University of Warwick, Department of Psychology

Group Behaviour in Financial Markets

A thesis submitted for the degree of Doctor of Philosophy

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DECLARATION

All material in this thesis is original, unless indicated otherwise in the text, and has not been previously submitted for a degree either at Warwick University or elsewhere. This material has also not yet been published, although this is intended in the future.

ABSTRACT

This thesis aims to revise the current understanding of the behaviour of different groups of traders in financial markets. Research involves statistical analysis of historic ‘Commitment of Traders’ reports, a U.S government dataset providing the long and short positions of core groups of traders, reported at weekly intervals over 17 years. Empirical work identifies a surprising level of consistency amongst different groups across 31 markets. A specific pattern is identified: speculators are found to increase their buying interest when prices are rising whilst commercial traders (or ‘hedgers’) increase their selling; the opposite pattern of behaviour occurs when prices are falling. The thesis explores the implications of this behaviour for existing models of financial markets by referencing a number of peer-reviewed studies. The agent-based computational model of Alfarano, Lux, and Wagner (2005) is implemented and analysed. A lack of validity is demonstrated in the interactions between the different types of traders in this model. These theoretical components are further shown to be typical of much of the literature in this area. An objective for the thesis is to correct this oversight by incorporating genuine patterns of trading behaviour into an existing computational model. The approach of Mike and Farmer (2008) is used for this purpose, being currently unique in that core components are calibrated from real-world data and no group-level representations are assumed. This model is extended to observe groups of traders with different levels of order-aggression: speculators are found to rely on market orders whereas commercial traders rely on limit orders. These preferences, in the absence of deeper theoretical considerations, are sufficient to account for the identified behaviour. A discussion is offered on the relevance of this finding for financial market regulators, who have typically focused on regulating types of traders, specifically speculators, rather than on types of trades.

For Natalia

1. INTRODUCTION

Contents:

Abstract:

This chapter provides an overview of the thesis subject, its chapters, and the motivations for research. This encompasses an introduction to financial markets, derivative markets, and the basic categorisations of different participants, as well as an overview of some ubiquitous statistical properties associated with financial market prices. Computational models capable of simulating these statistical idiosyncrasies often propose important group-level dynamics involving interactions amongst different types of traders. However, these components often lack any genuine empirical foundations. A central objective for this thesis is to correct this oversight by documenting genuine patterns of trading behaviour amongst participants and incorporating this knowledge into an existing computational model. As discussed in this chapter, more realistic representations of financial market participants could impose new constraints on existing theories and increase the behavioural realism of future computational models for more successful practical applications.

"The system of world financial markets can be viewed as a huge social science experiment."

Bouchaud, Farmer, and Lillo (2009, p. 63)

1.1 Aim and Objectives

This thesis aims to review and revise the current understanding of the behaviour of different groups of traders in financial markets and to offer new empirical research. For the first time, previously unexplored patterns of trading behaviour, that are apparently stable and durable across significant periods of time and a wide range of markets, are documented in detail. The thesis will consider the preferences and motivations underlying behaviour patterns, first by reviewing a significant number of peer-review papers on related subjects, and then by implementing recent agent-based computational models of financial markets. Extensions to an existing computational model are put forward for the first time to test a hypothesis for the patterns of behaviour uncovered from empirical sources. The result of these efforts is threefold: to highlight the relative stability of certain group-behaviours in financial markets, to present a computational model that incorporates this knowledge and can be readily extended in new directions in the future, and to move academic focus towards using this empirical information in more practical settings, such as for financial market regulation.

This thesis can be considered timely, being written in the aftermath of one of the most significant financial crises of the last 100 years, the so-called 'credit crunch' with dramatic stock market and housing crashes leading to the largest contraction in Western world economic output since the 1930s. A new perspective on market regulation in the twenty-first century is a clear objective for social science research. Increasing our understanding of how traders behave, interact and aggregate to create market behaviours, and exploring new approaches to the modulation of the volatility often associated with financial market prices are important, albeit lofty, goals. This thesis aims to present a set of findings and proposals relevant to these research aspirations, whilst acknowledging there are many different approaches to this broad and important subject area.

Economics, known for too long as 'the dismal science', is undergoing a paradigm shift, bringing in researchers from different domains to reflect more accurately the multi-disciplinary nature of the subject matter. Economics embraces psychology, sociology, statistics, physics and biology – to name a subset of disciplines – in a closely-grouped cluster of related interests. However, as Ormerod (1998) highlights, it was not until relatively recently that economics as a discipline actually began testing and developing theories with empirical data. Prior to this, economics was largely theoretical, relying on idealistic assumptions about human behaviour to permit a myriad of analytical solutions to different economic problems. More recently, a trend in academic literature has begun to correct this oversight, approaching traditional economic subjects from alternative and non-traditional perspectives. Research presented in this thesis can be considered part of this new behavioural and empirical economics, readily embracing the viewpoint of the subject as fundamentally a social science: concerned with people, their reactions, their preferences, their decision-making, striving to understand, and perhaps even predict, aggregate social behaviour within particular economic contexts.

The focus of this thesis is the psychologist's, on the behaviour, preferences and motivations of actual people operating in the context of financial markets, an area of interest to the social sciences that might be considered dissimilar to any other. Financial markets generate a phenomenal amount of empirical data, recording transactions between buyers and sellers, market prices, trade volumes and frequencies, across the globe 24 hours a day. There are detailed audit trails of the perspectives and behaviour of a huge array of different individuals, groups, nationalities, businesses and governments, all with differing viewpoints and objectives. This information is of inherent interest to psychologists concerned with decision-making, collective behaviour, or perception. The amount of data being recorded is ripe for a more empirically-orientated investigation into economic behaviour. Financial markets are influential, directly or more often indirectly, in the lives of millions of people every day; they influence economic trends that impact on the creation of jobs and levels of prosperity; they influence prices for core commodities that create food, housing and other central aspects of our lives. Despite this profound relevance, the behaviour of participants in financial markets remains ill-understood, and, as with much of traditional economics, has been investigated with assumption-laden theories about human behaviour. The goals of the research presented here are to provide insight into how some participants actually behave in financial markets, and to present a market model that incorporates this knowledge as a foundation for practical, future research. It is to be hoped that this will encourage more empirical research in this direction in and for the future.

This introductory chapter offers a broad overview of financial markets, derivative markets, and the basic categorisations of different participants that inhabit them. I briefly summarise what financial markets and derivative markets are, what they provide, and to whom. Following this, the chapter then briefly reviews research on the statistical characteristics of financial markets – these findings point to remarkable consistencies in market behaviour across time-periods, asset classes and national boundaries. This prior literature provides an important context for understanding the motivations and aspirations for the research presented in this thesis. The chapter concludes with an overview of the contents of each chapter and overall thesis objectives.

1.2 Introduction to Financial Markets and Derivative Markets

Like all markets, the basic function of financial markets is to match buyers and sellers. The term 'financial' refers to the numerous freely traded and highly active markets where the exchange of capital and credit occurs in the economy (Downes and Goodman, 1998). These include stock markets, currency markets, bond markets and commodity markets. Within the broad capacity of matching buyers and sellers, financial markets provide different economic services to different participants. These can be considered as primary and secondary services. An outline of these different services and the relevant groups who participate and benefit will now follow.

As a primary service, financial markets provide issuers of a product a means to raise capital by selling a right, obligation, or a primary good to a wider market-place. As examples, stock and bond markets provide funding to corporate and government entities; commodity markets provide producers of tangible goods or consumables a means to auction their products to a wider market of wholesalers and distributors. Primary markets allow newly created products to be bought and sold. As a secondary service, financial markets provide the opportunity to trade in a given product once it has been issued or produced. As examples, investors trade the right to participate in profit and wealth creation schemes arising from corporate or government activities via secondary stock and bond markets; primary goods can be augmented with value-adding features and traded to across a wider-economy of consumers. Secondary markets provide a crucial economic service by setting accurate prices based on interactions between product supply and demand.

Derivative markets are different from the markets for stocks, bonds or other financial products. A derivative is a financial instrument derived from and priced in relation to an underlying product that already exists. The vast majority of new derivative products therefore provide no direct source of funding to the issuer. As such, derivative markets offer in essence a secondary market service to participants; wealth is not increased or decreased directly with the use of derivatives, but rather, it is transferred. Derivatives provide a crucial risk-shifting and insurance function to a wide-range of industries and commercial activities and can be either OTC (over-the-counter) or exchange-traded. OTC refers to customised derivatives traded between pre-arranged counter-parties. In contrast, exchange-traded derivatives are standardised in location, grade and legal terms, with the exchange acting as an impersonal counter-party to guarantee transactions for all eligible participants.

Options and futures are common derivatives. An option gives the bearer the right, but not obligation, to buy or sell a product at a given price over a period of time; whereas, a futures contract provides the bearer with the obligation to buy or sell a product at a set date in the future (typically once a quarter). Futures contracts have no restrictions on closing out a position before the set date, and, indeed, doing so is standard procedure for the vast majority of open positions. Another class of derivatives is referred to as Exotic. These are typically OTC products structured in creative ways towards particular business objectives (Taylor, 2007).

The appetite for derivatives is growing at an astounding rate. For example, for G10 countries (and Switzerland) the notional amount of outstanding OTC derivatives in the month of December 2008 was valued at $591,962.9 billion. This figure represents a 7-fold increase in the last 10 years (BIS Quarterly Review, June 2009). The outstanding notional value of exchange-traded derivatives in December 2008 was $57,859.9 billion, a greater than 4-fold increase over the last 10 years. The total value of the turnover in both futures and options, on organised exchanges in 2008, was $2,213,345 billion (BIS Statistical Annex, June 2009). Although the two cannot be compared directly, as an indication of the size of this number, U.S. GDP in 2008 was $14,263 billion (U.S. Bureau of Economic Analysis). These markets are clearly very large and becoming increasingly significant to economies over time.

It is the unique dataset available for derivative markets that makes them the basis for empirical research presented in this thesis. The following chapter analyses group trading behaviour associated with 31 different derivative markets over the last decades. This research is conducted with the use of 'Commitment of Traders' data provided by the U.S. Commodity Futures Trading Association. These data report the long positions (held in anticipation of higher prices) and short positions (held in anticipation of lower prices) of different groups of participants in U.S. derivative markets. In order to understand the groupings of different traders as applied in this dataset, the following section considers what types of market participants can be considered a priori, as they relate to the different economic services provided by financial markets.

1.3 Introductory Classification of Different Groups of Participants

There are a number of ways of classifying different participants and this is a theme explored further in chapter 3. Based on their motivations for participating in financial markets, however, three separate groups of traders can be considered. These are as follows: 1) participants who rely on the primary service provided by financial markets, and raise capital from, or sell products to, a wider marketplace, 2) participants who rely on the secondary market service, and are active in markets in order to directly generate revenue via speculation, and 3) participants active in markets in order to guarantee their business revenues by transferring risks.

This latter group is typically associated with derivative markets, which help companies to lower their production or supply costs by offering a venue for ‘hedging’ – a strategy used to offset investment risk, thereby guaranteeing revenue in situations where there is either supply or demand uncertainty, or the path to market has time or situational constraints (Downes and Goodman, 1998). For example, Cadburys, the chocolate company, might hedge its supplies of cocoa in the futures market to limit the risk of a rise in the cocoa price. These hedging activities allow companies to concentrate on maximising rational production and increase productivity.

For derivative markets to provide this risk-shifting functionality, a sufficient number of participants must be willing to receive price risk. These include speculators such as market makers, hedge funds and managed futures funds. Derivatives provide an important venue for speculation and a low-cost way for participants to act on their beliefs about the suitability of prices. This influences prices for underlying products and maintains suitable prices for the wider economy. There is therefore a natural symbiotic relationship between these 2 groups of participants: participants who are active in markets in order to hedge risks from underlying businesses, and participants willing to receive those risks in return for possible profits.

The classification of different participants by their business objectives relates closely to the groups reported in Commitment of Traders data, which include large speculators and hedgers (hedgers are known as ‘commercial traders’ – discussed in detail in the following chapter). The above classification scheme therefore extends logically from the economic functioning of financial markets and offers a powerful means to segregate large numbers of participants. It can be no coincidence that the Commodity Futures Trading Association, the U.S. regulatory body charged with monitoring derivative markets and maintaining their economic functioning, segregates participants in this way.

Of interest to this current research, however, is how clear demarcations between trading objectives translate into differences and similarities in trading behaviour. If large numbers of market participants share similar objectives, such as to speculate or to hedge, does this manifest as particular forms of behaviour? A key related question is how much consistency in trading behaviour can be expected, given the dynamism and adaptation normally associated with financial markets. The below section provides an overview of research identifying surprising consistency in financial market behavior. This research suggests that other consistencies, such as in the behavior different groups of traders, may be equally possible.

1.4 Some Statistical Characteristics of Financial Markets

One of the earliest applications of the scientific approach to the study of economics was by the late Polish mathematician, Benoit Mandlebrot. Mandelbrot (1963) analysed empirical data on cotton and other commodity prices and found price changes (or ‘returns’, in financial parlance) did not form a normal distribution, as previously proposed (Bachelier, 1990); but rather, the distribution of returns had extremely pronounced tails. The probability of extreme price changes was much higher than under a normal, or Gaussian, distribution and subsequent research has shown this property of returns to be universally true of almost all financial markets (Campbell, Lo, and MacKinlay, 1997; Adler, Feldman, and Taqqu, 1998).

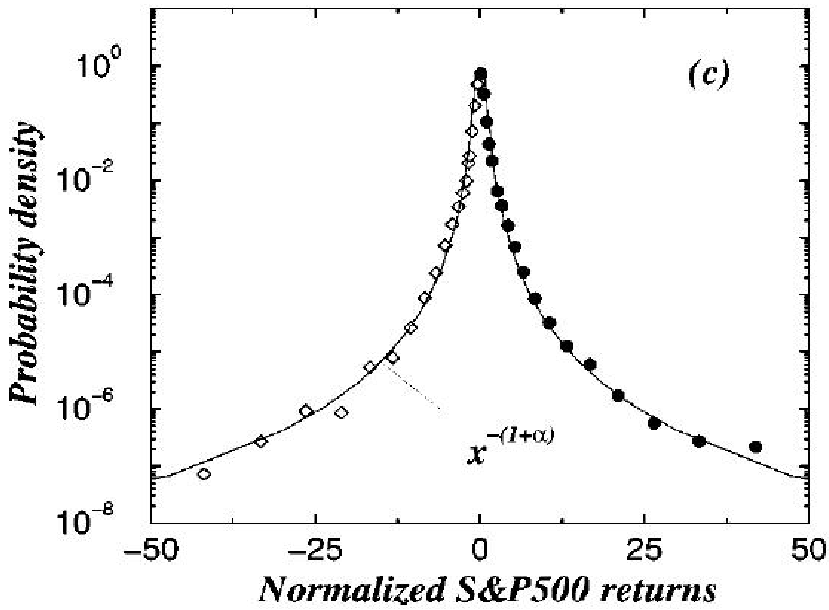
Furthermore, as Mandelbrot was the first to highlight, the functional form of the return distribution is consistent when measured across various time-scales, for example, from 1 minute up to 1 month. This 'time scaling' is also found to be universal across markets. The exponents characterising the power-law scaling of the tails of the return distributions are remarkably similar across markets, as the figures presented below will demonstrate. Whilst Mandelbrot carried out his research in the 1960s on a limit dataset consisting of just 2000 data points, subsequent research has confirmed these results based on a much more extensive analysis that include a wide cross section of markets.

Gopikrishnan, Plerou, Nunes Anarakm, Meyer, and Stanley (1999) utilise three different databases of financial market prices to substantiate Mandelbrot's findings: intraday data (high frequency measures of prices taken every 15 seconds, on average); daily data (spanning multiple decades); and monthly data (covering most of the history of the markets). Figure 1.1 is taken from this publication and demonstrates the clear non-Gaussian probability distribution of returns for the S&P500, a popular measure of the U.S. stock market. Figure 1.2 plots the cumulative return distributions for daily data from 3 of the world's largest stock market indexes, the Nikkei in Japan, the Hang-Sang of Hong Kong, and the S&P500 of North America. The similar form of the cumulative distributions is striking. The exponents for these tails, highlighted in Figure 1.1 with are obtained by power-law regressions to be 3.05, 3.03 and 3.34, respectively (Gopikrishnan et al., 1999, p. 5311). Such remarkable similarities in also characterise other markets. For example, Figure 1.3 presents the exponents for daily data from 1000 different stocks; by far the majority has exponents of approximately 3.

It is important to note that the fitting of power-laws is a relatively controversial area of statistics. Perline (2005) argues many findings of inverse power-laws are more accurately categorised as either weak-form inverse power-laws, where only some upper portion of the distribution follows an approximate inverse power-law, or false inverse power-laws, where only the most extreme values of the sample mimic an inverse power-law. Perline demonstrates how well-published examples of inverse power-laws in social and economic systems, such as those found in the early work by Pareto (1897) and Zipf (1947), involve important truncations to the data, and are therefore not representative of what Perline terms strong-inverse power-laws – where a power law forms for all ranges of the variable of interest. The work of Pareto and Zipf is referred to in more detail in chapter 3 of this thesis.

Perline's argument certainly applies to the research by Gopikrishnan et al., who acknowledgement that the tails of the market price distributions are characterized by an inverse power-law, rather than the entire distribution. Indeed, the classification of inverse-power law distributions has moved forward significantly in recent years (Clauset, Sahlizi, and Newman, 2009) and more formal categorizations in this area are possible. However, for the purposes of this chapter, the precise specification of the distributional form is of secondary relevance to the more general point: the findings of Gopikrishnan et al. demonstrate important similarities across numerous markets.

Figure 1.1 Linear-log Plot of the Probability Density Function for Normalised S&P500 Returns (Gopikrishnan et al., 1999, p. 5308)



Note the non-Gaussian nature of the distribution. The solid lines are power-law fits, the exponent for the positive (right-side) tail is 3.01 and 3.02 for the negative tail (left-side). Returns are normalised in the standard way, by subtracting each return the mean and dividing by the standard deviation of the total sample (see Gopikrishnan et al., 1999, p. 5308, Equation 3).

Figure 1.2 Comparison of Cumulative Distributions for the Positive Tails of the Normalised Returns for Daily Records of NIKKEI index (1984-1997) Hang-Seng index (1980-1997) and S&P500 index (1962-1996), (Gopikrishnan et al., 1999, p. 5311)

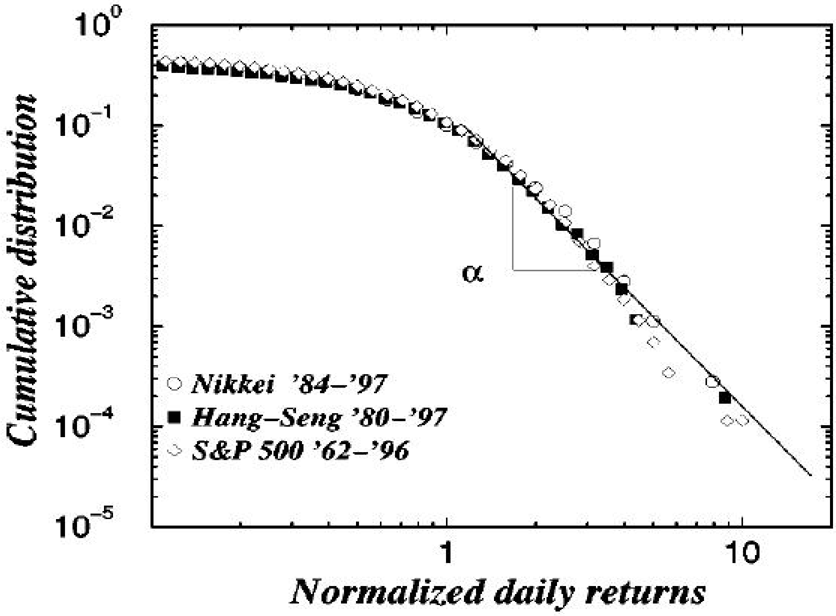
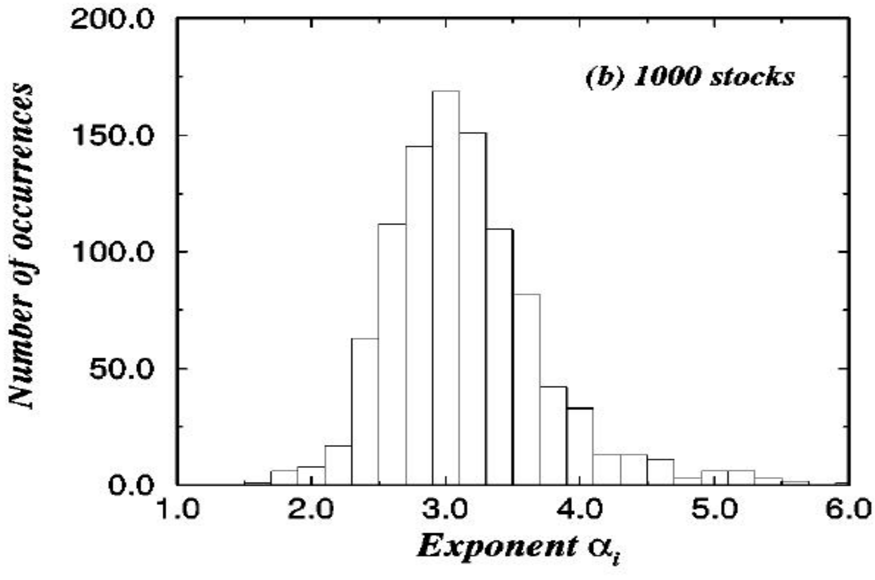


Figure 1.3 Histogram for the Power-law Exponents Fit to the Individual Cumulative Distribution Functions, for all x larger than two standard deviations, across 1000 U.S. Stocks (Plerou, Gopikrishnan, Nunes Amaral, Meyer, and Stanley, 1999, p. 6521)



There are other statistical properties that also appear ubiquitous across markets. As discussed at later stages in this thesis, these include significant autocorrelation in absolute returns (or market volatility, as it is commonly referred) that persist for up to several months, and insignificant autocorrelation in actual returns beyond appropriately 20 minutes (Ding, Granger, and Engle, 1983; Lundin, Dacorogna, and Muller, 1999). Other observable distributions also characterised by asymptotic power-law tails include the relative price of bids and offers (Bouchaud, Mezard, and Potters, 2002; Zovko and Farmer, 2002), trading volumes and trade frequencies (Gopikrishnan, Plerou, Gabaix, and Stanley, 2000).

1.5 Thesis Overview

Research reviewed above highlights ubiquitous characteristics across markets and points tantalisingly towards universal mechanisms underlying market behaviour (Gopikrishnan et al., 1999). My interest is to move beyond the purely statistical treatment of this subject and to explore the underlying human behaviour. If consistencies are apparent at the level of price characteristics, consistencies may also exist at other levels of market activity, such as in the trading behaviour of different participants. This can be reinforced by the observation, commonly accepted in the finance industry and increasingly so within academia, that financial markets are not exclusively driven by news or economic announcements. Rather, prices often reflect endogenous dynamics – such as the buying and selling behaviour of groups of participants. Indeed, this observation is, in part, the motivation for a large number of agent-based computational models of financial markets that aim to simulate market behaviour based on interactions between different types of traders. In some way, these internal elements in financial markets must result in the robust consistencies at the price level – this insight has lead to a large body of work, much of which is reviewed in this thesis.

In trying to understand the etiology of relatively subtle statistical properties, many physics-orientated economists have proposed quite precise interactions between different groups of traders in their computational models. Despite the end goal of this modelling – to replicate and understand empirical properties – the inputs and mechanisms involved in many models typically do not have the same level of empirical attention. There has been a tendency to make unrealistic assumptions at the group-level regarding the nature and behavioural characteristics of different participants. As Bouchaud, Farmer, and Lillo (2009, p. 145) highlight, “it would be extremely valuable to have a comprehensive empirical study that connects the heterogeneity of market participants with their strategy and with the properties of price dynamics”. This could offer a strong foundation for exploring statistical properties and imposing more realistic constraints on the many theories claiming to account for the nature of market prices.

Research presented in this thesis supports the process of moving towards more empirically-orientated group representations for use in agent-based models. The research documents recurring patterns of group trading behaviour, and thus, raises the explanatory requirements on market theories. This research is motivated by the conviction that theories in the future must also strive to account for empirical regularities identified in trading behaviour, rather than focus exclusively on the empirical properties of market prices, A model is proposed towards the end of this thesis that accomplishes this goal, with explanatory power at two levels of analysis, accurately replicating many statistical characteristics of market prices alongside realistic group trading behaviour. In addition to the academic relevance of this work, agent-based market models with higher levels of behavioural realism can offer cost-effective tools for exploring market dynamics. These tools may be used in the future for investment management (Farmer, 2001) or for market regulation (Darley and Outkin, 2007).

The structure of this thesis is therefore as follows. The next chapter analyses the buying and selling history of core groups of traders across a 17 year period, revealing important regularities in trading behaviour. These results are attained via a standard econometric methodology and a more bespoke, non-parametric methodology. Research focuses on the relationship between changes in positions and concurrent changes in markets prices. It finds strong evidence that speculators increase their buying during positive price changes and increase selling during negative price changes, whereas hedgers (or commercial traders) are seen to do the opposite. This pattern of trading behaviour is identified across a wide range of different markets, time-horizons and sizes of price change.

Chapter 3 moves focus onto agent-based models of collective and social behaviour, providing an overview of different approaches to using computational models in the social sciences. This includes a review of the objectives and necessary conditions for the successful application of this relatively new approach. A recent computational model of a financial market is described in detail and implemented. This model is capable of simulating many properties associated with realistic market prices. However, the group-level dynamics that form the basis of the approach are shown to lack validity. A number of suggestions are provided to help improve the behavioural realism of future models of financial markets.

