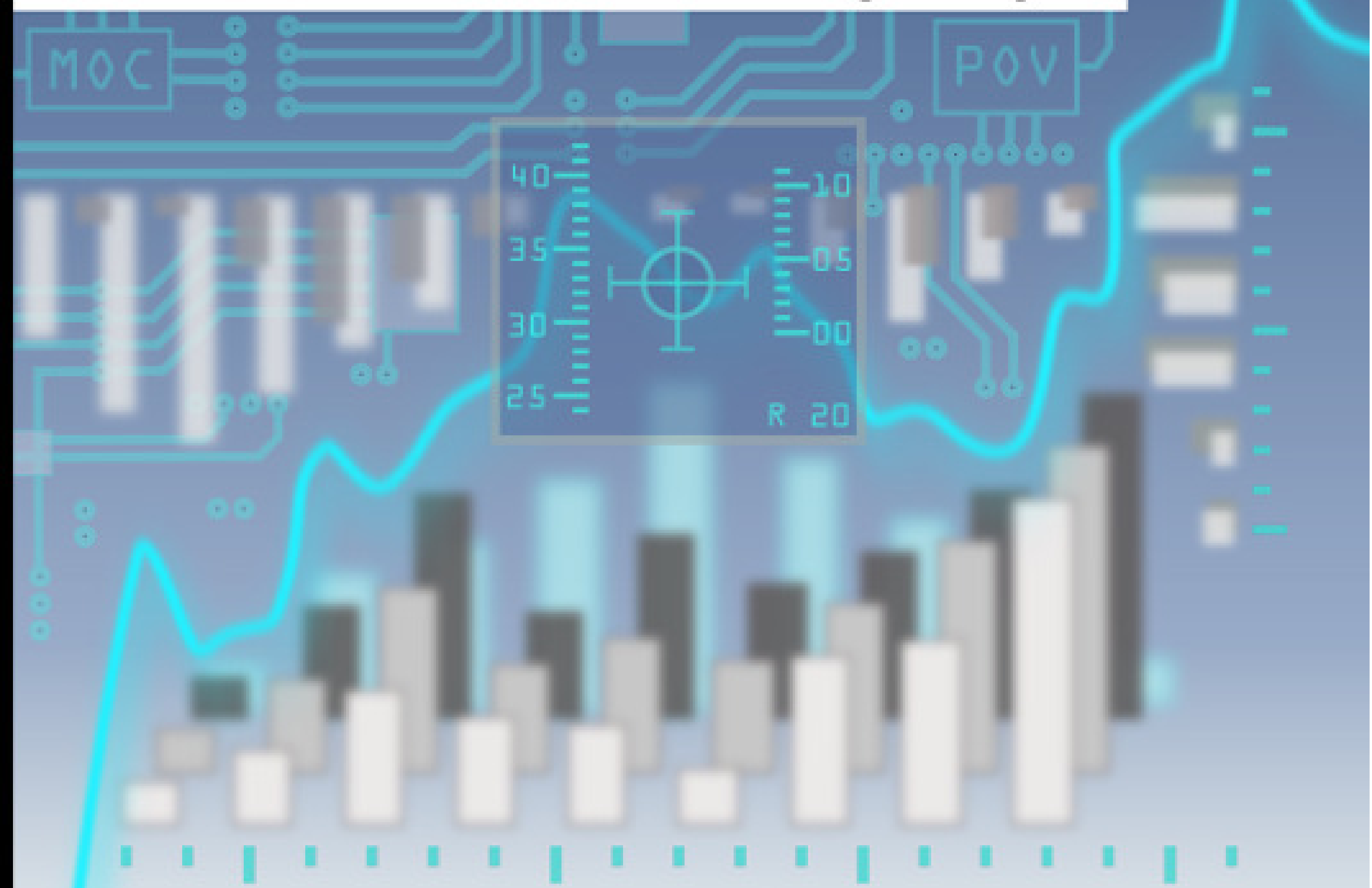
Algorithmic Trading & DMA

An introduction to direct access trading strategies



Barry Johnson

Algorithmic Trading & DMA

An introduction to direct access trading strategies.

By Barry Johnson

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For more information on this book visit the website at www.algo-dma.com

Printed in the United States.

In memory of my mother.

To my father.

Please donate to ***www.myeloma.org.uk*** *or* ***www.themmrf.org***

Myeloma (also known as multiple myeloma) is a type of cancer that affects the bone marrow's plasma cells. These cells are responsible for the production of antibodies for the immune system.

There is currently no cure for myeloma, but research is on-going to develop new treatments to slow its progress and improve patients' quality of life.

Myeloma is the second most common blood cancer, but funding for research and support is still a lot lower than other better-known cancers, so every donation can make a real difference.

Contents

Preface

Trading is still very much an art rather than a science.

The fundamentals of trading have not changed for decades (if not millennia). However, the modern trading environment bears very little resemblance to that of the 1980s, or even the early 1990s. Electronic trading has transformed the markets, making them more accessible than ever before. Tools like Direct Market Access (DMA) and algorithmic trading give investors a lot more control over how their strategies are executed. For instance, DMA enables investors to send orders to exchanges, using their broker's infrastructure.

Accessibility is great, but good traders are a special breed; they have a lot of experience and detailed market knowledge. Algorithmic trading distils some of this knowledge into pre-packaged rule-sets, or algorithms. A computerised system is responsible for executing orders by strictly following these rules, offering an efficient alternative to manual trading.

In order to get the maximum benefit from technologies like algorithmic trading and DMA it is vital to have a thorough understanding of them. Hopefully, by reading this book you should end up with a good fundamental knowledge of both of these topics, as well as trading and markets in general.

Who should read this book?

Algorithmic trading encompasses trading, quantitative analysis and computer programming. Hence, this book is targeted towards all three areas. It should serve as a good introduction for any investors, traders, salespeople, analysts, quantitative analysts (quants), or software developers who are new to this field.

The aim is to take the reader from the ground up, so very little knowledge of the markets or trading is assumed. There are also no requirements for any programming knowledge. We will review trading algorithms in some detail, but tables and diagrams will be used to illustrate their function rather than snippets of code. Similarly, whilst there is some mathematics in this book, it is not a mathematical text, so formulas are provided only where relevant. Examples are used to keep the math in context. References are given for those who might want to find the actual proofs.

Another aim of this book is to try to help bridge some of the gaps between the practice of trading and the theory. A phenomenal amount of research has been carried out into trading and markets. Digitisation has meant that huge amounts of data are now available for study. The fields of econophysics and "phynance" are also busily applying advanced techniques from physics to analyse the markets. Some of these studies are highly theoretical; however, there is also a large amount of empirical research, based on data from the world's major markets. Throughout this book there are sections providing reviews of relevant research and showing how this might be applied in practice. References to key academic papers are given, so it is also a good starting point for more advanced research.

A wide range of financial assets may be traded on the world's markets. One of the most interesting things about algorithmic trading and DMA is their potential to span across asset classes, catering for anything from stocks and bonds to derivatives. Hence, this book provides coverage for all the major types of asset, together with a thorough overview of the world's markets. Obviously, there is a slight bias towards equities, since these continue to lead the way in terms of adoption. Even so, there is a lot to be learned from other asset classes. So throughout this book examples will refer to asset XYZ, only discussing equities, bonds or derivatives when there are distinct differences.

An outline of the book

The book is divided into four main parts. The first two parts offer a general overview of trading and markets followed by a more detailed review of algorithmic trading and DMA. The last two parts offer an in-depth look at the implementation of these trading strategies together with a summary of some advanced trading techniques. Experienced users may prefer to skim over the first parts, whilst readers who just want an introduction should focus on parts I and II and perhaps part IV.

Part I: An overview of trading and markets

These chapters set the scene with a broad overview of the world's major asset classes and a summary of their respective markets. Market microstructure is also introduced to help highlight the main structural differences between the world's markets.

Chapter 1 introduces algorithmic trading and direct market access, highlighting their roles as core execution methods for institutional trading. After a brief review of each of these mechanisms, they are compared in terms of their efficiency, usability and performance. Some of the fears and myths, which have gathered around the use of algorithmic trading, are also addressed.

Chapter 2 introduces the theory of market microstructure, which focuses solely on the mechanics of trading, unlike economics or asset pricing. A basic grounding in this underlying theory is useful, allowing us to take advantage of the empirical research that has been carried out, and to appreciate the fundamental differences between the world's markets. The key components of market structure and design are discussed, before analysing the trading process in more detail. The principles behind transaction cost analysis are also introduced.

Chapter 3 rounds off the introduction by reviewing the world's major asset classes and their respective markets. Trading has been divided by asset class for decades. Still, over the last few years institutions have increasingly started to break down the walls, bringing them closer together. This is not a case of "one size fits all"; there are still huge differences between many of the world's markets, but there many common trends as well. There are also important lessons that they can learn from each other.

Part II: Algorithmic trading and DMA strategies

The second part of the book concentrates on the specifics of algorithmic trading and DMA. This starts with orders since these are the basic building block for all trading strategies. Next, trading algorithms are reviewed in more detail. Transaction cost analysis is then revisited, leading on to consider how to find the optimal trading strategy.

Chapter 4 focuses on orders. These may simply represent trade instructions, but there are a huge variety of different order types beyond the standard market and limit orders. Optional conditions allow control over factors such as how and when the orders become active and for how long. With markets increasingly comprising of multiple venues, the rules for order routing are also a key consideration. A detailed understanding of the mechanism and variety of order types and conditions is vital for both DMA and algorithmic trading.

Chapter 5 covers the various types of trading algorithm in more detail. They are classified using three main types, namely impact-driven (e.g. Volume Weighted Average Price (VWAP)), cost-driven (e.g. implementation shortfall) and opportunistic (e.g. liquidity seeking). For each algorithm, we examine their basic mechanism and discuss common variations. To enable comparison, a standard example order is used throughout. This, combined with charts showing the potential trading patterns, highlights the differences (and similarities) between the various algorithms.

Chapter 6 concentrates on the importance of transaction cost analysis. Costs have a significant effect on investment returns; therefore, both pre and post-trade analysis are vital. An example trade is used to decompose the transaction costs into their key components, such as market impact and timing risk. To put this in perspective, some comparisons of costs across the world's markets are provided.

Chapter 7 goes on to consider how the optimal trading strategy might be selected. A framework for trading decisions is examined; this assesses orders in terms of their difficulty. The impact of investment decisions/requirements, such as benchmarks or risk aversion, is also considered. The "trader's dilemma" of balancing the trade-off between cost and risk is visualised using the efficient trading frontier. This is then applied to the selection of trading algorithms. The effect of both requirements and asset-specific factors, such as liquidity and volatility, are then reviewed. A potential decision tree for algorithm selection is then proposed.

Part III: Implementing trading strategies

The third part of the book focuses on the specifics of implementing algorithmic trading and DMA strategies. The decisions related to order placement are discussed, as well as the common tactics that may be used to achieve the goals of algorithms. Methods for enhancing the performance of these strategies are then reviewed. The technological aspects of implementing these strategies are also considered.

Chapter 8 considers the intricacies of order placement. A considerable amount of market microstructure research has analysed how market conditions affect order placement decisions and execution probability.

Chapter 9 discusses execution tactics. These provide common order placement mechanisms to achieve the goals of trading algorithms. Based on the theory of order placement, common tactics/mechanisms are then described together with a summary of how they might be used by trading algorithms.

Chapter 10 considers some of the ways in which the performance of trading algorithms may be enhanced. To help make these strategies more proactive, short-term forecasting models for key market conditions, such as price, volume and volatility, are considered. There is also a review of cost estimation models for more cost-driven algorithms. Another potential area for improvement is the handling of specific events such as witching days or trading halts. Empirical market microstructure studies are reviewed to give an insight into how predictable the reactions to such events might be.

Chapter 11 reviews the main considerations for actually implementing trading strategies, with a focus on the required technology. Clearly, order management is a key component, so the mechanics of order entry and routing are described. The requirements for developing platforms for electronic trading strategies are then reviewed. The implementation and testing of trading rules is also discussed.

Part IV: Advanced trading strategies

The final part of the book focuses on techniques that are closer to the cutting edge, in terms of algorithmic trading, such as portfolio and multi-asset trading, handling news and artificial intelligence. All of these subjects are being tackled at present in one form or another; it is only a matter of time before they become as common as VWAP or implementation shortfall.

Chapter 12 highlights the potential for portfolio trading. Portfolio risk and diversification are discussed in more detail, together with a review of some common portfolio risk measures, such as beta and tracking error. Next, some additional goals for optimal portfolio trading, e.g. hedging and cash balancing, are examined. Based on this, the use of standard algorithms is considered, followed by a review of how best to tailor trading algorithms for portfolio trading.

Chapter 13 considers the potential for multi-asset trading. This ranges from straightforward approaches, such as incorporating cross currency execution, to more complex hedging and arbitrage. Hedging provides a mechanism for offsetting risk, generally via derivatives. Arbitrage extracts profits from mispricing between assets, and relies on hedging to stay risk-free. After looking at some examples, the chapter ends with a summary of additional considerations for multi-asset trading algorithms.

Chapter 14 examines the potential for incorporating news into trading algorithms. The main issue with this is the difficulty of accurately interpreting news. Complex artificial intelligence and natural language processing techniques are being employed for this. The impact of news and information flow has also been a key topic for microstructure research. Therefore, a summary of market reactions to news in terms of market conditions, such as price, volume and volatility, is provided. These may be used to enhance existing algorithms' performance when news breaks; more news-centric algorithms are also discussed.

Chapter 15 shifts the focus to data mining and artificial intelligence (AI). These techniques may be used to search for relationships between assets, often by analysing historical time series data for prices, volume etc. Potentially, they offer a means of short-term forecasting that may give better results than purely statistical measures, even in volatile markets. They may also be used for testing trading strategies and their associated parameters.

Appendices: A review of world markets by asset class

The appendices provide an overview of each of the major asset classes and their main markets. The focus is on their adoption of electronic trading and the provision of algorithmic trading and DMA. The regional differences between the Americas, Europe and Asia are also examined.

About the author

My background is software development, having spent more than twelve years working in major investment banks. Most of my experience is in electronic trading and risk analysis, spanning platforms for algorithmic and portfolio trading, as well as some for proprietary trading. The main focus has been equities, although listed derivatives, foreign exchange and fixed income have also played a part. The book evolved out of my desire to understand how market microstructure could be applied to create more efficient trading algorithms.

Acknowledgements

This book is based on a wide range of sources. It would not have been possible without all the information which other researchers and firms have made available through their own endeavours. In particular, thanks must go to all the researchers, firms and publishers who have given permission to use figures from their publications, as well as all the individuals who gave feedback on the various drafts. This project is also indebted to services such as the Social Science Research Network (SSRN) and Google Scholar, which made finding research so much easier.

Part I

An overview of trading and markets

This first part of the book sets the scene with a general overview of algorithmic and direct access trading. It also provides a brief review of the world's major asset classes and their respective markets.

- Chapter 1 covers the core execution methods that are used in institutional trading and details how and why algorithmic and direct access trading developed.

- Chapter 2 introduces market microstructure, the theory for the mechanics of trading. This highlights some of the fundamental differences between the world's markets.

- Chapter 3 offers a brief overview of all the world's major asset classes and their markets. More detailed reviews are provided for each asset class in the appendices.

Hopefully, by the end of these three chapters you should have a broad appreciation of the world's markets and trading in general. You should also have a clearer view of algorithmic and direct access trading and their use in the world's markets.

Chapter 1

Overview

Algorithmic trading is simply a computerised rule-based system responsible for executing orders to buy or sell a given asset.

Direct Market Access (DMA) enables clients to send orders to exchanges by using their broker's membership.

1.1 Introduction

Algorithmic trading and Direct Market Access (DMA) are important tools for the electronic trading of financial assets.

Nowadays, a bewildering array of assets can be traded electronically. Stocks and bonds, cash, certificates and a variety of derivatives contracts may all be bought and sold just at the push of a button. The technology to achieve this is still relatively new, but the fundamental market mechanics of buying and selling remain the same. Put simply, sellers need to find buyers (and vice-versa) as quickly and efficiently as possible. Corporations and governments issue assets in order to raise the cash (or capital) required to meet their needs. Likewise, investors and speculators must be able to easily buy and sell assets in order to see a return from their capital.

Over time, the world's markets have evolved to accommodate the differing requirements of both the issuers of financial assets and those who invest in them. The ease with which such trading takes place is commonly referred to as liquidity: Highly liquid markets (or assets) are more active and so usually much easier and cheaper to trade in. To improve liquidity, dedicated trading venues, such as exchanges, have often been established. However, there may not always be a natural buyer or seller to trade with, so markets also rely on intermediaries to "grease the wheels": Specialised traders, or dealers, trade for a set price with the aim of making a short-term profit. Brokers act as agents to place their clients' orders with the dealers, or match them with other clients' orders. Since both brokers and dealers facilitate the issuance and selling of assets they are often referred to as the "sell-side". In turn, institutional investors are often called the "buy-side".

To illustrate the trading process, Figure 1-1 shows some example trade flows from the point of view of an investor. Traditionally, a buy-side initiated trade is placed as an order with a broker's salesperson who must then communicate the order to a trader (or dealer). In turn, the trader would then either quote a price to trade against their own inventory or alternatively work the order on an exchange. This is shown as the pathway labelled A in Figure 1-1. Electronic trading simply offers a means of issuing such orders via computers.

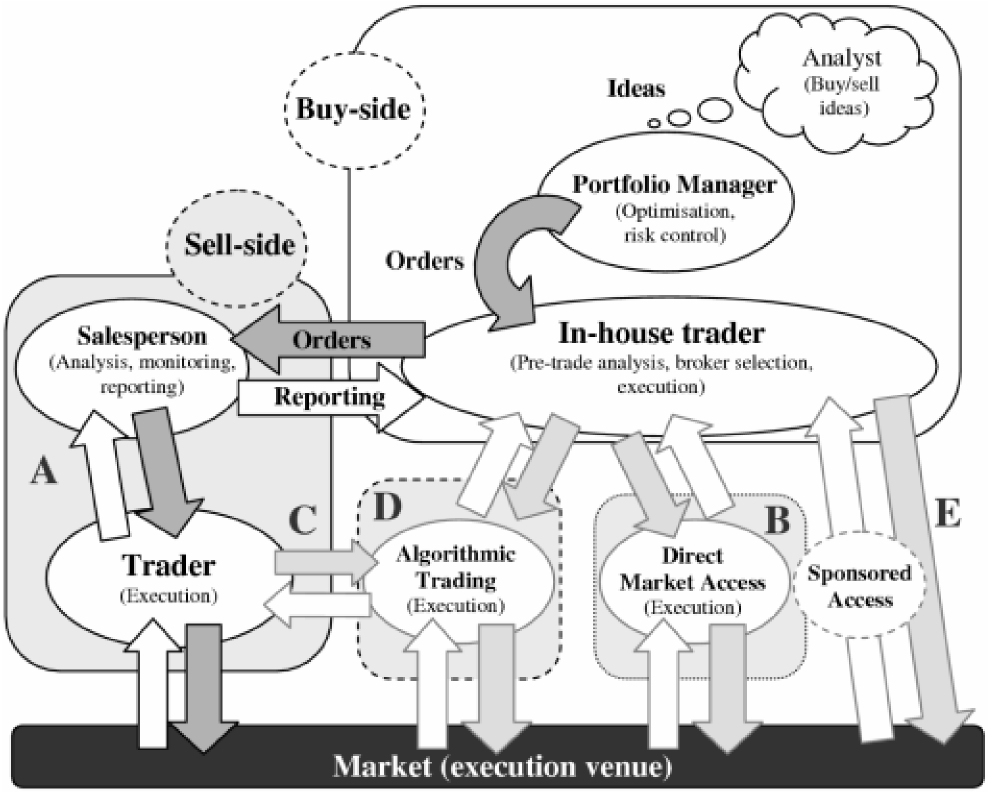

Figure 1-1 A comparison of the different order execution methods

Direct Market Access (DMA) is where brokers allow clients access to their order routing infrastructure, as shown by pathway B. This allows the buy-side to issue their electronic orders almost directly to the exchanges, effectively giving them much the same level of control over an order's execution as a sell-side trader has. Sponsored access takes this to the next level, for clients whose high-frequency trading strategies need ultra-low latency connections. Essentially, this allows clients to connect directly to the market, as shown in pathway E, using the broker's trading identifier, but their own infrastructure. Alternatively, the buy-side can organise membership of the specific market and so have native access.

