and Kill Switches

Beyond dark pools, some attention must be paid to recommendations for policy makers and regulators with regard to the expansion of high-frequency computer executed trading. Speaking on liquidity in a forum with former Fed Chairman Paul Volcker, Vanguard founder John Bogle revisited the famous words of an 18th century English poet when he mused, “[Samuel Johnson] had a saying, ‘Patriotism is the last refuge of the scoundrel.’ In this new fast-moving market, I’d advance the idea that *liquidity* is the last refuge of the scoundrel [emphasis in the original]” (Rostad, 2013, p.68). In light of studies revealing that 78% of all executed orders are HFT firms trading amongst themselves, and that nearly 40% of HFT orders are canceled in less than 50ms, supporters advancing HFT in the name of liquidity appear unjustified, even quite possibly, excessive (Zhang, 2010, p. 33) (Reed & Crapo, 2012, p. 36). While two of the three recurring recommendations—transaction taxes and minimum resting times—may adversely affect liquidity, the effect is not expected to be substantial, possibly having favorable impacts on volatility and exchange IT infrastructure. While the third recommendation, circuit breakers, is not expected to impact liquidity and volatility, outside of periods characterized as dangerous levels of volatility, however, it may place additional burdens on exchange infrastructure.

While few in industry suggest or even address a financial transaction tax (FTT), probably for the predictable reasons one might imagine, academia and policy makers have studied such a proposal, remaining unburdened by the bottom lines plaguing their corporate peers. As previously and tangentially addressed by Summers and Summers, a

small FTT would marginally increase transactions costs thereby discouraging speculations and encouraging long term investing (1989, pp. 262–263). Although, under Section 31 of the 1934 Securities Exchange Act, the U.S. does have a transaction tax of \$.0042 per trade, most acknowledge this fee, which ultimately funds the SEC budget, is too minimal to have positive impacts on volatility or adverse effects on liquidity (SEC, 2013) (Pollin, 2012, p. 98). Furthermore, raising the FTT to .05 percent of the trade for equities with a sliding scale for other asset classes, paid by both the buyer and seller, is estimated to raise treasury revenues by \$350 billion or 62% of the president’s 2015 projected budget deficit of \$564 billion (Pollin, 2012, p. 98)(OMB, 2014, p. 163). Nevertheless, allowing Lauer to voice the broader industry concerns with regard to a national FTT, he writes in 2012, “I do not believe a Financial Transaction Tax would have the intended consequences. We have seen dramatic evidence of fleeing liquidity in those markets that have adopted this tax [namely under European market reforms such as the .05 percent FTT applied in the U.K.]” (Reed & Crapo, 2012, p. 72).

Far less controversial for government, industry, and academia is the recommendation of a minimum resting time. Under such a regulation, limit orders could only be canceled after a minimum resting time on the books had expired. While specific recommendations range from 20 ms to an entire minute, general consensus appears that a pilot program should explore minimum resting periods of 50 ms to determine liquidity, spread, and volatility effects (Arnuk & Saluzzi, 2007, p. 5) (Reed & Crapo, 2012, pp. 36, 72). Brewer et al. of the California Institute of Technology examined the projected effects of minimum resting time using simulations, with conflicting conclusions. On the one hand, the authors’ research and simulations showed that, “requiring minimum resting times may be helpful in preventing instabilities in the market” such as the extreme volatility during the May 2010 flash crash (Brewer, Cvitanic, & Plott, 2012, p. 13). They do, however, add a caveat, pointing out that minimum resting times will only be effective when high frequency cancellations are the cause of such instability, a causal conclusion for which evidence is inconclusive. This ultimately leaves Brewer et al. less confident about resting times effectiveness in general (Brewer, Cvitanic, & Plott, 2012, pp. 13, 18).

The final recommendation, and perhaps most the innocuous, is the application of circuit breakers, also referred to as “automated kill switches” or simply “kill switches”. This reform would require exchange mechanisms to stop trading during periods of extreme volatility or uncertainty. Most sources were scant on details outlining when acceptable, healthy volatility suddenly crosses the line to intolerable, a factor not insignificant when considering implementation. Most approached the kill switches not by targeting the entire market, but rather HFT firm specific switches, in order to isolate rogue algorithms acting unpredictably, which is typically a result of bugs or glitches in the underlying logic (Reed & Crapo, 2012, p. 47). The most notorious example of which occurred on August 1st, 2012, when market maker and liquidity provider, Knight Capital Group, released untested algorithms on the broader market. Shortly after morning trading began, Knight Capital’s algorithm went on a purchasing spree, bidding up share values on a wide range of companies, from well-known large caps, such as General Electric, to the obscure, such as Wizzard Software Corp (WZE.A). Ultimately, share prices reached unsustainable levels; for instance WZE.A quickly reached \$14.76 a share, from its previous closing value of \$3.50 (Valetkevitch & Mikolajczak, 2012). When prices eventually returned to where they had begun the day, Knight’s algorithm sold the entirety of the group’s holding, locking in a \$440 million dollar loss within 45 minutes of the opening bell (Popper, 2012). In reality, two failures occurred in those first 45 minutes of trading. When automatic kill switches did not catch the errant code, then the fault became a human failure to monitor and stop the offending trading algorithm. When speaking on this episode Tabb correctly identified the problem when he wrote, “An electronic trading problem is only an electronic trading problem for at most a minute – after that it is a human problem” (Tabb, 2012, p. 17). While mandatory, automated, and firm specific kill switches may be able to stop unexpected algorithmic behavior, those switches are not expected to remove the sentient from the loop, monitoring both processes and trading decisions.