Chapter 4 applies the suggestions made in the previous chapter by extending a very recent computational model of a financial market to include realistic measures of trading behaviour, such as the long and short positions of different groups of traders. With this new, extended model, a hypothesis is formally tested for the patterns of trading behaviour documented in chapter 2. Specifically, different groups of participants are proposed to have particular order-type preferences. Commercial traders are considered less aggressive and therefore tend towards using limit orders, buying as prices decline and selling as prices increase; speculators are considered more aggressive, utilise relatively more market orders and aggressive limit orders, and typically trade in the direction of prices changes. These behavioural preferences are sufficient to account for the empirical regularities documented in chapter 2. Traditional economic theories that rely on deeper strategic considerations or distinctions between 'informed' or 'uninformed' decision-making are not required.

Chapter 5 applies these insights to the topic of market regulation by exploring the impact of speculators on market prices from both a model-based and an empirical perspective. The analysis generates mixed results, highlighting the need to extend the model developed in the previous chapter still further, to include new groups to order-flow level relationships. The findings also suggest that regulatory debate needs to focus on the role of liquidity in causing market volatility. A discussion is provided on the possibilities for new regulation focused on participant orders preferences, and therefore market liquidity. Chapter 6 summarises the research presented in this thesis and offers potential criticisms and areas for future research.

2. PATTERNS OF GROUP BEHAVIOUR IN FINANCIAL MARKETS

Contents:

Abstract:

This chapter presents evidence of systematic trading behaviour amongst different groups of financial market participants. Commitment of Traders reports provide the historic long and short positions of different groups of traders. A standard econometric methodology and a more bespoke, non-parametric methodology focus on the relationship between changes in positions and concurrent changes in market prices, as applied to 17-years of trading records collected from 31 different futures markets. Both methodologies find strong evidence that speculators increase their buying during positive price changes and increase selling during negative price changes, whereas commercial traders increase selling during positive price changes and increase buying during negative price changes. This trading behaviour is identified across a wide range of markets at different time-horizons and sizes of price change. Further evidence of proportionality in the trading behaviour of different groups of traders at different sized price changes is also presented.

"Striking regularity can emerge when human beings are confronted with a complicated decision problem."

Zovko and Farmer (2002, p. 392)

"If we are struck having to study every creature individually, it will be difficult to make much progress, so our underlying hope is that we can find some way to distil this marvellous collection of behaviour down to just a few prototypical ones."

Miller and Page (2007, p. 28)

2.1 Introduction

Research into the behaviour of different groups of traders is important for enhancing understanding of financial markets. The aggregate buying and selling of traders cause prices to change over time, often in dramatic and volatile ways. Despite this truism, academic research has tended to make assumptions at the group-level, relying on theoretically tractable notions of behaviour that lack empirical foundations. This chapter approaches the subject of group behaviour in financial markets empirically, with an extensive U.S. government dataset. As part of a long-running market surveillance programme, it documents changes in long positions (those that profit from higher prices) and short positions (those that profit from lower prices) of core groups of traders in U.S. futures markets. Changes in the positions of these different groups were aligned with changes in price, revealing regularities in group behaviour across many different markets.

This research is at a juncture between psychology and economics and therefore applies different styles of methodology. The first methodology is a customary econometric, parametric approach. It involves time-series modelling and the additional analysis of estimated parameters for the relationship between changes in traders' positions and price changes in different financial markets. The second methodology complements the first, and is non-parametric in its approach. Behaviours are standardised across markets and compared using a range of statistical tests. Both methodologies reach similar conclusions and provide important insights into previously undocumented patterns of trading behaviour across a range of markets, time-periods and scales of price change.

2.2 Theories of Financial Markets and Economic Agents

The following section briefly reviews the emergence of contemporary approaches to financial markets and trader behaviour, a subject that is returned to at later stages in this thesis. Traditionally in economics, agents are considered as 'homo-economicus', rational and self-interested, striving to maximise objectives whilst expounding the minimal amount of effort to do so. This behaviour has been termed 'utility maximising' in the literature (e.g. Neumann and Morgenstern, 1944; Becker, 1978). For the most orthodox approach to theoretical economics (e.g. Fama, 1965), agents are also considered homogeneous; in the sense that they all have access to relevant economic information, and act rationally and consistently based on this information (e.g. Arrow, 1989). Agents are seen as heterogeneous, but in the relatively limited sense that their tastes and preferences are allowed to differ.

Research as early as 1947 argued these assumptions of human economic behaviour are unrealistic. People may act based on preferences unrelated to strict utility maximisation, for example, people 'satisfice' rather than pursue optimal economic behaviour (Simon, 1947; 1992). Early observations against neoclassical agent representations became formalised and more widely accepted with the seminal publication of psychologists Kahneman and Tversky in 1979. These psychologists demonstrated, via a series of experiments, systematic deviations of people's decision-making from the utility maximising assumed in standard economic models. People display a preference for certainty of outcome, leading to asymmetric behaviour in different economic contexts. In the context of gains, we tend to prefer a sure gain over a larger, probable gain. In the context of losses, people tend to prefer larger, probable losses, rather than certain losses (Allingham, 2002). For detailed reviews see Luce (2000), Starmer (2000) and Birnbaum

(2008). Research into economic decision-making and how it differs from traditional theories marked an important shift in modern economics away from more idealised notions of economic agents that have a foundational role in many economic models (Halpern and Stern, 1998b). This current research also falls within this new, behavioural economic approach, where, rather than make convenient assumptions for the sake of theoretically tractable models, a goal is to study how economic agents behave and interact from an empirical perspective.

The debate between traditional economics and behavioural economics suggests a divide between the rational, 'homo-economicus' and the more irrational, non-optimal decision-maker. This divide is represented more directly in recent theories on financial markets which typically incorporate two different groups of traders. These are fundamentally orientated (or informational) traders and chartist (or noise, or liquidity) traders (Frankel and Froot, 1986; Hommes, 2005; Samanidou, Zschischang, Stauffer, and Lux, 2007). Fundamental traders are seen as rational, smart money traders acting on ‘real’ information such as company dividends, economic statistics or valuations. They correspond to the rational agent described above. In contrast, chartists are considered less-rational and reference more 'noisy' information such as recent market trends and price patterns to make erroneous trading decisions. They correspond to the non-optimal decision-makers. As discussed in chapter 3, it may be inappropriate to consider chartists irrational, in many contexts following what others are doing can be an effective strategy.

This second group of non-optimal traders are often considered to trade on the basis of positive feedback strategies, buying when prices rise and selling when prices decline (Shleifer and Summers, 1990). Examples of positive feedback strategies include trend-chasing and the use of stop-loss orders (that cut losing trades as prices move against the trade). Other examples include front-running by brokers (for example, placing orders in front of a large client order) and portfolio insurance (increasing risk exposure by buying as prices rise and reducing risk exposure by selling as prices decline). As discussed further in chapter 4, these trading behaviours are not consistent with the standard economic approach, where participants only respond rationally to changes in fundamentals, but do more plausibly describe the behaviour found in real markets.

Numerous models of financial markets involve interactions between these two groups of traders as a central component (Marengo and Tordjman, 1995; Steiglitz, Honig and Cohen, 1996; Bak, Paczuskim and Shubik, 1997; Lux and Marchesi, 1999; 2000; Alfarano, Lux, and Wagner, 2005) despite a lack of empirical evidence on the actual ecology and behaviour of different types of traders. The assumptions on market participants as being either fundamental or noise traders is a marked improvement on the traditional approach, as participants are considered more heterogeneous and diverse. However, this approach to categorising different types of traders can still be considered as overly theoretical. If agent-based simulations and theoretical models of financial markets are to become more directly useful as tools for investigating market scenarios in relatively realistic settings (e.g. Darley and Outkin, 2007), empirical representations of different types of traders are needed. This current research joins the general trend in economics away from theoretical notions of human behaviour, towards more empirically-grounded representations of how people actually behave in real-world economic scenarios.

2.3 Empirical Data on Trader Behaviour

Despite abundant high frequency information on trade prices, volumes, and bids/offers, publicly available information on the composition of markets and the behaviour of different traders is in fact very limited. This feature of the data associated with financial markets is, of course, intentional. Modern exchange traded markets are centralised and structured to ensure participants and their dealings are kept anonymous. As a result, empirical data on the behaviour of different participants is restricted and typically relates to either the local and private information held by brokers and dealers, or proprietary data collected by the organised exchanges. As discussed in the following chapter, Wiley and Daigler (1998) analyse data from the Chicago Board of Trade; Kein and Madhavan (1995), Aitken, Alemedia, Harris, and McInish (2007), and Darley and Outkin (2007) analysis data from Australian brokers, the New York Stock Exchange, and the NASDAQ stock market, respectively. Whilst the datasets used by these researchers may be quite detailed, they are typically limited in availability and cover only short periods of time. Fortunately, an alternative source of data on the behaviour of different types of market participants is available. This is found in the Commitment of Traders reports that include information from local sources and also cover a significant multi-decade time-period.

Responding to the lack of transparency in modern financial markets, regulatory bodies such as the U.S. Commodity Futures Trading Commission (CFTC) have special legislative powers to monitor markets (Section 4a(a) of the Commodity Exchange Act, 7 USC 6 a(a)). The CFTC's Market Surveillance Program collates daily market-data and position-information from all sources, including exchanges, clearing members, futures commission merchants, foreign brokers, and traders, known collectively as reporting firms (under regulations set out in Parts 15 to 21 of the CFTC’s regulations). Reporting firms must identify traders with long or short positions at or above reporting levels set by the CFTC for a given market, where reporting levels are updated over time to correspond to between 70-90 percent of the total open interest (or number of contracts outstanding) in a given derivative market. This position information is aggregated into different groups to maintain confidentiality and made publicly available every week via Commitments of Traders reports (COT data). Although restricted to U.S. Exchange traded derivative markets (not applying to stock markets or currency markets, for example), COT data provides objective documentation on market composition and traders positions unavailable in any other form. It is also longitudinal, covering many years of market activity, becoming reported at regular weekly intervals in 1991.

Currently, COT data is published every Friday by the CFTC and provides a breakdown of the previous Tuesday's open interest for markets in which 20 or more traders are subject to large-trader reporting. The release schedule has increased in frequency over the years since the reports first began in 1924. (The U.S. Grain Futures Administrator was founded in 1921.) Other data are provided, including current open interest (that is, the total number of contracts outstanding in a given market), spreading positions (for example, where a trader is long and short different contract expiries in the same market), the number of traders reporting, and various transformations of this information (such as concentration ratios representing the percentage of open interest held by the largest four reportable traders). An example output of COT data is shown in Table 2.1 with long and short positions ('Commitments') for different groups of traders.

Table 2.1 Example of CFTC Commitment of Traders Data for Wheat Futures

WHEAT -- CHICAGO BOARD OF TRADE FUTURES-ONLY POSITIONS AS OF 12/12/06								
NONCOMMERCIAL			COMMERCIAL		TOTAL		NONREPORTABLE POSITIONS	
LONG	SHORT	SPREADS	LONG	SHORT	LONG	SHORT	LONG	SHORT
(CONTRACTS OF 5,000 BUSHELS)			OPEN INTEREST: 417,081					
COMMITMENTS								
73,598	56,045	69,448	237,539	232,901	380,585	358,394	36,496	58,687
CHANGES FROM 05/25/2004		CHANGE IN OPEN INTEREST: -7,043						
-10,463	-1,186	126	3,462	-6,610	-6,875	-7,670	-168	627
PERCENT OF OPEN INTEREST FOR EACH CATEGORY OF TRADERS								
17.6	13.4	16.7	57.0	55.8	91.2	85.9	8.8	14.1
NUMBER OF TRADERS IN EACH CATEGORY (TOTAL TRADERS: 317)								
102	89	92	67	96	233	226		

The CFTC Form 40 identifies reporting traders as either commercial or non-commercial. A commercial trader is engaged in business activities hedged by the use of futures or options markets, where transactions are formally defined as representing “a substitute for transactions … to be taken at a later time in a physical marketing channel, and where they are economically appropriate to the reduction of risks” (CFTC Form 40 Statement of Reporting Trader, p. 4). Conversely, a non-commercial trader is not engaged in hedging activities, and as such can be considered a speculator in one of the many guises such a categorisation can represent (e.g. market maker, arbitrageur, hedge fund). A single trading entity cannot be classified as both commercial and non-commercial. In the event of a multi-faceted organisation being involved in both business objectives, separate corporate entities are required to distinguish between trading activities.

COT data also provide an aggregation of the current long and short positions of non-reporting traders (those below reporting requirements specified by the CFTC), where positions are derived by subtracting total reportable long and short positions from total open interest. The business objectives of these traders are not known; they could be commercial and / or non-commercial in nature. These participants are, by definition, the smaller traders making up only 10% to 30% of the total open interest in the market and are often assumed by researchers (as discussed in the following sections of this chapter) to represent small speculators and / or the general public.

Researchers investigating COT data have noted potential sources of error with regard to group categorisations and position reporting. For example, there are strong incentives to classify as a commercial trader due to the lack of imposed limits on position sizes (Sanders, Boris, and Manfredo, 2004). Furthermore, commercial positions can be speculative on a net basis, as changes in underlying cash positions are not directly monitored by the CFTC across all markets. (The CFTC Form 204 / 304 Statement of Cash Positions is used to determine if sufficient cash positions justify derivative positions for commercial traders in the Grains and Cotton markets, but this doesn't apply to all markets.) To counteract this issue, commercial traders are required to keep detailed records to justify transactions if called upon by the Commission (CFTC Regulation, Part 18).

Commercials are entitled to trade on expectations of future supply and demand conditions, as stipulated in the CFTC definition of bona-fide hedging (CFTC Regulation, 1.3(z)): hedges must reduce risk based on current or anticipated assets or liabilities. Whilst an essential function for commercial traders, there is an inherent and unavoidable speculation involved in basing transactions on anticipated future production, assets, or liabilities. This process is akin to speculative trading and could be extended to generate revenue directly from price changes in derivative markets.

Based on these factors, it is likely that pure hedge-positions are some subset of those reported by commercial traders (Sanders et al., 2004; Ederington and Lee, 2001). Whilst there is scope for misuse and possibly even abuse of these group categorisations, for the purpose of the current study, these limitations do not inhibit the overall value of COT data. These data still represent the most objective and long-term sampling of trading behaviour available. Other academics acknowledge the value of COT data and have employed the resource to study a range of different hypotheses.

2.4 Existing Research on Commitment of Traders Data

Much research interest into COT data inevitably surrounds the forecasting value of trader's positions (Kahn, 1986; Hartmark, 1991; Buchanan, Hodges, and Theis, 2001; Wang, 2001, 2003; Briese, 2008). The effect of trader behaviour on market volatility has also been studied using COT data (Chang, Pinegar, and Schachter, 1997; Wang, 2002), but is more often researched with relation to volume and open interest (e.g. Bessembinder and Seguin, 1993). An area of significant interest is the theory of normal backwardation originally put forward by Keynes (1930), but extended and explored by numerous economists since (Bessembinder, 1992; Chatrath, Liang, and Song, 1997; Chang, Choi, and Nelling, 2000; De Roon, Nijman, and Veld, 2000). Keynes argued that commercials require futures markets to transfer risks and effectively pay speculators a risk-premium for taking the other side of their trades. Although there is limited conclusive evidence to support the theory, partly due to the difficulties in calculating profit and losses amongst different participants, it does imply a broad division of activity between groups of traders, for which there is some empirical support in the literature.

Using various assumptions regarding COT data (such as positions being held over certain time-intervals), Chang (1985) estimates the profitability of the two groups and finds speculators tend to be profitable over the time-periods and markets studied whilst commercials tend to lose money. An inverse pattern between speculators and commercials is also seen in Wang's (2001) study on return predictability in the agricultural markets. Wang found, over time periods of up to 12 weeks, speculators traded as if they forecast price continuations whereas commercials forecast price reversals. As discussed in detail in chapter 5, Wang (2002) also studied the relationship of group net-positions (long positions minus short positions) to changes in foreign exchange market volatility, finding changes in the net-position of commercials associated with market volatility decreasing whilst changes in speculative net-positions associated with increasing volatility. Wang (2003) investigates monthly time-horizons during the 1990s to find changes in speculator net-positions to be positively correlated with future and concurrent returns whilst commercial net-positions are negatively correlated. Both types of traders are also found to relate differently to external information, such as changes in measures of market sentiment. A study by Sanders, Boris, and Manfredo (2004) on the energy markets also documents a similar inverse activity: during rising markets speculators increased long positions whilst commercials decreased long positions.

Sanders et al. (2004) assume the inverse activity between groups of traders results from a data constraint: due to the necessity of long open interest to equal short open interest and to the fact that commercials and speculators make up the majority of the open interest, these groups must behave inversely to one another. However, this account does not adequately explain possible consistencies in the sign and relative magnitude of trading behaviour. For example, Sanders et al. and Wang find speculators are buying into a rising market whilst commercials are selling, not the other way around. If the behaviour is consistent across a large number of markets, across an extended period of time, and across different time intervals and scales of price change, it should not be regarded as a data constraint, but rather, a recurring important feature of market dynamics. Although documented to some degree in the literature, the prevalence and significance of this trading behaviour has not been the focus of a comprehensive investigation until now.

The research-base of this thesis is the study of the behaviour of different groups of traders as related to concurrent price changes across 31 different financial markets. A variety of statistical techniques establish whether important patterns of trading behaviour exist amongst different types of market participants and whether this behaviour can be considered general to a large number of markets. This research therefore treats COT data differently to previous studies. To avoid obscuring important intra-group activities, long and short positions are referenced separately for each group (cf. the use of net-positions typical in other studies). Other COT variables, in addition to commercial and speculator positions, are also included for completeness. This study also uses the highest frequency, weekly time-intervals of COT data available, covers a multi-decade time period from 1991 to 2008, and a selection of markets that includes all major asset classes.

The remainder of this chapter is organised as follows. The methodology involved in pre-processing the dataset and aligning market prices and group long and short positions is outlined. The econometric methodology involving time-series modelling and the analysis of slope coefficients across markets is reviewed and associated results presented. The non-parametric approach then follows, with results from statistical tests comparing trading behaviour across markets and across different groups. A summary representation of group behaviour is presented. The standardisation procedure involved in the second methodology permits further analysis of whether behaviour scales proportionally across different sized price changes. The chapter ends with concluding remarks.

2.5 Methodology

COT data provides information on market composition including the long and short positions and total number of commercial, non-commercial (referred to as speculators henceforth) and non-reportable traders (referred to as other traders). In addition, the spread positions (where a trader may be long and short different contracts of the same market) are also reported, along with total open interest in a given market. From these available variables, the information referenced in the following analysis are commercial short and long positions (selling and buying behaviour of commercial traders), speculative short and long positions (selling and buying behaviour of speculators), other short and long positions (selling and buying by smaller traders), and total open interest (the total number of contracts outstanding). Total open interest is the sum of long or short positions and is included in this study for completeness and as a variable of separate interest. By measuring changes in open interest, overall fluctuations in the size of the market can be studied independently of the number of short and long contracts held by specific groups. The number of large traders in a given market is reported by COT data, but not considered directly relevant as it does not relate to behavioural characteristics. Similarly, to keep things as simple as possible, spread positions are also omitted from the following analysis.

2.5.1 Data Pre-Processing

COT data is retrieved from the CFTC dating from 1991, when the release scheme became weekly, through to the beginning of 2008. Some markets that are currently very active had not begun trading in 1991 and therefore are included in the sample, but have a later start date. The historic COT information is retrieved in .txt format and processed with a java program I developed to separate data into specific markets and variables and to order the data chronologically.

COT data for 31 U.S. Futures markets were selected with two constraints: first, each market being actively traded and secondly, the total sample of markets covering six major asset classes, including interest-rates, stock indexes, agricultural commodities, industrial commodities, metals, and currencies. Full details of the markets and time-periods covered are provided in Table 2.2.

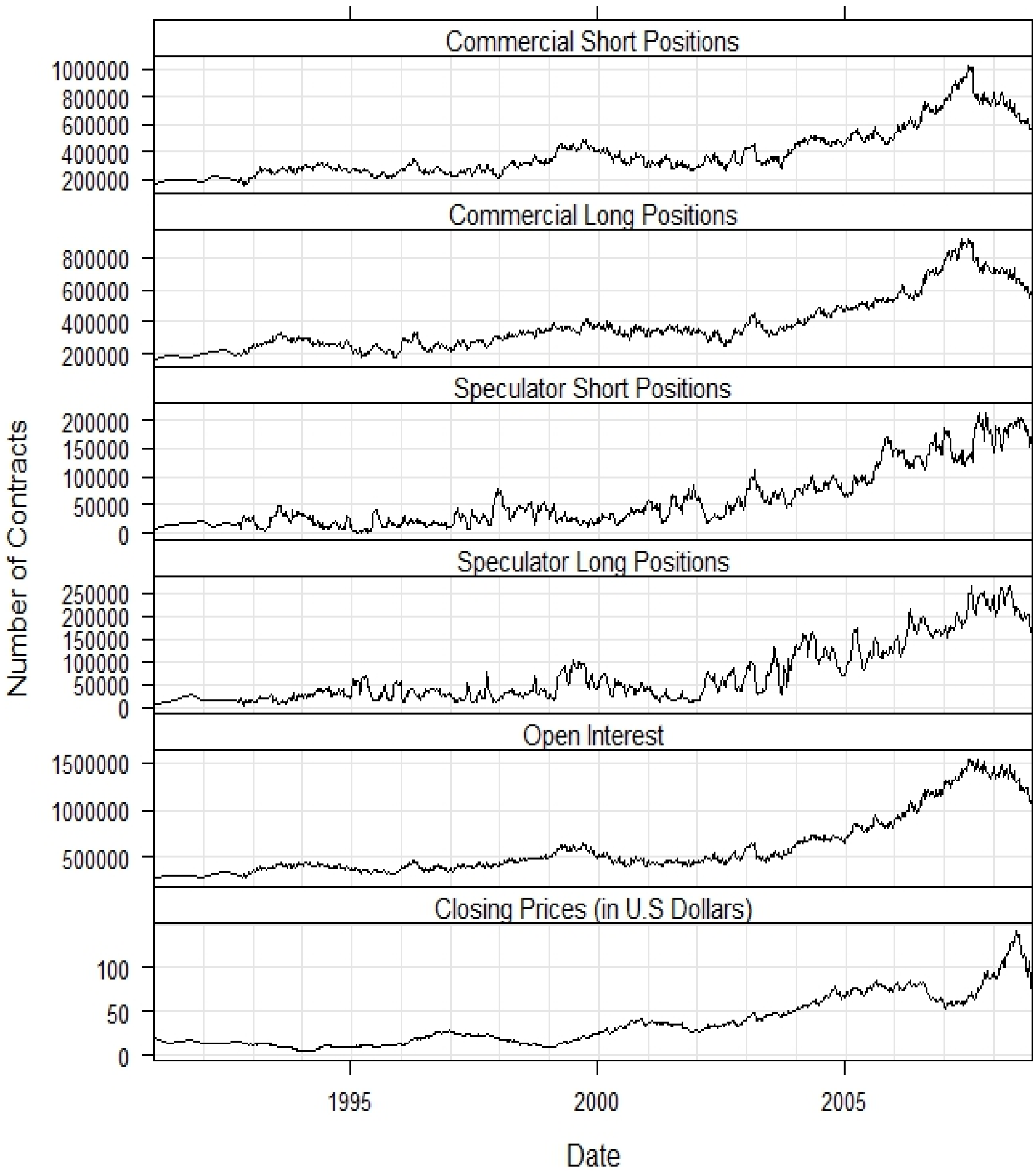
Historic continuous contract price data (from Trade-Station securities, a U.S. brokerage) was aligned with the relevant COT data for each market. Futures markets offer a multitude of separate contracts with separate expiries, e.g. March, June, September and December. The front-month is the most current, and often active, contract. Notably, the price data is for the front-month futures contract where the majority of trading activity occurs. This contract is assumed to be representative of all contract expiries referenced in the COT data.

The COT report is published on a Friday evening, providing information valid for the preceding week ending on a Tuesday. The price-series was therefore lagged by 3 days, so that each data-point in both price and COT-series covers the same period. Figure 2.1 demonstrates the alignment of price and COT data and provides a view of typical raw data. For brevity, non-reportable positions are omitted from the following plots as they are derived from the reportable positions and total open interest.

Table 2.2 Sample of U.S. Futures Markets Analysed

Asset	Futures Market	Exchange	COT Identifier	Start-Date
Interest-Rates	U.S. 30 year bond	CBOT	20601	15 January 1991
	U.S. 10 year note	CBOT	43602	15 January 1991
	U.S. 5 year note	CBOT	44601	15 January 1991
	U.S. 2 year note	CBOT	42601	15 September 1992
	Eurodollar	CME	132741	15 January 1991
Stock Indexes (e-mini products)	S&P500	CME	13874a	16 September 1997
	Nasdaq100	CME	209742	29 June 1999
	Dow Jones Industrials	CBOT	124603	21 May 2002
	Russell 2000	CME	239742	13 October 2002
Agriculturals	Corn	CBOT	2602	06 January 1998
	Wheat	CBOT	1602	06 January 1998
	Soybean	CBOT	5602	06 January 1998
	Sugar no.11	NYBOT	80732	15 January 1991
	Coffee	NYBOT	83731	15 January 1991
	Cotton no.2	NYBOT	33661	15 January 1991
	Live Cattle	CME	57642	15 January 1991
	Lean Hogs	CME	54642	02 April 1996
	Oats	CME	4603	06 January 1998
	Rough Rice	CBOT	39601	04 October 1994
	Cocoa	CBOT	73732	15 January 1991
Metals	Gold	NYBOT	88691	15 January 1991
	Silver	COMEX	84691	15 January 1991
	Copper	COMEX	85692	15 January 1991
	Platinum	COMEX	76651	15 January 1991
Industrials	Brent Crude	NYMEX	67651	15 January 1991
	Natural Gas	NYMEX	23651	15 January 1991
Currencies	British Pound	CME	96742	15 January 1991
	Euro	CME	99741	15 January 1991
	Japanese Yen	CME	97741	15 January 1991
	Canadian Dollar	CME	90741	15 January 1991
	Swiss Franc	CME	92741	15 January 1991

Figure 2.1 Crude Oil COT Data (top panels) aligned with Continuous Contract Crude Oil Futures Prices (bottom panel)



5.2.2 Econometric Methodology

To explore the research question within an econometric framework, changes in group positions can be considered a dependent variable to be explained in terms of changes in market prices as an independent variable. Differences in the sign and significance of estimated coefficients for group positions by trader type can therefore be interpreted and compared across markets. To begin, COT and price data are transformed into week-on-week percentage changes. Descriptive statistics across the various markets are reported in Table 2.3.