Algorithmic trading takes a slightly different approach to DMA: A computerised system is responsible for executing the orders to buy or sell a given asset, rather than being worked manually by a trader. So a computer program follows preset rules to determine how each order should be executed. Based on these rules, it splits off portions (or child orders) to send to the market, often tracking market conditions and events. Initially, such trading algorithms were used as a labour-saving device for busy sell-side traders, labelled pathway C in Figure 1-1. As these algorithms became more established, brokers started to offer their buy-side clients direct access to them, shown by pathway D. Together with DMA, allowing clients access to trade on markets in this way is also known as Direct Access Trading.

It is important to note that all of the labelled pathways in Figure 1-1 are only concerned with executing a given order. The actual investment decision is a completely separate process. In this case, it is shown as an idea from a buy-side analyst; it is this idea that leads to the decision to trade. This is then analysed and approved by the portfolio manager before being translated into an actual order to buy (or sell) a set quantity of asset XYZ. The order is then usually passed on to an in-house trader who decides on the most appropriate approach and on which broker/s to use. Alternatively, for more quantitative investment funds the order may well be generated by an automated system. Either way, algorithmic trading, DMA and the sell-side trader are all just a means to execute this order; hence, we can also refer to them as core execution methods.

In some ways, the term algorithmic trading is an unfortunate choice, particularly for such use by institutional investors. Trading tends to make people think of dealers buying low and selling high. Whereas the algorithmic trading systems, which are offered by the major brokers, only execute the orders they are given, as Figure 1-1 tries to show. Perhaps a more representative name for this process is "algorithmic execution".

Clearly, there are exceptions to every rule; there are no major technical reasons why trading algorithms could not also incorporate investment decisions. Indeed, as the buy-side starts to develop their own algorithms this may well become more commonplace. However, the main aim of this book is focus on how algorithms and DMA may be used to enhance order execution.

Over the last few years, algorithmic trading has become a hot topic. New reports keep predicting an increasing global market share, which is expanding from equities to foreign exchange, futures and options and even bonds. There has also been bad press; some headlines have foretold the end of trading, as we know it. Whilst the start of the sub-prime crisis in the summer of 2007, saw "algorithmic trading" blamed for both market volatility and some firms realising huge losses. Volatility is certainly higher; in part, this is due to the increase in speed achieved by electronic and algorithmic trading. However, any losses that firms have made are generally due to their investment strategy. If this is not suitable for the market conditions then losses will be realised. Algorithmic trading is the bullet, not the finger on the trigger. In section 1.10, some of the common fears and myths surrounding algorithmic trading will also be examined (and hopefully debunked).

Before we move on to consider each of these core execution methods in more detail, let's briefly review some fundamentals, such as risk, return and costs, from the perspective of both an investor and a trader.

1.2 Fundamentals

Investment theory tries to maximize profits and minimize risk by carefully choosing different assets. Arguably, the best known approach is modern portfolio theory (MPT) pioneered by Harry Markowitz (1952).

Modern portfolio theory models profits from the returns (or price changes) in a portfolio of financial assets. Volatility is often used as a proxy for the overall risk; this represents the standard deviation of the returns. Assets with higher returns are generally riskier. Portfolios can be made up of an almost infinite set of compositions, using a range of assets with various weightings. Plotting the risk-return characteristics of these allows an efficient frontier to be constructed, as shown in Figure 1-2 (a). This is the upper edge of the shaded region; it represents the portfolios with the highest returns for a given amount of risk. Consequently, an investor must focus on the overall makeup of their portfolio, as much as the risk and returns for individual assets.

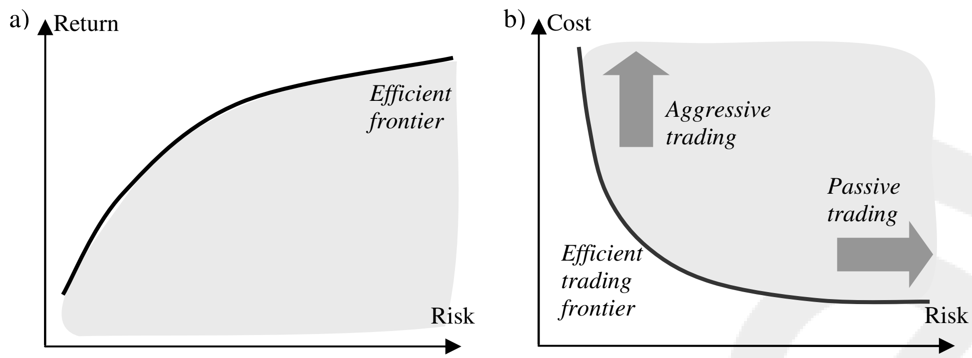

Figure 1-2 A difference in perspective

In order to build up this optimal portfolio we need to buy or sell the specific assets, and so send order/s to broker/dealers or direct to the markets, as we saw in Figure 1-1. Risk (or volatility) is again important, since it shows how much each asset's price might change by. However, returns are somewhat less important, since we are now focussed on executing the given order/s, often in the next second/s, minute/s or hour/s. Instead, cost becomes more important, as shown in Figure 1-2 (b). Executing each order has an associated cost, from the impact it has on the asset's price to broker and exchange fees. Trading faster with large or aggressively priced orders will generally have more impact and so cost more, although the speed of execution reduces the risk. Whereas trading more slowly or passively costs less but exposes us to risk from the asset's price volatility. This is what Robert Kissell and Morton Glantz (2003) refer to as the trader's dilemma. Striking the right balance between cost and risk is a question of taking into account the investor's priorities, as we will see in Chapter 7; it can be the key to achieving optimal execution.

1.3 Core execution methods

Institutional trading can broadly be classified as either agency or principal trading. In agency trading, the broker acts as a conduit to the market, as we saw in Figure 1-1. The client may also give trading instructions, such as to execute throughout the day or target a specific benchmark price or a certain percentage of the market volume. With principal trading, the broker/dealer agrees an up-front price for the asset, which they will fulfil either from their own inventory or by executing on the markets. Since principal trading is carried out with a specific dealer, rather than at an exchange, this is also referred to as "over-the-counter" (OTC) trading.

In terms of risk, the client is exposed to the market with agency trading. The price may move favourably (or not), there is also the possibility that the order may fail to be completed. The broker will strive to achieve best execution for the client, but at the end of the day they are acting as an agent for the client, they do not take on any of the risk. In comparison, with principal trades the risk is transferred immediately to the broker/dealer. Consequently, principal trading is more expensive because the dealer tries to offset this by incorporating it in the negotiated price. The investor must decide whether the up-front costs are worthwhile compared to the potential market risk.

In general, both types of trading are supported for most equities and for the standardised (or listed) futures and options contracts, which are traded on exchanges. The bond and foreign exchange markets have tended to be based more on dealers (or market makers), and so principal or OTC trading is more common (although agency trading is sometimes available for the more liquid assets).

Hence, the final destination for orders in Figure 1-1 also depends on the asset being traded. Algorithmic trading and DMA are generally only viable options when there is a well-established secondary market, such as an exchange. So direct access trading has historically centred on stocks and futures. Although algorithmic trading and DMA are rapidly spreading to most of the major asset classes, as we shall see in Chapter 3.

Agency trading may also be classified based on the execution method used to achieve it. “High-touch” trading is where orders are worked manually by a trader. Algorithmic trading is sometimes referred to as “Low-touch” trading, since it requires little or no handling by actual traders and so can be offered as a lower cost agency service. The final piece of the puzzle is DMA, which is also referred to as “Zero-touch”. With DMA the broker’s own electronic access to markets is extended out to their clients. The sell-side traders have nothing to do with the order; instead, the execution is handled manually by the client.

The increasing focus on transaction costs by the buy-side has meant a decline in the more traditional “High-touch” trading. Still, all these methods are in fact complementary, since they are trying to meet the same objectives, as Figure 1-3 tries to show.

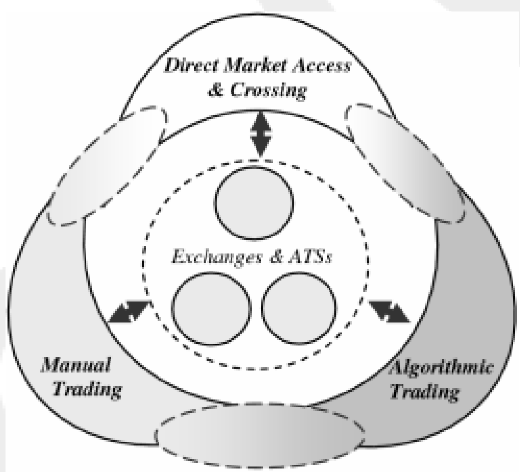

Figure 1-3 The range of core execution methods

Both buy (and sell-side) traders now have a wider choice of execution method than ever before. They can take complete control of the execution by using DMA (or native access), or they can delegate it to an algorithmic trading system. Vendors are even working on systems that allow traders to “pick and mix”. For instance, Neovest’s AlgoGenetics allows “meta-algorithms” to be created which can combine algorithms from a range of brokers together with DMA orders.

Continual evolution and the adoption of similar tactics mean that the boundaries between these methods are constantly blurring. For example, increasingly complex DMA order types, such as iceberg orders and smart order routing, are making it more difficult to differentiate between pure DMA and algorithmic trading.

Another example of the constant evolution of trading strategies is crossing. Block trading is a specialisation for handling large orders of single assets. The advent of platforms such as ITG's POSIT allowed investors to participate in electronic crossing, rather than use brokers' block trading desks for such orders. This trend has continued with the success of the so-called "dark pools" of liquidity offered by the hidden crossings of Alternative Trading Systems (ATS). Although the probability of execution is lower than a broker-mediated block trade, these approaches offer the potential of getting a better price. As with DMA, it is the client's responsibility to manage these orders. Therefore, crossing is shown together with DMA in Figure 1-3. Sourcing liquidity via these "dark pools" has also become extremely important for algorithmic trading.

1.4 Institutional trading types

In the previous section, we focussed on the methods used to actually execute orders. The orders themselves are invariably sourced from the buy-side, in other words institutional or hedge fund investors, as part of their overall trading strategy. Figure 1-4 shows the broader range of trading types, which are widely adopted by different kinds of investors.

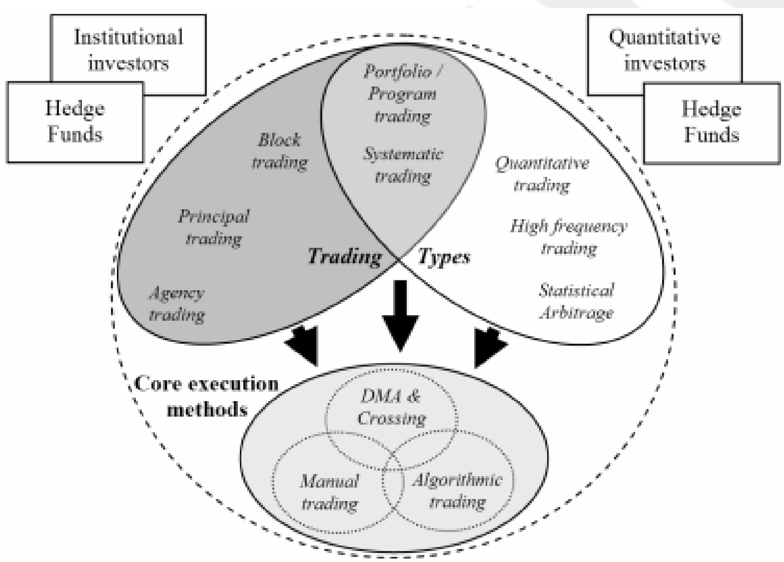

Figure 1-4 Different trading types

Traditionally, institutional investors, such as investment and pension funds, maintain large portfolios with specific investment criteria. Orders are generated when they need to change the make-up of their portfolios. For single assets, they may choose to trade in either an agency or a principal fashion, whilst block trading may be used for larger orders.

Quantitative investment funds adopt more highly automated strategies, as do some hedge funds. For those targeting short-term arbitrage opportunities or generating revenue by market making, this means much higher trading frequencies. So they are even more focussed on low-cost execution methods, such as algorithmic trading and DMA.

Portfolio trading is sometimes referred to as basket or **program trading**. It provides investors with a cost-effective means of trading multiple assets, rather than having to trade them individually. Typically, this is used when they need to adjust or rebalance their portfolios. The trading list represents the assets that must be bought or sold to transform the investor's current portfolio to their desired target. Portfolio trading is a broker provided service, which allows for economies of scale, and so it generally offers a cheaper alternative for handling such transitions. As with single stock institutional trading, the investor may choose to negotiate a principal trade with a broker/dealer, or have a broker trade the list in an agency fashion. We will revisit this topic in more detail in Chapter 12.

Systematic, black-box, quantitative and high frequency trading are terms which all sound like references to algorithmic trading, and are sometimes mistakenly used as such. However, they have as much to do with the style of investment as the actual trading. In fact, they are all forms of systematic trading (or investment), and are sometimes referred to as **Automated trading**. Predominantly, these strategies are adopted by either quantitative investors or proprietary trading desks.

Systematic trading, as its name suggests, is all about consistently adopting the same approach for trading. This may be used to dictate points for trade entry and exit, for instance by comparing market prices with boundary conditions, e.g. Bollinger bands. Alternatively, it may require an intricate set of rules, which accommodate a wide range of intraday conditions such as price, volume or volatility.

Quantitative trading (sometimes referred to as "Black-box" trading) is often confused with algorithmic trading. Here the trading rules are enforced by adopting proprietary quantitative models. [1] The difference is fairly subtle, but quantitative trading systems instigate trades whereas algorithmic trading systems merely execute them. Therefore, quantitative trading systems need to focus on a wider range of goals in addition to the actual execution strategies. These may range from tracking indicators to determine trade initiation and closeout, to monitoring the overall portfolio risk.

High frequency trading aims to take advantage of opportunities intraday. The time scales involved range from hours down to seconds or even fractions of a second. Effectively, it is a specialised form of black-box/quantitative trading focussed on exploiting short-term gains. Some high frequency strategies adopt a style similar to a market maker, trying to keep a relatively neutral position except to take advantage of any price discrepancies. For such strategies, monitoring the overall position/inventory risk and incorporating this information into the pricing/trading decisions is vital.

Statistical arbitrage represents a systematic investment/trading approach, which is based on a fusion of real-time and historical data analysis. The main difference from high frequency trading is that strategies may span over longer timeframes. Other than this, the goals are generally the same, both try to take advantage of mispricing whilst minimising the overall exposure to risk. Strategies try to find trends or indicators from previous data (intraday and/or historical) and then use these to gain an edge. Time series analysis, data mining and even artificial intelligence are employed to try to isolate useful information from the mass of data that is available.

[1] Such models have sometimes been termed "black-boxes", since their actual mechanisms are closely guarded, although obviously their creators have a clear understanding of how they work.

Regardless of which of these trading types are actually chosen, each of them may be implemented using one or more of the core execution methods, as shown in Figure 1-4.

1.5 Electronic trading

In their time, the invention of the telegraph and telephone revolutionised trading, allowing prices and orders to be communicated remotely. Still, it was the advent of the computer that has most affected trading. Before we go into any more detail on algorithmic trading and DMA techniques, it is worth briefly reviewing the development of electronic trading. Some of the more notable milestones in this journey are shown in Table 1-1.

Year	*Event*
1969	Instinet's "Institutional Networks" started, allowing electronic block-trading.
1971	NASDAQ electronic bulletin board started, allowing OTC trading of stocks.
1972	Cantor establish first electronic marketplace for U.S. Government securities.
1976	NYSE's Designated Order Turnaround (DOT) system routes small orders.
1978	U.S. Intermarket Trading System (ITS) established, providing an electronic link between NYSE and the other U.S. stock exchanges.
1980	Instinet introduces PSE Scorex, enabling DMA to U.S. exchanges.
1981	Reuters pioneered electronic monitor dealing service for FX.
1982	Tokyo Stock Exchange introduces its Computer-assisted Order Routing & Execution System (CORES).
1986	London Stock Exchange's "The Big Bang" shifts to screen trading. Paris Bourse introduced an electronic trading system.
1987	ITG POSIT offers scheduled block crossings for stocks.
1988	MTS platform created electronic secondary market for Italian government bonds.
1992	CME launches first version of GLOBEX electronic futures platform.
1993	EBS (Electronic Brokers System) adds competition for spot FX.
1997	U.S. SEC order handling rules change results in the creation of Arca, Brut, Island and Bloomberg Tradebook ECNs.
1998	Eurex offers the first fully electronic exchange for futures.
1999	EuroMTS launched for European government bond trading. eSpeed available for client bond trading.
2000	ICAP's BrokerTec bond trading platform launches.
2001	Liquidnet ATS created, allowing "dark pool" buy-side crossing for equities.
2006	NYSE starts moving equity trading to its Hybrid platform.
2007	U.S. Regulation NMS, European MiFID regulations come in force.

Table 1-1 Some of the key milestones in the adoption of electronic trading

In the 1960s, computer networks were used to route prices to computer terminals, effectively making ticker-tape machines obsolete. Soon afterwards, computers were used to start transmitting orders and trades. Systems supporting fully electronic trading began to appear in the 1960-70s. Suddenly, traders could issue orders remotely; there was no longer a technical need for them to be physically based on an exchange floor.

Early on, electronic trading was mainly focussed on handling relatively small orders. The bulk of trading was still carried out over the phone or in person on exchanges. However, by the mid 1990s many of the world's major stock exchanges were trading a considerable proportion of their volume electronically. Since then the shift to fully electronic trading has become almost inevitable.