C. CONCLUDING: TREES, FORESTS, AND THEIR IMPLICATIONS

This thesis began by first building a solid understanding of global and domestic financial market by exploring the evolution of concepts, principles, and structures of

those markets. From that foundation, the original capital asset pricing model, first proposed by Sharpe in 1964 was examined in a broad review of literature, focused not just on the model, but also its critics. Following the academic evolution of CAPM, the thesis proceeded to explore research focusing on the effects and properties of the modern market phenomena of dark pools and high-frequency trading. Now, with a more sophisticated understanding of liquidity, sensitivity, and volatility, the thesis proposed a short-term adjustment to CAPM's β , labeled β' , based on liquidity metrics derived from both sides of the limit order book.

Nevertheless, considerable obstacles to implementation of such a model exist and are beneficially appreciated under information operation paradigms. Denial, closely related to operations security, is one such obstacle and impedes the model in large part due to the proliferation of alternative trading systems and internalizers. These dark pools and broker/dealer internalizers have a variety of motivations, though none as promoted as the protection against information leakage for large institutional orders. Even though some of these systems hide liquidity by design and others hide it by consequence, the effect is the same; accurate assessments of broader market liquidity is impaired. Algorithms designed to detect liquidity, present false liquidity, and otherwise manipulate limit order books present another potential obstacle. Although not always malicious, these algorithms are addressed as another weakness for the proposed model. Though not a specific obstacle for the proposed pricing assessment, the final obstacle to asset pricing, in general, is misinformation and deception in the marketplace. As algorithms increasingly make pricing decisions in fractions of seconds, credible assessments have been neglected. Such neglected assessments have real cost, not only in lost execution opportunity, but also in infrastructure and complexity. Critical to long-term and short-term success is striking the appropriate balance between investment made in verification and time spent in execution. In conclusion, the thesis offered recurring recommendations for policy makers and regulators, principally regarding the proliferation of dark pools and increasing share of high-frequency/algorithmic trading.

As market landscapes shift, careful deliberation and anticipation of unintended third order effects will continue to be paramount, before even incremental policy changes

should be adopted. Moving forward, it will be just as critical to balance those effects with the unavoidable temptation to embrace the idea, as Mitchell did in 1929, that the markets are “fundamentally sound” (Galbraith, 1961, p. 102). Given that Knight Capital was responsible for roughly 11 percent of all market activity between January and May—well before their August ruin—demonstrates that concentrating exchange activity into the hands of few could have devastating effects on the many (Popper, 2012). Compounded with few reporting requirements, aging IT infrastructure, and the anonymous cloak dark pools provide, participants, regulators and monitoring agencies continue to be “hopelessly outgunned,” both in enforcement and forensic reconstruction (Reed & Crapo, 2012, p. 19). These discouragements aside, the future of global equity markets, in general, and the U.S, in particular, appears quite bright. Never have transaction costs been lower or liquidity higher, as U.S. markets continue to show “strength and resiliency” five years after the end of the most recent financial crisis (Reed & Crapo, 2012, p. 1)(Hau, 2006, p. 863).

D. SUGGESTIONS FOR FUTURE WORK

First and foremost, testing the modified capital asset pricing model proposed in Chapter III, with a statistically significant dataset from historical limit order books, for accuracy, is the most pertinent and obvious focus of future work. Beyond this, reassessing the accuracy of the model periodically as the focus of market participants shift may be significant, in light of the adaptive market hypothesis discussion in Chapter IV. If the modified model were found to be considerably accurate at estimating short-term returns, as anticipated, the AMH would suggest a degradation of these predictive powers overtime, as market focus shifts to eliminate these advantages. Many of the challenges explored in the second half of Chapter IV and in this chapter, also warrant additional examination. Specifically, advocated recommendations should be scrutinized in simulations where natural experiments are unavailable. Given encouraging results, pilot programs would provide the next logical step, before widespread implementation is ultimately adopted.

E. PARTING VIGNETTE

In September 2008, at 1:30 in the morning, an *Orlando Sentinel* article, first published six-years prior, in 2002, announced the imminent bankruptcy filing of United Airlines (UAL). At that hour, a single page-view of the article was sufficient for the Google News algorithms to promote the “breaking” news as among the “most viewed stories” of the day. The piece was then posted to Bloomberg, and the comedy of errors that followed ultimately resulted in a 76% loss of United Airlines’ market value in six minutes, all because neither human nor algorithm simply checked the publication date of the original source (Leinweber, 2011, p. 110). By the time trading was halted, UAL had lost more than \$1 billion in value, and although much of that value was restored after trading resumed, the company still finished the day down more than 10%, even after calmly explaining that they were not, in fact, entering bankruptcy for a second time in six years (Maynard, 2008). Algorithmic and human errors abound in this costly anecdote. Google News failed to account that very few stories are read at 1:30 am, and so those that are may unintentionally be promoted to a wider audience than appropriate. The staffer that posted the story to Bloomberg failed to check the publication date, simply relying on Google’s historical credibility to promote timely items to most read status. Finally, the financial scrapers and bots, tools of their underlying algorithms, combing the news of the day, failed to check the simplest of metadata—a timestamp. Somewhat surprising, although not shocking, the stock price failed to recover after the company publically addressed the rumors, emphatically denying the bankruptcy murmurs. Unfortunately, it was too late—the seeds of doubt had been sown and residual fear remained more difficult to remove than it was to plant. United Airlines finished the day as a company \$120 million lighter in value, because of at least three missteps from algorithms and humans alike—not counting the originator, the as yet unidentified misanthrope, the midnight bearer of the otherwise expired news.

Our decisions to do something positive ... can only be taken as the result of animal spirits—a spontaneous urge to action rather than inaction, and not as the outcome of a weighted average of quantitative benefits multiplied by quantitative probabilities.

—Economist John Maynard Keynes (1883–1946)

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