As typical of other financial market data, Table 2.3 shows evidence of non-normal distributions in both changes in prices and group positions. This non-normality is considered inevitable to financial market data and no-further efforts are taken here to further transform the dataset. (Future research could formalise these non-normalities with the use of the Anderson-Darling test but such a study is considered irrelevant for current purposes.) Preliminary diagnostic tests find all these data to be stationary based on the Augmented Dickey-Fuller test at $p < 0.05$ (results not shown).

COT data and market prices can be considered time-series panel data. The time dimension is important as weekly observations cannot be considered independent. Rather, past events can influence future events and therefore lags in behaviour may be significant. It is therefore crucial to maintain chronological ordering of observations and test this ordering for potentially relevant information (Wooldridge, 2006). The weekly percentage changes in all variables are tested for significant partial autocorrelations ($p < 0.05$) across 6 lags and reported in Table 2.4. The majority of markets have significant lags. Future research could extend the analysis to explore the time-invariance of results.

Table 2.3 Descriptive Statistics – Evidence of Non-normal Distributions

Market		Market Prices					Commercial Short					Commercial Long					Speculator Short					Speculator Long				
	N	Median	Low	High	Skew	Kurtosis	Median	Low	High	Skew	Kurtosis	Median	Low	High	Skew	Kurtosis	Median	Low	High	Skew	Kurtosis	Median	Low	High	Skew	Kurtosis
U.S. 30 year bond	832	0.00	-0.11	0.15	1.17	10.03	0.00	-0.23	0.31	0.43	1.88	0.00	-0.23	0.34	0.37	3.19	0.00	-0.52	1.32	1.11	5.85	0.01	-0.61	1.45	0.95	5.61
U.S. 10 year note	832	0.00	-0.09	0.12	1.73	16.91	0.01	-0.18	0.41	0.58	5.40	0.00	-0.15	0.32	0.53	2.66	0.00	-0.85	6.69	12.79	261.35	0.01	-0.84	3.04	4.50	42.65
U.S. 5 year note	830	0.00	-0.02	0.07	2.18	16.15	0.00	-0.22	0.39	0.64	4.13	0.00	-0.23	0.43	0.67	3.42	0.00	-1.00	4.04	6.05	84.81	0.01	-1.00	2.59	3.55	29.89
U.S. 2 year note	793	0.00	-0.01	0.02	0.56	2.68	0.00	-0.29	0.58	0.80	4.08	0.00	-0.35	0.72	1.07	8.30	0.00	-1.00	6.93	5.56	50.25	0.00	-1.00	73.55	26.10	708.73
Eurodollar	827	0.00	0.00	0.01	4.22	33.85	0.01	-0.21	0.27	-0.87	5.99	0.01	-0.16	0.37	0.16	11.75	0.01	-0.59	3.24	4.28	40.10	0.01	-0.69	1.44	1.78	13.57
S&P500	554	0.00	-0.14	0.12	-0.35	4.43	0.04	-1.00	3.29	2.16	22.85	0.05	-1.00	2.71	1.55	14.29	0.04	-1.00	2.93	2.59	16.23	0.05	-1.00	2.63	1.81	10.22
Nasdaq100	477	0.00	-0.17	0.12	-0.44	2.69	0.06	-0.79	1.91	0.54	6.54	0.06	-0.90	7.96	9.10	128.00	0.04	-0.85	1.62	1.33	8.45	0.03	-0.75	2.54	1.97	16.72
Dow Jones Industrials	325	0.00	-0.20	0.12	-1.56	16.43	0.05	-0.86	2.31	1.15	14.25	0.04	-0.93	2.81	2.89	24.52	0.04	-0.73	1.13	0.22	3.68	0.03	-0.70	0.97	0.15	3.01
Russell 2000	306	0.00	-0.07	0.09	-0.12	0.16	0.03	-0.78	1.41	1.20	12.77	0.02	-0.91	1.31	0.62	7.21	0.01	-0.89	2.15	2.19	15.40	0.02	-0.93	4.97	6.59	69.04
Corn	554	0.00	-0.14	0.11	-0.33	8.90	0.00	-0.22	0.34	0.84	3.75	0.00	-0.13	0.20	0.28	2.01	0.01	-0.61	0.99	0.81	4.97	0.00	-0.32	0.77	1.17	6.28
Wheat	554	0.00	-0.15	0.15	0.21	5.99	0.00	-0.30	0.50	1.02	4.65	0.00	-0.17	0.22	0.32	1.99	0.01	-0.55	0.95	1.10	6.69	0.00	-0.36	0.63	0.85	4.61
Soybean	554	0.00	-0.13	0.10	-0.18	1.74	0.00	-0.18	0.28	0.30	0.62	0.01	-0.19	0.22	-0.07	0.92	0.01	-0.51	0.78	0.42	2.03	0.00	-0.39	0.85	1.09	3.65
Sugar no.11	811	0.00	-0.27	0.77	5.77	85.94	0.00	-0.39	0.48	0.47	3.89	0.01	-0.52	0.43	-0.44	5.44	0.01	-1.00	17.57	14.87	314.30	0.01	-0.81	2.73	3.32	23.48
Coffee	807	0.00	-0.15	0.28	0.80	6.65	0.00	-0.29	0.50	0.93	4.22	0.00	-0.35	0.62	0.92	5.35	0.01	-0.67	3.11	3.39	21.08	0.00	-0.61	1.57	2.03	10.59
Cotton no.2	806	0.00	-0.15	0.12	0.08	5.77	0.00	-0.35	0.58	1.04	4.74	0.00	-0.26	0.97	3.79	39.71	0.00	-0.78	14.01	17.53	408.10	0.00	-0.91	2.31	2.67	15.39
Live Cattle	834	0.00	-0.11	0.07	-0.16	3.33	0.00	-0.36	1.09	4.48	71.45	0.00	-0.24	0.70	2.25	31.57	0.01	-0.70	2.22	3.40	26.83	0.00	-0.49	1.76	2.88	31.59
Lean Hogs	635	0.00	-0.10	0.18	0.69	5.16	0.01	-0.39	0.93	1.94	11.02	0.01	-0.25	0.94	4.13	36.01	0.00	-0.64	1.74	1.94	11.14	0.01	-0.65	0.78	0.91	3.44
Oats	554	0.00	-0.21	0.14	0.09	4.33	0.00	-0.48	0.66	0.87	9.63	0.01	-0.50	1.10	1.26	8.80	0.01	-0.95	20.83	11.84	184.55	0.00	-0.53	1.20	1.50	9.78
Rough Rice	720	0.00	-0.11	0.09	0.15	3.88	0.00	-0.48	0.59	0.57	4.71	0.00	-0.46	1.02	1.50	10.78	0.00	-0.74	8.45	9.71	152.68	0.01	-0.78	6.30	8.34	123.76
Cocoa	807	0.00	-0.13	0.18	0.73	5.14	0.00	-0.17	0.42	1.28	8.00	0.00	-0.20	0.28	0.36	2.96	0.01	-0.83	6.53	9.02	153.96	0.01	-0.64	2.27	3.32	29.53
Gold	833	0.00	-0.09	0.14	0.62	10.22	0.00	-0.43	0.81	1.12	7.88	0.01	-0.42	0.63	0.44	3.03	0.01	-0.64	3.20	3.70	33.08	0.00	-0.76	3.77	4.38	42.11
Silver	833	0.00	-0.17	0.25	0.03	9.39	0.00	-0.33	0.53	1.29	6.91	0.00	-0.64	0.81	0.87	3.67	0.00	-0.77	5.36	4.88	45.98	0.00	-0.42	1.28	2.47	22.99
Copper	832	0.00	-0.16	0.18	0.02	1.12	0.00	-0.45	1.32	3.08	39.89	0.00	-0.35	0.72	1.60	8.67	0.00	-0.87	4.47	4.22	34.13	0.00	-0.88	5.85	8.75	143.58
Platinum	828	0.00	-0.16	0.14	-0.31	3.27	0.00	-0.44	0.88	1.05	7.71	-0.01	-0.73	1.37	1.92	8.95	0.00	-1.00	16.47	9.03	124.75	0.01	-0.67	1.91	2.50	17.26
Brent Crude	833	0.00	-0.28	0.37	0.03	4.99	0.00	-0.18	0.28	0.05	1.45	0.01	-0.17	0.18	-0.13	0.46	0.01	-0.76	2.26	3.07	19.50	0.00	-0.78	2.15	2.48	15.10
Natural Gas	833	0.00	-0.14	0.20	0.07	7.72	0.01	-0.35	1.02	5.22	62.61	0.01	-0.23	0.75	3.37	33.92	0.02	-0.70	7.59	7.97	93.41	0.00	-0.86	66.05	28.00	796.66
British Pound	825	0.00	-0.10	0.11	-0.09	9.35	0.02	-0.91	3.65	2.48	14.95	0.04	-0.94	11.61	10.41	193.57	0.00	-0.89	16.96	9.61	128.84	0.00	-1.00	22.65	7.98	83.82
Euro	500	0.00	-0.04	0.05	-0.06	0.51	0.03	-0.79	1.83	1.24	13.17	0.05	-0.78	4.81	6.36	95.74	0.01	-0.93	44.50	20.41	437.81	0.00	-0.83	6.61	10.62	167.11
Japanese Yen	831	0.00	-0.04	0.07	0.58	2.17	0.03	-0.79	2.11	1.49	9.51	0.02	-0.76	1.15	0.35	4.31	0.01	-0.72	3.51	4.12	31.33	0.00	-1.00	48.59	18.34	403.58
Canadian Dollar	824	0.00	-0.06	0.04	-0.42	3.44	0.02	-0.83	1.27	0.55	4.40	0.03	-0.78	2.47	2.19	13.63	0.01	-1.00	44.61	21.53	548.45	0.00	-0.98	7.63	6.73	71.33
Swiss Franc	822	0.00	-0.08	0.08	0.38	4.66	0.03	-0.95	4.49	3.37	22.11	0.03	-0.92	8.77	7.57	103.29	0.01	-1.00	6.54	4.31	27.34	0.01	-1.00	61.50	21.52	544.98

Table 2.3 Continued. Descriptive Statistics – Evidence of Non-normal Distributions

Market		Other Short					Other Long					Open Interest				
	N	Median	Low	High	Skew	Kurtosis	Median	Low	High	Skew	Kurtosis	Median	Low	High	Skew	Kurtosis
U.S. 30 year bond	832	0.00	-0.35	0.63	0.89	3.81	0.00	-0.32	0.61	0.71	3.36	0.00	-0.16	0.25	0.34	1.45
U.S. 10 year note	832	0.00	-0.59	1.60	3.52	47.11	0.00	-0.61	1.71	3.24	32.54	0.01	-0.16	0.41	0.81	7.90
U.S. 5 year note	830	0.00	-0.36	3.58	11.50	226.79	0.00	-0.74	5.80	12.82	248.30	0.00	-0.17	0.26	0.44	2.25
U.S. 2 year note	793	0.01	-0.71	1.79	3.87	37.51	0.01	-0.71	1.17	1.46	8.38	0.01	-0.22	0.28	0.33	1.82
Eurodollar	827	0.00	-0.38	0.79	2.16	29.22	0.00	-0.43	0.79	1.48	18.21	0.01	-0.17	0.35	-0.70	10.41
S&P500	554	0.02	-0.81	3.13	2.84	19.82	0.02	-0.82	1.99	2.27	12.80	0.04	-0.66	0.48	-1.60	3.89
Nasdaq100	477	0.04	-0.97	4.71	3.25	19.61	0.04	-0.90	6.49	5.44	48.28	0.05	-0.74	0.70	-1.36	3.76
Dow Jones Industrials	325	0.02	-0.68	1.46	1.19	5.13	0.03	-0.85	5.31	5.46	56.16	0.04	-0.65	0.40	-1.63	3.75
Russell 2000	306	0.05	-0.92	4.20	3.01	20.29	0.01	-0.80	5.24	3.87	23.19	0.02	-0.69	0.46	-1.31	5.19
Corn	554	0.00	-0.17	0.23	0.43	4.32	0.00	-0.36	0.40	0.32	6.85	0.00	-0.11	0.15	0.33	2.01
Wheat	554	0.01	-0.27	0.43	0.52	2.98	0.00	-0.34	0.43	0.45	2.96	0.00	-0.17	0.20	0.49	2.91
Soybean	554	0.00	-0.24	0.36	0.49	3.46	0.00	-0.34	0.52	0.51	5.49	0.00	-0.13	0.13	-0.01	0.26
Sugar no.11	811	0.01	-0.57	1.13	1.12	8.62	0.01	-0.37	0.66	0.47	3.71	0.00	-0.23	0.23	-0.06	2.19
Coffee	807	0.00	-0.51	1.48	1.92	9.76	0.00	-0.42	0.90	1.41	10.25	0.00	-0.19	0.35	0.68	3.80
Cotton no.2	806	0.00	-0.70	2.27	4.43	67.64	0.01	-0.44	0.47	-0.10	2.70	0.00	-0.19	0.34	0.83	5.41
Live Cattle	834	0.00	-0.32	0.62	1.14	11.11	0.00	-0.36	0.73	0.88	10.86	0.00	-0.33	0.41	0.47	15.57
Lean Hogs	635	0.01	-0.23	0.37	0.15	1.48	0.00	-0.41	0.79	0.94	6.93	0.01	-0.23	0.22	-0.05	1.45
Oats	554	0.00	-0.55	1.51	1.95	10.92	0.00	-0.30	0.55	0.94	3.45	0.00	-0.28	0.36	0.48	4.53
Rough Rice	720	0.00	-0.82	1.13	1.32	6.83	0.00	-0.62	1.74	2.63	27.64	0.00	-0.25	0.26	0.35	1.94
Cocoa	807	0.01	-0.77	2.02	2.40	15.03	0.00	-0.43	1.30	1.77	12.79	0.00	-0.14	0.24	0.34	2.43
Gold	833	0.00	-0.63	1.92	2.11	17.37	0.00	-0.46	0.50	0.26	2.93	0.00	-0.19	0.32	0.64	2.63
Silver	833	0.00	-0.80	4.34	10.49	193.97	0.00	-0.20	0.32	0.01	2.13	0.00	-0.19	0.22	0.26	2.02
Copper	832	0.00	-0.59	1.34	1.55	14.36	0.00	-0.30	0.53	0.43	2.73	0.00	-0.28	0.24	-0.02	2.02
Platinum	828	0.00	-0.94	18.46	24.11	650.67	0.00	-0.41	0.69	0.64	2.98	0.00	-0.28	0.48	0.37	2.75
Brent Crude	833	0.01	-0.54	0.48	0.17	1.96	0.01	-0.49	0.54	0.17	2.71	0.01	-0.12	0.11	-0.29	0.05
Natural Gas	833	0.01	-0.59	1.02	1.72	9.72	0.01	-0.57	0.95	2.70	22.20	0.01	-0.27	0.74	4.58	48.56
British Pound	825	0.01	-0.89	18.38	22.51	586.88	0.00	-0.83	2.27	2.41	13.53	0.02	-0.65	0.70	-0.37	2.49
Euro	500	0.01	-0.77	3.91	7.59	105.90	0.01	-0.35	2.47	8.68	139.56	0.03	-0.48	2.95	9.28	163.10
Japanese Yen	831	0.00	-0.67	2.76	3.77	34.67	0.01	-0.80	1.81	1.95	11.32	0.02	-0.58	0.60	-0.74	3.71
Canadian Dollar	824	0.00	-0.60	1.66	1.82	10.75	0.00	-0.60	0.67	0.63	4.48	0.01	-0.44	0.56	0.07	3.39
Swiss Franc	822	0.01	-0.80	9.21	15.86	365.30	0.00	-0.99	68.52	28.09	796.71	0.02	-0.58	0.75	-0.50	2.79

Table 2.4 Significant Partial Autocorrelation (P < 0.05), Lags 1 to 6

Market	Market Prices						Commercial Short						Commercial Long						Speculator Short						Speculator Long					
	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
U.S. 30 year bond			0.11	0.07			0.07	-0.07				-0.07	0.07				-0.06		-0.15	-0.14					-0.09	-0.10	-0.06			-0.06
U.S. 10 year note			0.13	0.12			0.13					-0.12	0.17	0.06				-0.08	-0.09			-0.08	0.20			-0.11				
U.S. 5 year note	0.17	0.15	0.08		-0.10			-0.08	-0.07				0.08				-0.08		-0.07	-0.15							0.07			-0.08
U.S. 2 year note	-0.07			0.08		0.08					-0.07		0.08			-0.10	-0.09		-0.08	-0.07	-0.11							0.17		
Eurodollar	0.25	0.11	0.06	0.12		-0.10						-0.06			0.07	0.06		-0.07	-0.07	-0.07					-0.10			-0.07	-0.06	
S&P500	-0.15		0.12		-0.08								-0.18			-0.07			-0.07	-0.07					-0.22	-0.08				0.08
Nasdaq100	-0.12		0.11			0.12	-0.19	-0.19						-0.12	0.11				-0.08	-0.13		0.08			-0.10	-0.18				
Dow Jones Industrials	-0.25		0.10			0.09	-0.10	-0.15					-0.16	0.15						-0.10			-0.09		-0.17					
Russell 2000	-0.11								0.13				-0.20		0.10					-0.11	0.15				0.14					
Corn			0.16				0.30	-0.12					0.23				-0.14		0.22				-0.11		0.18					
Wheat				0.08			0.26				-0.10	-0.09						-0.11	0.17	-0.12				-0.09	0.12			-0.08		-0.09
Soybean	0.09			0.09			0.23			-0.07			0.18	-0.07			-0.09	-0.09	0.10						0.10	-0.10				
Sugar no.11	-0.08	-0.09	0.19				0.20	-0.07	-0.08				0.13	-0.06		-0.06	-0.08								0.10	-0.12		-0.08	-0.08	
Coffee		0.09		-0.09	-0.07		0.22	-0.07				-0.08	0.11	-0.07		-0.15	-0.07	-0.09				-0.08	-0.09		0.14			-0.13	-0.07	-0.07
Cotton no.2							0.25		-0.06				0.11	-0.08	-0.12	0.15	-0.12					0.12			0.13		-0.10			
Live Cattle		-0.13		0.09	0.08			-0.08	0.11	-0.10		-0.07						-0.06		-0.07		-0.11	0.09	-0.09		-0.08		-0.06		
Lean Hogs					-0.09		0.29						0.30		0.16	0.09		0.13				0.07	-0.07	0.08	0.10				-0.08	
Oats							0.24			-0.09		-0.09	0.09						0.32	-0.13					0.07				-0.08	-0.09
Rough Rice		0.12	-0.08			-0.07	0.18			0.11				0.09						-0.07										
Cocoa		-0.08	-0.06				0.17			-0.09	-0.07	-0.06	0.10	-0.09		-0.07				-0.07		-0.08				-0.06	-0.08		-0.06	
Gold						-0.11	0.12	-0.06	-0.08		-0.06	-0.07			-0.07	-0.10	-0.07	-0.10			0.07			-0.07	0.10	-0.08	-0.08	-0.06		-0.07
Silver					-0.10		0.19	-0.10	-0.07	-0.10		-0.11	0.06		-0.07	-0.12	-0.12				-0.06	-0.11	-0.12		0.15	-0.07		-0.11		
Copper		0.08							-0.08	-0.08						-0.10	-0.07				-0.06					0.13		-0.10		
Platinum							0.13	-0.07		-0.11	-0.10						-0.07							-0.07	0.08			-0.13	-0.07	-0.09
Brent Crude			0.17				-0.06	-0.12	-0.15	0.24		-0.14		-0.18	-0.16	0.19		-0.10	-0.06					-0.11	0.06		-0.08		-0.06	
Natural Gas		0.09				-0.09	0.08	0.19	0.07	0.22	0.06	-0.19	0.15		0.10	0.30	0.08	-0.15												
British Pound	-0.08			-0.15			-0.15						-0.12	0.11								-0.09								
Euro			0.08				-0.15		-0.11	-0.10								-0.08											0.10	-0.07
Japanese Yen							-0.09		-0.08		-0.07	-0.07	-0.12		-0.07	-0.09		-0.07			-0.09	-0.09		-0.09						
Canadian Dollar		0.11					-0.06	-0.10		-0.10				-0.09													-0.09		0.12	
Swiss Franc						-0.06	-0.11						-0.12	0.22	0.06	-0.08							-0.08		0.47	0.17	0.32	0.2	0.31	0.36

Table 2.4 Continued. Significant Partial Autocorrelation (P < 0.05), Lags 1 to 6

Market	Other Short						Other Long						Open Interest					
	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
U.S. 30 year bond	-0.17	-0.12	-0.10	-0.08	-0.11	-0.07	-0.20	-0.13		-0.10	-0.06	-0.08	0.14				-0.11	-0.09
U.S. 10 year note	-0.21	-0.07	-0.07		-0.07	-0.06	-0.24	-0.11	-0.14	-0.06		-0.10	0.22				-0.06	-0.16
U.S. 5 year note	0.07						-0.15						0.09		-0.08			-0.10
U.S. 2 year note	-0.25	-0.11	-0.10			-0.09	-0.32	-0.08			-0.07	-0.08	0.11			-0.09	-0.12	
Eurodollar		-0.06					-0.15	-0.08					0.06					-0.10
S&P500	-0.21	-0.10			-0.08		-0.07						-0.27	-0.13				
Nasdaq100	-0.18						-0.19	-0.09					-0.26	-0.21	-0.09			
Dow Jones Industrials	-0.22						-0.22	-0.14					-0.26	-0.17	-0.10			
Russell 2000	-0.20						-0.12	-0.10		0.11			-0.19					
Corn	0.08									-0.07	-0.10		0.41		-0.08			-0.08
Wheat	-0.23			-0.09	-0.08	-0.13	-0.21			-0.11			0.16			-0.09	-0.07	
Soybean					-0.08								0.30			-0.07	-0.07	
Sugar no.11	-0.14	-0.07	-0.07	-0.09	-0.07			-0.11		-0.06			0.22	-0.08	-0.08			
Coffee	-0.21	-0.10	-0.12		-0.11		-0.20	-0.15	-0.07	-0.07	-0.13		0.13	-0.09		-0.07		
Cotton no.2	-0.22	-0.10	-0.06			-0.09	-0.13						0.11		-0.08		-0.06	
Live Cattle			-0.09		-0.07			-0.12	-0.11	-0.16	-0.06	-0.09	0.12		-0.06	-0.13	-0.09	-0.07
Lean Hogs	-0.09											-0.07	0.23					
Oats	-0.11	-0.11		-0.07						-0.09			0.21			-0.11		-0.08
Rough Rice	-0.08		-0.07				-0.07			-0.08	-0.07		0.11					
Cocoa	-0.15	-0.10				-0.07	-0.14	-0.11					0.16		-0.12		-0.08	
Gold	-0.29	-0.15	-0.13				-0.15		-0.06				0.10	-0.08	-0.08		-0.08	
Silver	-0.18	-0.07	-0.12				-0.13			-0.06	-0.11		0.18	-0.07	-0.12	-0.10	-0.06	
Copper	-0.20	-0.17		-0.09			-0.18		-0.06	-0.10	-0.07	-0.06	0.09		-0.11	-0.13	-0.08	
Platinum	-0.09						-0.15		-0.08		-0.07	-0.08	0.08	-0.07		-0.09	-0.15	-0.06
Brent Crude	-0.30	-0.27	-0.20			-0.07	-0.23	-0.22	-0.16			-0.06		-0.29	-0.24	0.30		-0.13
Natural Gas	-0.31	-0.15					-0.19	-0.10		0.12			0.13	0.10	0.08	0.31	0.09	-0.20
British Pound		-0.07					-0.14		-0.11		-0.06		-0.16	-0.10	-0.10	-0.11		-0.10
Euro		-0.17					-0.09	-0.14						-0.11				-0.08
Japanese Yen	-0.17	-0.13	-0.10	-0.09		-0.08	-0.20					-0.08	-0.15	-0.10	-0.07	-0.06		-0.11
Canadian Dollar	-0.12	-0.11	-0.13	-0.09			-0.19	-0.07	-0.09			-0.08		-0.15	-0.06			-0.12
Swiss Franc	-0.08	-0.08				-0.07							-0.16	-0.11	-0.10	-0.09		-0.07

I. Time Series Models and Slope Coefficients

The autocorrelations unique to each market are incorporated into multiple regression time-series models in order to estimate the ceteris paribus effect of changes in market prices on changes in groups of traders' positions. As represented in Equation 2.1, each group's position across each market is treated separately as a dependent variable, with market returns and the significant lags of both prices and group position treated as independent variables. The estimated slope parameter therefore represents the relationship between change in positions and concurrent price changes, holding other factors constant. This slope coefficient is of interest in comparing different group behaviours across the sampled markets.

Equation 2.1 Group Position's Regressed On Concurrent Returns and Significant Lags of Both Position's and Concurrent Returns

$$P_t = \alpha + \sum_{i=0}^{k} \beta_i R_{t-i} + \sum_{i=1}^{k} \gamma_i P_{t-i} + \varepsilon_t$$

Table 2.5 reports the slope coefficients and significance for each group inventory across all markets and reveals a consistent pattern of trading behaviour. The slope co-efficient for speculators and commercials, in particular, are of the same sign across the majority of markets: changes in speculators inventory tends to be are positively correlated with market prices whereas commercial traders are negatively correlated. The majority of coefficients are also found to be significant ($p < 0.05$). The consistency of this result across markets is surprising and indicates that groups of commercial traders and speculators trade in a consistent way in relation to market prices. Speculators increase long positions during rising prices and decrease short positions. The opposite behaviour is observed during declining prices. In contrast, commercials increase short positions during rising prices and decrease long positions. Again the opposite behaviour is observed during price declines. Other (smaller, or non-reportable) traders, whose status as either commercial or speculators is unknown, have a similar, but less pronounced pattern to speculators. Open interest is typically found to be positively correlated with prices, particularly for positive price changes.