The equities markets have clearly led the way in electronic trading. In the early stages, the New York Stock Exchange (NYSE) and NASDAQ (National Association of Securities Dealers Automated Quotations) were undoubtedly at the forefront. By the 1990s, though, the focus had shifted to Europe where trading floors started closing as exchanges shifted to fully electronic order books. Then in 1997, the U.S. saw a major shake-up with the Securities and Exchange Commission (SEC) order handling rules, which allowed new competition in the form of Electronic Communication Networks (ECNs). These new venues saw a huge expansion around the millennium, followed by a fierce round of takeovers and consolidations. Over the last few years, innovation has still continued at a rapid pace, particularly in terms of new variants of the block crossing Alternative Trading Systems (ATSs), such as Liquidnet. Two of the major ECNs, namely BATS and Direct Edge have even become exchanges in their own right (or are in the process of doing so). Further changes are likely as the full effects of the U.S. Regulation-NMS (National Market System) and Europe's Markets in Financial Instruments Directive (MiFID) take effect. In fact, Multilateral Trading Facilities (MTFs), Europe's equivalent to ECNs, are starting to become significant competition for the major European exchanges.

The bond markets have been slower to adopt electronic trading, in part due to them being centred more on market makers rather than exchanges. Europe has again played an important part in the evolution of electronic bond trading, most notably with Italy's MTS (Mercato Telematico dei Titoli di Stato), which has become Europe's leading centre for government bond trading. In the U.S., a mass of electronic systems appeared around the millennium; however, since then the consolidations and closeouts have been brutal. The electronic market for bonds is now dominated by a handful of major players.

Foreign exchange has also shifted towards electronic trading. ECNs are well established and even "dark pool" ATSs have started to appear.

The derivatives marketplace is more complex. The majority of trading is still carried out over the counter (OTC). Still, there is also a sizeable market for exchange-listed derivatives. The Chicago Mercantile Exchange (CME) launched the first version of its GLOBEX platform back in 1992; though, initially this was primarily for after-hours trading. Six years later Eurex became the first fully electronic exchange for futures. Electronic trading is now commonplace for most of the world's major future and options exchanges.

Overall, the rapid proliferation of electronic trading has made the world markets accessible to a much wider range of users. Without this innovation, algorithmic trading, DMA and automated crossing simply would not exist. Note that we will cover the individual markets in more detail in Chapter 3, and the appendices.

1.6 Algorithmic trading

An algorithm [2] is a set of instructions for accomplishing a given task. So a trading algorithm is just a computerised model that incorporates the steps required to trade an order in a specific way. Admittedly, for the algorithm to react to ever changing market conditions these rules can become quite complex. Hence, in this book we shall break them down and consider these decisions in isolation as well as showing how they may then be grouped together to build actual trading algorithms.

For example, given an order to buy 20,000 of asset XYZ the rules might dictate placing

[2] The word algorithm derives from the term algorism, which was used by the 9th century Persian mathematician Abu Abdullah Muhammad ibn Musa al-Khwarizmi in referring to the rules of arithmetic.

the whole quantity as a limit order at the current best market price. Alternatively, they might work the order over the day, splitting it into segments. The rules determine the type, price and quantity for each of these child orders, often based on a mixture of historical and live market data. A computerised system is responsible for handling the algorithm's instructions, so the execution is fully automated. The system ensures that each corresponding child order is split and placed on the market. It then monitors these child orders, adjusting or cancelling them, as and when it becomes necessary.

Let's consider a very simple trading algorithm that aims to achieve an average market price. It does this by dividing each order into uniform slices, which are traded sequentially. Given an order to buy 10,000 of asset ABC over the next five hours, our simple algorithm will trade 1,000 ABC every half hour, by sending a market order to the exchange. Figure 1-5 shows the resultant trading pattern for these child orders.

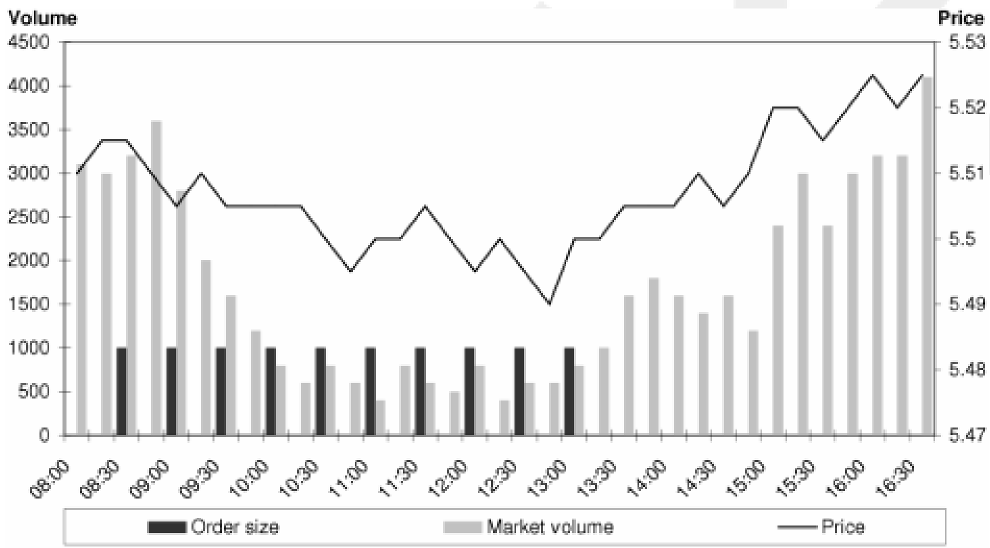

Figure 1-5 A simple example algorithm

Table 1-2 shows another way of viewing our algorithm, as a trading schedule with the target quantity specified for each time period.

Time	08:30	09:00	09:30	10:00	10:30	11:00	11:30	12:00	12:30	13:00
Trade	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000
Total	1000	2000	3000	4000	5000	6000	7000	8000	9000	10000

Table 1-2 A simplified trading schedule

Clearly, our example algorithm is far from perfect; it is predictable and it takes no account of either market prices or volumes. Modern trading algorithms have evolved from this simplistic order slicing strategy to the point where their trading patterns are unrecognisable in comparison. Complex algorithms must be expertly defined and implemented. So the actual trading rules upon which these algorithms are based are defined by experienced traders and quantitative analysts. They are designed to target the best execution, given the specified objectives.

Types of trading algorithms

At present, there are literally hundreds of different trading algorithms available. Each broker or vendor provides their own range of trading algorithms, catering for specific goals. Unsurprisingly, the driving forces for many of these algorithms are price, volume or liquidity. Some algorithms rigidly adhere to a given trading schedule whilst others may be more dynamic, adapting in real-time to ever changing market conditions. Obviously, it is vital for the objectives to be clearly defined for an algorithm to have a chance of achieving its goals.

If we ignore the various names that are used we can start to distil the existing algorithms into a handful of basic types. Table 1-3 shows a summary of the more commonly adopted trading algorithms, which are presently in widespread use.

Key driver		***Algorithms***
Schedule	*Time*	Time Weighted Average Price (TWAP)
	Volume	Volume Weighted Average Price (VWAP)
Predetermined benchmark	*Volume*	Percentage Of Volume (POV)
	Price	Implementation Shortfall (IS)
	Ratio	Pairs / Spread trading
Dynamic Benchmark	*Price*	Price Inline
		Market On Close (MOC)
Liquidity		Liquidity-based algorithms Smart order routing

Table 1-3 A summary of common trading algorithms

Often, trading algorithms are designed to meet (or beat) specific benchmarks, such as the Volume Weighted Average Price (VWAP) or the market closing price. Others try to minimise overall transaction costs whilst some try to trade more opportunistically. There are also algorithms that are driven by liquidity, spanning multiple execution venues or "dark pools" to seek additional liquidity. In Chapter 5, we will cover the whole range of trading algorithms in more detail.

The evolution of trading algorithms

The origins of algorithmic trading may be traced back to electronic trading systems developed as efficiency aids for sell-side traders. Around the millennium, brokers started to realise that these tools could also be offered to clients. Within a few years, every major brokerage was offering algorithmic trading services, and client uptake has steadily increased. Vendors are also starting to create frameworks that make it easier for the buy-side to create their own trading algorithms.

The first generation of trading algorithms were natural evolutions of simple order slicing. They focussed on meeting specific benchmarks, starting with a Time Weighted Average Price (TWAP) and progressing on to the ubiquitous Volume Weighted Average Price

(VWAP). The simplicity of calculating a VWAP and its more accurate reflection of daily price moves meant that for several years VWAP reigned supreme.

Both the early TWAP and VWAP algorithms tended to be statically driven. So as soon as an order was received a specific trading schedule was determined, which then drove the trading algorithm. For VWAP, this schedule would be based on a historical volume profile, essentially this is a representation of how trading volume progresses through an average day. Though, using statically created trading schedules increasingly proved vulnerable, since other market participants could easily spot and take advantage of such regular trading patterns. To combat predatory trading, algorithms started to incorporate more randomisation. Consequently, there was a natural progression from purely schedule driven algorithms to more dynamic strategies. For example, the Percentage of Volume (POV) algorithm bases its execution in response to the live market volume instead of trading based on a historical volume profile.

The second generation of trading algorithms were created in response to the application of transaction cost analysis (TCA). This analysis breaks down all the various costs associated with trading. TCA highlighted that the effect an order has on the asset's price (its market impact) was not the only significant cost. Indeed, other factors, such as timing risk and opportunity cost, could actually outweigh the market impact. André Perold (1988) coined the term implementation shortfall to represent the actual costs of trading. Essentially, this reflects the difference between the market price when the investment decision was actually made (the decision price) and the actual executed price. The increasing popularity of TCA meant investors started to re-examine their use of benchmarks. In fact, VWAP began to be replaced by decision price. In general, the first generation trading algorithms were not designed to be price or risk sensitive; they were more focussed on reducing the overall market impact. Hence, brokers needed to develop algorithms that were more price- and cost-centric, the most notable of which being the Implementation Shortfall (IS) based algorithms. These new algorithms tried to tackle what Robert Kissell and Morton Glantz (2003) termed the trader's dilemma: trading too fast brings high market impact costs whilst trading too slowly exposes us to considerable risk. Suddenly, algorithms started incorporating complex market models to estimate potential transaction costs, as they attempted to determine the optimum trading strategy for each order.

The third generation of algorithms have resulted from the ongoing search for liquidity, triggered by the rapid proliferation of Electronic Crossing Networks (ECNs) and Alternative Trading Systems (ATSs) in the U.S. equity market. Having so many potential execution venues meant a raft of simple order routing systems were created. Another important factor has been the increasing order book transparency as markets have transitioned to electronic trading. Many of the first generation algorithms focussed solely on the best bid and offer quotes, often because that was all that was available. As order book data becomes increasingly available, more and more algorithms are taking advantage of this for their order placement decisions. The combination of multiple venues and increasing transparency has helped transform simple order routing systems into complex liquidity-based algorithms. These constantly examine the order books of different venues to decide where best to place orders.

Off-market trading has also shifted to new electronic venues, in particular the "dark pools" or ATSs that have proven so successful for U.S. equities. Algorithms now routinely interact with these "dark pools" to find additional liquidity at set price points, trying to achieve best execution. At first, this started with dedicated liquidity-seeking algorithms, but increasingly this behaviour is also being incorporated in other algorithms, such as Implementation

Shortfall or even VWAP. Thus, new hybrid strategies are starting to evolve.

In parallel with the search for liquidity, another shift in algorithm behaviour is taking place. Customisation and adaptability are becoming key focuses for algorithms, allowing brokers to more easily offer client-centric trading algorithms.

Exactly what the next generation of trading algorithms will offer is hard to predict, but it is certain that they will keep evolving.

1.7 Direct Access Trading

Direct access trading represents the shift in access and control of execution to the buy-side. Investors and buy-side traders can now get direct access allowing them to place orders on many of the world's financial marketplaces. Originally, direct access trading was synonymous with DMA; however, the introduction of crossing and algorithmic trading has meant institutions now have an even broader choice of execution methods.

Direct Market Access

Direct Market Access (DMA) extends the principle of remote access to a broker's clients. Its roots trace back to the 1980s with vendors such as Instinet. Although used by some institutional clients, many of the early adopters of DMA were retail users. Certainly, vendors targeted the retail market with their DMA systems. This gave day traders, or SOES bandits (named after NASDAQ's Small Order Execution System), an unprecedented level of access and control over their orders.

Institutional users became interested in the prospect of DMA in the 1990s. In particular, this was led by hedge funds and statistical arbitrageurs. Many of the initial DMA offerings were provided by software houses and small agency brokerages. However, after the millennium the larger brokers started investing in DMA in a big way. In 2000, Goldman Sachs acquired REDIPlus whilst in 2004 Bank of America Securities bought Direct Access Financial Corp., Sonic Trading Management went to Bank of New York and Lava Trading became part of Citigroup. Suddenly, the DMA marketplace was dominated by major brokers; DMA had become a key selling point for institutional use.

With DMA, the client can take advantage of the broker's infrastructure to send their orders to the exchange, much like the broker's own orders. Hence the moniker "Zero touch", since the order execution is controlled by the client. This requires the client traders to have access to an Order Management System (OMS) or Execution Management System (EMS), which is linked to the broker. Prime brokerage agreements are often established to organise the clearing and settlement of any executions, and any other custodial or financing requirements.

Clearly, information leakage is a key concern for institutional users. Therefore DMA services are generally run by brokers as a separate entity to protect the client orders from being viewed by the rest of the broker's traders, and in particular their proprietary desks.

Sponsored access

Sponsored access caters for buy-side clients with high-frequency trading strategies. This allows the client to connect to the market using use their broker's unique market identifier (or MPID), but without having to go through their entire infrastructure. Although the markets generally require the broker to monitor the trading, ensuring that no excessive risks are taken. The monitoring may be carried out pre-trade, either with a fast, dedicated system or by using a solution from a third-party vendor, such as FTEN. Whilst this adds some overhead, the client should still get faster access than normal DMA.

Alternatively, some sponsored access may rely on post-trade monitoring. This has been termed "naked access", since this does not allow the broker to prevent erroneous trading. Given the increased regulatory attention, the future for such "naked access" is uncertain.

Crossing

Institutions often need to trade in large sizes, but large block orders can expose them to substantial price risk. Traditionally, these large orders were handled by brokers off the trading floor. This is sometimes referred to as the "upstairs market" since historically such negotiations took place upstairs in broker's offices, well away from the exchange floor.

Often block trading is undertaken on a principal basis, although agency trading is also catered for. In a principal trade, the broker/dealer assumes all the risk by taking the required position onto their inventory. To work such large block orders they may need to find new counterparties who require the asset, or they may split the order into smaller quantities and work them on the market.

Crossing systems provide an electronic mechanism allowing investors to carry out their own block trading anonymously. These systems aggregate orders and then match them at set points throughout the day. For instance, ITG's POSIT matches orders at over a dozen set times daily. In comparison, Alternative Trading Systems (ATS), such as Liquidnet, generally provide continuous electronic order matching. These anonymous trading venues ensure the order details (size and sometimes price) are hidden; hence, they have often been referred to as "dark pools" of liquidity. Effectively, they offer the buy-side the chance to cut out the broker as an intermediary and trade anonymously with each other. Due to the size of the orders involved, they have become significant sources of liquidity.

Note that it is important to remember that orders placed on crossing systems or ATSs are not guaranteed to execute. Instead, the focus is on achieving a better price and minimising information leakage. In fact, the probability of execution can be much lower than on the main exchanges, depending on the liquidity of the asset and the size of the block order. Consequently, such orders tend to require some monitoring. In order to guarantee execution other trading methods, such as algorithmic trading or DMA, may be used in tandem. For example, we could place an order to buy a million shares of XYZ on a crossing system in the morning. As the day progresses if it still has not executed we could reduce the quantity by 10 or 20% every hour and work this separately. This allows us to hold out for the best price from crossing, whilst still ensuring that the order is executed. Indeed, there are now trading algorithms that offer this kind of approach.

Direct Liquidity Access

Managing an order on a crossing network or ATS is essentially the same as DMA. This similarity has meant that vendors now offer solutions that enable access to both mechanisms. To reflect this some brokers/vendors have started using the term Direct Liquidity Access (DLA) for their services.

DLA type services are not necessarily just a combination of DMA and crossing provision. They may also incorporate features such as liquidity aggregation, where smart order routing or custom trading algorithms are used to seek out sufficient liquidity at the desired price.

Direct Strategy Access

Client access for trading algorithms was initially handled over the phone. Nowadays, more and more OMSs and EMSs can handle algorithmic trading. So clients now have direct access to algorithms, much as they have direct access to orders via DMA. In fact, some brokers, such as UBS, have started using the term Direct Strategy Access (DSA).

1.8 Comparing execution methods

Although all the core execution methods are complimentary, there are still some significant differences between them. To illustrate this Table 1-4 shows two simple example orders. The first order is simply a limit order to buy asset ABC within a fixed price limit, whilst the second order targets the daily VWAP as a benchmark.

Order	***Trading method***		
	Manual	*DMA/Crossing*	*Algorithmic*
1.	"Buy 10,000 ABC with a limit of 53"	Buy limit order 10,000 ABC at 53	No direct equivalent
2.	"Buy 100,000 ABC Trade VWAP over the day Don't go above 53"	No direct equivalent	Buy 100,000 ABC Algorithm: VWAP Start time: Now End time: Close Price limit: 53

Table 1-4 Different trading methods for some example orders

Manual trading can deal with any type of order. The instructions are simple and easy to understand. It is also popular because it allows the client to discuss the order with the broker. This gives them an opportunity to gain new market information and analysis (or "colour") which may even lead them to alter their trading strategy. Such information can be vital to clients, and is one of the main reasons why manual trading is still so widespread.

DMA is perfect for simple order types such the first order in Table 1-4. It allows clients complete control over how and when orders are placed. However, there is not usually a single equivalent order that can handle something like the example daily VWAP trade. DMA caters solely for low-level access. So instead, the client must try to reproduce the strategy that a trader might adopt manually. Therefore, to achieve best execution a client will need considerable market experience, as well as having the time to analyse and decide how best to place each child order. Whilst this may suit some clients, clearly this is a more time consuming approach. That is why, for many clients, either manual or algorithmic trading offer a more practical alternative.

Likewise, order crossing can easily handle simple limit orders, but not more complicated order types. Again, it is up to the client to monitor the order's status, possibly cancelling and re-routing it if executions are not forthcoming on the ATS. Since such crossing networks tend to deal with larger order sizes, a client may actually prefer a dual trading strategy, whereby most of the order is left on the ATS for potential crossing whilst a smaller portion is traded on the exchange to try to ensure execution. Such strategies are starting to be offered by new liquidity-based trading algorithms.

Algorithmic trading is intended to cope with more complex trading strategies, so the example VWAP order in Table 1-4 poses no problems. Upon receiving the order, a VWAP trading algorithm will then decide how it should be handled. Some algorithms adopt a static approach, splitting orders based purely on information from historical data. Alternatively, ones that are more dynamic incorporate a mixture of historical and live market data in their decisions. As required, the algorithm will then send child orders to the market, selecting the most appropriate order type/price and size; then continually monitor their progress. Essentially, this is no different to what happens for traders working such orders manually or via DMA, except that the trading algorithm provides a fully automated process. Clearly, in order for the execution to meet the client's objectives it is vital that any requirements such as limit prices, benchmarks etc. are fully specified. As we can see from Table 1-4, the algorithm parameters (the start and end times and the limit price) are similar to how we might ask a trader to work the order. Admittedly, this is a more constrained approach than just talking to a trader over the phone. However, brokers are constantly introducing new algorithms and refining their parameters to try and make it easier to issue appropriate orders and to cope with any required customisations. They have even started introducing algorithms that look at the order details and decide the most appropriate trading strategy/algorithm for it.