The residuals of the time-series models are each analysed and the Ljung-Box test finds no significant autocorrelations, indicating that the lags included in the models are sufficient for the study. The residuals are non-normally distributed however, as an inevitable result of the non-normal distributions of the input variables. As stated above, financial market data is typically non-normally distributed and such heteroskedasticity is expected for the current analysis, although the White correction for heteroskedasticity could be employed for future research.

Table 2.5 Slope Coefficients for Weekly Change in Group Positions and Concurrent Change in Prices

Market	Commercial Short		Commercial Long		Speculator Short		Speculator Long		Other Short		Other Long		Open Interest	
	Slope Coefficient	P < 0.05	Slope Coefficient	P < 0.05	Slope Coefficient	P < 0.05	Slope Coefficient	P < 0.05	Slope Coefficient	P < 0.05	Slope Coefficient	P < 0.05	Slope Coefficient	P < 0.05
U.S. 30 year bond	0.94	*	0.00		-1.36	*	2.96	*	-0.05		0.77	*	0.48	*
U.S. 10 year note	0.12		-0.93	*	1.77	*	3.72	*	-0.54		1.96	*	-0.13	
U.S. 5 year note	-0.06		-2.30	*	-2.51	*	5.36	*	-1.89	*	3.46	*	-0.79	*
U.S. 2 year note	-0.24		-4.02	*	-2.04		-9.11		-1.78		7.45	*	-1.57	
Eurodollar	2.89	*	-3.90	*	-31.01	*	15.29	*	-1.98		4.99	*	-0.18	
S&P500	1.26	*	-0.54		-0.10		0.77		-1.43	*	0.08		0.03	
Nasdaq100	1.13	*	-1.10		-0.65	*	0.43		-1.11		2.67	*	0.22	
Dow Jones Industrials	-0.63		2.99	*	1.00		0.23		1.94	*	-2.84	*	0.70	
Russell 2000	0.39		-1.89	*	-1.49	*	2.18	*	-3.47	*	4.77	*	-0.43	
Corn	0.93	*	-0.36	*	-1.95	*	1.58	*	0.12		0.53	*	0.14	*
Wheat	1.10	*	-0.22	*	-1.43	*	1.15	*	-0.01		0.25		0.22	*
Soybean	1.06	*	-0.54	*	-1.47	*	2.16	*	0.15		0.55	*	0.36	*
Sugar no.11	1.07	*	-0.89	*	-4.20	*	3.09	*	-0.97	*	1.08	*	0.25	*
Coffee	1.01	*	-0.88	*	-2.37	*	2.18	*	-0.58	*	0.38	*	0.18	*
Cotton no.2	2.12	*	-1.10	*	-6.34	*	3.90	*	-1.91	*	0.92	*	0.33	*
Live Cattle	0.88	*	-0.28	*	-2.23	*	2.48	*	0.82	*	-0.34	*	0.46	*
Lean Hogs	1.18	*	-0.23	*	-0.62	*	1.63	*	0.23	*	0.29		0.46	*
Oats	0.76	*	-0.90	*	-0.03		0.86	*	-0.44		0.94	*	0.35	*
Rough Rice	1.68	*	-0.71	*	-0.84		2.04	*	-1.39	*	1.30	*	0.53	*
Cocoa	0.70	*	-0.41	*	-2.53	*	2.75	*	-0.85	*	0.62	*	0.18	*
Gold	2.53	*	-2.21	*	-2.39	*	5.11	*	-1.24	*	2.00	*	0.90	*
Silver	0.99	*	-1.65	*	-2.23	*	1.57	*	-0.39		0.24	*	0.39	*
Copper	0.85	*	-0.92	*	-1.86	*	1.49	*	-0.70	*	0.54	*	0.13	*
Platinum	1.64	*	-1.79	*	-3.64	*	2.54	*	-0.99		0.91	*	0.82	*
Brent Crude	0.30	*	-0.18	*	-1.49	*	1.84	*	-0.03		0.42	*	0.09	*
Natural Gas	0.36	*	-0.07		-1.54	*	2.21	*	0.06		0.31	*	0.19	*
British Pound	10.41	*	-13.53	*	-18.43	*	31.35	*	-6.32	*	4.92	*	0.44	
Euro	4.43	*	-2.85	*	-15.93	*	5.04	*	-3.66	*	-0.01		1.02	*
Japanese Yen	7.12	*	-5.90	*	-10.84	*	14.31	*	-5.08	*	6.45	*	-0.72	
Canadian Dollar	5.85	*	-9.40	*	-26.90	*	13.20	*	-4.21	*	2.77	*	0.10	
Swiss Franc	13.01	*	-9.61	*	-17.72	*	17.25	*	-6.82	*	19.83	*	-0.27	

II. Different Time-horizons

The following procedure investigates consistencies in slope coefficients across different time-horizons. Log weekly changes are aggregated to represent cumulative returns over time, from these series, the log change over different time-windows is calculated again for both prices and group inventories. The time-windows of interest include 2 weeks, 4 weeks and 8 weeks.

The above analysis is then repeated on these new time-windows. Significant lags are calculated over 2, 4, and 8 week returns (results not-shown) and incorporated into time-series models to compare estimated slope coefficients. Tables 2.6 to 2.9 document these results. Notably, a very similar pattern of group behaviour, particularly amongst commercials and speculators, is identified. However, the significance of the coefficients degrades as sample sizes decrease with the larger price windows.

Table 2.6 Slope Coefficients for Change in Group Positions and Concurrent Change in Prices, 2 Weeks Time-horizon

Market	Commercial Short		Commercial Long		Speculator Short		Speculator Long		Other Short		Other Long		Open Interest	
	Slope Coefficient	P < 0.05	Slope Coefficient	P < 0.05	Slope Coefficient	P < 0.05	Slope Coefficient	P < 0.05	Slope Coefficient	P < 0.05	Slope Coefficient	P < 0.05	Slope Coefficient	P < 0.05
U.S. 30 year bond	1.14	*	-0.24		-1.72	*	3.95	*	-0.47	*	0.86	*	0.48	*
U.S. 10 year note	-0.02		-1.26	*	-3.54	*	-0.18		-1.29	*	1.51	*	-0.50	*
U.S. 5 year note	0.11		-3.10	*	-4.30	*	7.81	*	-4.39	*	3.75	*	-0.96	*
U.S. 2 year note	-0.08		-4.22	*	0.67		-13.08		-5.07	*	6.81	*	-1.76	
Eurodollar	3.63	*	-4.21	*	-34.96	*	14.42	*	-4.45		3.25		0.22	
S&P500	0.72		-1.23		-1.33		-1.47		-3.52	*	0.82		-0.83	*
Nasdaq100	1.55	*	0.21		-0.27		0.79		-1.79	*	2.12	*	0.48	
Dow Jones Industrials	0.97		2.76	*	0.74		0.28		1.81		-0.21		1.70	*
Russell 2000	-0.03		-2.35	*	-1.80		3.12	*	-5.10	*	4.52	*	-1.71	*
Corn	1.31	*	-0.39	*	-2.73	*	2.18	*	0.19		0.63	*	0.26	*
Wheat	1.41	*	-0.14		-1.62	*	1.47	*	0.01		0.40	*	0.33	*
Soybean	1.28	*	-0.52	*	-2.09	*	2.39	*	0.32	*	0.76	*	0.44	*
Sugar no.11	1.33	*	-0.93	*	-4.65	*	3.47	*	-1.19	*	1.17	*	0.35	*
Coffee	1.12	*	-0.96	*	-2.88	*	2.38	*	-0.68	*	0.25	*	0.16	*
Cotton no.2	2.66	*	-1.07	*	-5.33	*	5.19	*	-1.90	*	0.91	*	0.59	*
Live Cattle	1.12	*	-0.26		-2.95	*	2.96	*	1.11	*	0.04		0.51	*
Lean Hogs	1.52	*	-0.40	*	-0.72		1.98	*	0.29		0.27		0.56	*
Oats	0.95	*	-0.82	*	-3.43		1.20	*	-0.20		1.00	*	0.47	*
Rough Rice	1.76	*	-0.75	*	-1.14		2.85	*	-1.61	*	1.19	*	0.46	*
Cocoa	0.74	*	-0.43	*	-2.06	*	3.05	*	-0.22		0.75	*	0.21	*
Gold	2.58	*	-2.21	*	-2.36	*	5.35	*	-0.72		2.04	*	1.01	*
Silver	1.30	*	-1.69	*	-2.98	*	2.05	*	-0.20		0.39	*	0.57	*
Copper	1.02	*	-1.00	*	-2.19	*	1.70	*	-0.63	*	0.57	*	0.13	*
Platinum	1.80	*	-2.03	*	-4.25	*	2.98	*	-1.84		0.96	*	0.87	*
Brent Crude	0.34	*	-0.17	*	-1.42	*	1.95	*	-0.12		0.39	*	0.12	*
Natural Gas	0.46	*	-0.12		-2.25	*	2.30	*	-0.15		0.34	*	0.17	*
British Pound	11.27	*	-10.90	*	-23.34	*	33.08	*	-3.73		5.87	*	0.29	
Euro	3.43	*	-3.28	*	-7.94	*	4.88	*	-3.79	*	0.75		0.94	*
Japanese Yen	6.62	*	-6.83	*	-11.43	*	11.63		-5.38	*	6.61	*	-1.13	*
Canadian Dollar	6.44	*	-10.16	*	-28.51	*	13.84	*	-4.89	*	2.47	*	0.12	
Swiss Franc	13.00	*	-8.68	*	-16.86	*	21.08	*	-6.17	*	19.84	*	-0.66	

Table 2.7 Slope Coefficients for Change in Group Positions and Concurrent Change in Prices, 4 Weeks Time-horizon

Market	Commercial Short		Commercial Long		Speculator Short		Speculator Long		Other Short		Other Long		Open Interest	
	Slope Coefficient	P < 0.05	Slope Coefficient	P < 0.05	Slope Coefficient	P < 0.05	Slope Coefficient	P < 0.05	Slope Coefficient	P < 0.05	Slope Coefficient	P < 0.05	Slope Coefficient	P < 0.05
U.S. 30 year bond	0.88	*	-0.33		-1.21	*	3.85	*	-0.41		1.12	*	0.31	
U.S. 10 year note	0.03		-1.44	*	-3.69	*	-1.24		-1.14	*	1.39	*	-0.61	*
U.S. 5 year note	0.44		-3.27	*	-5.58	*	1.74		8.42	*	16.61	*	-1.12	*
U.S. 2 year note	-0.09		-6.86	*	-19.08		32.74		-6.51	*	1.74		-2.85	
Eurodollar	2.00		-6.40	*	-44.53	*	8.03		-4.69		4.89		-0.61	
S&P500	-0.48		-1.15		-0.11		-1.16		-2.57	*	0.56		-0.79	
Nasdaq100	1.12	*	0.91		-0.29		1.16	*	-1.18		2.68	*	0.46	
Dow Jones Industrials	1.27		3.79		1.94		1.16		0.64		2.02		1.73	*
Russell 2000	0.36		1.00		2.89		1.68		-2.72		5.96	*	0.26	
Corn	1.07	*	-0.31	*	-2.68	*	1.62	*	0.18		0.23		0.16	
Wheat	1.45	*	-0.02		-1.54	*	1.41	*	0.13		0.57	*	0.32	*
Soybean	1.72	*	-0.40	*	-2.68	*	2.78	*	0.62	*	0.98	*	0.73	*
Sugar no.11	1.46	*	-0.82	*	-7.14	*	3.96	*	-0.98	*	1.24	*	0.45	*
Coffee	1.23	*	-1.15	*	-3.64	*	2.70	*	-0.62	*	0.42	*	0.17	
Cotton no.2	3.32	*	-1.26	*	-6.50	*	6.44	*	-1.41	*	1.30	*	0.77	*
Live Cattle	1.94	*	-0.35		-3.53	*	3.98	*	1.29	*	0.21		0.68	*
Lean Hogs	1.88	*	-0.60	*	-1.36	*	2.82	*	0.47	*	0.19		0.71	*
Oats	0.86	*	-0.36		-0.76		1.39	*	-0.04		0.80	*	0.57	*
Rough Rice	1.88	*	-0.71		-0.76		2.70	*	-0.66		1.89	*	0.64	*
Cocoa	0.79	*	-0.35	*	-1.83	*	3.23	*	-0.14		0.62	*	0.36	*
Gold	3.39	*	-2.13	*	-2.89	*	5.64	*	-1.03		2.24	*	1.19	*
Silver	1.60	*	-1.89	*	-4.18	*	2.42	*	-0.68		0.35	*	0.61	*
Copper	0.98	*	-1.11	*	-2.23	*	1.75	*	-0.51	*	0.55	*	0.14	
Platinum	1.88	*	-2.63	*	-4.43	*	3.26	*	-1.34		1.31	*	0.86	*
Brent Crude	0.29	*	-0.17	*	-1.20	*	1.67	*	-0.04		0.41	*	0.11	*
Natural Gas	0.62	*	-0.19		-3.03	*	3.31	*	-0.30		0.55	*	0.21	
British Pound	10.74	*	-10.63	*	-28.32	*	29.49	*	-2.58		7.58	*	1.56	*
Euro	3.24	*	-2.82	*	-25.61		4.73	*	-1.39		-0.27		1.16	*
Japanese Yen	7.00	*	-7.18	*	-11.81	*	2.55		-6.43	*	7.23	*	-1.21	*
Canadian Dollar	9.14	*	-12.15	*	-35.01	*	16.63	*	-5.42	*	3.61	*	0.97	
Swiss Franc	12.58	*	-13.57	*	-20.92	*	14.90		-4.90	*	17.04		-0.83	

Table 2.8 Slope Coefficients for Change in Group Positions and Concurrent Change in Prices, 8 Weeks Time-horizon

Market	Commercial Short		Commercial Long		Speculator Short		Speculator Long		Other Short		Other Long		Open Interest	
	Slope Coefficient	P < 0.05	Slope Coefficient	P < 0.05	Slope Coefficient	P < 0.05	Slope Coefficient	P < 0.05	Slope Coefficient	P < 0.05	Slope Coefficient	P < 0.05	Slope Coefficient	P < 0.05
U.S. 30 year bond	0.54		0.39		-0.29		2.87	*	-0.44		0.70		0.08	
U.S. 10 year note	-0.29		-1.22	*	8.72	*	-1.68		-0.94		0.43		-0.65	
U.S. 5 year note	0.22		-2.28	*	-4.00		6.19		8.22	*	15.66	*	-0.72	
U.S. 2 year note	-1.50		-10.39	*	-16.18		58.50		-4.89		6.12		-5.04	
Eurodollar	0.62		9.98	*	-27.85		-5.48		9.58	*	3.36		-1.30	
S&P500	-0.73		-0.65		-0.59		0.08		-3.48	*	0.47		-0.72	
Nasdaq100	0.36		0.17		-0.59		0.74		-2.16		2.37		-0.19	
Dow Jones Industrials	0.87		-2.27		1.20		3.10		1.75		1.31		0.60	
Russell 2000	-0.08		2.22		1.77		0.76		-1.99		4.26		0.10	
Corn	0.85	*	-0.30		-2.68	*	1.20	*	0.00		-0.07		0.02	
Wheat	1.11	*	0.09		-1.46	*	0.95	*	0.16		0.49		0.35	*
Soybean	1.57	*	-0.35		-2.58	*	2.60	*	0.62	*	0.60	*	0.65	*
Sugar no.11	1.35	*	-0.61	*	-7.71	*	3.68	*	-0.61	*	1.08	*	0.48	*
Coffee	0.78	*	-0.74	*	-2.82	*	1.45	*	-0.24		0.26		0.09	
Cotton no.2	3.23	*	-1.13	*	-16.76	*	7.21	*	-1.30	*	1.10	*	0.46	*
Live Cattle	1.49	*	-0.54		-4.01	*	3.64	*	1.28	*	-0.06		0.57	*
Lean Hogs	2.15	*	-0.71	*	-2.07	*	2.73	*	0.67	*	0.56		0.75	*
Oats	0.75	*	-0.55		-1.88		1.04		-1.21	*	0.44		0.32	
Rough Rice	2.18	*	-1.24		0.94		4.12		-0.67		1.48	*	0.65	
Cocoa	0.69	*	-0.17		-1.57		2.33	*	0.14		0.19		0.33	*
Gold	3.65	*	-2.30	*	-4.39	*	5.17	*	-0.37		2.61	*	1.28	*
Silver	1.46	*	-1.40	*	-3.90	*	1.86	*	-1.10		0.43	*	0.65	*
Copper	0.58	*	-0.92	*	-2.46	*	1.17	*	-0.46	*	0.29	*	0.01	
Platinum	1.06	*	-1.70	*	-5.15	*	1.96	*	-1.42		0.94	*	0.35	
Brent Crude	0.16	*	-0.13		-0.81		1.15	*	-0.01		0.16		0.05	
Natural Gas	0.59	*	-0.18		-2.10		2.30	*	-0.48		0.30		0.10	
British Pound	6.61	*	-4.98	*	-18.66	*	15.16		2.28		5.20	*	1.26	
Euro	1.24		0.30		-4.80		6.30	*	1.37		2.35	*	2.31	*
Japanese Yen	2.16		-6.60	*	-10.57	*	1.78		-4.03	*	4.93	*	-2.24	*
Canadian Dollar	7.31	*	-13.03	*	-30.68		13.44	*	-5.96	*	2.59	*	-0.12	
Swiss Franc	7.08	*	0.42		-20.92	*	-9.92		-2.51		-8.60		-0.76	

III. Statistical Comparison of Commercials and Speculators

The above results find the sign of coefficients associated with commercial and speculators to be broadly consistent across markets and over different time scales. Change in speculators' long and short positions are positively correlated with market prices, whereas changes in commercial positions are negatively correlated with prices. The statistical significance associated with the different trading behaviour displayed by commercials and speculators can be tested more formally in the following way.

A multiple regression is fitted with a categorical variable for trader group, as being either commercial or speculator (note other COT variables are excluded here), and an additional categorical variable for position (either long or short). Change in group inventory is regressed on to these categorical variables and 6 lags of market prices and group inventory. The three-way interaction between market prices and the qualitative variables of group and position sign represent the relationship between change in prices and inventory, moderated by group and position sign. That is, the joint effect of 3 independent variables on change in inventories is tested.

As documented in Table 2.9, the three-way interaction is significant across all time-horizons for the majority of markets. This result indicates trading behaviour can be considered significantly different across market participants. Change in positions for commercial traders, when changing from long to short positions, is significantly different to the change in positions for speculators when changing from long to short positions. This conclusion is supported by a within subjects repeated measures ANNOVA, comparing the estimated slope coefficients for each market across each group (see Tables 2.5 to 2.8). The results are significant for every time-horizon and shown in Table 2.9. This analysis supports the conclusion that commercials and speculators display very different patterns of trading behaviour.

Table 2.9 Three-Way Interactions Between Position-Sign, Group and Prices; ANNOVA of Coefficients for All Markets; Per Time-horizon, Significance at P < 0.05

Market	1 Week	2 Week	3 Week	4 Week
	Interaction Between Position-Sign, Group and Price			
U.S. 30 year bond	*	*	*	*
U.S. 10 year note	*	*	*	
U.S. 5 year note	*	*	*	*
U.S. 2 year note				
Eurodollar	*	*	*	*
S&P500	*			
Nasdaq100	*	*		*
Dow Jones Industrials	*			
Russell 2000	*	*		
Corn	*	*	*	*
Wheat	*	*	*	*
Soybean	*	*	*	*
Sugar no.11	*	*	*	*
Coffee	*	*	*	*
Cotton no.2	*	*	*	*
Live Cattle	*	*	*	*
Lean Hogs	*	*	*	*
Oats		*		
Rough Rice	*	*	*	*
Cocoa	*	*	*	*
Gold	*	*	*	*
Silver	*	*	*	*
Copper	*	*	*	*
Platinum	*	*	*	*
Brent Crude	*	*	*	*
Natural Gas	*	*	*	*
British Pound	*	*	*	*
Euro	*	*	*	
Japanese Yen	*	*	*	
Canadian Dollar	*	*	*	*
Swiss Franc	*	*	*	
	Different Position-Sign Group Coefficients			
ANNOVA, Coefficients from All Markets	*	*	*	*

IV. Summary Coefficients for Commercials and Speculators

To provide a summary of this behaviour across all the markets in the sample, the following analysis treats each market 1 to as a categorical variable in a multiple regression of each group's positions on market returns . This has the effect of relaxing assumptions of consistent mean price and inventory change across markets, which is inevitably unrealistic. In Equation 2.2, is an adjustment to the intercept for each market. The data for all the markets is therefore grouped together, and as with the above regression, all 6 lags are also included for positions and returns as dependent variables. The summary slope coefficients for commercials and speculators are significant in every case and documented in Table 2.10.

Equation 2.2 Group Position's Regressed On Concurrent Returns and Significant Lags of Both Position's and Concurrent Returns, with a Categorical Variable for Each Market

$$P_t = \alpha + \sum_{i=0}^{k} \beta_i R_{t-i} + \sum_{i=1}^{k} \delta_i P_{t-i} + \sum_{n=1}^{N} \lambda_n M_n + \varepsilon_t$$

Table 2.10 Summary Slope Coefficients for Change in Group Positions and Concurrent Change in Prices Across Different Time-horizons, Significance at $p < 0.05$

Time Horizon	Commercial Short		Commercial Long		Speculator Short		Speculator Long	
	Slope Coefficient	P < 0.05	Slope Coefficient	P < 0.05	Slope Coefficient	P < 0.05	Slope Coefficient	P < 0.05
1 Week	1.24	*	-1.04	*	-2.55	*	2.61	*
2 Week	1.41	*	-1.1	*	-3.21	*	3	*
4 Week	1.46	*	-1.13	*	-3.31	*	3	*
8 Week	1.02	*	-0.92	*	-2.72	*	2.09	*

Note the size of the coefficients do not move uniformly with the increasing time-horizons, this is a result of changes in sample size; smaller sample sizes are associated with larger time-horizons.

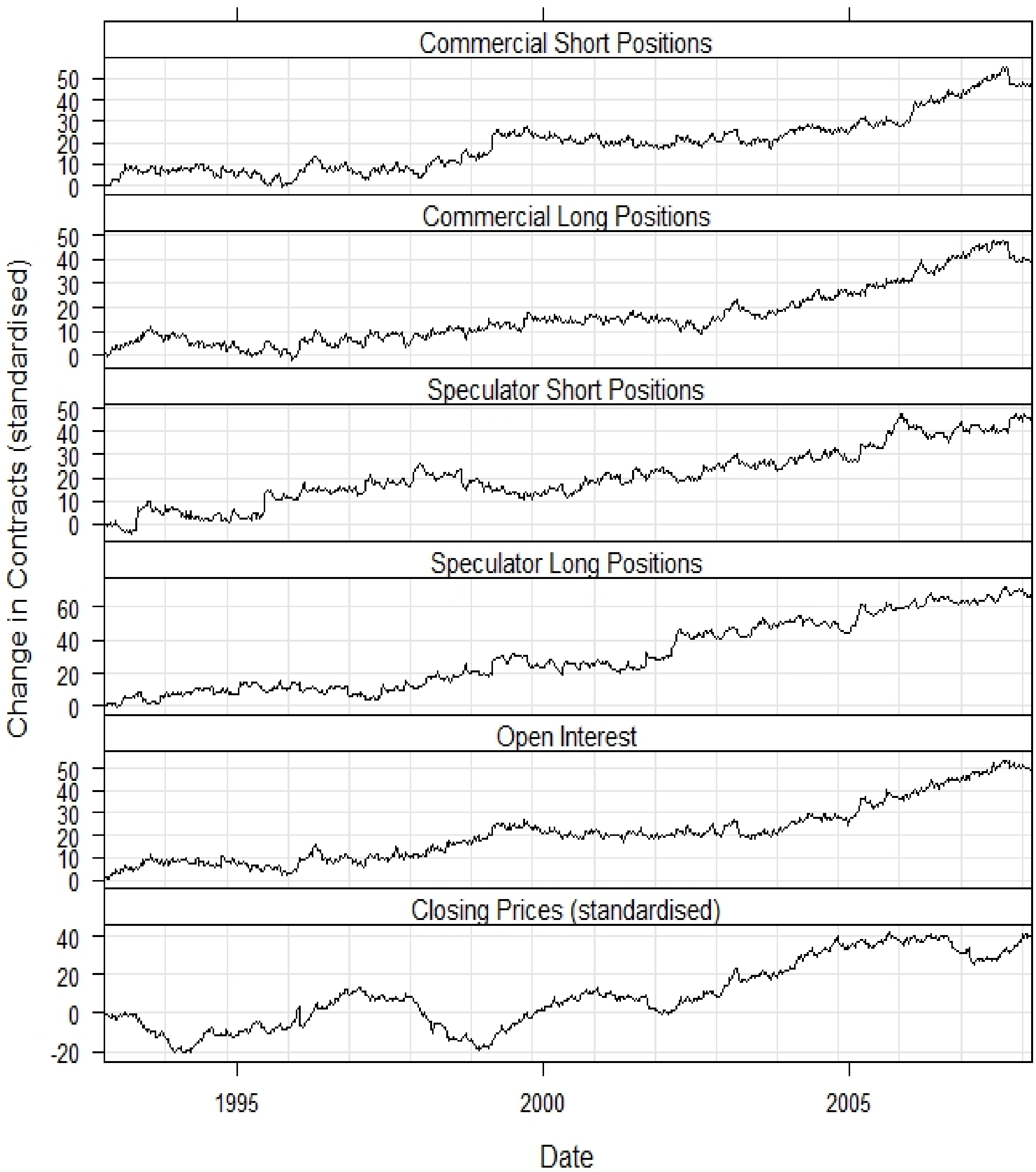
2.5.3 Alternative Methodology

The above econometric analysis treats behaviour as a time-series variable, where behaviour is considered continuous and related to past behaviour in a persistent way. An alternative viewpoint is to consider behaviour as more discrete, and uniquely related to particular scenarios or conditions. The following bespoke methodology follows this second viewpoint and applies a standardisation procedure, as outlined in the following section, to categorise different market scenarios and isolate underlying group behaviours. Examples of trading behaviour are then grouped together to form meaningful sample sizes and compared statistically across markets. A benefit of this methodology is that it permits direct comparisons of behaviour across different scales of price change. In the following analysis, the buying and selling patterns of different groups of traders during smaller price changes is also compared to the buying and selling patterns during larger price changes.