Another way of comparing execution methods is to try to rate them in terms of factors such as:

- Efficiency
- Usability
- Performance/Cost

These are broken down in more detail in Table 1-5.

Factors		***Manual***	***Direct Access***		
			DMA	*Crossing*	*Algorithmic*
Efficiency	Capacity	★	★	★	★★★
	Speed	★	★	★	★★★
Usability	Control	★	★★★	★	★
	Transparency	★	★★★	★	★
	Anonymity	★★	★★	★★★	★★
	Market conditions	★	★	★	★★
	Market knowledge	★★★	★	★★	★★★
	Asset knowledge	★★★	★	★★	★★★
Performance/ Cost	Performance	★★	★★	★★	★★
	Commission	★	★★★	★	★★
	Risk/Cost control	★★	★	★	★★
Other	Regulations	★★	★	★	★★

Graded from weakest (★) to strongest (★★★)

Table 1-5 Comparing the core methods for trading

Efficiency

Efficiency has been one of the key drivers for the sell-side; a skilled trader is a valuable commodity, anything that helps make them more productive is clearly beneficial. For some segments of the buy-side, typically hedge funds, speed is becoming ever more important. Low latency trading mechanisms allow them to capitalise on opportunities as soon as they see them.

In terms of capacity, algorithmic trading is clearly the winner; computers can easily handle thousands of orders simultaneously. Additional capacity can often be added by setting up another computer server, provided the underlying infrastructure (networks, links to exchanges etc.) is good enough. In comparison, manual trading is quite an expensive option.

Traders are inherently good at multi-tasking; however, there is still a limit to how many orders a person can handle at any one time, beyond this level the quality of execution may suffer. DMA has similar capacity issues since all that has really happened is a shift of the manual trading from the broker to the buy-side. Capacity is less of an issue when using crossing systems since this tends to be a more passive trading style. Though, the orders still need to be monitored, and if they have not crossed after some time, alternative trading methods may need to be used.

With respect to speed, algorithmic trading is again the best option. Computerised systems are perfect for monitoring and analysing thousands of variables in fractions of a second. Exchanges used to have latencies of around 300 milliseconds, at present they are now competing to offer services with latencies below 10 milliseconds. To put this in perspective a blink takes between 100-150 milliseconds (as noted by David Burr (2005)). Even complex analytics for determining the most appropriate reaction can be calculated in fractions of a second. In other words, a trading algorithm can spot an opportunity and send an appropriate order to the exchange before we even notice the quote flickering on our monitor. Speed has become such a key issue that some exchanges and ATSs now offer co-location services, essentially allowing member's computer servers to be placed in their machine rooms to virtually eradicate any network delays.

Usability

Usability is obviously a major issue for most users. A convoluted trading method is unlikely to be popular, even if it gets good results.

Direct control over how their orders are handled has significantly improved for the buy-side. DMA allows them to place and manage orders as if they were a broker/dealer. In comparison, both manual and algorithmic trading represent a slight loss of control, since the client can only issue general trade instructions or select an appropriate trading algorithm. Clearly, it is often easier to communicate such instructions to a person, but trading algorithms are continually evolving to try to be as intuitive as possible. They are also becoming highly customisable, catering for an ever-expanding range of trading requirements.

Transparency is closely related to control. If we cannot dictate exactly how something is done, we would at least like to be able to monitor it closely to ensure that it is doing what we want. Competitive advantage means that brokers cannot divulge the exact inner workings of their algorithms, but they should be still be able to explain the behaviour for specific orders. It is also important to get a broad understanding of how each trading algorithm works, so as to be able choose the most appropriate one for our orders.

Anonymity is important as well, since information leakage is one of the key concerns for many investors. Over the last few years, the anonymity offered by crossing networks has helped these systems gain a substantial market share, particularly in the U.S. DMA and algorithmic trading can also provide anonymity, since most brokers segregate the trading for their prime brokerages to ensure client privacy.

Another factor that affects usability is changing market conditions, in part triggered by electronic and algorithmic trading and by the competition between venues. Across many of the world's markets average order sizes have significantly decreased whilst trading volumes have rocketed. So orders, which might have immediately filled five years ago, must now be split to prevent market impact. Similarly, having multiple execution venues fragments the available liquidity, making it harder to trade. Algorithmic trading is the best suited to handling such conditions; computer capacity means it can closely monitor each venue and decide where best to trade, for thousands of orders. Neither DMA, nor manual trading can match this.

Market and asset specific knowledge are also key to achieving best execution. This can be as simple as knowing when markets are open and understanding the supported order types. Alternatively, it might mean having in-depth experience of how each asset trades. For manual or algorithmic trading, the orders are being handled by a dedicated expert or system, so orders can be easily delegated to these methods. It does not matter whether the order is for U.S. bonds or Japanese equities they will handle the complexities of each market and asset type. Whereas for DMA, and to a lesser extent crossing, there is less inbuilt guidance, it is up to the client to determine how best to trade. That said, many OMSs and EMSs often have built-in rules to prevent simple errors such as selecting an unsupported order type.

Performance / Cost

Execution methods have to deliver in terms of both performance and cost. Performance may be measured by comparing the average execution price to a specific benchmark. Note that it is also important to consider the variability, or volatility, of these averages. For any specific order, manual trading should generally be able to beat the performance of an algorithm, since traders can often infer much more subtle signals from the market. However, the rule based nature of algorithms means that they should provide more consistent results, since they do not get tired or distracted. Therefore, in terms of overall performance algorithms and manual trading are relatively evenly matched. Admittedly, traders probably still have the edge, but algorithms are improving all the time.

It is also important to get the balance right between performance and efficiency. An experienced trader should generally be able to outperform most trading algorithms; however, this may consume a large proportion of their time. Overall, better performance might be achieved by having the trader manually work the more difficult orders whilst delegating the others to trading algorithms.

When examining performance, the investment goals should be considered as well. For instance, trading passively may save the bid offer spread and so result in a good average price, but this may be at the expense of fully completing the order. If, the next day, the asset price shifts then completing the order may be more expensive than if we had traded more aggressively the day before. Transaction cost analysis (TCA) has played a key role in making traders and investors examine such costs more thoroughly.

For markets where brokers still charge commissions, e.g. equities, this is clearly a very visible cost of trading. Until the 2007-09 financial crisis, overall commissions have been steadily declining. Figure 1-6 charts their progression over the last few years, in terms of \$/share. It also highlights the differences between DMA, algorithmic and manual (high touch) trading. From a broker's point of view, the low touch services (DMA and algorithmic trading) have relatively low labour costs hence the lower charges. The costs for high touch / manual trading also reflect the fact that traders can offer additional information to clients, such as market colour or sentiment.

Overall, TCA has highlighted the fact that hidden costs, such as market impact and timing risk, are more significant than visible costs, such as commissions. Most algorithms are adept at reducing overall market impact, by splitting the order into smaller sizes.

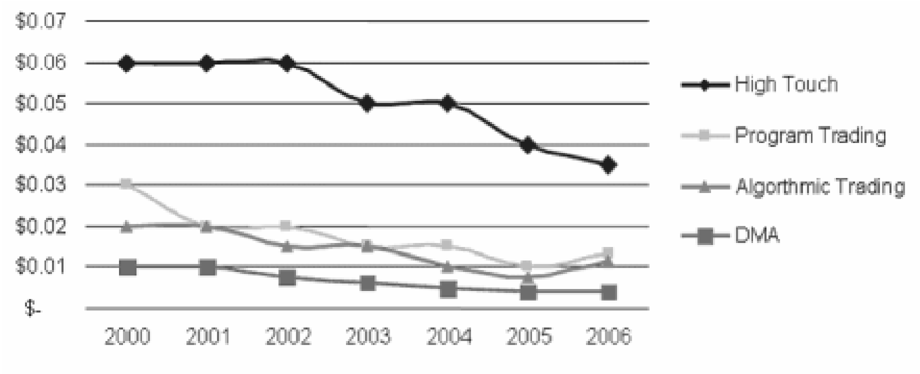

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Figure 1-6 U.S. equity average commissions

Similarly, crossing is an equally efficient, if not better, means of reducing market impact. Minimising timing risk and opportunity costs is more complex. The second generation of algorithms introduced cost-centric models, typified by Implementation Shortfall, which are better suited to this. We shall cover this in more detail in Chapters 5 and 6.

Other reasons

Market regulation, such as Regulation NMS in the U.S. and MiFID in Europe, means that brokers and investors must be able to demonstrate that they achieved best execution. Electronic trading has made this somewhat easier, since detailed audit trails are relatively simple to maintain. Therefore, algorithmic trading is arguably one of the best choices to cater for such regulations, since its rule based nature provides consistent and easily auditable trading decisions, as well as coping well with fragmented marketplaces.

1.9 How much are these execution methods used?

The sell-side brokerages have had electronic trading for years. Internally, almost all their trading is electronic, except for the few markets where there is still considerable floor-based activity. Similarly, automated trading systems and trading algorithms have long been established. Hence, most studies focus on the uptake of these technologies with the buy-side institutions. For example, Figure 1-7 shows estimates from the Aite Group consultancy for the breakdown of trading methods adopted by U.S. institutions.

The growth trends for algorithmic trading and DMA are clearly visible, as is the decline in "High touch" (and higher cost) manual trading. A report by the TABB Group (2008) estimates that by 2007 algorithmic trading, DMA, crossing and program trading together accounted for 63% of the U.S. institutional equities trades. Still, in 2008 they also note that the market crisis led to a slight shift in the trends. Algorithmic trading continued to increase, reaching 24% of buy-side flow, up 2% from the year before. However, high touch trading via sales traders also increased, recovering to 44% (back from 37% in 2007), as institutions sought to cope with the heightened levels of volatility.

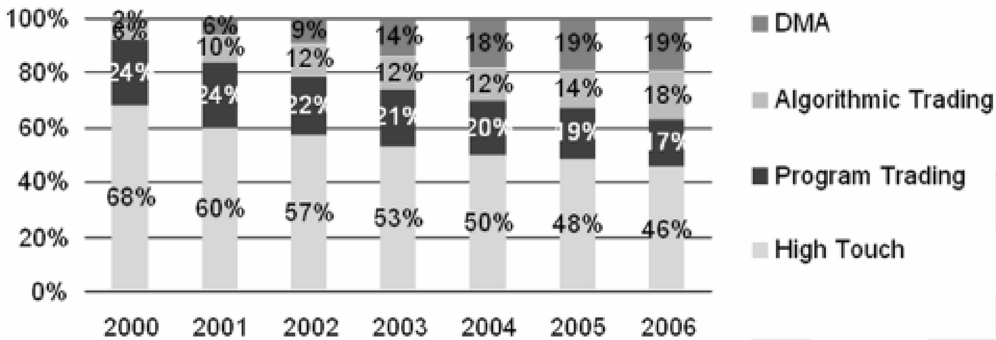

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Figure 1-7 Estimates for the use of different trading methods by U.S. institutions

1.10 Fears and myths

Algorithmic trading has attracted a lot of publicity; there has also been a lot of marketing and hype. So in this section let's examine some of the common fears and myths that have attached themselves to this topic. Broadly speaking, these may be categorised into three main issues, namely safety, performance and usefulness.

Safety of algorithmic trading

Some of the commonest concerns about algorithmic trading are that:

- Algorithms are fundamentally changing the market
- Algorithms will replace traders
- Algorithms can leak alpha to proprietary traders

There can be no doubt that electronic trading has transformed the world markets. Marketplaces are seeing waves of fragmentation and consolidation as competition for market share drives the creation of new execution venues whilst existing ones are bought, merge or fail. The emergence of crossing systems is a perfect example of this cycle. Order sizes are shrinking, so off-exchange crossing becomes increasingly popular. In response, the exchanges introduce new mechanisms to try to regain liquidity from the crossing networks, and the cycle begins again. All the while, these market shifts offer opportunities for astute investors and traders who are ahead of the market. Coping with this constant change is clearly difficult. Nevertheless, Pandora's Box has already been opened, for better or worse, so we may as well look inside and find ways to deal with the new market reality.

Algorithmic trading is a natural evolution from electronic trading. Computers are ideally suited to working in complex multi-venue markets, since they can easily monitor the order books of a range of execution venues. If everyone used VWAP algorithms for their trading then clearly some self-reinforcement of trading patterns would occur, much like if everyone used the same technical analysis. However, people's views differ: Indeed, the very reason that the world's markets function is because investors and traders have a diverse range of opinions. Therefore, they target different prices and use a range of alternative trading strategies. There is no reason why algorithmic trading should alter this diversity.

Job security is also an issue. Eye-catching news headlines have proclaimed the end of the trader, but then we're all going to be replaced with robots in 2075 aren't we? It is important to remember that electronic and algorithmic trading are simply tools. Certainly, job roles are evolving, for example, salespeople are becoming sales traders. Sell-side desks are now covering multiple asset classes. Not long ago, it was predicted that principal or risk trading would become more commonly used than agency trading. The 2007-09 financial crisis and the transformation of the financial sector have given a new lease of life to agency trading. In fact, during this crisis principal trading looked far more endangered. In such markets, traders and investors need to be flexible to take advantage of any tools that help give them an edge and drive profits.

An article in the CFA Magazine (2006) titled 'Hype and Algorithms' poses a good counterpoint to the fear that algorithms will take over the world. In the article, Joe Gawronski, COO of Rosenblatt Securities, highlights the fact that:

> *"Algorithms can't react in the true sense of how I define a reaction. Everything they do is based on a rule that's been provided, whereas traders can change their mind on the fly. There's no way to incorporate into algorithms the random facts and observation that may give a trader a "feel" for the market."*

Artificial Intelligence (AI) may offer a solution to this; however, this is still some way off. AI first took of in the 1950s, but it was not until 1997 that IBM's Deep Blue computer could beat the world chess champion. In the same CFA article James Finnegan, editor of the Financial Engineering News, points out:

> *"People equate black-box algorithms with super computers developed to play chess and mistakenly assume there will one day be an algorithm that is so smart, quick, and innovative that even the best traders in the world won't stand a chance. However, the difference is that although there are billions and billions of permutations with chess, there is a defined board and a very strict set of rules, so a computer with enough memory can learn every move. That's not the case with markets."*

Beyond all the hype, algorithmic trading will certainly have a major impact. For instance, good algorithms may be just as efficiently used by a salesperson as a sales trader. It should also open up new avenues for trading, expanding the potential of multi-region and multi-asset trading.

Another concern for investors is information leakage. There is still some suspicion that brokers can garner information from client order flow and use this for their own proprietary trading. That said, the buy-side has more power and control than it has ever had. Off-exchange crossing networks even allow the buy-side to completely bypass brokers. Given that commissions are declining, it is vital for brokers to retain order flow. Reputation is paramount. Brokers have to ensure that their proprietary trading desks are truly isolated from the brokerage operations. This holds true for all the major brokers, whose prime brokerage units are often segregated, located on separate floors or even buildings.

Performance of algorithmic trading

Another common fear is that trading algorithms have now become commoditised and there is little differentiation between them. There is some truth to this, in that there are only so many ways of implementing an algorithm that targets a benchmark like VWAP. However, being commoditised is not altogether a bad thing; it is important to have a certain level of standardisation. We just have to look at the markets to see how standardised products have better liquidity and so lower trading costs. Similarly, standardised algorithms, at least in terms of their parameters and basic functions, would allow clients to swap between brokers more easily, thus encouraging more competition.

Commoditisation is less of an issue for the more complex cost driven and opportunistic algorithms. Here the performance is dependent on the quality of their quantitative models, so brokers can add significant value. Indeed, there can be considerable variation in the performance of these algorithms between brokers.

Algorithm choice is also an important factor: If an unsuitable type of algorithm is chosen then performance is bound to suffer. This can be addressed by a combination of education and improving the available pre-trade analytics. Another solution is the increasing provision of systems that can automatically suggest the most suitable algorithm for a specific order. Post-trade analysis is vital to check the actual performance. Note that both the mean and standard deviation of performance need to be considered.

There is also the feeling that brokers hold back the best performing algorithms for themselves. Fundamentally, proprietary desks, particularly those employing high frequency trading or statistical arbitrage adopt different strategies to investors. They are usually keen to stay market neutral and so strategies tend not to build up large positions, instead acting more like sophisticated day traders. Thus, any algorithms they use tend to be highly specialised, often based on market making. That's not to say brokers don't run different algorithms. Newer versions of algorithms need extensive testing, so these will be used internally before being made available to clients. In general, algorithms are a valuable marketing resource which brokers are keen to make available as soon as they are ready.

Finally, it is important to remember that algorithmic trading is just a tool, not a panacea. It is not designed to generate profits (or alpha), simply to help control costs and provide best execution.

Usefulness of algorithmic trading

The success of algorithmic trading means that less people are still questioning its usefulness. Although there are still a few issues rooted from the early days of algorithmic trading, namely that:

- Algorithms are complicated to use
- They only really work for liquid assets or small orders

Algorithms sometimes have a reputation of being complicated, but as we saw in the example in Table 1-4, they require parameters that look very similar to the instructions we might give to a trader. Most algorithms will have sanity checks, so if an order is unusually large, or the price limit is miles away from the actual market price then the order may be rejected, just to be safe. Nevertheless, as with any computer program, it is important to bear in mind the "Garbage In Garbage Out" maxim, and assume that it will not be as forgiving with any typos.

Algorithm selection from the hundreds available may seem like an ominous task. That said, any one broker probably offers a maximum of a dozen trading algorithms. Therefore, it is simply a case of using pre-trade analytics to estimate the potential impact and risk of an order. Increasingly, brokers are rationalising their suites of algorithms to make selection even easier. They are also starting to provide more client-focussed solutions that cater for specific requirements. Some brokers even provide services that suggest the most appropriate algorithm, based on the order size and the asset's liquidity and volatility.

In terms of algorithms only being able to cope with liquid assets or small orders, this may have been true for the first generation of algorithms. Modern algorithms are much more versatile. In particular, the introduction of cost-centric and liquidity seeking algorithms means they can now support a much broader set of requirements.

Illiquid assets pose a specific problem, namely signalling risk. This represents the information leakage to other market participants from our trading strategy. Imagine using the simplistic algorithm we saw in Figure 1-5 for an illiquid asset. The regular large buy orders would scream, “We have a buyer”, whereas for a more heavily traded asset they would not stand out as much. Consequently, it is often necessary to hide our actual intentions as much as possible, by using special order types and by seeking liquidity from alternative sources such as crossing networks. We shall cover this in more detail in Chapters 8 and 9. Interestingly, these techniques are increasingly being applied to more liquid assets.

One area where algorithms do need more work is coping with unexpected events or news. Human traders can often deal with this much more effectively. That said, the next generation of algorithms are already starting to look at how best to incorporate additional information to deal with such situations. We will look at this in more depth in Chapters 10 and 14.

1.11 Summary

- Direct Market Access (DMA) enables clients to send orders to exchanges by using a proxy for their broker’s membership, giving them a similar level of control for an order’s execution to a sell-side trader.
- Algorithmic trading is a computerised rule-based system responsible for executing orders to buy or sell a given asset. A computer program follows preset rules to determine how each order should be executed. Algorithmic execution is perhaps a more representative name.
- Systematic, black-box, quantitative and high frequency or automated trading are terms that are sometimes mistakenly used as references to algorithmic trading. In fact, they are more to do with the style of investment than the execution.
- So far, there have been three main generations in the evolution of trading algorithms:
  - The first algorithms were natural evolutions of simple order slicing, focussing on specific benchmarks, such as TWAP or VWAP. Initially, these were schedule driven, often based on historical data. Later, more dynamic versions incorporated market conditions, leading to tracking algorithms, such as percentage of volume.
  - The second generation of trading algorithms were created in response to the application of transaction cost analysis. Implementation shortfall algorithms strive to minimise cost by balancing both market impact and risk.
  - The third generation of algorithms are focussed more on liquidity, resulting from the fragmentation of major markets and the arrival of “dark pools”.
  - Continual evolution and the adoption of similar tactics mean that the boundaries between these methods are constantly blurring. Increasingly, complex DMA order types are making it difficult to differentiate between them and trading algorithms.

- Comparing algorithmic trading and DMA with manual trading:
  - In terms of speed and capacity, algorithmic trading is clearly the winner; computers can handle thousands of orders simultaneously, responding in fractions of a second.
  - In terms of performance, experienced traders still have the edge over algorithms since they can infer more subtle signals from the market. Though, as algorithms continue to evolve, the gap is closing. Algorithms also offer the prospect of more consistent results. Note that selecting the appropriate algorithm is vital.

Chapter 2
Market microstructure

Market microstructure focuses on the key mechanisms involved in trading. It also helps explain many of the costs that arise.

2.1 Introduction

Economics tends to abstract itself from the underlying mechanics of trading. Similarly, asset-pricing theory focuses solely on the fundamental values of assets. Whereas the field of market microstructure [1] concentrates on the actual trading process, analysing how specific mechanisms affect both observed prices and traded volumes. Market microstructure helps explain many of the costs that prevent assets from achieving their fundamental values.

Interest in market microstructure has grown rapidly over the last two decades, alongside the rapid changes in the structure and technology of the world markets. Structural shifts have arisen due to globalization, the demutualization of many exchanges (to become profit-based enterprises) and increasing intra-market competition. Regulation has also played its part. For example, in the U.S., Securities and Exchange Commission (SEC) governance led to the creation of ECNs (Electronic Communications Networks), which have aggressively competed with exchanges for market share. The pace of technological change has also helped, as tools like DMA and algorithmic trading open up markets, lowering the barriers for entry and altering the balance between investors, brokers and dealers.

What topics does market microstructure actually cover? We can break down the theory into three key areas:

- Market structure and design
- Trading mechanism research
- Transaction cost measurement and analysis

The purpose of this overview is to provide a basic introduction to these key areas. For further reading, a concise practitioner's guide is given by Ananth Madhavan (2002). Whilst comprehensive reviews of the academic literature are provided by Bruno Biais, Larry Glosten and Chester Spatt (2005), Hans Stoll (2001) and an earlier work by Madhavan (2000). A more detailed conceptual review of trading and markets in general may be found in Larry Harris's (1999) book 'Trading and Exchanges'.

[1] Mark Garman (1976) first used the term "market microstructure" in an article on market making. However, published market microstructure research dates back to the 17th Century, when Joseph De la Vega (1688) was analysing trading practices and pricing on the Amsterdam stock exchange.

2.2 Fundamentals

Before covering the key concepts of market microstructure in more detail, let's first address some of the fundamental features of trading and markets.

Markets exist to accommodate trade. A marketplace is intended to bring different participants together, allowing them to trade. Since supply and demand are not always evenly balanced, most markets also rely on intermediaries, such as brokers or dealers, to facilitate trading.

Liquidity characterizes the ease of trading on a given market or for a specific asset. Trading in highly liquid markets is much easier, and more efficient, than trading in illiquid ones. Given the importance of trade, and particularly given its increasingly global nature, it is useful to be able to compare markets in terms of their efficiency. The cost of an asset is not necessarily a fair measure since many other economic factors, such as currencies, interest rates or inflation, may affect this. Therefore, measures based on liquidity are often used instead.

Market function

The fundamental purpose of a market is to bring buyers and sellers together. Broadly speaking, the capital markets may be categorised into primary and secondary markets, based on the two stages of an asset's lifecycle. [2] The primary market deals with the issuance of new assets/securities. Subsequent trading of these assets takes place on the secondary markets.

New government bonds are generally issued via specialised auctions. For equities, the primary market is concerned with initial public offerings (IPOs), follow-on offerings and rights issues. Similarly, new corporate debt is generally placed using underwriters (usually a syndicate of banks).

Historically, the secondary market for bonds has often been "over the counter" (OTC), although there are now also substantial inter-dealer and dealer-to-customer markets. The situation is similar for the trading of foreign exchange and many derivative assets. Whilst for equities the main marketplaces are exchanges, although increasingly these must now compete with other venues such as ECNs and Alternative Trading Systems (ATSs).

The secondary markets are vital since investors will be more willing to provide capital if they know the assets may readily be traded. This flexibility allows them to withdraw capital when needed and to switch between assets. Thus, market microstructure research has mainly focussed on the efficiency of the secondary markets. In particular, examining the diverse range of market structures and trading mechanisms, as we will see in sections 2.3 and 2.4.

Participants

Conventionally, market roles have been defined by trading needs. The "buy-side" corresponds to the traditional customers, namely institutional and individual investors. Whilst the "sell-side" represents the brokers, dealers and other financial intermediaries who service customer needs. Brokers act as agents to facilitate the actual trading, whilst dealers (or market makers) trade on their own behalf trying to profit from offering liquidity. Speculators act independently, trading for themselves.

In comparison, the market microstructure models in academic literature tend to classify the participants based on the information they possess:

[2] Note this distinction is less meaningful for foreign exchange and derivatives.

Chapter 3
World markets

Investors, traders and trading systems are increasingly covering multiple markets and asset classes. Therefore, it is important to have a basic grounding in all the major world markets.

3.1 Introduction

The world's financial markets are vast, in terms of both their sheer size and the diversity of products they incorporate. Broadly speaking, we can break them down into several main categories, namely the:

- Capital markets
- Foreign exchange markets
- Money markets
- Derivative markets

The capital markets provide medium and long-term financing via stocks and fixed income assets, whilst the foreign exchange market enables the transfer of money across currencies. Short-term financing is provided in the money markets, which are closely linked to both fixed income and foreign exchange. The derivatives markets provide a means of trading financial contracts, which are in turn based on underlying assets. The underliers may include stocks, bonds, currencies, commodities or even other derivatives. In fact, so much commodity trading is handled via derivatives the commodity market has effectively been subsumed into the derivatives market.

Each market has its own strong identity. Even though many of the same players (brokers and investors) are involved in them, they are still often treated separately. In part, this is due to their different market structures. Conventionally, trading for equities and listed derivatives has centred on exchanges, whilst for many of the other asset classes over the counter (OTC) trading has predominated.

In the following sections, we will briefly cover the main asset class types and how they are traded. We shall then consider some of the major trends that are affecting the world's major markets. Finally, to try to put things in context we will compare the main world markets in terms of their overall sizes, trading volumes and the uptake of electronic and algorithmic trading.

Note that Appendices A-F provide more detailed reviews of each of the major markets. For even more in-depth analysis the reports compiled by consultancies such as the Aite Group, Celent, Greenwich Associates and the TABB Group are invaluable.

3.2 Asset classes

Financial assets generally provide their issuers with a means of financing themselves, and investors with an opportunity to earn income. For example, stocks represent a share in the firm that issued them, whereas fixed income assets correspond to loans. Foreign exchange is a transfer of cash deposits in different currencies. Derivatives offer a way of trading on the future price of assets, providing both a means of insurance and an opportunity for speculation.

Equity

Stocks allow companies to finance themselves by actually making their ownership public; each share represents a portion of the firm's inherent value, or equity. This value represents what the corporation's remaining assets are worth once all the liabilities have been deducted. A finite number of shares are issued by public corporations, although they may also choose to issue new ones or buy back some of the outstanding shares. Firms may also make periodic dividend payments to shareholders.

Shares are forward looking investments, since they represent a portion of the firm's total equity. Investors expect the value of their shares to increase or dividends to be paid in order to compensate them for the risk of bankruptcy.

Determining the fair value for equities is non-trivial. Present value theory states that the value of an asset corresponds to a discounted sum of its future payments. This may be based on the present value of their future dividend payments. In turn, this depends on future earnings, which can be difficult to predict. Firms may also choose to reinvest some of their income rather than increasing dividend payouts. Consequently, there are countless different valuation methods that may be applied to companies, each trying to tackle the range of possibilities.

A detailed review of equities and the associated markets may be found in Appendix A.

Fixed income

Fixed income assets, such as bonds, allow both governments and corporations to publicly issue debt for periods of up to 30 years, or even perpetually. The issuer is obliged to repay the holder a specific amount (the principal) at a set date in the future (the maturity date). Many names are given to these assets, but for the purposes of this chapter, we will just use the term bond. The issuer of a bond will usually pay interest (the coupon) to the holder at a given frequency for the lifetime of the loan, e.g. every 6 months. Alternatively, zero coupon bonds make no such payments; instead, their price is discounted by an equivalent amount.

These debts can be issued by governments, other agencies and by companies. They may also be issued based on pools of loans, which is the essence of asset-backed securities. Similarly, mortgage-backed securities are the equivalent for real estate debt. The effective interest rate, which the issuer must pay, depends on the maturity date of the contract as well as their credit rating and the current market rates. Bonds will sometimes have additional collateralization or protection to reduce their credit risk. They may also be differentiated in terms of their seniority when it comes to bankruptcy hearings. An indenture for each contract specifies any additional conditions. All of these features mean that bonds are much more bespoke assets than equities. In fact, there are more than three million different bonds in the U.S alone, which is two hundred times more than the number of equities available globally. This diversity can pose serious liquidity problems, since for many assets it will be difficult to

Part II

Algorithmic trading and DMA strategies

This is the main part of the book; it details the specifics of algorithmic trading and DMA, starting with orders, the basic building block for all trading strategies.

- Chapter 4 covers the wide range of different order types and conditions, which are available on the world's markets, together with examples.

- Chapter 5 reviews the different types of trading algorithm, from impact and cost-driven to more opportunistic strategies. Charts are used to show the trading patterns and highlight the differences (and similarities) between the various algorithms.

- Chapter 6 concentrates on transaction cost analysis. An example trade is used to decompose the transaction costs into their key components.

- Chapter 7 considers how the optimal trading strategy may be found by assessing orders in terms of their relative difficulty. This is then applied to the selection of trading algorithms.

Hopefully, by the end of these four chapters you should have a good understanding of the principles of algorithmic trading and DMA, together with how they may be applied to achieve "best execution".

Chapter 4
Orders

Orders are the fundamental building block for any trading strategy.

4.1 Introduction

Orders represent execution instructions. They allow investors and traders to communicate their requirements, both from the type of order chosen as well as with a range of additional conditions and directions. This chapter focuses on the basic mechanics of these various order types and conditions.

The two main order types are market orders and limit orders. In terms of liquidity provision, these are complete opposites. Market orders demand liquidity; they require immediate trading at the best price available. Whereas limit orders provide liquidity, they act as standing orders with inbuilt price limits, which must not be breached (a maximum price for buys and a minimum price for sells).

The conditions that may be applied to each order allow the trader to control many features of the execution, for example:

- Both how and when it becomes active
- Its lifetime/duration
- Whether it may be partially filled
- Whether it should be routed to other venues or linked to other orders

A wide range of trading styles can be achieved just by combining these conditions with limit and market orders. Indeed, many venues have gone on to support an even broader spectrum of orders, all essentially derived from basic market and limit orders. These include:

- Hybrid orders, such as market-to-limit
- Conditional orders, such as stops and trailing stops
- Hidden and iceberg orders
- Discretional orders, such as pegged orders
- Routed orders, such as pass-through orders

New order types are continuing to evolve. Some venues even offer orders that behave like algorithms, such as targeting the VWAP or participating in a set percentage of the market volume. Indeed, the line between them and trading algorithms is becoming increasingly blurred. Dynamic order types are very similar to trading algorithms, since they both alter based on market conditions. One way of differentiating between the two is that dynamic orders generally only focus on one specific variable, often the current market price (e.g. stop orders, pegging orders). Whereas trading algorithms base their decisions on a range of conditions, from volume to volatility. For the purposes of this text, we shall adopt this classification, so trading strategies such as VWAP and volume participation will be discussed further in Chapter 5. We shall also discuss how orders are actually used to implement algorithms and trading strategies in Chapter 9.

The examples in this chapter are broadly based on examples from the major exchanges. Some venues, notably the London Stock Exchange (LSE) (2006) and the Chicago Mercantile Exchange (CME) (2006), provide excellent materials with detailed examples for their order types. So it is always worth checking for such documentation. Another useful guide to the various types of orders is Larry Harris's (1999) book 'Trading and Exchanges'.

Finally, before we start covering the different order types and conditions in more detail, it is worth noting a few of the key assumptions made in the examples for this chapter. Firstly, they are all based around order books. Fundamentally, all trading involves order books, whether it is a phone-based OTC transaction or electronic trading via DMA, RFQ or a trading algorithm. The only real difference is that for quote-driven markets the order book is completely private and belongs to the market maker, whereas for order-driven markets the order book is usually centralised and much more transparent. Secondly, the examples generally cater for continuous trading periods, although some separate ones are highlighted for call auctions. This is simply because for most of these order types continuous trading is the most relevant period. Also for convenience, we usually assume that an execution will occur when we place an order that matches. Obviously, in real markets hundreds of participants can be issuing orders at the same time so regardless of a match our orders will sometimes be beaten to it. Lastly, the examples generally assume that the marketplace adopts a price/time priority, though for some cases the effect of different priorities is also highlighted.

So let's start by reviewing the mechanism of market and limit orders in more detail.

4.2 Market orders

The market order is an instruction to trade a given quantity at the best price possible. The focus is on completing the order with no specific price limit, so the main risk is the uncertainty of the ultimate execution price.

Market orders demand liquidity, a buy market order will try to execute at the offer price, whilst a sell order will try to execute at the bid price. The immediate cost of this is half the bid offer spread. We can see this using the sample order book shown in Figure 4-1.

Buys				Sells			
Id	Time	Size	Price	Price	Size	Time	Id
B1	8:25:00	1,000	100	101	1,000	8:25:00	S1
B2	8:20:20	1,500	99	102	800	8:20:25	S2
B3	8:24:00	900	98	102	1,200	8:24:09	S3

Figure 4-1 An example order book

A market order to buy 1,000 ABC can cross with sell order (S1) achieving a price of 101. We should then be able to immediately close out this position with an equivalent order to sell, which crosses with the buy order (B1) at 100. Hence the overall cost of both our market orders has been (101 – 100) which equals the spread, or half the spread each way.

For orders that are larger than the current best bid or offer size, most venues allow market orders to "walk the book". If they cannot fill completely from the top level of the order book, they then progress deeper into the book (increasing the price for buys, or decreasing for sells) until the order is completed. If the order still cannot be completed some venues will cancel it, such as the LSE, whilst others may leave the residual market order on the order book, e.g. Euronext.

Thus, the execution price achieved depends on both the current market liquidity and the size of the market order. For example, if we issue a market order to buy 2,000 ABC, the order book in Figure 4-2(a) shows that this can potentially cross with the sell orders S1 and S2. Receiving fills of 1,000 at 101 from order S1, and 1,000 at 102 from S2 gives an average execution price of 101.5. The resultant order book (b) shows that order S1 has been completed and S2 now only has 500 on offer (the buy side is unchanged and so is omitted).

Buys		Sells			
Size	Price	Price	Size	Time	Id
1,000	100	101	1,000	8:25:00	S1
800	99	102	1,500	8:20:25	S2
1,500	98	104	2,000	8:19:09	S3
		106	3,000	8:15:00	S4

(a) before

	Sells			
	Price	Size	Time	Id
.	~~101~~	~~1,000~~	~~8:25:00~~	~~S1~~
.	~~102~~	~~1,000~~	~~8:20:25~~	~~S2~~
.	102	**500**	8:20:25	S2
.	104	2,000	8:19:09	S3
.	106	3,000	8:15:00	S4

(b) after

Figure 4-2 The effect of a market order on the order book

In this example, as well as paying half the spread there is an additional cost that corresponds to the price jump from 101 to 102, resulting in a higher average execution price. This additional cost represents the market impact of our order. It is dependent on both the size of the order and the current market conditions, particularly the liquidity. For instance, if the example had been for an order of 5,000 we can see from Figure 4-2(a) that it would require crossing with orders S1 to S4, resulting in an average execution price of 103. Consequently, large orders often have a greater market impact than smaller ones.

Market conditions can also change rapidly. Again using the example from Figure 4-2 let's assume the owner of order S2 suddenly cancelled just before our market order to buy 2,000 hit the order book. In which case, our market order must now cross with order S3, the fill of 1,000 at 104 raises the average execution price to 102.5.

Sometimes market orders can actually achieve better prices than expected. This price improvement could be because the market order executed against a hidden order, such as an iceberg order, so a better price may be possible than the order book suggests. We will cover these order types later on in this chapter.

With no price limit, the performance of market orders is clearly dependent on current market conditions. Similarly, large market orders can have significant market impact, so it may be worth splitting such orders into smaller ones. If performance is more important than the speed (and certainty) of execution then a limit order may be a better choice.

4.3 Limit orders

A limit order is an instruction to buy or sell a given quantity at a specified price or better. A buy limit order must execute at or below this limit price, whereas a sell order must execute at or above it.

Limit orders will try to fill as much of the order as they can, without breaking the price

Chapter 5
Algorithm overview

Trading algorithms are predefined sets of rules for execution, each targeting a specific goal, whether it is matching the VWAP or seeking liquidity.

5.1 Introduction

An algorithm is basically a set of instructions for accomplishing a given task. Therefore, a trading algorithm simply defines the steps required to execute an order in a specific way. Brokers/vendors provide a range of trading algorithms, each with distinct goals. Some strive to match or beat a specific benchmark, or try to minimise overall transaction costs whilst others seek to trade more opportunistically. To achieve these goals, some approaches rigidly adhere to a given trading schedule whilst others are more dynamic, adapting to ever-changing market conditions.

Although the individual rules may be quite straightforward, the wide array of different events and possibilities that must be catered for mean algorithms can rapidly become quite complex. A common way of tackling this complexity has been to split the problem in two. For instance, Vladimir Kazakov (2003) decomposes VWAP trading into determining the optimum trading strategy and then realising this with optimal execution. The strategy concentrates on the trading schedule and benchmark, whilst the execution focuses on choosing appropriate orders to achieve this. Similarly, Robert Kissell and Roberto Malamut (2005) propose breaking algorithmic trading down into macro and micro level decisions. Again, the macro level makes strategic choices, based on the overall objectives. The micro level considers more tactical details, such as the specifics of order submission.