I. Standardisation Procedure

Price changes across all markets are categorised into particular sizes and particular signs to represent specific market conditions. To categorise price changes and compare group behaviour in this way, a normalised measure of change is required. The technique developed here is similar to calculating a coefficient of variation, but avoids using a constant mean as a measure of scale. Due to variation in the volatility of financial time-series, each variable in a series (price and COT data) is divided by a rolling standard deviation derived from the previous 10 weeks. Change in a time-series from one week to the next is therefore represented as a unit of its recent volatility, allowing underlying characteristics of the different markets to be compared across a dimensionless scale. Figure 2 depicts a standardised time-series for the crude Oil market. Note the y-axis now represents change in units of standard deviation.

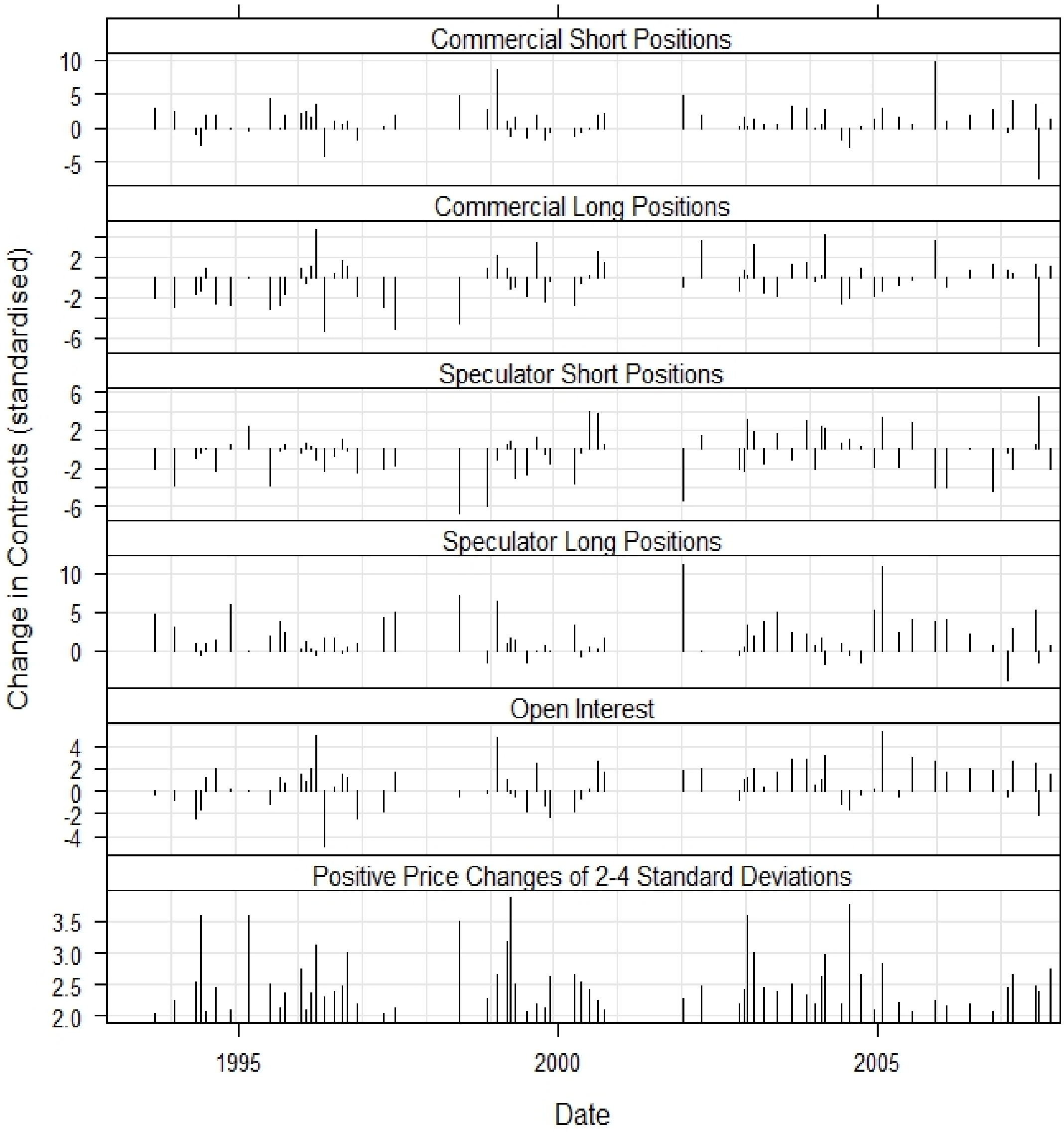
Figure 2.2 Standardised Time-series for Crude Oil



To categorise price movements of a specific size, price changes of a target size are identified together with corresponding changes in contracts across the various groups. For example, Figure 2.3 marks changes in position associated with positive price changes of between 2 and 4 standard deviations. This data series is inhomogeneous with respect to time (that is, the period of time between each data point varies) but broadly homogeneous with respect to market movement (a data point occurs each time prices move a given magnitude). This categorization was carried out for positive and negative price changes of >=1 and <2 standard deviations, >=2 and <4 standard deviations, >=4 and <8 standard deviations, and >=8 and <16 standard deviations. Each observation in this new series is therefore independent of time period; that is, a discrete observation occurs every time prices move a specific increment rather than over a specific period of time.

To summarise then, an original aligned time-series (as in Figure 2.1) is standardised (Figure 2.2), and categorised into price changes of a specific size and sign with associated changes in contracts (Figure 2.3) across commercial traders, speculators, other traders, and open interest. In this way, conditions are held constant for meaningful comparisons of trading behaviour to be conducted.

Figure 2.3 Observations of Positive Price Changes of 2-4 Standard Deviations in the Crude Oil Market and Associated Changes in Group Positions



In the following analysis, the distributions of changes in short and long positions associated with different sized price changes for the different market groups are presented. These changes are shown to be significant. The changes in short and long positions are also shown to be similar across markets, and, as with the above econometric analysis, the behaviour of commercials and speculators found to differ significantly.

II. Example Distributions of Group Behaviour Under Specific Conditions

The distribution of changes in contracts across group behaviours in the Crude Oil market during similar sized price changes are presented in Figures 2.4 and 2.5. These are derived from a Gaussian Kernel Density estimate and are plotted with the median values of the distribution. Note that the sample size for positive price changes of 2-4 standard deviations (N=68) is different to that of negative 2-4 standard deviation price changes (N=39) as Crude Oil has been in a broad up-trend over the sample period and therefore more positive price changes have occurred.

Note in Figure 2.4 that the sign of the median change in contracts, in particular for commercial and large speculators, has a pattern that is broadly reversed for negative price changes (Figure 2.5). During positive price changes, commercials increase their short contracts (top-left plot of Figure 2.5) and reduce long contracts (top-right plot of Figure 2.5). Speculators tend to do the opposite, increasing their long exposure during positive price changes and decreasing short positions (upper-middle plots in Figure 2.5). These findings confirm the results from the econometric analysis (Tables 2.5 through to 2.10). In accordance with the econometric findings, the following results also demonstrate this pattern of trading behaviour as entirely standard and occurring with apparent regularity across a wide range of markets.

Figure 2.4 Crude Oil, Density Plots (with Medians Highlighted) for Changes in Positions During Positive Price Changes of 2-4 Standard Deviations (N=68)

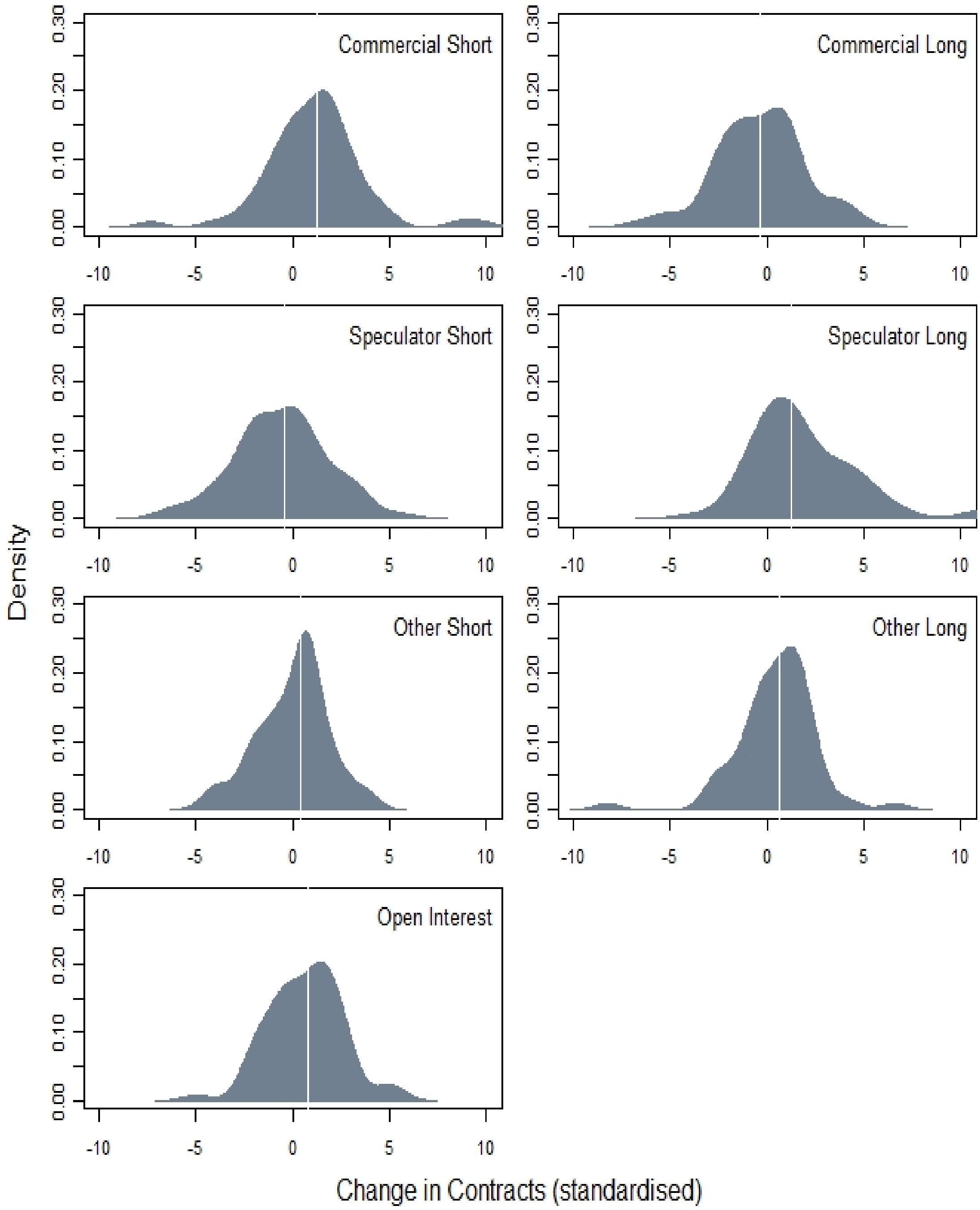
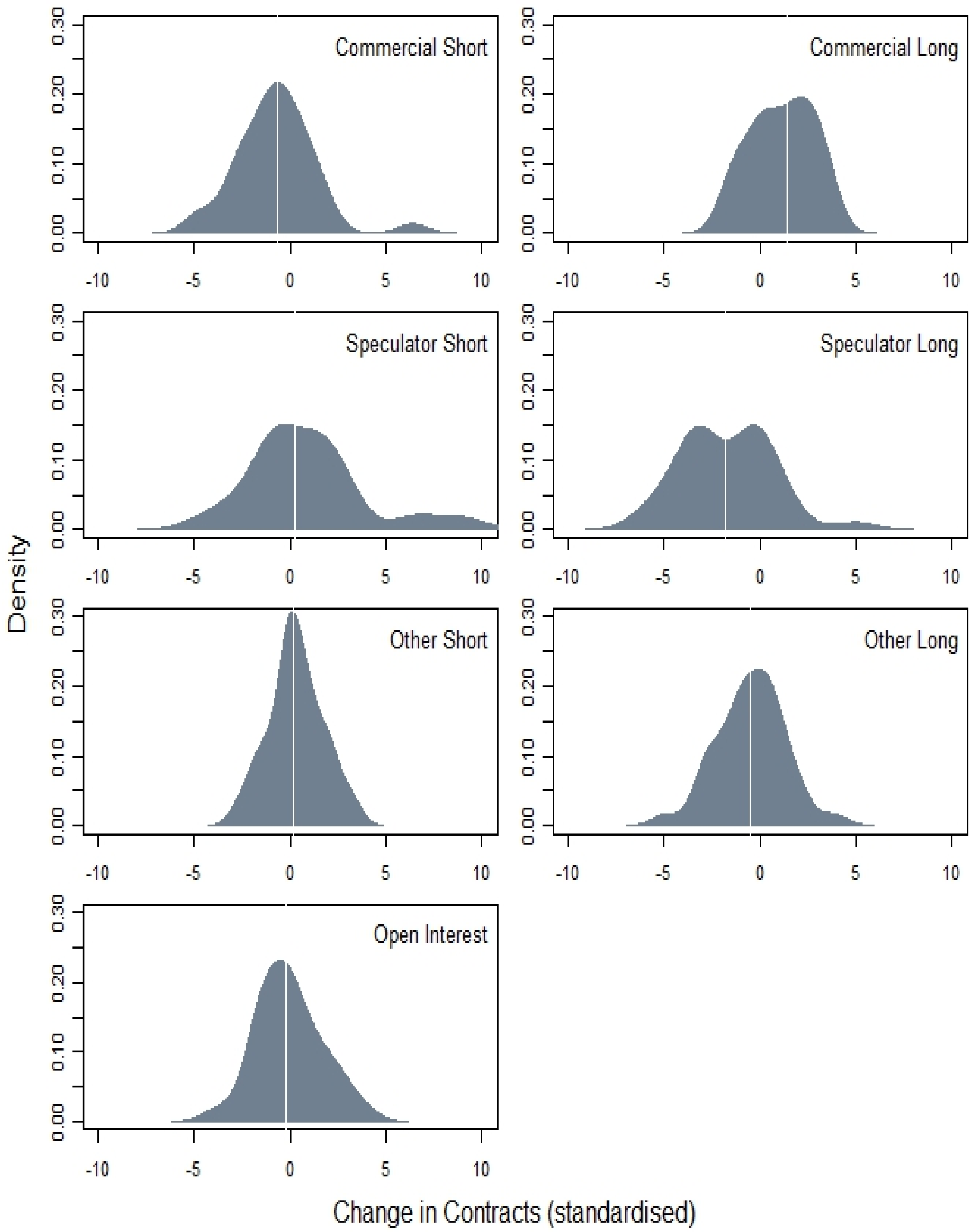


Figure 2.5 Crude Oil, Density Plots (with Medians Highlighted) for Changes in Positions During Negative Price Changes of 2-4 Standard Deviations (N=39)



III. Positions Change Significantly as Price Changes

To test the hypothesis that changes in group behaviour are non-randomly related to market prices, a non-parametric, bootstrap methodology is employed. A random permutation of a standardised dataset (as depicted in Figure 2.2, for Crude Oil) is generated. Specifically, the COT variable time-sequence is reshuffled whilst week-on-week price changes are held constant. Shuffled data are categorised as the real data were. By repeating this procedure 10,000 times, the distribution of change in COT variable medians under the null hypothesis of no relation to price is constructed.

I find a large number of markets have non-random changes in COT variables with a clear pattern in the direction of significance. Table 2.11 presents changes in COT variables associated with positive price changes of 1-2, 2-4, 4-8 and 8-16 standard deviations. Significant positive changes are denoted '+' and significant negative changes are denoted '-'. Significance is at the 5% level. Note the 1-2 standard deviation category in the first column for each COT variable in the table. For the majority of markets, change in commercial short positions and speculator long positions are positive, whilst changes in commercial long and speculator short positions are negative. As Table 2.12 demonstrates, this pattern of results is reversed for negative price changes. As with the findings from the econometric study across different time-horizons (Tables 2.6 to 2.8), the significance of the results declines with the larger sized price changes (or time-horizons). This effect may relate to the much smaller sample sizes associated with larger sized price changes. These finding can be investigated further by comparing group behaviours across markets.

Table 2.11 Changes in COT variables Associated with Positive Price Changes of 1-2, 2-4, 4-8 and 8-16 Standard Deviations (Significant Differences to Randomised Samples)

Market	Commercial Short				Commercial Long				Speculator Short				Speculator Long				Other Short				Other Long				Open Interest			
	1-2	2-4	4-8	8-16	1-2	2-4	4-8	8-16	1-2	2-4	4-8	8-16	1-2	2-4	4-8	8-16	1-2	2-4	4-8	8-16	1-2	2-4	4-8	8-16	1-2	2-4	4-8	8-16
U.S. 30 year bond	+	+	+						-				+	+	+		-					+			+			
U.S. 10 year note					-	-	-		-	-	-			+							+	+						
U.S. 5 year note		+				-								+			-					+						
U.S. 2 year note																												
Eurodollar									-	-			+															
S&P500																												
Nasdaq100													+															
Dow Jones Industrials																												
Russell 2000																												
Corn		+	+	+	-			+	-	-	-	-		+	+			+	+									+
Wheat	+	+	+		-	-			-	-	-		+	+	+							+				+	+	+
Soybean	+	+	+	+	-	-			-	-	-		+	+	+	+											+	+
Sugar no.11	+	+	+		-	-	-		-	-	-		+	+	+		-	-	-		+	+	+				+	
Coffee	+	+	+		-	-	-		-	-	-		+	+	+													
Cotton no.2	+	+	+		-	-			-	-	-		+	+			-	-			+	+						
Live Cattle	+	+	+		-				-	-			+	+	+		+	+	+							+	+	
Lean Hogs	+	+		+		-	-			-	-		+	+		+					+				+			+
Oats	+	+	+												+						+	+			+	+		
Rough Rice	+	+												+												+		
Cocoa	+				-	-			-	-			+	+	+						+	+						
Gold	+	+	+		-	-	-		-	-			+	+	+		-	-			+	+	+	+	+		+	
Silver	+	+	+	+	-	-			-	-			+	+		+		-										
Copper	+	+	+		-	-	-			-	-		+	+			-	-	-		+	+						
Platinum	+	+	+		-	-	-		-	-			+	+	+						+		+		+		+	
Brent Crude	+	+			-	-			-	-			+	+	+							+						
Natural Gas	+	+	+						-	-	-		+	+	+		-											
British Pound	+	+			-	-			-	-	-		+	+	+		-	-			+	+	+					
Euro		+							-	-			+	+	+													
Japanese Yen		+			-	-			-	-				+	+			-			+	+						
Canadian Dollar	+	+			-	-	-		-	-	-		+	+	+		-	-			+	+	+					
Swiss Franc	+	+			-	-	-		-	-	-			+			-	-			+	+	+					

Significant positive changes are denoted '+' and significant negative changes are denoted '-'.

Table 2.12 Changes in COT variables Associated with Negative Price Changes of 1-2, 2-4, 4-8 and 8-16 Standard Deviations (Significant Differences to Randomised Samples)

Market	Commercial Short				Commercial Long				Speculator Short				Speculator Long				Other Short				Other Long				Open Interest			
	1-2	2-4	4-8	8-16	1-2	2-4	4-8	8-16	1-2	2-4	4-8	8-16	1-2	2-4	4-8	8-16	1-2	2-4	4-8	8-16	1-2	2-4	4-8	8-16	1-2	2-4	4-8	8-16
U.S. 30 year bond	-					+			+				-	-	-							-			-			
U.S. 10 year note					+	+	+		+	+	+			-														+
U.S. 5 year note					+	+			+								+	+			-	-						
U.S. 2 year note																					-							
Eurodollar									+	+												-						
S&P500																												
Nasdaq100																												
Dow Jones Industrials				NA				NA				NA				NA				NA				NA				NA
Russell 2000				NA				NA				NA	-			NA	+		+	NA				NA				NA
Corn	-	-	-						+	+	+		-	-	-	-			-			-				-		
Wheat	-	-	-		+				+	+	+		-	-	-											-	-	-
Soybean	-	-	-	-	+	+			+	+	+		-	-	-							-	-				-	
Sugar no.11	-	-	-	-	+	+	+		+	+	+		-	-	-		+	+			-	-	-				-	
Coffee	-	-	-		+	+	+		+	+	+		-	-	-													
Cotton no.2	-	-	-		+	+			+	+			-	-			+	+										
Live Cattle		-	-										-	-	-		-	-	-							-	-	
Lean Hogs	-	-		-	+	+							-	-		-		-	-						-	-		-
Oats	-	-	-																		-	-				-		
Rough Rice	-	-												-														
Cocoa	-	-	-		+	+			+	+			-	-	-	-												
Gold	-	-	-		+	+			+	+			-	-	-						-	-	-	-	-	-	-	
Silver	-	-	-	-	+	+			+	+			-	-												-		
Copper	-	-	-		+	+	+		+	+	+	+	-	-			+	+			-	-						
Platinum	-	-	-		+	+	+		+	+	+		-	-	-						-	-	-		-	-	-	
Brent Crude	-	-			+	+							-	-														
Natural Gas	-	-							+	+			-	-	-										-			
British Pound	-	-			+	+			+	+	+		-	-	-		+	+			-	-	-					
Euro		-							+	+	+		-	-														
Japanese Yen	-	-				+			+	+	+		-	-			+	+			-	-	-					
Canadian Dollar	-	-			+	+			+	+	+		-	-	-		+	+			-	-	-					
Swiss Franc	-	-	-		+	+	+		+	+	+		-	-			+	+			-	-	-					

IV. Positions Change with Price in a Similar Way Across Markets

To test whether group behaviour differs across markets, each market is compared with average behaviour across the remaining markets. Specifically, for a given target market, observations are pooled across all non-target markets. By re-sampling averages from this pool of observations, a market-average distribution can be created against which the target average is compared.

For example, to compare the average change in COT variables for the Crude Oil market during 2-4 standard deviation positive price changes, a distribution is constructed by re-sampling 10,000 averages (where N = 68, as per Figure 4) from all observations of 2-4 standard deviation positive price changes seen in other markets (that is, all markets excluding Crude Oil). The second column for each COT variable in Table 2.13 documents markets with significant differences (at a 5% significance level) for this category of price change. For Crude Oil, change in trader positions cannot be considered significantly different from other markets. That is, the trading behaviour is similar across markets.

Table 2.13 Positive Price Changes of 1-2, 2-4, 4-8 and 8-16 Standard Deviations

(Significant Differences to the Average Market's Behaviour)

Market	Commercial Short				Commercial Long				Speculator Short				Speculator Long				Other Short				Other Long				Open Interest			
	1-2	2-4	4-8	8-16	1-2	2-4	4-8	8-16	1-2	2-4	4-8	8-16	1-2	2-4	4-8	8-16	1-2	2-4	4-8	8-16	1-2	2-4	4-8	8-16	1-2	2-4	4-8	8-16
U.S. 30 year bond					+	+				+			-	-														
U.S. 10 year note	-	-	-										-		-													
U.S. 5 year note									+	+	+		-		-	-												
U.S. 2 year note					+	+	+		+	+	+		-	-														
Eurodollar	-	-	-	-				-						-	-					-			-	-	-	-	-	-
S&P500	-	-			+								-	-	-	-	+	+	+							-		
Nasdaq100														-				+	+	+								
Dow Jones Industrials				-							-	-											+					
Russell 2000		-			+				+	+				-				+		+								
Corn		+	+				+	+		-	-	-																
Wheat		+		+				+		-			+													+		
Soybean																												
Sugar no.11			+		-										+		-	-	-								+	
Coffee											-																	
Cotton no.2	+	+	+		-				-				+	+	+													
Live Cattle						+											+	+			-	-	-			+		
Lean Hogs	+			+	+			+	+								+								+			+
Oats										+											+							
Rough Rice		+			+	+			+																	+	+	
Cocoa						-								+														
Gold	+	+			-	-							+					-									+	
Silver																					-	-						
Copper					-													-	-									
Platinum																									+			
Brent Crude																							-	-				
Natural Gas									-																			
British Pound						-											-	-				+	+	+			-	
Euro																											-	-
Japanese Yen										-					+						+	+			-	-	-	
Canadian Dollar						-	-																			-		
Swiss Franc						-	-		-	-		+		+		+		-				+	+			-	-	

This procedure is repeated for each market and all price change categories. For many price change categories, less than 20% of the markets can be considered to have significantly different group behaviour. Whilst findings of non-significant differences does not necessitate no differences between group behaviours, the results are indicative of similarity in the relative magnitude and sign of changes in positions amongst traders in the same groups, across a majority of markets.