As an example, let's take a simple order to buy 6,000 of asset ABC over the next hour and time-slice its execution so that we trade 1,000 every ten minutes. We can represent this task with some pseudo-code:

```
for timer = 1 to 6
        quantity = 1000
        trade(quantity)
        sleep(10 minutes)
```

This code will not win any awards, but it does highlight that we are following a specific trading schedule until the order is completed. Obviously, we can make the trading algorithm more sophisticated by incorporating historical data or live market conditions. For instance, the quantity could be based on the best bid or offer size rather than just setting it to 1,000.

Exactly how we trade is a separate decision, for which the `trade()` function simply acts as a placeholder. A variety of approaches might be adopted, so the `trade()` function could:

- always place market orders
- always place limit orders
- dynamically choose the optimal order type based on market conditions

By separating the execution logic from the trading pattern in this way, we can create a common set of functions, which we will refer to as execution tactics. These are then available for all trading algorithms, and may be used interchangeably. This makes it much easier to customise our trading strategies. For example, we might default to a more passive execution style, but then change to use a more aggressive one when we get behind target or when conditions become more favourable.

So trading algorithms deal with the big picture, they primarily focus on how best to break up the order for execution. At the micro level are the actual mechanisms for managing order submission. We shall cover such execution tactics in more detail in Chapter 9.

5.2 Categorising algorithms

Although there are a wide variety of trading algorithms out there, if we strip off the customisations, we can start to see a small set of core strategies that are commonly provided by most brokers/vendors.

One way of classifying these algorithms is based on the benchmarks that they use. For example, the benchmark for implementation shortfall algorithms is predetermined, whilst for VWAP it is dynamic, and Market-on-Close seeks to match a future closing price.

Another way of classifying algorithms is based on their fundamental mechanisms. Ian Domowitz and Henry Yegerman (2005a) describe these as a continuum, which ranges from unstructured strategies, such as liquidity seeking algorithms, to highly structured approaches, such as a VWAP algorithm. Jian Yang and Brett Jiu (2006) go on to extend this approach by splitting this continuum into three main categories, namely:

- Schedule-driven
- Evaluative
- Opportunistic

Purely schedule-driven algorithms follow a strictly defined trading trajectory, generally created statically from historical data. For instance, historical volume profiles have often been used to implement VWAP algorithms; they represent intra-day historical volume averages. These profiles may then be used as a template for how the order should be split over time.

At the other end of the spectrum, opportunistic algorithms are completely dynamic. They react to favourable market conditions, trading more aggressively to take advantage of them. Then as conditions become less favourable, they trade more passively, if at all. Hence, liquidity-seeking algorithms are a good fit for this category.

Evaluative algorithms represent the middle ground between these two extremes. Often they combine aspects of each approach. Indeed, Yang and Jiu (2006) suggest that at the macro level they may behave in a more schedule-driven fashion whilst at the micro-level they focus on balancing the trade-off between cost and risk. Algorithms targeting implementation shortfall are good fit for the evaluative category.

This mechanistic style of classification focuses more on how algorithms are implemented,

Chapter 6

Transaction costs

Transaction costs can have a significant effect on investment returns. Therefore, it is important to both measure and analyse them if "best execution" is to be achieved.

6.1 Introduction

Each time an asset is bought or sold transaction costs are incurred. In economic terms, Robert Kissell (2006) describes them as costs paid by buyers, but not received by the sellers. They can have a considerable effect on investment returns, for instance, Ed Nicoll (2004) estimated total annual transaction costs of approximately $120 billion for the $12 trillion U.S. equity market. This is based on costs per order ranging from 20 basis points (bps) up to 200 (or 2%) of the value. The wide range is partly due to the different characteristics of each asset and order, but is also due to the different ways transaction costs may be assigned.

One of the most common ways to examine transaction costs has been to compare the actual performance of a portfolio with its "paper" equivalent. A paper portfolio is simply a virtual portfolio traded at benchmark prices, but without accounting for any costs.

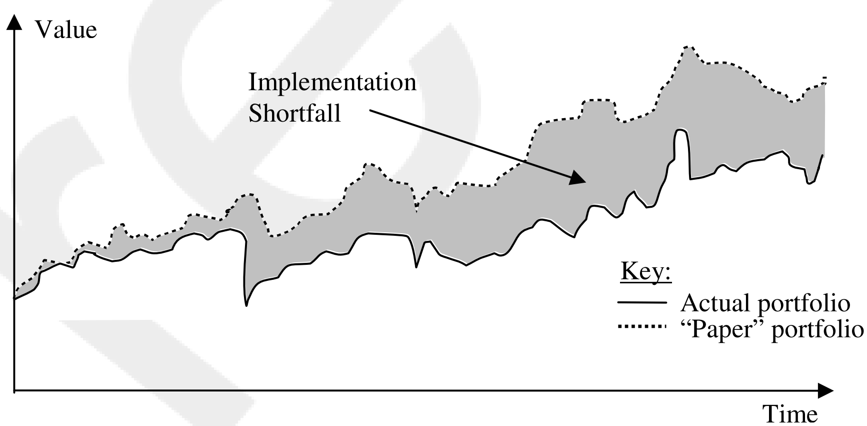

Figure 6-1 Comparing the performance of a portfolio

The difference in performance between a portfolio and its theoretical "paper" equivalent was termed the "implementation shortfall" by André Perold (1988), as shown in Figure 6-1. Alternatively, this is sometimes referred to as "slippage".

A specific example of the impact of transaction costs is given by David Leinweber (2002) for the returns of a fund based on the Value Line portfolio. The Value Line Investment Survey is a weekly stock analysis newsletter focussed on the U.S. Between 1979 and 1991 the paper portfolio achieved an annualized return of 26.2%, whereas the actual fund actually managed 16.1%. Much of this difference is directly attributable to transaction costs, since the fund made the same trades as recommended in the newsletter. [1]

Whilst transaction costs are inevitable, they can be minimised. Therefore, in order to maximise investment returns it is important to accurately measure transaction costs and to analyse them to understand how and why they occur.

6.2 The investment process

Transaction costs span the entire investment process. They may be tracked from the initial decision to buy/sell an asset through to the actual orders and executions that achieve it.

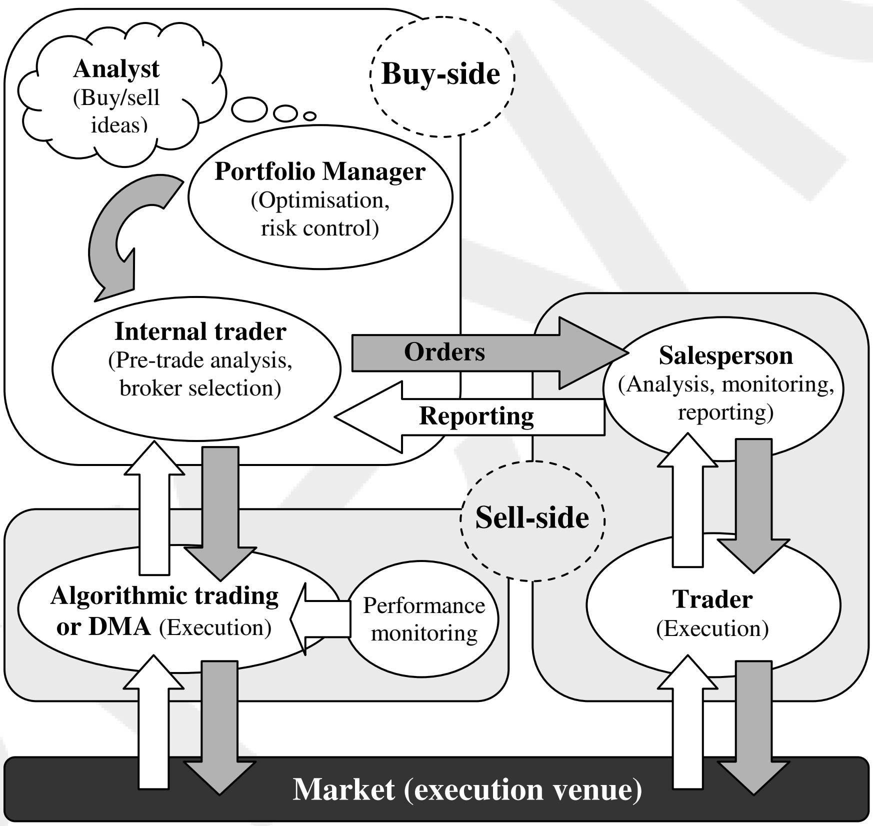

Figure 6-2 The investment process

[1] Leinweber notes that some of the shortfall was due to enforced delays before trading, ensuring that the fund did not front-run the newsletter subscribers.

Chapter 7

Optimal trading strategies

Selecting the best trading strategy for any given order is a case of carefully balancing the investment objectives with market conditions.

7.1 Introduction

Best execution has become an increasingly commonplace term of late. Market regulators are trying to put in force rules and guidelines to ensure that client orders are executed with the most favourable terms, based on their objectives and on market conditions. Clearly, the overall transaction cost is a key component to best execution. Therefore, it is important to note that the speed of execution (reflecting timing risk) and its completeness (reflecting opportunity cost) can have as much significance as price.

Unfortunately, there are no hard and fast rules for how to achieve best execution. The judgement depends on factors such as the choice of benchmark and the investor's level of risk aversion, as well as their overall goals.

So how do we go about determining the optimal trading strategy for a given order? We will start by examining an example trading decision framework, as described by Wayne Wagner (2006) and shown in Figure 7-1. This framework illustrates the process from the point of view of a buy-side trader:

<u>Step</u>

1. A portfolio manager initially notifies them of the order.
2. If there are any specific restrictions then the trader must use the designated broker.
3. Otherwise, the trader must assess how difficult the order will be to trade.

3.1 For orders that will provide much needed liquidity to the markets, the trader should strive for the optimal price.

3.2 Similarly, for orders that are judged easy, the trader has a lot of leeway in how best to deal with them.

3.3 Tough orders may be sub-categorised based on whether:

- They are a large percentage of the average daily volume (ADV).
- The asset is exhibiting significant trading momentum.
- The investor has flagged the order as urgent.

Depending on the perceived difficulty, the trader then must select the most appropriate method of trading. This may mean using trading algorithms, DMA, trying to cross the order, or negotiating a principal transaction with a dealer.

Part III

Implementing trading strategies

This part of the book delves further into the nitty-gritty of implementing trading strategies; it also shows how they may be enhanced and looks at the infrastructure required to make them work.

- Chapter 8 covers order placement, using empirical market microstructure research to analyse how market conditions affect execution probability.
- Chapter 9 focuses on execution tactics, which provide common mechanisms to achieve the goals of trading algorithms.
- Chapter 10 considers ways to enhance the performance of trading algorithms, using models for short-term forecasting and cost estimation, as well as handling special events.
- Chapter 11 reviews the infrastructure requirements associated with algorithmic trading and DMA, such as order management and the design of trading platforms.

Hopefully, by the end of these four chapters you should have a deeper understanding of the technical issues required to actually implement algorithmic trading strategies.

Chapter 8
Order placement

Order placement decisions are important to the success of any trading strategy.

8.1 Introduction

Order placement decisions are a key part of trading. Executing too aggressively could result in significant market impact; it also broadcasts our intentions to other market participants. Whereas trading too passively may result in us failing to complete the order, which could lead to a sizeable opportunity cost. Therefore we need to find the right balance which best achieves our objectives.

Based on these requirements, we need to select each order's size and price, and any special order types or conditions (if appropriate). Increasingly, marketplaces consist of multiple competing execution venues. So, for multi-venue markets we also need to choose the best destination. The possibility of hidden liquidity must also be taken into account. Hence, order placement decisions are affected by a wide range of factors, such as:

- current market conditions (price, volatility and liquidity)
- projected future trends
- historical results

Another way of looking at order placement is in terms of execution probability. Factors such as liquidity and price trends help us to estimate the likelihood of an order executing. Therefore, we can adjust orders to try to maximise their chance of being filled. This provides a more quantitative basis for actual order selection, and enables us to choose between execution venues.

To make best use of orders it is vital to understand the actual mechanisms that are involved in order matching. As we saw in Chapter 2, trading consists of three main stages:

1. Price formation
2. Price discovery / trade execution
3. Reporting, clearing & settlement

Consequently, order placement decisions are closely linked to both price formation and price discovery (or execution). So we shall start this chapter by reviewing these two fundamental mechanisms in some more detail, before moving on to consider the specifics of order placement and execution probability.

8.2 Price formation

Price formation is a multi-stage process. The fair value of an asset reflects its actual value whereas the market price reflects what people are prepared to pay. The market price may also reflect their expectations for the future value. If demand is high and supply is limited, assets will often trade at a premium to their fair value. Conversely, if demand is low then discounting may occur.

This division is also reflected in price analysis. Fundamental analysts tackle the problem by striving to determine the fair (or present) value of the asset. So the actual market price will be the key determinant of whether it is worth trading or not. Conversely, technical analysts tend to base their pricing solely from trends in the market price and volume.

Given the importance of the market price, market transparency also plays a key part in price discovery. A market maker's two-way quote only gives one view on pricing. Similarly, if only the best bid and offer quotes are displayed from an order book then effectively this is the same as a two-way quote. This adds a degree of uncertainty since traders cannot tell what other liquidity might be available. This additional risk could lead to orders being priced more aggressively than is necessary. On the other hand, if quotes are sought from multiple dealers or more of the order book is visible then traders can see the range of available prices and sizes. By using such visible liquidity, they can then adjust their own valuations to determine their own target price for the asset.

Valuation

The value of an asset is clearly a fundamental component of its price. Many books have been dedicated to this subject alone. Though, for the purposes of this chapter, the discounted cash flow model will suffice as our pricing model: Present value theory states that the present value of an asset corresponds to a discounted sum of its future payments. The discount rate takes account of the time value of money as well as other factors such as risk. Thus, asset prices will be higher for larger cash flows and lower when the discount rate increases.

Fixed income assets, such as bonds, offer fixed levels of interest for a given period of time and so have very clearly defined future payment streams, or cash flows. Present value theory lends itself well to the pricing of these assets.

Valuation for assets such as equity shares in a company is more complex, since the cash flows are less predictable. Nevertheless, present value theory has also been applied to stocks, dating back to work by Robert Wiese (1930) and John Williams (1938). Discounted cash flow models make valuations based on the present value of future dividend payments, which in turn depend on future earnings. Though, there are further complications when valuing stocks. For example, companies with high returns on capital will often reinvest income rather than increasing dividend payouts. Also, unlike bonds, companies could last forever (in theory), perpetually issuing dividend payments. Thus, Myron Gordon (1962) developed his growth model, where valuations are based on the current stock price and dividend, together with the expected rate of dividend growth and a discount rate. Other models have gone on to incorporate multiple growth periods, or finite horizons.

Other assets can also be complex to price, as we saw in Chapter 3. Foreign exchange is affected by both macroeconomic information, such as interest rates, and order flow. Derivatives reflect the price of their underlying assets combined with estimates for factors such as volatility and interest rates. Thus, appropriate adjustments must be made for their corresponding pricing models.

Regardless of how these valuations are actually determined, the amount of information

Chapter 9

Execution tactics

Execution tactics focus on the micro level decisions that need to be made when trading. They are responsible for the actual execution, monitoring the order book and managing order submission.

9.1 Introduction

Execution tactics represent the micro-level choices that must be made during trading. Typically, this means order placement and management. The division of labour between trading algorithms and execution tactics is clearest for the earlier schedule based algorithms. For example, in an all day VWAP algorithm the trading schedule might be based around 15 minute volume “buckets”. During the first period, it might aim to trade 3,000, then 2,000 in the next and so on. So for each 15-minute period an execution tactic may be tasked with trading a specific amount. It might simply choose to place a single limit order at the best bid or offer; alternatively, it could slice the amount into a series of smaller orders, as shown in Figure 9-1. In some ways, an execution tactic may be thought of as a mini-algorithm, with a trading horizon of seconds or minutes rather than hours.

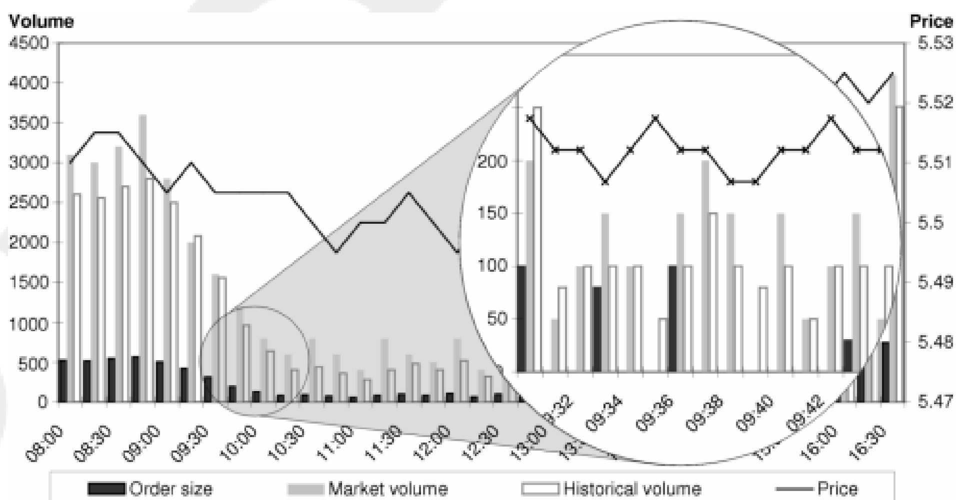

Figure 9-1 Comparing trading algorithm and execution tactic horizons

In order to achieve their objectives, execution tactics often adopt a range of common trading mechanisms. As we saw in Chapter 4, dynamic orders are becoming increasingly sophisticated, so there are often crossovers between common trading tactics and the actual underlying order types. For instance, pegging is obviously related to pegged orders, whilst hiding relies on iceberg and hidden order types. Though, not all venues support these order types, so trading tactics can provide a convenient abstraction. The tactics can then either use the native order types, or adopt an order placement strategy that essentially mimics the required behaviour for venues that do not support them. Alternatively, trading tactics may also employ more complex logic than is currently available via native order types.

As trading algorithms have evolved, many now track market conditions on a tick-by-tick basis. One way of adapting to changing conditions is to use different execution tactics. When market conditions are favourable, an aggressive approach may be employed; then as they become less favourable, it could switch back to using a more passive one.

Note that it is important to realise that there does not have to be a one-to-one relationship between trading algorithms and execution tactics. Some algorithms may use several execution tactics in parallel, leaving passive ones to trade over a longer horizon whilst quicker, more aggressive techniques take advantage of favourable prices.

9.2 Designing execution tactics

The simplest execution tactics are static; so all the logic resides with the trading algorithm. Effectively, these merely consist of splitting child orders to the market with an appropriate price. Passive approaches will adopt limit orders priced at or behind the market whilst aggressive ones use either market or marketable limit orders.

Neutral tactics are more flexible. They may start out passively, seeking price improvement, but if they fail to execute within a certain amount of time they will update or cancel the extant orders, replacing them with more aggressively priced ones. The deadline for execution may just be a fixed period (say five minutes). Alternatively, it could be determined from a limit order model, as we saw in Chapter 8.