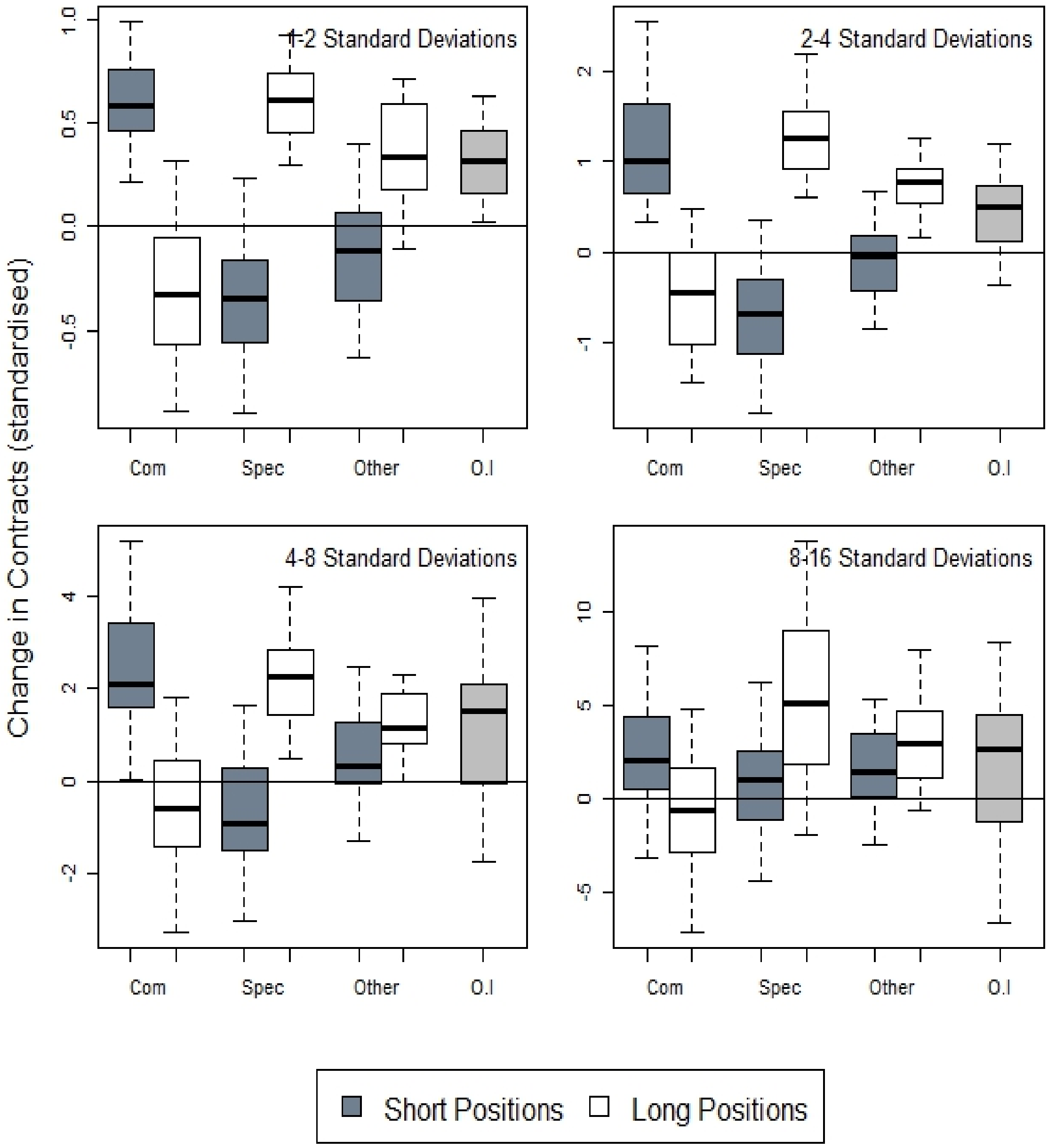
Table 2.14 Negative Price Changes of 1-2, 2-4, 4-8 and 8-16 Standard Deviations

(Significant Differences to the Average Market's Behaviour)

Market	Commercial Short				Commercial Long				Speculator Short				Speculator Long				Other Short				Other Long				Open Interest			
	1-2	2-4	4-8	8-16	1-2	2-4	4-8	8-16	1-2	2-4	4-8	8-16	1-2	2-4	4-8	8-16	1-2	2-4	4-8	8-16	1-2	2-4	4-8	8-16	1-2	2-4	4-8	8-16
U.S. 30 year bond																												
U.S. 10 year note	+	+	+																							+	+	+
U.S. 5 year note		+																										
U.S. 2 year note	+	+	+	+									+	+								+	+	+		+		
Eurodollar					-	-	-							+			-	-	-							-	-	
S&P500	+			NA	-			NA		-	-	NA				NA			+	NA	+			NA				NA
Nasdaq100				NA	-		-	NA	-		-	NA	+			NA		+		NA				NA			-	NA
Dow Jones Industrials				NA	-	-		NA	-	-		NA	+			NA				NA	+	+		NA				NA
Russell 2000		+		NA				NA				NA	-			NA	+	+	+	NA				NA				NA
Corn																		-	-									
Wheat																												
Soybean			-																									
Sugar no.11			-		+	+									-						-		-					
Coffee					+					+	+																	
Cotton no.2					+				+					+	+	+												
Live Cattle	+							+									-	-	-		+							+
Lean Hogs		+	+			+	+	+										-										
Oats						-				-																		
Rough Rice									-				+															
Cocoa																												
Gold																						-						
Silver				-					+							-												
Copper	-	-																										
Platinum	-	-	-										-		-								-	-	-			
Brent Crude									-					-														
Natural Gas									+																			
British Pound	-									+	+	+				+	+			+		-						
Euro						-	-																			-		
Japanese Yen	-				-					+			+					+										-
Canadian Dollar	-									+			-				+	+										
Swiss Franc																					-							

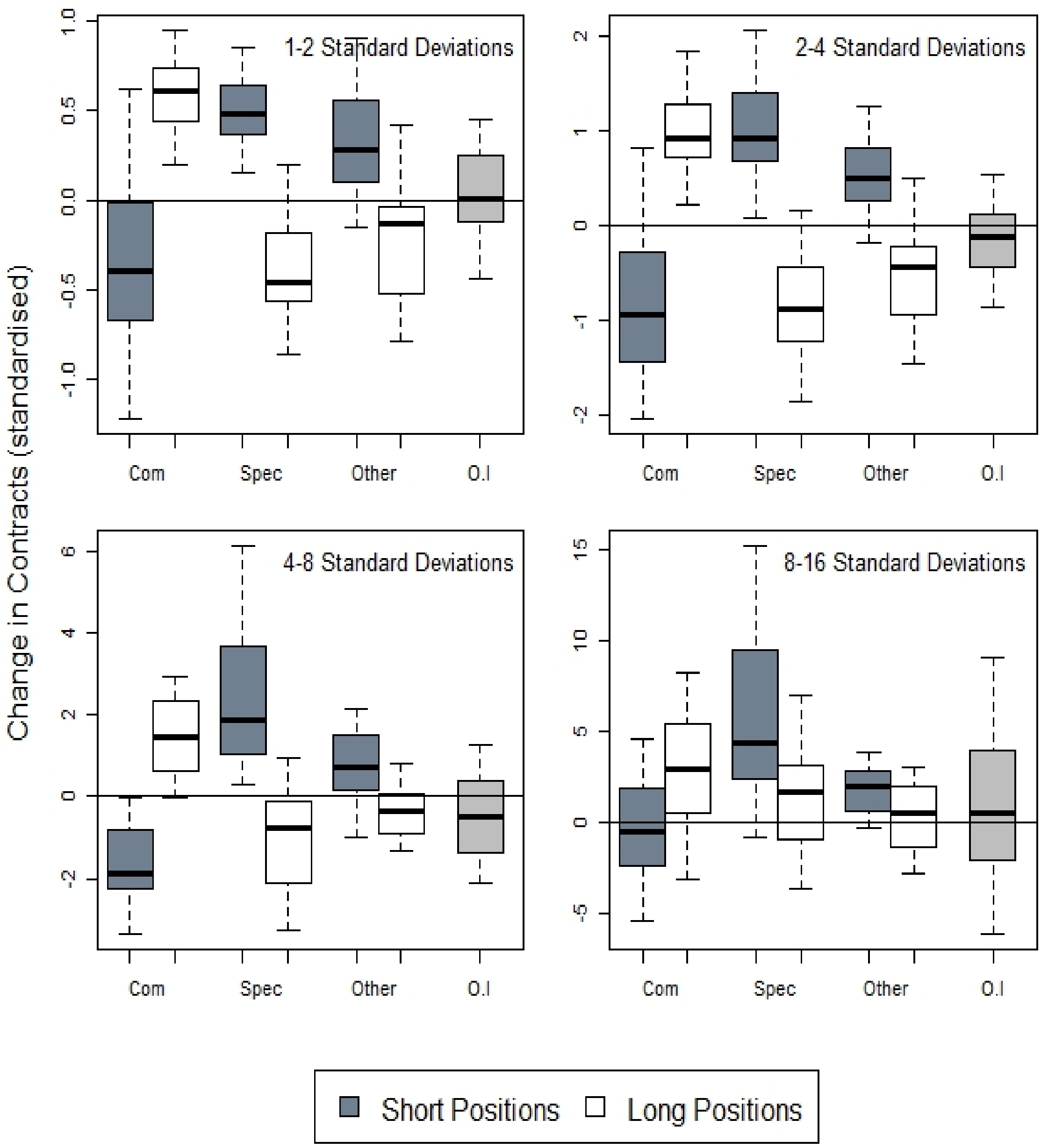
To further demonstrate the similarity in group behaviour across markets, the median change in positions for each market is examined. The distribution of these medians is presented for positive (Figure 2.6) and negative price changes (Figure 2.7). These plots clearly demonstrate the general pattern identified in the econometric analysis. During positive price changes, commercial traders tend to increase their short positions and decrease long positions, whilst speculators decrease short and increase long positions. During negative price changes, the pattern is reversed. The smaller, non-reportable traders display a pattern of behaviour broadly similar to speculators. The inverse of these behaviour patterns is seen during negative price changes. Open interest measures the total size of the market and is seen to mostly increase during positive price changes along with increasing demand for a product. During negative price changes, open interest may increase or decrease. The pattern of change in contracts is similar across the four price change categories. Further, changes in contracts are approximately, proportional to the size of the price change.

Figure 2.6 Median Change in Contracts for All Markets Sampled During Positive Price Changes of 1-2, 2-4, 4-8 and 8-16 Standard Deviation. For Groups: Com=Commercial, Spec=Speculators, Other=Non-reportable, and O.I=Open Interest



The range denoted on the y-axis for each plot in Figure 2.6 and 2.7 increases as the price change size increases (from 1-2 to 8-16 standard deviations); the broad pattern of behaviour across the different groups of traders remains consistent.

Figure 2.7 Median Change in Contracts for All Markets Sampled During Negative Price Changes of 1-2, 2-4, 4-8 and 8-16 Standard Deviation. For Groups: Com=Commercial, Spec=Speculators, Other=Non-reportable, and O.I=Open Interest



V. Commercials and Speculators Trade in Significantly Different Ways

In the above econometric study, Table 2.9 demonstrates that speculators and commercials trade in significantly different ways. This results can be verified and the same research question addressed within the alternative methodology. The Wilcoxon signed-rank test for the null hypothesis that two related samples come from an identical population (Wilcoxon, 1945), compares the difference in buying behaviour (change in long positions) and separately, the difference in selling behaviour (change in short positions) for commercial and speculative traders in the same market. Table 2.6 and 2.7 demonstrate for the majority of markets studied that the behaviour of commercials and speculators is significantly different under the same price change categories. This finding is most apparent for the 1-2 standard deviation price change category with the largest number of observations. The behaviour of commercials and speculators differs significantly for more than 80% of markets (in Table 2.6 and Table 2.7, significance at a 5% level is denoted as previously).

As noted above, because it takes more time, on average, for a large price change to occur, there are fewer observations and reduced statistical power for larger price change categories. Markets denoted with NA in Table’s 2.6 and 2.7 have sample sizes less than 8 observations and are therefore inappropriate for the Wilcoxon signed-rank test.

Table 2.15 Positive Price Changes of 1-2, 2-4, 4-8 and 8-16 Standard Deviations, Significant Differences Between Commercial and Speculator Buying (Change in Long Positions) and Selling Behaviour (Change in Short Positions)

Market	Buying Behaviour				Selling Behaviour			
	1-2	2-4	4-8	8-16	1-2	2-4	4-8	8-16
U.S. 30 year bond					-			
U.S. 10 year note	-	-			-			
U.S. 5 year note	-	-						
U.S. 2 year note								
Eurodollar	-							-
S&P500				NA				NA
Nasdaq100	-			NA				NA
Dow Jones Industrials			NA	NA			NA	NA
Russell 2000				NA				NA
Corn	-	-		NA	-	-	-	NA
Wheat	-	-		NA	-	-	-	NA
Soybean	-	-			-	-	-	
Sugar no.11	-	-	-		-	-	-	
Coffee	-	-	-	NA	-	-	-	NA
Cotton no.2	-	-		NA	-	-		NA
Live Cattle	-	-		NA	-	-	-	NA
Lean Hogs	-	-		NA	-	-	-	NA
Oats		-		NA				NA
Rough Rice				NA		-		NA
Cocoa	-	-	-	NA	-	-		NA
Gold	-	-	-		-	-	-	-
Silver	-	-	-	-	-	-		
Copper	-	-			-	-		
Platinum	-	-	-		-			
Brent Crude	-	-			-	-		
Natural Gas	-	-			-	-	-	
British Pound	-	-	-	NA	-	-		NA
Euro	-		-	NA	-	-		NA
Japanese Yen	-	-		NA	-	-		NA
Canadian Dollar	-	-	-	-	-	-		
Swiss Franc	-	-	-	NA	-	-		NA

Table 2.16 Negative Price Changes of 1-2, 2-4, 4-8 and 8-16 Standard Deviations, Significant Differences Between Commercial and Speculator Buying (Change in Long Positions) and Selling Behaviour (Change in Short Positions)

Market	Buying Behaviour				Selling Behaviour			
	1-2	2-4	4-8	8-16	1-2	2-4	4-8	8-16
U.S. 30 year bond	-	-	-	NA	-	-	-	NA
U.S. 10 year note	-	-	-	NA		-		NA
U.S. 5 year note	-	-		NA	-			NA
U.S. 2 year note				NA				NA
Eurodollar				NA	-	-	-	NA
S&P500				NA				NA
Nasdaq100				NA				NA
Dow Jones Industrials			NA	NA			NA	NA
Russell 2000	-		NA	NA			NA	NA
Corn	-	-		NA	-	-	-	NA
Wheat	-	-		NA	-	-	-	NA
Soybean	-	-		NA	-	-	-	NA
Sugar no.11	-	-	-	NA	-	-	-	NA
Coffee	-	-	-	NA	-	-	-	NA
Cotton no.2	-	-			-	-		
Live Cattle	-	-		NA		-		NA
Lean Hogs	-	-	-	NA				NA
Oats				NA			-	NA
Rough Rice				NA				NA
Cocoa	-	-		NA	-	-		NA
Gold	-	-	-	NA	-	-	-	NA
Silver	-	-		NA	-	-	-	NA
Copper	-	-	-	NA	-	-	-	NA
Platinum	-	-	-	NA	-	-	-	NA
Brent Crude	-	-		NA		-		NA
Natural Gas		-		NA	-	-	-	NA
British Pound	-	-		NA	-	-	-	NA
Euro	-			NA	-	-	-	NA
Japanese Yen					-	-	-	
Canadian Dollar	-	-		NA	-	-	-	NA
Swiss Franc	-	-		NA	-	-	-	NA

VI. Proportionality in Group Behaviour Across Different Sized Price Changes

As noted in section 1.4, there is evidence of striking similarities in the statistical properties of market prices across financial markets. One finding relates to the scaling of the return distributions (Figure 1.1) across different time-horizons and different markets (Figure 1.2). The exponents characterising the power-law scaling of the tails of the return distributions is typically around 3 (Figure 1.3). Asymptotic power-law tails also describe the relative price of bids and offers in the limit order book (e.g. Zovko and Farmer, 2002). Given this evidence, it is reasonable to investigate the possibility of scaling, or ‘self-similarity’, in trading behaviour at different relative scales of price change, a research direction that is also supported by findings presented here of consistency in trading behaviour when compared across different markets. This current section begins research in this new direction by exploring how group behaviour during smaller price changes compares to group behaviours during larger price trends. This is made uniquely possible with the alternative methodology introduced here that separates price changes into different standardised categories. There are methodological difficulties associated with this investigation however, most notably due to the non-independence of samples taken from a single market.

The standardisation procedure outlined above involves sampling observations of different size price changes from the same market. However, when observations of different standard deviation multiples are taken from a single market they may overlap in time. For example, an 8 standard deviation price change may take many months to occur, and during this period many smaller 1 or 2 standard deviation price changes have also occurred. Therefore, it is not appropriate to compare the group behaviours associated with these 1, 2 and 8 standard deviations due to the lack of independence between the data points. An alternative methodology must be constructed. The approach taken here involves randomly determining which price change size to sample from a given market, and doing this in a sequential order so as independent samples are maintained.

The methodology is applied to each market as follows. A price change size is randomly selected between 1 and 5 standard deviations (higher thresholds are not directly targeted due to their relatively low-frequency of observation). The process then reads from the starting point through the weeks until a target price change is captured, for example, a 2 standard deviation price change as presented in Figure 2.3. The changes in COT variables over the same time period are also documented in line with the above studies. This time period is then excluded to maintain independent samples, and the next interaction of the methodology begins at the subsequent week. This process continues until all weeks in the dataset have been exhausted, and repeats separately for both positive and negative price changes – as price changes of different signs are compared separately.

As an example, the methodology generated 42 independent observations of positive price changes in the Oil market ranging from 1 to 7 standard deviations in size. In order to create more meaningful sample sizes, observations from each of the markets are grouped together for the following statistical comparison. This is considered reasonable given evidence of broad consistencies in group behaviour across different markets, as outlined in detail above. The grouping of observations from all markets creates a sample size of 891 for positive price changes and 765 for negative price changes for each of the 7 COT variables investigated.

To test how COT variables scale across different sized price changes, a quadratic regression model is fitted to the sampled data for each COT variable. Change in group position at scale is regressed against price returns at scale . Note indexes the period of time over which a price change of a given size and sign took place. The variable tests the curvature in order to classify the data into one of the following categories: (a) evidence of curvature across price change sizes where there is no significant intercept; or (b) evidence of curvature across price change sizes with significant intercept. The category with significance intercept implies an underlying drift in COT variable continuing separately from the size of price changes. Actively traded markets will often transact large amounts of volume without prices moving significantly, where traders change their long and short positions whilst prices remain in relative balance. This process is reflected in significant intercepts in the modelling described here. Equation 2.3 represents the regression model.

Equation 2.3 Quadratic Regression Model for Scaling Categorisation

$$P_S = \alpha + \beta \, R_S + \gamma \, R_S^2 + \varepsilon_S$$

If the coefficient for the quadratic term is equal to zero (at 5% significance) there is no evidence of proportionality and a linear model is fit to the data to categorises further into (c) no evidence of curvature with a non-significantly intercept (note this category provides evidence most consistent with self-similarity across price change sizes); or (d), no evidence of curvature with significantly intercept. Results from this categorisation procedure are presented in Tables 2.17 and 2.18.

Table 2.17 Results from Scaling Categorisation, Positive Price Changes

Behaviour Scaling Category	Commercial Short	Commercial Long	Speculator Short	Speculator Long	Other Short	Other Long	Open Interest
Curved, Non-significant Intercept		*					*
Curved, Significant Intercept						*	
Non-curved, Non-significant Intercept	*			*			
Non-curved, Significant Intercept			*		*		

For positive price changes, there is no evidence that changes in commercial shorts, speculator short positions, speculator long positions, and other short positions do not scale proportionately at different sizes of price change. The categorisation results for commercial short and speculator long positions, in particular, show no significant intercept implying direct proportionately across different price change sizes. This reflects a surprising level of self-similarity in certain trading behaviours at different scales of price change; large price changes, that may take many months to occur, can be considered similar to smaller price changes in terms of typical group-level behaviour.

The results for negative price changes presented in Table 2.18 also show evidence suggestive of proportionality in the behaviour of commercial short and other long positions.

Table 2.18 Results from Scaling Categorisation, Negative Price Changes

Behaviour Scaling Category	Commercial Short	Commercial Long	Speculator Short	Speculator Long	Other Short	Other Long	Open Interest
Curved, Non-significant Intercept		*		*	*		*
Curved, Significant Intercept			*				
Non-curved, Non-significant Intercept	*					*	
Non-curved, Significant Intercept							

These results indicate certain COT variables may be considered self-similar at different scales. However, additional dynamics associated with changes in traders' positions are unrelated to the size of corresponding price changes. These effects may relate to autocorrelation in position changes, as shown in the Table 2.4 above, and active trading that occurs in the absence of large price changes.

For those group behaviours where evidence is consistent with proportionality at different scales, such as the behaviour of speculators during positive price changes, these results suggest larger price changes cannot be considered as outliers or anomalies, a view taken by some researchers (e.g. Sornette, 2003), but rather, extensions of typical market behaviour (Mandlebrot and Hudson, 2004).

2.6 Conclusion

An investigation of the trading behaviour of different groups of market participants reveals important consistencies across 31 financial markets over a 17-year period. An econometric analysis demonstrates the ceteris paribus effect of changes in market prices on changes in traders inventories as significant and varying systematically with different groups of traders. This evidence finds that commercial traders and speculators trade in significantly different, yet consistent, ways. During positive price changes, speculators increase their buying whilst commercials increase their selling. During negative price changes the opposite pattern occurs. A more bespoke methodology supports these conclusions, also demonstrating that trading behaviour cannot be considered significantly different across a wide-range o markets. A further study into the behaviour of traders at different scales of price change finds evidence consistent with self-similarity in the behaviour of speculators, commercial and smaller, non-reportable traders under specific market conditions.

Similar findings of the systematic behaviour of traders in relation to market prices have been alluded to in previous studies involving COT data (e.g. Wang 2001; 2002; 2003, Sanders, Boris, and Manfredo, 2004) but have not been the focus of a comprehensive investigation until now. Sanders et al. (2004) explain the inverse behaviour between the net positions of commercial and speculative traders in terms of a data constraint, arising from the fact that long open-interest must equal short-open interest. However, this fails to account adequately for the consistency of this finding across different markets and additional findings of similarities across time-horizons and different scales of price change. These group trading behaviours may relate more fundamentally to market dynamics and require a deeper explanation.

The current findings support a notion of asymmetric objectives and hence trading behaviours that are consistent with Keynes' theory of normal backwardation in which commercials pay speculators a premium. To account for evidence of systematic biases in the behaviour of different groups however, a broader socio-economic account may be required, one that relates observable behaviour to goals, objectives and constraints amongst different populations of traders. Researchers have moved towards such an account with comparisons of markets to eco-systems, where different groups of traders are seen as analogous to species, and interact to determine complex system-wide behaviour patterns (Lo 2004; 2005; Farmer 2002).

The level of explanation required to account for these surprising consistencies in trading behaviour is an interesting subject discussed in later chapters of this thesis. The theory developed here is that these patterns of trading activity can be explained most parsimoniously via a behavioural explanation related to group order-type preferences. This is in contrast to more economically-orientated accounts in terms of differences in information or rationality, positive feedback, noise, or fundamental trading (e.g. Wang 2003); such theories are developed further in many agent-based computational models of financial markets (e.g. Bak, Paczuski and Shubik, 1997; Lux and Marchesi, 1999; 2000).

Empirical evidence of group-level behaviour patterns suggests that agent-based computational models of markets should strive to be consistent with regularities in the behaviour of different market participants. Although documented here in certain futures markets, these regularities may equally apply to other financial markets such as stock markets (Darley and Outkin, 2007). Modelling practices of this kind may enable agent-based models to be used more effectively as regulatory tools as they would achieve higher levels of realism. This subject is explored in further detail in the following chapter.

3. BEHAVIOURAL REALISM IN AGENT-BASED MODELS OF FINANCIAL MARKETS

Contents:

Abstract:

Agent-based models simulate collective behaviour as an emergent feature of complex interactions amongst 'agents' and their associated behaviour and decision-making rules. This chapter reviews a cross-section of agent-based models developed in the social sciences, noting objectives, necessary conditions, and requirements that can be applied to the agent-based modelling of financial markets. Models of financial markets have tended to make assumptions at the agent level, proposing important interactions between different groups of traders, yet relying on theoretical and often implausible representations of different traders. An example model reviewed in this chapter (Alfarano, Lux, and Wagner, 2005) generates realistic price behaviour for specific markets, but lacks behavioural validity when simulated group behaviour is compared to actual group behaviour, as documented in Commitment of Traders reports. From this analysis, a number of suggestions are provided to improve the behaviour realism of future models for more practical applications.

"Computational models allow us to consider rich environments with greater fidelity than existing techniques permit, ultimately enlarging the set of questions that we can productively explore."

Miller and Page (2007, p. 26)

"We have to take onboard the factor that represents probably the most egregious omission of conventional neoclassical economic theory, and that brings us most firmly into the realm of statistical physics. That factor is interaction."

Ball (2004, p. 214)

3.1 Introduction

An overall objective of the scientific approach is to assess a theory empirically, and then based on results, refine or reject a theory before further testing takes place. Agent-based modelling with computer simulations provides a unique tool when analytical or experimental approaches to theory-testing fail to be appropriate (Bankes, 2002). Various academic disciplines involve subjects engaged in large-scale interaction. From economics and finance, sociology, social psychology, to anthropology and history, the study of large collections of interacting people and the subsequent outcomes that emerges from these interactions is standard practice. The study of large-scale interaction amongst components is also common in non-social-science domains, for example, atomic physics and molecular chemistry. Systems of large-scale interaction, whether of social origin or otherwise, result in collective behaviour that may be difficult to derive analytically or test experimentally. In these situations, agent-based computational models offer researchers a rigorous means to test theories. Component characteristics and interaction rules can be conjectured, collective behaviour simulated, and results validated against empirical sources (Weidlich, 2000).

Programming a computer to carry out a task, such as simulate interactions between theoretical agents, by its very nature, involves abstraction, engaging with a concept whilst ignoring different details at different levels (McConnel, 2004). More precisely, ‘object-orientated’ programming involves focusing on common attributes and ignoring details of specific cases, in order to develop useful and reusable classes in a computer language. The software development process therefore has parallels with the building of scientific theories; both strive for simplicity of process and a parsimonious view of a complex object. Object-orientated programming, in particular, is well-suited to simulating large numbers of agents. An agent can be represented via a particular object of a class in a programming language, with associated gains in program efficiency. This combination of software development and scientific theorising is becoming increasingly utilised in psychology (Sun, 2006) and the social sciences (Silverman and Bryden, 2007), alongside a more established user-group in the physical and computer sciences (Wolfram, 2002).

Research into different systems involving large-scale interactions has identified that emergent collective behaviour has many features in common. One of the most prominent is the finding of right-skewed distributions and possible power-laws to describe relationships between the size of an event and its frequency. For example, the size of an earthquake and how often it occurs follows a power-law (Bak, 1997). The mathematical relationship described by a power-law is not at all inevitable, yet it may exist to represent a variety of disparate phenomena, including, for example, the relationship between the size and frequency of populations in cities or causalities in human conflicts (Zipf, 1965; Buchanan, 2000; see also the discussion on Perline, 2005, in chapter 1). Although many systems of interaction have overwhelming differences in terms of subject matter and content, the level of interaction involved in many systems results in their having other important features in common. Often, underlying causes of collective behaviour cannot be easily attributed to a single or simple set of precursors, instead, causality is distributed. Additionally, causality is often found to be non-linear: the size of a particular event may not be proportional to its cause (Watts, 2001).

Per Bak (1997) provides an account of distinct characteristics common to systems of complex interactions, describing systems as self-organising into a critical state with associated scale-free, or fractal, behaviour patterns. Research into self-organised criticality is seen by some researchers as one of the most important scientific developments of the 20th century and has been extended to account for social phenomena, such as the behaviour of economies and financial markets (Bak, Chen, Scheinkman, and Woodford, 1993; Krugman, 1996; Arthur, Durlauf, and Lane, 1997). The approach provides theoretical underpinnings for a philosophy of 'catastrophism', the view that extreme events can happen relatively often. This is opposite to the more conventional view, where change is incremental and always proportionate to the size of the cause. (Bak, 1997). With the recent financial 'credit crunch' crisis still lingering, a view of economics and markets as being stable and in-equilibrium seems more and more unrealistic. It may be argued that the use of agent-based computer simulations is well-suited to the study of economic phenomena, capable of reproducing the large-scale interactions and complex emergent behaviours involved.

Financial markets are a particularly relevant example of a complex, evolving system involving large-scale interactions. Every time a trade takes place in a market, a direct interaction between a buyer and seller has occurred. The largest financial markets regularly trade millions of times a day. Estimating the global and financial scale of all the transactions taking place in financial markets is difficult, but it is likely to be trillions of dollars per day. The behaviour of market prices is a result of all the individual interactions between traders buying and selling to one another. Research into this collective behaviour documents characteristics common to other systems of interaction. For example, as described in chapter 1, price fluctuations of financial markets are well described with power-laws that relate the frequency of a price change of a particular size to its magnitude (Gopikrishnan, Plerou, Nunes Anarakm, Meyer, and Stanley, 1999; Plerou, Gopikrishnan, Nunes Anarakm, Meyer, and Stanley, 1999). The causality underlying price changes in markets is also apparently non-linear and distributed. For example, the 1987 stock market crash had no apparent news releases of proportional significance to the size of the 23% drop in stock prices (Cutler, Poterba, and Summers, 1989). Building on the modelling of complex interactions in other domains, agent-based models offer researchers a unique tool to develop theories of market behaviour.

This chapter is primarily focused on agent-based approaches to understanding how and why financial markets behave the way they do. To different extents, researchers employing agent-based models have been successful at reproducing statistical characteristics of market prices. A number of example approaches are reviewed in this chapter (see chapter 1 for a more detailed outline of the statistical characteristics of market prices). However, concerns remain over the validity and realism of many of these models. Most notably, simplifying assumptions are often made at the group-level, where different groups of traders are presumed to co-exist in financial markets. Models often propose important interactions between these groups and their associated trading characteristics to determine price behaviour. It is clear from a review of the literature on theories of market behaviour that the group categorisations employed in many agent-based models result from convenient theoretical assumptions and have avoided due empirical scrutiny. Whilst the previous chapter documented evidence of systematic trading behaviour in real-world groups of traders, this chapter will demonstrate that trader group dynamics and agent-level representations typically employed in agent-based models fail with regard to their behavioural validity. More verifiable and useful descriptions of different types of traders, such as those provided in the previous chapter of this thesis, offer a route towards more empirically grounded models of financial markets.

The goal of moving towards higher level of behavioural realism is shared with other researchers into agent-based market simulations (LeBaron, 2000; Alfarano, Lux, and Wagner, 2006). Alfarano et al. propose that a natural next step for researchers in the field is to move towards models capable of calibration to represent particular financial markets. This can enable models to be more useful for investment management (Farmer, 2001) or market regulation (Darley and Outkin, 2007). A renewed focus on validation must bring a renewed focus on how traders in financial markets actually operate and in what useful ways this behaviour can be represented. The results presented in the previous chapter inform on this process. The trading behaviour of commercial traders and speculators is characterised by consistent biases towards buying or selling depending on the direction of market prices. This empirical insight and the group categorisation provided by Commitment of Traders (COT) data could prove useful in modelling the strategic behaviour of agents and market behaviours that emerges from these interactions. By incorporating empirically derived group-level representations, theories of financial markets can be constrained further towards a higher level of validity.

The chapter continues with a broad introduction to agent-based modelling in the social-sciences: the origins of the approach, strengths, practical applications, and potential weaknesses. This introduction provides a context for reviewing the necessary conditions and objectives that can also be applied to the agent-based modelling of financial markets. A number of financial market models and agent-orientated approaches are reviewed here, with a focus on the approach of Alfarano, Lux, and Wagner (2005). This particular model is selected for more detailed review as it is a relatively recent addition to the literature, relies on only a few parameters and is therefore considered parsimonious, and is also unique in that the authors claim it can be calibrated to represent the statistical characteristics of specific markets. This claim is tested in this chapter using a study of the Oil market during the period 1991 to 2008. This study finds that, despite successes, the model relies on traditional group categorisations and, depending on the interpretation of these categorisations, either lacks behavioural realism when compared to the real-world, or, alternatively, the model rests on assumptions that cannot be tested objectively. The chapter concludes with detailed suggestions for improving the realism of future agent-orientated models of financial markets.

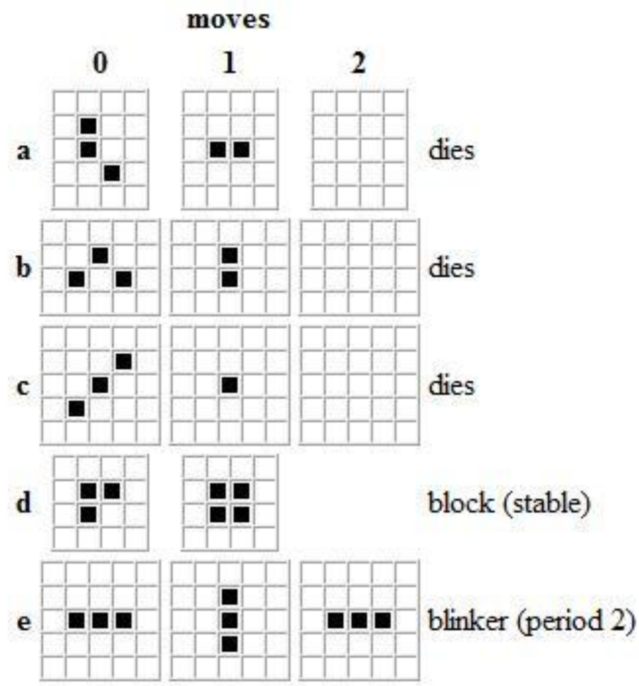
3.2 Origins of Agent-based Modelling

The origin of agent-based models can be seen in the early computation experiments known as cellular automata, the most famous of which is 'The Game Of Life'. The game involves a grid of cells, like a chess board, where each cell can shift between a finite number of states determined by the local interactions between different cells. This is the basic computational template for many other agent-based models. The Game Of Life was initially devised by the mathematician John Conway (Gardner, 1970) and has since taken on a wider following on the internet (e.g. www.ibiblio.org/lifepatterns/). The game involves setting initial conditions for a computational experiment, and then simulating system-wide patterns of behaviour over various time steps. The behaviour that emerges from simple interaction rules and changes of states within cells on a grid is surprisingly unpredictable. This study of cellular automata has become important for a range of academic disciplines, including physics, biology (Wolfram, 2002), and philosophy (Dennet, 1995).

The Game Of Life starts with a simple configuration of 'live' cells on a grid. Conway's rules for the birth, death and survival of individual cells are then applied as follows:

every cell with two or three live neighbours survives for the next generation; cells with four neighbours are removed from the population, as are cells with just one neighbour; empty cells next to exactly three live neighbours are 'born', that is, they become live. Each application of these rules simultaneously across grid is considered one move of the game. The initial starting pattern of the cells and subsequent interactions result in cells changing location, often in unusual and unexpected ways. Some examples taken from the original publication of how the system can evolve based on starting configurations are presented in Figure 3.1. Different time-steps are representing horizontally from left to right; different initial starting conditions are represented vertically.

Figure 3.1 Simple Examples from The Game Of Life (Gardner, 1970, p. 121)



Note the initial configuration of cells can result in a series of changes and then a static pattern (a to d in Figure 3.1). In other cases, the initial configuration is self-perpetuating leading to continuous alternation between patterns (e). The Game of Life can simulate an important and basic feature common to many real-world systems of interaction: continuous change. Simple interaction rules can result in continuous fluctuations in the global behaviour of a system. Agent-based models often operate in a similar way to Conway's original formalisation. Agents (or cells) occupying a landscape (or grid) change states as a function of their interactions. Agent states and rules of interaction can be programmed to be analogous to real-world situations, and, from these dynamics, to simulate realistic collective behaviour.

One technical consideration is how to handle cells on the edges of the grid that have fewer neighbouring cells than those not on the out-skirts. In a simple 2-D topology involving interactions across a grid, this is most often achieved with a torodial arrangement. Cells on the bottom edge of the grid are considered neighbours to those at the top, whilst those on the right edge of the grid loop over to be considered neighbours to those on the far left, and vice-versa (this is typically programmed via modular arithmetic). With this basic formulation, the only intervention in the model by researchers occurs at the onset, with the setting of initial conditions. The system then evolves over various iterations, or time steps. Successful examples of this broad approach applied to specific social-settings are now reviewed.

3.3 Examples Models in Social Science

Thomas Schelling (1972; 1978) applied principles of cellular automata to study segregation on the basis of individual preferences. Although commonly discussed in terms of geographical segregation based on racial preferences, Schelling's model is sufficiently abstract to apply to any form of segregation not directly organised, for example based on income, religion or language. Segregation of the geographical kind is often visible on trips to almost any metropolitan area; residents tend to segregate quite clearly into different racial groups. For example, many European cities have a 'China-town'. In America, according to Schelling, it is easy to find localities where people of 'white' Caucasian or 'black' skin colour are more than three-quarters of the total. That is, racial segregation is naturally common place. Schelling modelled segregation by proposing a cellular automaton style grid to be analogous to the map of a city where constituent cells can be compared to people living in a property. Similar to The Game Of Life, the location of 'black' or 'white' cells in Schelling's grid evolve over time, based on the following interaction rule: if greater than a third of the directly neighbouring cells on a grid are of a different colour, the cell moves to another, randomly selected available location. Through this simple mechanism, quite dramatic and notably realistic levels of racial segregation can occur. For Schelling, this result demonstrated how "underlying motivation can be far less extreme than the observable pattern of separation" (1978, p, 154), and, more generally, that collective behaviour is not necessarily representative, or follows on directly, from the behaviour or preferences of individual agents within a system.

This general theme was taken further by Craig Reynolds (1987) in his agent-based simulations of flocking behaviour in birds, fish and other animals. Flocks of birds move in distinct patterns of apparent synchronisation and structure. Reynolds used a computer simulation to demonstrate that this coordination is not planned, or the result of a deliberate collective intelligence, but rather emerges from local interactions within a flock. Reynolds's virtual birds, or 'boids', are programmed to react to others within a certain distance. Just three simple rules, separation, alignment, and cohesion, describe behaviour at the level of the individual boid: 1) separation: steer to avoid crowding local flock-mates; 2) alignment: move towards the average heading of local flock-mates; and

3) cohesion: an individual moves towards the average position of local flock-mates. From these rules of interaction remarkably accurate simulations of flocking behaviour emerge. The 1992 Tim Burton film, ‘Batman Returns’, was the first to apply this methodology in the now standard practice for computer-based animation. Reynolds noted, with reference to the potentially vast size of collective animal behaviour (for example, herring migrations can occur in schools up to 17 miles long, containing millions of fish) that it is unrealistic to give simulated boids complete information of the flock; it leads to obvious failures in the simulated behaviour (1987, p. 30). Reynolds demonstrates how global knowledge of the flock location is not involved in boids' decision-making. This is an example of a possible theory for a phenomenon being falsified with the use of an agent-based simulation. Reynold demonstrated, quite conclusively, that local interactions, based on the simple rules outlined above, are the most plausible explanation for coordinated flocking behaviour.

More recently, results from an agent-based simulation have been applied to economic social situations. One example is the study of crime. Traditionally, economists viewed crime as a type of market, with decisions to participate made in a rational and utilitarian manner (e.g. Becker, 1991). However, as Ormerod (1998) highlights, these economic explanations fail to account for typical characteristics of real-life crime statistics. For example, low correlations are often found between crime levels and unemployment; equally, situations can persist where high levels of unemployment accompany low levels of crime. Ormerod notes crime statistics typically have a higher variance than corresponding socio-economic variables and none of these real-life features of crime statistics are consistent with a theory where individuals rationally turn to crime to avoid impoverished circumstances. In place of more standard economic models, Ormerod proposes that economic agents are involved in direct social interactions and the resulting positive feedback effects, where an effect may amplify over time within a population, accounts for characteristics common to real-life crime statistics. Ormerod simulates the evolution of crime levels over time in the following way.

A population is divided into three discrete groups of people that can be defined as: 1) those not susceptible to crime; 2) those that have not committed a crime, but may do so in the future; and 3) those who are active criminals. Individuals within a population move between these groups, not due to a rational response to economic conditions, but based on social influence effects within the population. The probability of individuals changing groups is directly related to the proportion of the population in each group. Whilst socio-economic variables are also included in the model, interaction effects mean the impact of economic variables can be significantly different depending on the current state of the system. This system becomes non-linear, and causality becomes more distributed, paralleling the observation made in the introduction. Overall, Ormerod finds that the behaviour exhibited by the model can successfully replicate real-world crime statistics, including, more specifically, the possibility of abrupt changes in the level of crime. This behaviour was seen in New York City in the late 1990s, when a 'zero tolerance' policy was cited as the primary contributing factor to a dramatic reduction in crime. It may be that crime-levels, as is the case with other measures of collective behaviour, are inherently volatile and that dramatic shifts occur with more regularity than was assumed by New York City regulators.

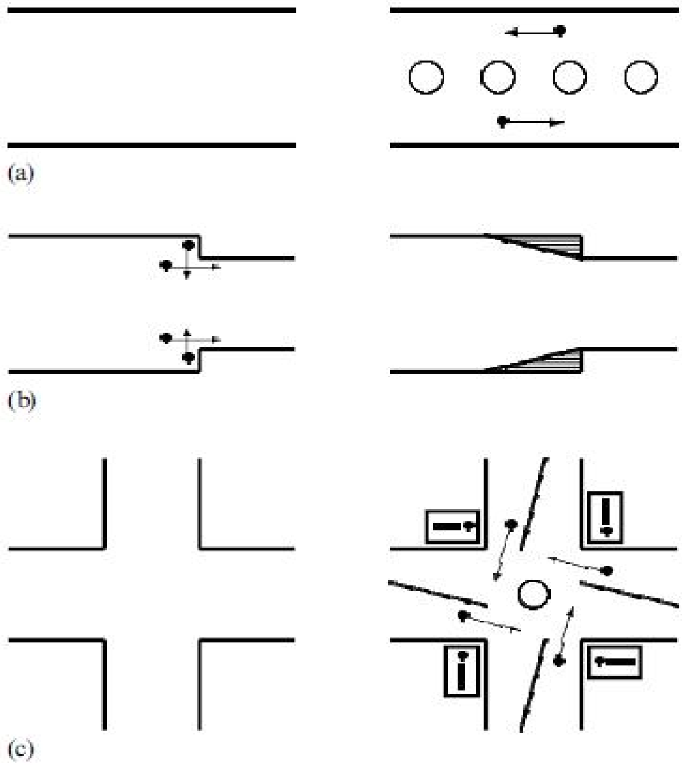
Ormerod extended the agent-based modelling approach to a separate economic problem: accounting for company extinction-rates within an economy. As with other systems of complex interactions, there is evidence of power-law distributions in industrialised economies in the form of company extinction rates and how they vary over time. Based on the work by Sole and Manrubia (1996) and Newman and Palmer (2003), Ormerod (2005) investigated the power-law distribution relating the number of company extinctions to their frequency of occurrence (see also Ormerod, 2002) using agent-based simulations. A model is proposed with the by-now familiar cellular automata grid. But rather than the grid representing physical locations, as with Schelling's example, each row and column is analogous to a separate company with a number in each cell (being at the intersection of two companies) representing the impact a company has on another. If the number is positive, the relationship is considered beneficial and cooperative; if negative, companies compete and are damaged by their relationship to one another; if zero, there is no important relationship between firms. In Ormerod's simulation, the starting numbers are determined randomly. For each time step, a single cell in each row changes randomly and the impact of all other companies on each individual company is summed to determine company extinction. If the sum is greater than zero, the company survives, if less than zero, it is considered extinct and immediately replaced by a new company (derived from a randomly chosen 'parent' company). Different variations of this model allow for shock events to impact the system, but, even from these simple collections of rules, a precise power-law relationship emerges between the levels of company extinction and their frequency, similar to that found in real economic statistics.

Ormerod's account of extinction patterns by way of interaction effects in the economy is capable of simulating real-world behaviour that emerges from complex interactions. However, the model applies to patterns of data and does not offer any immediate application to real-world problems. Sugarscape is a large-scale agent-based model of an evolving economy with more pragmatic aims (Epstein and Axtell, 1996). Designed to investigate all manner of political, social and environment hypotheses, Sugarscape, named after the agents' objective to acquire sugar, is both sophisticated and complex. Agents are provided with rules enabling them to fight, collaborate, exchange cultural traits and material goods; agents can even reproduce. From extensive interaction rules, many real-world collective behaviour patterns emerge in the model's simulations. These include the Pareto distribution, relating individual wealth to its frequency with a power-law (e.g. Lorenz, 1905). This particular agent-based model continues to be developed. A collaboration between various U.S. Institutions aims to extend the Sugarscape model into more pragmatic settings of policy recommendations and resource allocations (Ball, 2004). The application of this technology towards a more realistic and socially-aware regulatory approach is an exciting agenda for the future of agent-based models, and discussed further in chapter 5.

The application of agent-orientated simulations to real-world problems has already begun in more domain-specific areas, such as the simulations of pedestrian behaviour to improve event planning and regulation. Helbing, Farkas, and Vicsek (2000) respond to an observation that a growing population and improved transportation links are leading to more panic events at large crowd gatherings (www.angel.elte.hu/~panic/disasters/) to develop an agent-based model capable of simulating this crowd behaviour. For Helbing et al., a significant oversight often made by safety engineers is to assume exits are used uniformly during panics. Agent-based models can demonstrate how clogging at certain exits will often emerge if individuals are subject to social interaction effects, a preferred velocity, and physical friction caused by close proximity to others. Helbing et al. propose simulations can even be tailored to specific locations to prepare event management teams and test event locations for suitable evacuation procedures.

This approach to pedestrian modelling has also been applied in other areas. Helbing, Molnar, Farkas, and Bolay (2001) simulate pedestrian motion to provide specific recommendations for more efficient pedestrian facilities. By varying the arrangement of walkways, entrances and exits, and room shapes, and simulating different population sizes and agent-characteristics, more efficient geometric boundaries can be developed which optimise pedestrian flow-rates. Figure 3.2 demonstrates results from the optimisation procedure applied by Helbing et al. (2001). The conventional facility (on the left in Figure 3.2) is compared to the improved pedestrian facility (on the right). Their results demonstrate (a) two-way flow of pedestrians can be stabilised with the use of a series of columns or trees, making it less attractive for individuals to use breaks in the opposite stream to overtake and potentially obstruct those walking in the opposite direction; (b) bottlenecks can be improved by the use of a funnel-shaped construction; and (c) the use of a tree in the centre of a roundabout and attractive features such as posters on the outskirts (denoted with exclamation marks in Figure 3.2) improves flow efficiency. The application of simulations of this kind to real-world problems is practical and cost-effective. As Ball (2004, p. 138) highlights, “planning can be fitted to human nature”, rather than the other way around.

Figure 3.2 Practical Recommendations From Agent-based Simulations of Pedestrian Flows (Helbing et al., 2001, p. 373)



A further example is the modelling of traffic flows. Patterns of traffic activity have been measured in countries including the U.S.A (Daganzo, 1996) and Germany (Kerner and Rehborn, 1996; 1997; Helbing and Treiber, 1999) to reveal important consistencies in behaviour. These findings have encouraged a large amount of research into how characteristics of traffic flow can be effectively modelled with agent-based simulations (Helbing and Schreckenberg, 1999; Wolf, 1999). Research demonstrates that the properties of traffic flows can be grouped into three distinct categories: 1) free flow, when traffic moves readily; 2) synchronised flow involving consistently moving traffic with occasional oscillations in speed; and 3) traffic-jams, when a traffic grid-lock occurs (e.g. Kerner and Rehborn, 1997). This has led researchers to establish statistical parallels between different traffic states and the behaviour of particles in changing states of matter, when moving from gas, to liquid, to solid (Treiberm, Hennecke, and Helbing, 1999; Ball, 2004). Drivers in agent-based models of traffic behaviour are considered to have: 1) preference for a given speed; 2) brake to maintain a constant distance from other vehicles; 3) imperfect reactions that can lead to errors (Helbing, Hennecke and Treiber, 1999); and in some cases, 4) preference for a smooth changing of speed (Schreckenberg, Barlovic, Knospe, and Klupfel, 2001). From these simple behavioural rules and characteristics, agent-based models can simulate traffic behaviour that is statistically consistent with the empirical observations on traffic flows.

This research has also been made directly useful to other real-world problems. Dynamic traffic simulations, based on real-time measurements of traffic density, speed, and vehicle composition, are now capable of predicting traffic levels very accurately (Treiber, Hennecke and Helbing, 2000; Schreckenberg, Chrobok, Hafstein, and Pottmeier, 2003). Treiber and Helbing (2001) extend research to demonstrate how traffic flows could be improved substantially with the use of variable speed limits that respond dynamically to traffic density. Treiber and Helbing show optimal traffic flow could be achieved most effectively with the use of automated systems to control the speed of vehicles, arguing that the existence of even a small number of cars with automated response systems could almost eliminate traffic jams. Research by Brockeld, Barlovic, Schadschneider, and Schreckenberg (2001) also document how the optimisation of traffic lights can improve traffic conditions in major cities. This research on traffic flows is a particularly powerful demonstration of the potential for agent-based simulations to successfully model, categorise, and even predict, complex collective behaviour.

3.4 Conditions and Objectives for Agent-Based Modelling

The above examples can help formalise necessary conditions and objectives for developing agent-based models in the social sciences, and in particular, for their use in studying financial markets. A clear objective of using the approach is to support theory development when other more analytical or experimental approaches are not appropriate. This tends to be in situations that involve interactions on a particularly large-scale. In such situations, the collective behaviour of a system may not relate to the behaviour or preferences of individuals within the system, at least not directly, and can therefore be explored most effectively via computational simulations. Agent-based models also permit a change of focus in theory-building, away from studying the characteristics of individual units, towards studying potentially complex relationships between individual units and the particular form of the interactions that occur. Interactions and other features inherent to a system may be more directly pertinent to theoretical accounts than knowledge of the individual agents. This premise can be tested effectively with agent-based models.

Effective agent representations are still important in successful agent-based modelling, especially if an additional objective is to make useful predictions where other approaches may be unable to do so. As Farmer, Patelli, and Zovko (2005) discuss in relation to developing theories for financial market behaviour, the problem must be divided into two separate parts. The first and, according to Farmer et al., easier part of the problem is understanding of how situational factors and constraints inherent to a system invoke particular behaviour patterns. With regard to financial markets, Farmer et al. use the example of how different types of orders to buy and sell are submitted and demonstrate how even relatively subtle patterns of market behaviour can relate to associated restrictions. These observations are explored more fully in the following chapter. The second and more challenging part of the problem, according to Farmer et al., relates to how individual agents and their characteristics interact to determine collective behaviour. In the study of markets, this relates to particular agent representations, strategies, expectations, and interaction channels. Research that shares this objective is reviewed further in this current chapter. When both strands of research naturally join, a strong explanation can be represented within an agent-based modelling framework and offer useful predictions for complex behaviour.

Agent-based models, then, are tools that allow researchers to test the validity of different theories and develop means to make useful predictions for systems involving complex collective behaviour. However, as Ormerod and Rosewell (2006) highlight, agent-based models face a variety of issues in verification and validation which are new, precisely because they offer an opportunity to model a wider class of phenomena. Due to the simulation involved, verification, whether the model does what we think it is supposed to do, blends into validation, the extent to which a computer model is an accurate representation of a phenomena, as there is typically no single result that the model must match. Testing a range of model outcomes therefore provides a test only in respect to a prior judgment on the plausibility of the potential range of outcomes.