Tactics that are more dynamic tend to consider market conditions when making order placement choices. For example, as we saw in Chapter 8, the order book conditions that generally tend to encourage traders to place less aggressively priced orders are:

- wider spreads
- sufficient depth, or prices further apart, on the opposite side of the order book
- insufficient depth, or prices close together, on our side of the order book

Given favourable conditions, a passive price-driven tactic may well price its orders further from the market, seeking price improvement. Alternatively, risk/cost-driven tactics may opt to weigh up the potential costs and decide whether it is better to wait or take an immediate hit. Opportunistic tactics may trade aggressively to take advantage of the current conditions.

So, broadly speaking, execution tactics may be classified based on the goals that drive their usage, just as we categorised trading algorithms in Chapter 5. Some common examples are shown in Table 9-1.

In general, impact-driven tactics seek to further reduce market impact by splitting the order into smaller quantities or by hiding a portion of it. Price/risk-driven approaches strive to dynamically adjust based on the market conditions. Similarly, the opportunistic ones look to take advantage when conditions are favourable.

Chapter 10

Enhancing trading strategies

Traders routinely base their decisions on a mix of current market conditions as well as anticipating how these might change in the future. Incorporating such logic into algorithmic trading strategies is a key to enhancing their performance.

10.1 Introduction

Having gone through the basics of both trading algorithms and execution tactics, this chapter aims to highlight some of the ways in which they may be enhanced. These mechanisms are rule-based approaches that respond to market conditions. Though, we can only ever estimate what conditions might be like in the future.

In Chapter 5, we used charts to compare the typical order placement patterns for different trading algorithms. However, during the execution it is important to remember that we just cannot tell what the future holds, as Figure 10-1 tries to show.

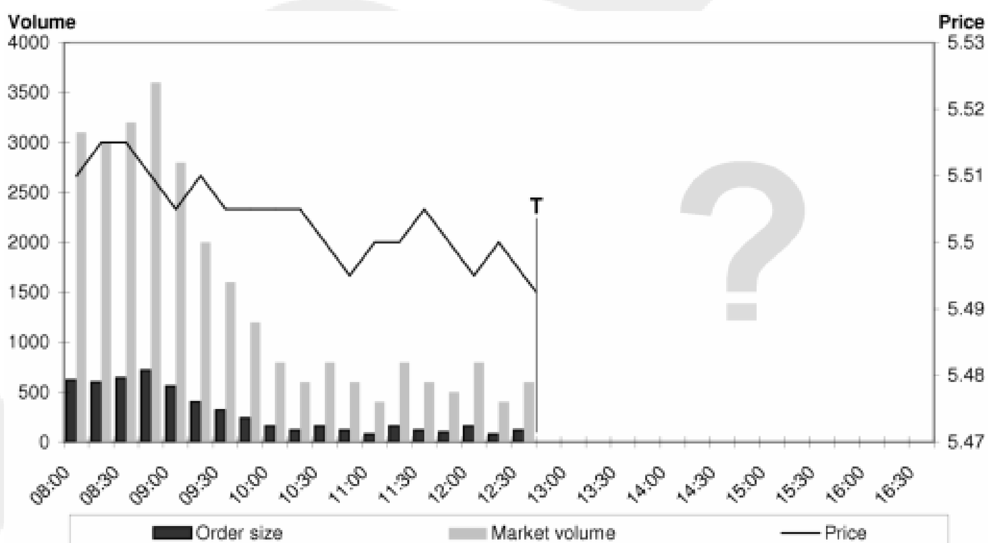

Figure 10-1 Uncertain market conditions

From time T to the close, we do not know exactly what will happen to the market price, volume or liquidity. Hence, trading algorithms and execution tactics are inherently reactive. If a sudden shift occurs in the marketplace, such a reactive approach can be caught out and forced to play catch up, at less favourable prices.

One way of enhancing computerised trading strategies is to incorporate short-term prediction models for key market conditions, such as volume and price. These allow strategies to take a more proactive approach, placing more passively priced orders (provided the forecasts are correct). For instance, a percent of volume (POV) algorithm that only ever trades in response to market volume could incur significant market impact, since it would always be chasing the market. A short-term prediction of trading volume allows the algorithm to layer orders, ensuring it takes part in the market volume rather than simply responding to it. Similarly, for price adaptive trading algorithms, a short-term price prediction will allow them to place appropriate limit orders to take advantage of price trends. If the prediction proves to be inaccurate, the orders may be cancelled.

Estimating potential transaction costs has also become more important, particularly for cost-based algorithms such as implementation shortfall. Many of these cost models are based on a framework by Robert Almgren and Neil Chriss (2000) which uses a random walk model to estimate the current market price in terms of costs.

Another potential enhancement is better handling of specific events, which in turn may be either predictable or not. For example, futures have finite lifetimes, so expiration is a predictable factor for these contracts. Whilst on witching days when major derivatives contracts expire, such as for the S&P 500 index, there will be sizable increases in trading volume, and short-term volatility, on the stock markets. Changes to stock indices are another example, since announcements are made some time before they occur. Given how many investment firms track the major indices, these changes have relatively predictable effects on the short-term trading for the affected stocks, depending on whether they are being added or removed from the index. Unpredictable events are generally triggered by information or news. They may be harder to forecast, but their short-term effects can still be quantified. For instance, trading interruptions, such as halts or volatility auctions, are usually followed by periods of much higher volatility and volumes, although these often dissipate after a few hours. In Chapter 14, we will cover the impact of news in more detail.

10.2 Forecasting market conditions

Traders and investors and have sought to predict prices for as long as markets have existed. Forecasting other market conditions such as volume, liquidity and volatility have also become more important.

Longer-term predictions are more useful for investment decisions. Execution is generally more focussed on short-term price trends. Therefore, the focus of this section is on short-term predictions, typically intraday. Short-term changes in market conditions are closely related to market liquidity. Factors such as order book depth and imbalance can give vital insights for how trade flow will react in the immediate future. In fact, many short-term predictions may be based just on recent market conditions. In Chapter 15, we will see how artificial intelligence can also be used for forecasting.

Predicting asset prices

At the simplest level, an asset's price merely represents what someone else is willing to pay. Imbalances in supply and demand can be a useful indicator for short-term price movements.

Chapter 11
Infrastructure requirements

Algorithmic trading is just as reliant on its infrastructure as the financial theory upon which its rules are based.

11.1 Introduction

So far, in this book we have focussed on the theory behind trading strategies. However, implementing them also involves a considerable amount of infrastructure. Figure 11-1 shows a high-level overview of the main components that are required for algorithmic trading and DMA.

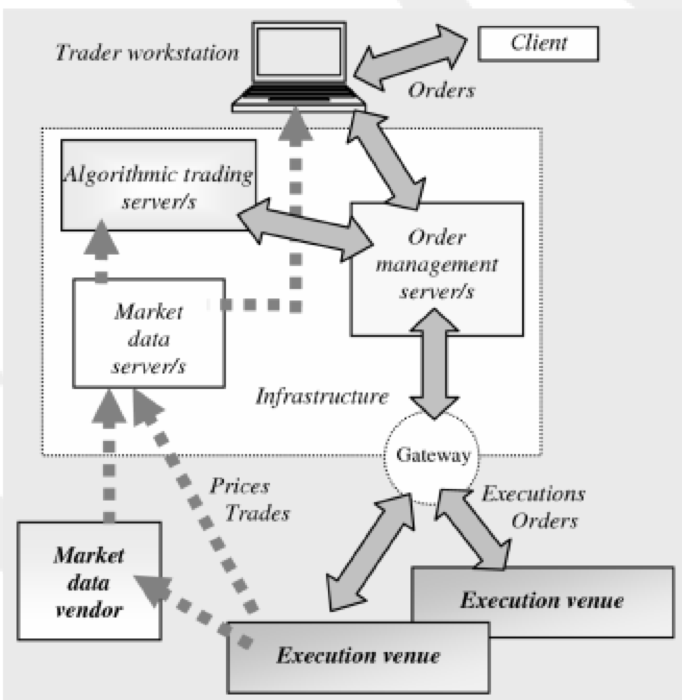

Figure 11-1 A high level view of the infrastructure required for electronic trading

Clearly, order management is a key part of this process, without it nothing much would happen. Before we move on to look at some of the technical considerations for implementing trading algorithms let's first review the mechanics of order management.

11.2 Order management

Order management plays an important role in any trading. Just as orders are the basis of any strategy, so they must be entered and routed to the appropriate destination, as Figure 11-1 shows. Executions (or fills) and updates/confirmations must be propagated back so that we can track the status of any given order. This is all catered for by a wide range of platforms, available from brokers and third-party vendors. There are two main types, namely order management systems (OMSs) and execution management systems (EMSs). Table 11-1 summarises some of the key functions offered by these platforms.

Function		***OMS***	***EMS***
Portfolio management	Modelling and rebalancing, "what-if" analysis	✓	
	Portfolio accounting	✓	
Risk management	Position management and P&L	✓	
	Risk management/exposure analysis	✓	
	Cash management	✓	
	Commission tracking	✓	
Analytics	Pre-trade analysis	✓	✓
	Post-trade analysis	✓	✓
	Real-time execution benchmarks		✓
Execution	Real time market data	✓	✓
	Order book depth		✓
	Connectivity to brokers/routing networks/FIX	✓	✓
	DMA/Trading algorithms/crossing	○	✓
Operations	Trade confirmations/allocations	✓	✓
	Connectivity to back-office systems/STP	✓	✓
	Exception reporting /reconciliations	✓	✓

Table 11-1 Typical OMS/EMS functions

Note that directories of the main OMS and EMS platforms may be found on the Advanced Trading website. [1]

Order management systems were originally developed to help improve workflow. They also encompass post-trade functionality, handling reporting and account allocation ready for clearing and settlement. They may also include portfolio-based functionality.

Execution management systems trace their roots back to the trade blotters and simple order entry screens that traders have relied on for decades. The adoption of DMA and algorithmic trading has led these to become increasingly sophisticated. Similarly, the increasing focus on transaction cost analysis has meant that many such systems now incorporate detailed pre-trade analytics.

At present, the level of convergence between OMSs and EMSs is growing rapidly. Fundamentally, though, whichever platform we use the mechanics of order entry and their subsequent routing are much the same. So let's examine each of these steps more closely.

[1] Advanced Trading directories are available at www.advancedtrading.com/directories

Part IV

Advanced trading strategies

This final part of the book focuses on some of the more advanced techniques that are still at the cutting edge of algorithmic trading.

- Chapter 12 considers how algorithms may be used for trading portfolios. It also looks at the potential for portfolio-optimised algorithms that take account of portfolio risk and diversification.
- Chapter 13 introduces multi-asset trading and reviews many of the common cross-asset trading strategies. It highlights the additional factors that must be considered when creating algorithms for these.
- Chapter 14 examines the potential for incorporating news. This covers the various sources of information and the analytics used to create meaningful indicators. There is also a review of market reactions to news events.
- Chapter 15 shifts the focus to data mining and artificial intelligence (AI). This shows how they may be applied to enhance trading performance by mining for relationships and providing short-term predictions.

Hopefully, by the end of these four chapters you should have a good idea of some of the techniques that may be more commonly adopted in the not too distant future.

Chapter 12
Portfolios

Portfolio trading is not just about multi-tasking. Significant risk reductions can be achieved by tracking and managing portfolio risk.

12.1 Introduction

Portfolio trading provides investors with a cost-effective means of trading whole baskets of assets. This may be used to convert new cash flows, liquidate existing positions, or a combination of the two for portfolio rebalances. It may even be used to assist the transition of entire investment portfolios, also known as transition management.

Just as with single asset trading, portfolios are traded on either an agency or principal basis. Agency trades may simply be worked on "best efforts", or target benchmarks such as the VWAP or daily close. Principal trades are agreed for a specific strike time, at which point a snapshot of all the asset prices is taken. Quotes may be obtained from a number of brokers, although information leakage is obviously a key concern. Hence, trading may also be performed blind, in which case the broker is just given a description of the portfolio. This offers only an approximate value, number of assets, and factors such as weightings for the countries, indices and/or sectors. Clearly, with such blind trades the broker/s will tend to quote more conservatively to protect themselves from the additional uncertainty.

There are some hybrid trading types as well, namely incentive agency and guaranteed benchmark trades. An incentive agency trade means the broker's commission depends on the performance relative to the benchmark, whilst a guaranteed benchmark trade enforces a strict target that the broker must meet.

Portfolio trading is also an important tool for risk control and efficiency. Most brokers provide comprehensive pre-trade and real-time trading analytics, which allow investors to more precisely assess the impact of trading. This information may also be useful for their hedging strategies. Detailed post-trade analytics allow accurate performance measurement. The high level of automation associated with portfolio trading also enables the streamlining of post-trade allocation and settlement.

One of the key considerations when trading baskets of assets is portfolio risk. So we will start this chapter by reviewing this in more detail. Then after seeing how transaction cost analytics may be applied, we shall focus on optimal portfolio trading strategies. This includes techniques such as hedging and determining the optimal portfolio makeup. Finally, we will consider a how best to apply trading algorithms for executing portfolio trades.

Chapter 13
Multi-asset trading

Multi-asset trading is nothing new; however, trading between different asset classes poses a whole new set of issues for trading algorithms.

13.1 Introduction

Multi-asset trading is starting to attract nearly as much hype as algorithmic trading. In its simplest form, it means single systems that allow investors and traders to manage trading across multiple asset classes. Though, in terms of algorithmic trading the most interesting prospect is cross-asset trading. This offers the potential of simultaneously trading a wide variety of different asset types using a single trading strategy.

Historically, the world markets have been highly segmented, both regionally and across asset classes. Electronic trading has helped open up markets, allowing a much broader range of access. Trading any asset globally is rapidly becoming a straightforward technical issue. Increasing numbers of order (OMS) and execution management systems (EMS) now provide unified platforms that enable trading across a range of asset classes. Similarly, communications protocols such as FIX have expanded to cater for equities, bonds, FX and an array of derivatives.

Hedge funds are arguably the principal driver behind the current trend towards multi-asset trading. Their strategies are becoming increasingly complex as they constantly seek new sources of profit, or alpha. Risk management has also become progressively more sophisticated in its use of derivatives for hedging. Consequently, the overall buy-side use of derivatives has spiralled over the last few years, leading to increased demand for multi-asset support.

The sell-side has had to evolve to cope with a new era of lower margins and higher volumes. Many firms have started reorganizing themselves; the old asset class silos are disappearing. Equities and derivatives businesses are merging, in some cases even fixed income and equities desks are integrating. Sales desks are becoming more customer-focussed, able to cater for trading a wide range of assets. The aim is to try to achieve greater efficiencies of scale and so reduce the overall costs. Cross-asset trading strategies also offer them a significant means of differentiation, as well as the benefits associated with being first-to-market.

Competition amongst execution venues is also helping. As we saw in Chapter 3, the competition is now truly global and has even started to span across asset classes. Exchanges are increasingly catering for equities, derivatives and even fixed income trading. For example, both NYSE and NASDAQ have expanded to offer trading in ETFs, futures and options. The NYSE has even relaunched its bond-trading platform. Many of the European and stock exchanges also handle bonds, whilst some of the Nordic exchanges also cater for derivatives. In Asia, Australia, Korea and Singapore have all seen mergers between their stock and derivatives exchanges. Likewise, the major derivatives exchanges have started branching out into other asset classes as well. For instance, Eurex also caters for bond trading whilst the ISE has created its own stock market. Competition is also increasing between the "dark pool" ATSs. Indeed, if some of the newer ATS entrants in FX and options prove successful, we may see mergers and takeovers in this arena as well.

Regulations will also play an important part in the expansion of multi-asset trading. In Europe, MiFID means that regulations now span across a broad section of asset classes, which should help clear the way for cross-asset trading. Though, in the U.S. the disparate regulatory bodies mean that it may be more complicated, as evidenced with difficulties over newer assets such as ETFs and single stock futures.

Another factor that will be crucial to the growth of multi-asset trading is the provision of unified mechanisms for clearing and settlement. Prime brokerage services will need to expand across the various asset classes. Netting agreements for collateralization and margin requirements will also have to encompass a much wider range of assets.

Although the divisions between the world's markets are becoming increasingly blurred, the exact outcome of all this change is still uncertain. At present, very few execution venues actually provide cross-asset trading. Some of the reasons for this are highlighted in an article by Ivy Schmerken (2006): Many exchanges still run separate platforms and matching engines for each asset class, some may have half a dozen different systems. Whilst there may be interest, the demand has still not been sufficient to justify the expense of merging these systems. That said, as exchanges migrate to new platforms support for multiple asset classes is becoming a key consideration. Another important factor is that whilst linked orders may be convenient, such "one-stop shopping" runs counter to broker's best-execution obligations. In the short-term, many of the cross-asset trading solutions are likely to be from brokers and other third-parties. Complex orders can easily be split into multiple legs and routed to different venues. Reduced latencies have also helped to reduce the legging risk for such strategies. Hence, it is likely that for the foreseeable future much of the innovation in cross-asset trading will be provided by specialised algorithms/platforms as brokers seek to continue to differentiate themselves with new value-added services.

13.2 Multi-asset trading strategies

Despite all the hype, cross-asset trading is nothing new. Cash positions in stock, bonds and commodities have been hedged with futures and options ever since the creation of derivative contracts. The ability to protect against a broad spectrum of risks has made derivatives a virtually indispensable tool. Cross-asset arbitrage is nothing new, either. In particular, index arbitrage and basis trading have been around for decades. Though, the high cost of entry has meant that historically such arbitrage has been monopolised by market makers, dealers and proprietary traders. More recently, electronic trading has helped lower the cost of entry. Easier access and decreasing transaction costs have made cross-asset trading viable for a much wider range of investors and traders. On the downside, it has also substantially reduced the timescales; many opportunities might now only last minutes, seconds or even less.

Ten years ago, the precursors of modern trading algorithms were efficiency tools, helping traders cope with the ever-increasing order flow. Finally, they were packaged up into discrete strategies and made available to clients as trading algorithms. Dealers' hedging and

Chapter 14
News

Information is everything. Automated news handling and interpretation can be complex, but these techniques offer the potential to further enhance trading strategy performance.

14.1 Introduction

The world's markets are driven by information, much of which is reported in news headlines and stories. Adapting to breaking news events can give traders a significant edge over the rest of the market. Over the last few years, the incorporation of news into algorithmic trading systems has attracted more and more attention.

Clearly, the relentless increase in both the speed and capacity of computers offers a massive potential for news-based analysis. Nevertheless, people are still much more adept at interpreting news and events than machines. Computer-based news analysis is a non-trivial task. Part of the difficulty is simply the fact that news is often based on unstructured text so it is difficult for rule-based systems to process it, and even harder for them to reliably interpret it. The increasing digitisation of news to computer-readable formats is helping to bridge this gap. Complex artificial intelligence and natural language processing techniques are also being employed. As we shall see in the following sections, progress is being made on computer-based analysis, but there is still quite a long way to go.

14.2 Types of news

News items can represent a wide variety of information. Broadly speaking, we can categorise most news items into three main classes: global/regional, macroeconomic and corporate.

Event	***Examples***
Global/regional	Political events, wars and terrorism, natural disasters
Macroeconomic	Interest rate, US non-farm payroll, Gross Domestic Product (GDP) announcements
Corporate	Mergers and acquisitions, bankruptcies, board/executive changes, product releases, quarterly/annual reports, dividend announcements

Table 14-1 Key news types

Table 14-1 shows some examples. Note that all three types of news can have distinct effects on the volume and volatility of both markets and specific assets. Though, the full effects of global/regional news can be quite difficult to interpret. Hence, this chapter focuses on the impact of both macroeconomic and corporate news.

Macroeconomic news

Most macroeconomic news comes in the form of regular announcements that provide information on key economic indicators. There is a wide range of different indicators; some of the main ones for the U.S. economy are shown in Table 14-2.

Class	***Announcement Type***	***Freq***	***Time***
GDP	*Gross Domestic Product (GDP)*	Q	8:30
Consumption	*Personal Consumption Expenditures*	M	8:30
Investment	*Business Inventories*	M	8:30
	Durable Goods Orders	M	8:30
	Factory Orders	M	10:00
	Construction Spending	M	10:00
	New Home Sales	M	10:00
Net Exports	*Trade Balance*	M	8:30
Government Expenditure	*Government Budget*	M	14:00
FOMC	*Target Federal Funds Rate*	6W	14:15
Money supply	*M2*	W	16:30
Real Activity	*Non-Farm Payrolls/Employment*	M	8:30
	Initial Unemployment Claims	W	8:30
	Industrial Production Capacity Utilization	M	9:15
	Retail Sales	M	8:30
	Personal Income	M	8:30
	Consumer Credit	M	15:00
Prices	*Producer Price Index (PPI)*	M	8:30
	Consumer Price Index (CPI)	M	8:30
Forward-Looking	*Index of Leading Indicators*	M	8:30
	ISM/NAPM Index	M	10:00
	Consumer Confidence Index	M	10:00
	Housing Starts	M	8:30

Table 14-2 Some of the key U.S. macroeconomic announcements

The classification scheme is based on those commonly adopted in economic literature. In the U.S., most of the announcements are made monthly (M), although some are issued quarterly (Q) or weekly (W). Indicators may also be referred to as procyclical or countercyclical; this just shows whether they move in the same direction as the economy or not. For instance, GDP and Non-Farm payrolls are procyclical indicators, whilst unemployment claims is a countercyclical one.

The *Gross Domestic Product* (GDP) is probably the best-known indicator of an economy. It represents the total value of goods and services produced by a country, usually over a year. Another way of expressing GDP is:

$$GDP = Consumption + Investment + Net\ Exports - Government\ Expenditure$$

GDP announcements are generally made quarterly and often in several stages, beginning

Chapter 15
Data mining and artificial intelligence

Trading is a complex process; markets keep getting faster and the volumes of data keep escalating. Data mining and artificial intelligence offer the potential to give traders an edge by spotting or predicting trends.

15.1 Introduction

Trading algorithms and execution tactics are inherently reactive, responding to market conditions based on predefined rules. In Chapter 10, we saw how they may be enhanced by using short-term prediction models for key market conditions, such as volume and price. These allow a more proactive approach, placing more passively priced orders.

However, in volatile markets, such as those during the 2007-09 financial crisis, sudden unexpected shifts can occur. These are hard to predict and can wrong-foot forecasts based on statistical analysis of historical data. Techniques such as data mining and artificial intelligence offer the potential to improve short-term predictions for key market variables, even during volatile markets. This is because they can incorporate a much wider range of factors in their forecast models. They may also be able to cope better with today's more complex marketplaces, where trading is fragmented between multiple venues.

Data mining is all about finding and confirming trends and/or relationships, some of which may be obvious whilst others may be much more subtle. Many of these techniques are purely statistical in nature. Certainly, much of the market microstructure analysis we have already seen in Chapters 8 and 10 may be viewed as a form of data mining. Likewise, textual analysis can be incorporated. So associations may also be inferred from information in news stories or company reports, as we saw in Chapter 14.

Artificial Intelligence (AI) systems are designed to adapt and learn, and so they can effectively think for themselves. There are two main types, namely conventional AI and computational intelligence. Conventional AI is a top-down approach, which applies logic and rules to make decisions. Essentially, trading algorithms are an example of conventional AI. Computational intelligence takes a bottom-up approach, and is inspired by biological mechanisms. For instance, neural networks try to reproduce the action of our brain's neurons, whilst genetic computation simulates evolution.

In terms of trading and finance, there are three main applications for these techniques: [1]

- Prediction
- Finding associations/relationships

[1] As suggested in a review by Stephen Smith (1998).

- Generating trading strategies

All of these are quite closely related. Prediction and association mining often use similar methods to find relationships in the data. These may form the basis of new trading rules or strategies. Artificial intelligence systems are able to test a huge number of variations in parallel, seeking the optimal solution. Hence, they can also help in the creation, testing and fine-tuning of rules for trading strategies/algorithms and their associated parameters.

In the following sections, we will review these techniques and survey some of the reports on their effectiveness, particularly for short-term forecasts. We will also consider how they might be incorporated to enhance execution.

15.2 Data mining

As its name suggests, data mining is all about data. By applying analytical techniques, trends and/or relationships may be found within data, or between different datasets.

Data mining techniques

Dongsong Zhang and Lina Zhou (2004) provide a nice overview of data mining for the financial markets. There are several main types, namely:

- Classification and clustering analysis
- Time-series mining
- Association rule mining

These employ a range of different statistical analysis/inference methods. They may also incorporate AI-based mechanisms such as neural networks and genetic algorithms.

Classification and clustering analysis

Classification and clustering analysis both seek to identify common features in the data. Any commonalities may then be used for predictions, since if the results are known for one entity (or may be accurately estimated) they are likely to be comparable for those with similar properties. Note that often such predictions will focus on the direction rather than the potential value. For example, specific conditions might be used to determine whether a stock index or exchange rate will increase or decrease in a certain time span. These analyses may also be used for risk management or for spotting potential investments.

Classification may be strictly hierarchical, in which case properties such as country, currency, industry and sector are useful. Other factors such as the financial ratios (e.g. price to book) may also be used. Cluster analysis may also be applied to create intermediate hierarchies, based on results such as price returns or volatility.

Alternatively, a more geometric approach may be taken. This is often achieved using AI-based techniques, which we shall cover in section 15.3. For instance, the k-nearest neighbour algorithm classifies based on a majority vote from its neighbours. Likewise, probabilistic neural networks employ a weighted vote for each category based on the distance from test cases. Support vector machines may also be used to seek the plane/s which optimally separate/s any categories or clusters.

Time-series mining

In finance, time series analysis is often used for forecasting. As we saw in Chapter 10, regression-based models, such as ARMA, are used to make short-term predictions for prices or volatility. Historical volume profiles are another example, using average-based models to

Appendices

The following appendices provide an overview of each of the major asset classes and their main markets. The focus is on their adoption of electronic trading and the provision of algorithmic trading and DMA. They also examine the regional differences between the Americas, Europe and Asia.

Invariably, any review of the world markets will date rapidly given how quickly the markets are changing. Nevertheless, the main sources of information remain the same, namely the:

- World Federation of Exchanges (WFE) (www.world-exchanges.org)
- Bank for International Settlements (BIS) (www.bis.org)
- Securities Industry and Financial Markets Association (SIFMA) (www.sifma.org)

Each of these organisations publishes annual (and sometimes monthly) statistics for the world's major markets.

For analysis that is even more comprehensive, the reports by consultancies, such as the Aite Group, Celent, Greenwich Associates and the TABB Group, are invaluable.

Note that no particular reading order is required for these appendices. You may prefer to jump straight to the markets that are most relevant to you. Still, it is worth coming back to review the other material since there is a lot to gain from seeing how things are done in the other markets.

Appendix A

Equity markets

The world's equity capital markets account for a quarter of the global financial market value, as we saw back in Chapter 3. Historically, stock markets have developed around strong inter-dealer networks, usually centred on major exchanges. In part, this is due to the highly standardised nature of stocks. Trading on these exchanges is still mainly carried out by brokers. They act as intermediaries, acting as an agency through which to trade orders on the exchanges; broker/dealers may also be prepared to deal in principal with OTC trades. The equity markets have proven to be ideally suited for implementing electronic and algorithmic trading. Hence, the levels of adoption of these techniques are still significantly higher for the equities markets than any other asset class.

Asset specific

The equity in a corporation represents the value of the remaining assets once all the liabilities have been deducted. A share in a company (also known as stock) represents a portion of this total equity. A finite number of shares are issued by public corporations. Though, they may periodically choose to issue new shares or buy back some of the outstanding ones. If the company performs well its value (and so its share price) should increase. However, if it fails and falls into bankruptcy, shareholders rights are subordinate to those of creditors, so they are typically left with little or nothing. Therefore, shares are forward looking investments; investors expect the value of their shares to increase in order to compensate them for the risk of default. Alternatively, periodic dividend payments may also be made by the company to reimburse investors.

Growing companies tend to need cash so they will often rely on share price rises to appease investors. Whereas more established companies may prefer to issue larger dividends. This flexibility explains part of the appeal of issuing shares for companies.

The kind of equity issued by a company may differ in terms of voting rights and in the distribution of dividends and assets, in case of bankruptcy. The two main types are common stock and preferred stock. Common stock allows the holder to vote in certain corporate decisions, such as the election of directors, issuance of new shares and approving takeovers. Preferred stock has priority over common stock when dividends are issued and in liquidation; however, they tend to have less voting rights.

The total value of the outstanding shares is referred to as the corporation's market capitalisation, or market cap. In U.S. terms, a large-cap, or blue-chip, stock has a value of greater than $10 billion. Mid-caps have values between $1 and $10 billion, small-caps are below $1 billion and micro-caps have values less than $100 million. The values for these categories will vary for other countries, but the relative sizes will be similar.

Pricing and trading

Determining the fair value for equities is non-trivial. Present value theory states that the value of an asset is the discounted sum of its future payments. For stocks, these correspond to their future dividend payments, which in turn depend on future earnings. Though, dividend payments can be difficult to predict. Firms may also choose to reinvest some of their income rather than increasing dividend payouts. A range of estimation models try to take such factors into account. Alternatively, cross-sectional regression analysis may be used to infer prices by comparing key ratios such as Price/Earnings (P/E) with similar firms, or across whole sectors/industries.

Investors also have varying information about each company and so their valuations will be dissimilar. Thus, market prices reflect the average of all these valuations combined with the effects of supply and demand. Consequently, the market capitalisation will often be different to the fundamental value of a corporation's (its assets minus its liabilities).

In terms of trading, stocks are readily transferable in a domestic context, so markets like the U.S. have seen a huge amount of local competition, between both exchanges and other execution venues. Electronic access and remote memberships, for foreign investors/traders, are helping to increase access to venues. There is also a buoyant depositary receipt market for trading foreign stocks. Essentially, these are just proxies allowing foreign stocks to be traded locally (they are covered in more detail in Appendix F). Together, all these factors mean that stocks are starting to become truly global assets that may be traded 24 hours a day. For instance, Mark Howarth (2004) uses Sony as an example to demonstrate how such trading is now possible for many major firms. Table A-1 shows some of the potential trading venues for this throughout the day.

Time *(Japan Standard Time)*	***Trading venue***
08:00 – 09:00	Tokyo pre-trade
09:00 – 15:00	Tokyo
15:00 – 24:00	London, GDR IOB
18:00 – 24:00	Tokyo after-hours markets
22:30 – 05:00	U.S. ADR
05:00 – 08:00	U.S. after-hours markets

Table A-1 Potential trading venues for a Japanese stock

Once the Tokyo stock exchange has closed, trading may continue either on its after-hours platform (ToSTNeT) or on other local after-hours markets, such as SBI JapanNext. Trading can also shift to London stock exchange's International Order Book (IOB). Similarly, before London closes the U.S. opens, allowing depositary receipts to be traded here and on after market venues until Tokyo opens again.

World equity markets

The world's equity markets continue to be centred on stock exchanges. However, an increasing array of new execution venues such as Electronic Communications Networks (ECNs) and Alternative Trading Systems (ATSs) have brought both competition and fragmentation. That said, the high level of electronic trading and access via DMA and algorithmic trading mean that the world's equity markets have arguably the highest level of client-side accessibility.

Table A-2 shows the world's top fifteen stock exchanges in terms of their domestic market capitalisation and total value of share trading for 2007 and 2008, based on data from the World Federation of Exchanges (WFE) (2009). Clearly, the U.S. dominates the world's equity trading with both the NYSE and the NASDAQ exchanges. The Tokyo, Euronext and London stock exchanges also have significant market shares and turnovers.

Exchange	***Domestic market cap in $ billions***		***Total value of share trading in $ billions***	
	2008	*2007*	*2008*	*2007*
NYSE Euronext U.S.	9,209	15,651	33,639	29,114
Tokyo Stock Exchange	3,116	4,331	5,607	6,413
NASDAQ OMX (U.S.)	2,396	4,014	36,447	28,116
NYSE Euronext Europe	2,102	4,223	4,411	5,640
London Stock Exchange	1,868	3,852	6,272	10,334
Shanghai Stock Exchange	1,425	3,694	2,600	4,029
Hong Kong Exchanges	1,329	2,654	1,630	2,134
Deutsche Börse	1,111	2,105	4,679	4,325
TSX Group	1,033	2,187	1,716	1,635
BME Spanish Exchanges	948	1,781	2,411	2,970
SIX Swiss Exchange	857	1,271	1,500	1,883
Australian Stock Exchange	684	1,298	1,213	1,372
Bombay Stock Exchange	647	1,819	302	344
National Stock Exchange India	600	1,660	725	751
BM&FBOVESPA	592	1,370	724	598

Source: WFE (2009)

Table A-2 Major world stock markets

Although some global execution is possible, stock markets are generally focussed on domestic trading. In part, this is due to the much higher level of regulation for the stock markets. Still, over the last few years exchanges have started to become truly global entities. The mergers between NYSE and Euronext, NASDAQ and OMX are a good example of this. Hence, global competition is likely to increase significantly in the coming years.

Electronic trading has become ubiquitous for the world's stock markets, particularly for the sell-side. Buy-side levels of adoption of DMA and algorithmic trading are also high, especially in the U.S. Figure A-1 shows both the current levels of adoption of algorithmic trading and projections for 2010, based on estimates from the Aite Group (2007a) consultancy. Clearly, it will still take some time before the levels of adoption for algorithmic trading in Europe and Asia reach those of the U.S.

American equity markets

North America obviously dominates the region with some of the world's largest exchanges, as shown in Table A-2. The markets in Canada and Latin American are much smaller.

References

Aite Group (2007a) 'Algorithmic Trading: Top 10 Keys to Success in 2007', *Aite Group (www.aitegroup.com)*

Almgren and Chriss (2000) Almgren R. and Chriss N., 'Optimal Execution of Portfolio Transactions', *Journal of Risk,* vol:3, p 5-39

Biais, Glosten and Spatt (2005) Biais B., Glosten L. and Spatt C., 'Market microstructure: A survey of microfoundations, empirical results, and policy implications', *Journal of Financial Markets,* vol:8 (2), p 217-264, doi:10.1016/j.finmar.2004.11.001

Burr (2005) Burr D., 'Vision: In the Blink of an Eye', *Current Biology,* vol:15 (14), p 554-556

CFA Magazine (2006) Opiela N., 'Hype and Algorithms Is algorithmic trading the way of the future or "just okay"?', *CFA Magazine, March-April 2006*

CME (2006) 'Developer's Guide for CME iLink 2.X', *Chicago Mercantile Exchange (www.cme.com)*

De La Vega (1688) de la Vega J., 'Confusion de Confusiones'

Domowitz and Yegerman (2005a) Domowitz I. and Yegerman H., 'Measuring and Interpreting the Performance of Broker Algorithms', *Algorithmic Trading, A Buy-Side Handbook 1st edition (2005), publisher The Trade (www.thetradenews.com)*

Garman (1976) Garman M., 'Market Microstructure', *Journal of Financial Economics,* vol:3 (3), p 257-75

Harris (1999) Harris L., 'Trading and Exchanges: Market Microstructure for Practitioners', *publisher Oxford University Press, USA*

Howarth (2004) Howarth M., 'Best execution across multiple pools of liquidity via FIX', *FIX Global (www.fixglobal.com),* Vol 1 Issue 1 Q1 2004

2008 Market Survey Results', *www.isda.org*

Kazakov (2003) Kazakov V., 'Optimal VWAP trading on the ASX', *PhD Thesis*

Kissell (2006) Kissell R., 'The Expanded Implementation Shortfall: Understanding Transaction Cost Components', *Journal of Trading,* Summer 2006

Kissell and Glantz (2003) Kissell R., Glantz M. and Malamut R., 'Optimal trading strategies: quantitative approaches for managing market impact and trading risk', *publisher American Management Association*

Kissell and Malamut (2005) Kissell R. and Malamut R., 'Understanding the Profit and Loss Distribution of Trading Algorithms', *Guide to Algorithmic Trading, Institutional Investor Inc.,* Spring 2005

Leinweber (2002) Leinweber D., 'Using information from trading in trading and portfolio management: ten years later', *Working paper*

LSE (2006) 'Guide to Trading Services', *London Stock Exchange,* July 2006

Madhavan (2000) Madhavan A., 'Market microstructure: A survey', *Journal of Financial Markets,* vol:3 (3), p 205-258, doi:10.1016/S1386-4181(00)00007-0

Madhavan (2002) Madhavan A., 'Market Microstructure: A Practitioner's Guide', *Financial Analysts Journal,* vol:58 (5), p 28-42, doi: 10.2469/faj.v58.n5.2466

Markowitz (1952) Markowitz H., 'Portfolio Selection', *Journal of Finance,* vol:7 (1), p 77-91

Nicoll (2004) Nicoll E., 'Reducing Transaction Costs and Recapturing Value for Your Plan', *Pension Observer Winter 2004*

Perold (1988) Perold A., 'The implementation shortfall: paper versus reality', *Journal of Portfolio Management,* Spring 1988

Schmerken (2006) Schmerken I., 'Exchanges Gamble On Multi-Asset Trading', *Advanced Trading (www.advancedtrading.com),* January 2006

Smith (1998) Smith S.N.P., 'Trading Applications of Genetic Programming', *FE News,* Sep 1998, vol:6

Stoll (2001) Stoll H.R., 'Market Microstructure', *Handbook of the Economics of Finance,* vol:1(1), p 553-604

TABB Group (2008) Berke L., 'US Institutional Equity Trading: Crisis, Crossing and Competition', *TABB Group (www.tabbgroup.com)*

Wagner (2006) Wagner W.H., 'Creating A Hierarchy of Trading Decisions', *Journal of Trading,* Winter 2006

WFE (2009) 'WFE Annual Report 2008', *World Federation of Exchanges (www.world-exchanges.org)*

Yang and Jiu (2006) Yang J. and Jiu B., 'Algorithm Selection: A Quantitative Approach', *Algorithmic Trading II, publisher Institutional Investor, New York,* vol:13)

Zhang and Zhou (2004) Zhang D. and Zhou L., 'Discovering golden nuggets: data mining in financial application', *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on,* vol: 34 (4), p 513-522, doi:10.1109/TSMCC.2004.829279

Note: this is only a small sample; there are over 500 references in total.

Index