Ormerod and Rosewell suggest that validation of agent-based models therefore requires a particularly clear description of what is and what is not being explained. A model should be judged by the extent to which it accounts for a phenomenon more parsimoniously than previous models have done so. Ormerod and Rosewell also stress that the micro-macro link involved in agent-based modeling requires a new perspective on validation: empirical data on the macro level must be combined with empirical data on the micro level. This approach is applied later in this chapter to test the assumptions involved in a particular agent-orientated model of a financial market. I assess simulated group behaviour (the micro-level) in additional to simulated price behavior (the macro-level). This testing of multi-leveled assumptions in agent-based models is fundamental; agent representations and interactions should be realistic and, where possible, relate closely to empirical evidence. When used this multi-level approach is used effectively, agent-based models can provide powerful accounts of previously ill-understood phenomena, for example, racial segregation based on preferences, the flocking of birds, and the patterns of activity in economies and other social phenomena, such as pedestrian and traffic flows. Each of these examples reviewed above have further conditions in common that make the use of agent simulations appropriate and effective.

Firstly, a large amount of empirical data on the collective behaviour of a phenomenon is available. Whether this is crime-statistics or traffic flows on a German motorway, models can use real-world data to benchmark and falsify different approaches; and if successful, to calibrate models to specific conditions. The real-time tests of traffic predictions by Treiber and Helbing (200l) are one such example of real-data interacting with agent-based models. (Notably, large amounts of data may not always be required if the model attempts to explain a relatively small number of specific emergent phenomenon at the system level.) As a second condition, agent-based models require the data collected on empirical behaviour to be sufficiently non-arbitrary and unique, so as underlying processes can be meaningfully modelled and the success of different theories adequately discriminated. For example, Ormerod (2002) identifies the distinct power-law in company extinction rates as a target for judging the effectiveness of a model of company interactions. The distinct statistical characteristics of traffic flows also make it more amenable to computational modelling.

A final, essential condition for agent-based modeling relates to the realistic representation of agents. The behaviour and preferences of component agents in a model must be sufficiently constrained so that a set of states and interaction rules may adequately represent behaviour within a system. These operational definitions of behaviour may relate closely to inherent situational constraints. For example, agents in vehicles are restricted to decisions associated with driving their cars; the effective modelling of these decision-constraints and characteristics gives rise to powerful explanations for traffic behaviour.

Representing the agents and their behavior in financial markets is a difficult problem. Traders and their decision-making are not well-understood; strategies are inevitably extremely diverse and potentially complex. The behaviour of different types of traders may also adapt and evolve significantly over time. Although not true of all agent-based approaches, many have approached this problem by representing just two types of traders. The following sections review the emergence of the typical agent representations applied in financial models and a number of specific approaches.

3.5 Modelling Markets: Representing Agents as Fundamental or Noise Traders

The fission between two separate groups of traders, one rational and the other irrational, is considered a reasonable simplifying assumption for agent representations in a number of agent-based models of financial markets. However, there is no clear analogy between these theoretical groups and those found in the real-world – there is no explicit divide between rational and irrational market participants in real markets. Whilst advocates of this approach may claim this is of course just a simplifying representation of the real world, the question explored in this chapter is whether these group representations are the most sensible, effective or parsimonious ones available. This section briefly reviews the theoretical developments that led to the wide-ranging adoption of two separate groups of fundamental and noise traders in many market models.

The emergence of the current status-quo for representing groups of traders relates closely to the standard economic account of financial markets and its subsequent revisions. Briefly, the standard economic approach is known as 'the efficient market theory' and proposes market prices accurately or 'efficiently' reflect underlying valuations. In its most extreme form, this is considered a result of the access to complete information and homogeneous rational decisions on behalf of agents. The efficient market theory began with Samuelson's (1965) proof that stock prices follow a random walk if rational market participants require a fixed rate of return. It gained prominence with Fama's (1965) demonstration of random walks in stock prices (see, for example, Malkiel, 2007). This approach to financial markets is encapsulated in the fundamental traders typical of many modern agent-based models. These traders are considered to act rationally on the basis of information on fundamental information, such as information on earnings or valuations, and act to arbitrage away any available opportunities immediately to keep prices efficient.

Given this description of market behaviour, many commentators highlighted the inherent paradox in the original version of the efficient market theory (e.g. Black, 1986; Grossman and Stiglitz, 1980; Kyle, 1985): if all traders respond homogeneously to new information, how can anyone trade, or profit for that matter, as there is no-one to trade with? This observation led to subsequent revisions to the approach with the inclusion of a new group of market participants: noise traders who act irrationally on the basis of noise or erroneous information and provide profits for the fundamental traders. This new group thereby maintains the plausibility of a theory of efficient markets, albeit in a much changed form, and has provided clear group representations for researchers to employ in their agent-based models. The next section reviews a subset of these models in more detail, with focus on the approach by Alfarano, Lux, and Wagner (2005).

3.6 Examples of Agent-Based Models of Financial Markets

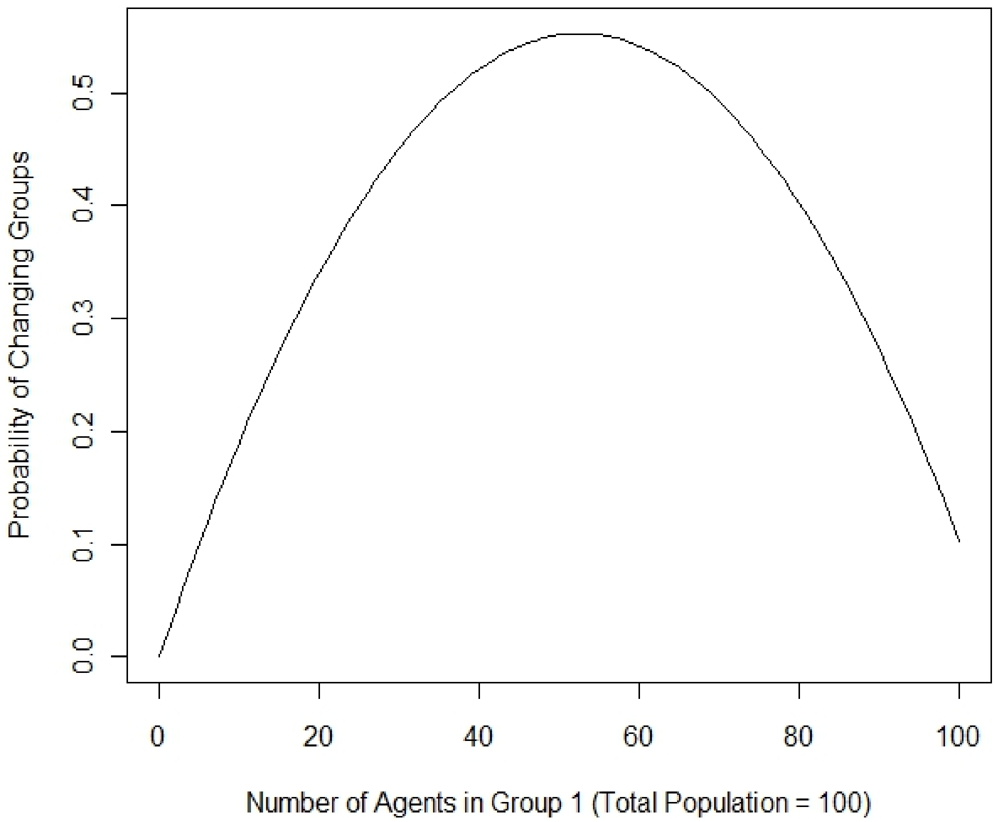
Agent-based modelling of financial markets has generated significant research interest (see reviews by LeBaron, 2000; Levy, Levy and Solomon, 2000; Samanidou, Zschischang, Stauffer and Lux, 2007). This section reviews five market models (in order: Kirman, 1991; Bak, Paczuski, and Shubik, 1997; Arhur, Holland, LeBaron, Palmer, and Tayler, 1997; Darley and Outkin, 2007; and Alfarano, Lux, and Wagner, 2005) to provide a broad time-line and overview of developments in this area.

To recap, the above section reviewed the necessary conditions for agent-based modelling, namely: 1) a large quantity of empirical data to validate and potentially calibrate models; 2) sufficiently non-arbitrary characteristics of collective behaviour displayed, and 3) realistic and useful agent-level representations and interactions. The study of financial-markets, for the first two conditions at least, is relatively well-suited, offering a large amount of thoroughly documented empirical data on market prices. As reviewed in chapter one, the characteristics of this data are also sufficiently non-arbitrary to enable meaningful models to be pursued. On the last necessary condition, however, typical agent representations have lagged behind a more general trend in modern economics towards increased realism and empirical testing. Fortunately, agent interactions (in contrast to agent representations) have been well represented within many market models, and this has contributed to the success of many approaches in replicating important features of price behaviour.

Alan Kirman (1991) proposed one of the first agent-based models of a financial market. Extending previous work relating to the behaviour of ants and social contagion effects within a population (Kirman, 1990), Kirman proposes a mathematical function to describe the effect of direct interactions between agents within a market. This marked an important break from traditional economic models that permits only indirect interaction between agents on the basis of price changes (Ormerod, 1998). In standard models, for example, if demand for a particular product increases in relation to the supply, the price will rise, and as a result, fewer agents purchase a product. However, there is empirical support for more direct forms of interaction, or herding, between economic agents. For example, Trueman (1994) and Welch (1996) find herding effects in broker forecasts and Grinblatt, Titman and Wermers (1995) document similar effects in the behaviour of fund managers. Crowd dynamics are also considered important in the etiology of speculative bubbles and market crashes (e.g. Kindleberger, Aliber, and Solow, 2005). This increasing focus on direct interactions in market situations relates to the famous observation made by Keynes (1936). The actions of investors are comparable to judging a beauty competition: in markets we devote our intelligences to anticipating what average opinion expects the average opinion to be. Keynes's observation relates to the herding effect Kirman formalises: traders constantly try to anticipate the actions of other traders.

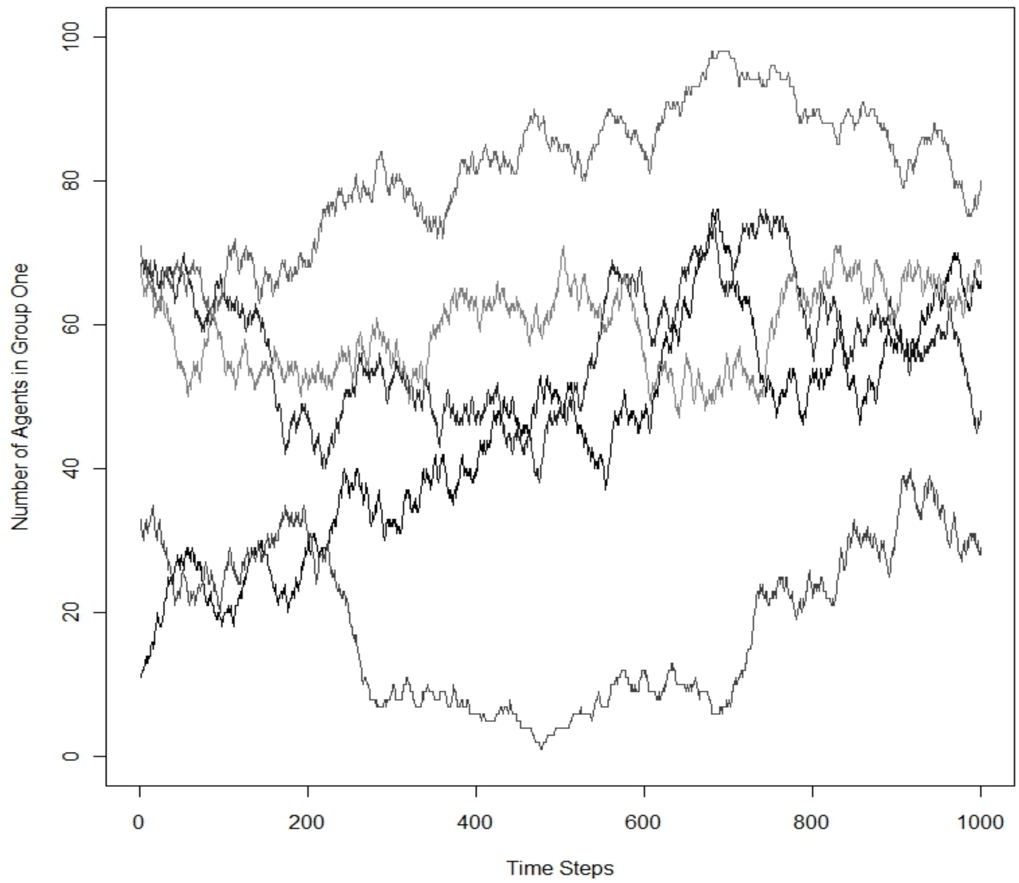
In Kirman's agent-based model, then, traders switch between two groups, the probability of changing groups is determined by the relative size of each group. In other words, market agents herd or follow the majority. This creates positive feedback effects whereby the initial impact of an event can magnify over time. In this context, a trader joining a different group impacts on the probability of a subsequent trader joining the same group, and so on. Figure 3.3 presents an example of Kirman's herding function, relating the number of agents in group 1 (x-axis) to the probability of moving groups (y-axis); when the number of agents in group 1 is high or low, there is a lower probability of an agent switching to the other group.

Figure 3.3 Kirman's (1991) Herding Function



Examples of the output of this function, representing the number of agents in a given group over 1000 time-steps, are presented in Figure 3.4. The starting number in a group is determined randomly between 1 and 100; group size then evolves based on the function in Figure 3.3.

Figure 3.4 Example Changes in Group Size (from a Population of 100 Agents with Two Separate Groups) Applying Kirman's (1991) Herding Function



As a stochastic Markov chain (for example, Meyn and Tweedie, 2005) probabilistic switching between groups in Kirman’s model is determined randomly, and for any given manifestation the outcome is unpredictable. However, the statistical properties of multiple manifestations can be predicted accurately. In Kirman's market model, this switching between different states based on majority opinion is considered to be representative of the non-equilibrium endogenous dynamics found in real markets – and as a result, the volatile price changes found in the real world are also simulated relatively accurately by the model.

In Kirman's approach, the two groups correspond to agents involved in two different types of trading strategies. As reviewed above, the fundamental approach, where prices are considered to revert back to equilibrium value, involves buying below equilibrium value and selling above it. In contrast, the noise trader or chartist approach references erroneous information such as price movements, and may extrapolate future prices based on the past. For Kirman, following closely Keynes's observation from above, each agent therefore observes a noisy measure of the overall majority opinion of the market as being either fundamentalist or chartist, and then follows the majority based on his observation – namely, the agent *acts* like a fundamentalist or chartist. This observation is separate from the actual proportion in each group (which is determined using the herding function from Figure 3.3) and cannot be known perfectly by any agent. The market's forecast for the price change over the next period is a combination of the fundamentalist view (fundamental value minus current price) and the chartist view (current price minus previous price) weighted by the proportion of agents acting like fundamentalists and chartists. The actual price series is determined by the market forecast each period, plus an index of fundamental variables (determining the actual value of the market). Simulated prices from Kirman's model are qualitatively similar to real markets, generating intermittent periods of stability and occasional market 'bubbles'. Although unable to generate more specific quantitative characteristics, subsequent researchers have extended this framework to achieve much closer alignment to the real-world.

A model capable of generating more realistic market prices is put forward by Bak, Paczuski, and Shubik (1997). A market is characterised by two types of agents, noise traders who trade randomly and fundamental traders who maximise utility based on: 1) randomly determined dividend return; 2) level of risk aversion; and 3) a personal level of 'stickiness', that is, how quickly a trader reacts to changes in dividends. Fundamental traders buy if the stock's dividend is high enough above a constant interest rate and sell if the dividend is relatively low, but can vary further in their characteristics due to differences in risk aversion and reaction speeds. The price updating process involves agents placing orders into a virtual order book, and, when buyers and sellers overlap, a trade takes place. With N traders and N/2 shares available, each agent is only able to own 1 share, meaning half the agents are potential buyers and half potential sellers. Note there are no short positions in this model. At each time-step, an agent is chosen at random to either update a bid (a price to buy) or offer (a price to sell) or do nothing. If a buyer is willing to buy at or above the price at which someone is willing to sell, a trade takes place, and vice-versa for traders who are already owners of a share and wishes to sell. This incremental updating of prices on the basis of buy and sell orders is in line with the actual functioning of real markets, which typically trade on the basis of a continuous double auction (to be described in detail in the following chapters).

Using this framework, Bak et al. simulates a number of different agent and interaction scenarios to assess the conditions required for realistic prices to emerge. In keeping with the original efficient market hypothesis, one such configuration that Bak et al. experiment with is a market characterised by only fundamental agents. Interestingly, after an initial period of trading activity, a market characterised by only fundamental traders simply stops transacting. All fundamental traders who have already bought will only sell at a price above a certain price *p*, and all those agents who are willing to buy will only do so at a price below *p*. Therefore, no agents take any further action. This finding resonates with Black et al.'s critique of the efficient market hypothesis, as described in section 3.5. Even a relatively diverse population of fundamental traders cannot adequately explain the price variation found in real-world financial markets.

A second scenario tested by Bak et al. involves direct interaction between traders. In this variant of the model, after each trade takes place, an agent's subsequent bid or offer is randomly chosen from an existing bid or offer. This results in a new price being chosen with a probability related to the number of agents with the same price. This is a process similar to Kirman's herding function described above, the probability of joining a group relates to the number of agents in the same group. A further modification in Bak et al.'s model has noise traders being affected by the overall volatility of the market price, whilst including a stochastic drift in orders back towards the current price. The increment by which bids and offers update, instead of being constant over time, dynamically reflects recent price changes. For example, agents update their orders plus or minus the price change over the last 50 time steps. The inclusion of these two factors, 1) new prices chosen based on a probability related to the number of agents already with a given price (a form of direct interaction between agents), and 2) positive feedback effects based on recent price volatility, result in emergent behaviour in the model that is consistent with real markets. As described in chapter 1, distinct characteristics of market prices include fat-tailed distributions, scaling behaviour, and autocorrelation in absolute returns (or market volatility). These features are successfully replicated within the Bak et al. framework. The authors conclude these characteristics originate in collective, crowd behaviour, and use their model to propose specific underlying mechanisms.

The Santa Fe Artificial Stock Market is a more complex and sophisticated agent-based financial market introduced by Palmer, Arthur, Holland, LeBaron and Taylor (1994) and extended over a number of papers (Arthur, Holland, LeBaron, Palmer and Tayler, 1997; LeBaron, Arthur, Palmer, 1999). The model, now publicly available, allows researchers to study how learning agents which adapt over time can help to explain the empirical observations made of financial market data. Unlike other agent-based markets, traders in this model all begin identically and then use machine-learning techniques to evolve their decision-making rules to maximise a utility function. The object of all agents in the model is the same, to maximise a formal measure of expected utility – an approach that is therefore consistent with neoclassical economic representations of human decision-making.

The information each agent has access to is divided into the usual categories: fundamental and chartist information. Chartists in the Santa Fe model, although typically associated with noise traders, do not make decisions randomly or on the basis of noise, as is the case in the Bak et al. model, but rather, decisions are made as a result of specific technical trading rules and indicators, such as the location of the current price in relation to a moving average of the recent prices. Agents in the Santa Fe model, with different updating speeds, reference the historic performance of different combinations of chartist and fundamental information to change trading rules via an optimisation algorithm. Therefore, based on an agent's experience, it learns to weigh specific chartist and fundamental rules as relevant in order to maximise its utility. The particular combination of rules and parameters adjust over time as the agent gains more experience. At an aggregate level, this results in a marketplace that involves dynamic and evolving agents, similar, in principle, to real market environments.

The results from this agent-based experiment show the importance of the speed by which agents update and re-learn their decision-making rules. In a slow-learning regime, in which agents learn and adapt their behaviour every 1000 time periods on average, overly stable and unrealistic prices emerge. However, when agents update and re-learn every 250 time periods on average, complex outcomes emerge with no stable price equilibrium and other characteristics more in common with real markets. Arthur et al. find, in this second learning regime, agents are also more likely to use and profit from technical analysis trading rules, that is, making trading decisions based on chartist information rather than fundamental information. This suggests a very different origin to the existence of noise traders / chartists than originally proposed by Black and others in the 1980s. Rather than providing profits to more rational traders, these traders are seen to emerge naturally in the Santa Fe model as a consequence of the complexity of the market environment.

The Santa Fe agent-based model is unique in that no agents are behaving irrationally or randomly, nor are agents involved in any form of direct social influence or explicit herding (in the sense of Kirman's or Bak et al.'s model). Agents simply strive to maximise utility at all times and are therefore consistent with more traditional agent representations. However, agents differ from those associated with standard economic accounts in that they rely on inductive logic: they are learning by trial and error rather than a priori optimal decision-making strategies. Therefore, agents adapt and evolve in pursuit of their economic goals and, from these evolving dynamics, realistic market price characteristics can emerge.

The authors make the important observation, made separately by the financier George Soros (1987; 1994), that market environments are generated by people's expectations, and as a result, perfect rationality cannot be well-defined. In markets, economically optimum behaviour relates to what other traders are expecting and how they are acting. Inductive learning and adaptation are therefore central to agents' survival and profitability. In the terminology of Soros (1987), markets have a 'reflexive' quality; they are self-referential, and thus, “the market becomes driven by expectations that adapt endogenously to the ecology that these expectations co-create” (Arthur et al., 1997, p.

38). These results demonstrate how realistic market characteristics can emerge quite naturally as a result of inductive learning and adaptive agents.

The inclusion of technical analysis rules in the Santa Fe model introduces positive feedback dynamics that can be seen as analogous to more explicit herding formulations seen in the Kirman and Bak et al. models. An underlying premise of technical analysis is that price changes in a market must result from the expectations and actions of other traders, and therefore price movements are relevant to future market behaviour. In the Santa Fe model, trading rules such as “if the price is greater than a 5 period moving average of past prices” (Arthur et al., 1997, p. 28) allow traders to infer and be influenced by the expectations and actions of other traders. This is not in a direct sense, as Kirman originally envisioned, as there are no direct interactions between agents, but equally, it is not in the indirect sense assumed in standard economic models – where, for example, higher prices are assumed to reduce demand and increase supply. Instead, traders may observe price changes to identify trends that are likely to continue, and as a result, higher prices may actually increase demand and reduce supply. To paraphrase Keynes, agents devote their intelligence to anticipating what average opinion expects the average opinion to be; this principle is encapsulated with technical trading rules, and offers a profitable source of information to agents in the Santa Fe model. Rather than associating the use of technical analysis with irrationality and noise trading, as is more typical in the literature, technical analysis is very possibly a logical methodology for anticipating and responding to the behaviour of others in a constantly evolving, self-referential market environment.

A similar direction to interaction between agents is pursued by Darley and Outkin (2007) in their model of the NASDAQ stock market. No explicit herding effects, deliberate randomness, or irrationality, is introduced into market agents. In contrast, heterogeneous agents are modelled with a suite of advanced machine-learning methodologies to learn and co-evolve over time. In research funded by NASDAQ Inc., the U.S stock exchange, the objective of Darley et al.'s model was to provide recommendations on precise questions relating to the decimalisation of NASDAQ stocks and the impact it could have on market participants, price volatility and trading volumes. Markets on NASDAQ were quoted in fractions of a point and typically moved in increments of 1/8 or 1/16 up until 2001. From 1998 onwards, plans were in place to move towards decimalised prices, and before implementing this change, NASDAQ used agent-based modelling to investigate different pricing schemes and how best to introduce the new regime. Towards these goals, researchers interacted with and interviewed many actual market participants, including market makers, brokers, traders and large investors. With additional access to unique proprietary data sources provided by NASDAQ, Darley et al. calibrated their simulation by explicitly modelling the strategies of individual participants. Strategies then evolved over time, based on performance measured with utility functions relating profitability to variance of returns. Many of the predictions made by the agent-based model as a result of decimalisation, such as a surge in trading volume and a regime shift in market maker strategies, proved to be accurate.

The Darley et al. model, in keeping with other agent-based markets, stipulate two broad groups within a finite population of traders. These groups are classified as market makers and investors. Investors are analogous to fundamental traders, who operate with a fuzzy definition of fundamental value, where the fundamental value changes randomly and is updated exogenously. Each investor has a different degree of 'informedness' based on their knowledge of the fundamental value weighed by a randomly determined error-rate. Market makers, in the Darley et al. model, are similar to chartists from other agent-based simulations: they rely on price-based information and must provide continuous bids and offers to the market. They have no knowledge of fundamental value, and post quotes based on information derived from prices, volumes, and also their own interactions with the market (for example, how many times they deal at bids or offers). Markets makers were a focus in the Darley et al. model, due to their sensitivity to market pricing. The model involves sophisticated techniques to be as analogous as possible to real-world strategies and evolve performances over time. These include neural networks, reinforcement learning, genetic algorithms, and other machine-learning techniques. In this way, a complex heterogeneous market place was constructed within a precise replication of NASDAQ exchange rules and trading processes (such as obligatory posting of bids and offers on a public board). This model is unique in reflecting a real-world market so accurately; considerable efforts were made to calibrate the model with regard to its agent representations and realistic distributions of prices and trading volumes. From this highly complex and sophisticated agent-based simulation, statistical characteristics of real markets readily emerge, and, as with the Santa Fe model, without direct herding or noise trading components to the model.

The success in providing NASDAQ with precise policy recommendations encourages Darley et al. to envision broader uses for agent-based financial market models in the future. One clear application is towards studying different regulatory approaches for managing financial markets. Darley et al. suggest the relationships between market rules, trading volume, price volatility, market liquidity and agent strategies can be studied and understood more clearly with agent-based technology. Indeed, this claim parallels the application of simulations to other regulatory arenas. This chapter has already reviewed the development of optimal structures for maximising pedestrian flows (Helbing et al, 2001), recommendations for reducing traffic jams (e.g. Treiber et al, 2001) and models for economic regulation (Ball, 2004), all of which gain from the use of agent-based modelling. Simulations have even been applied to the safety of boating trips on the Colorado river (Daniel and Gimblett, 2000) and other outdoor recreational activities (Manning, Itami, Cole, and Gimblett, 2005). With these precedents, it is logical to suggest models of financial markets can be used to aid market regulators by increasing understanding and control over emergent market behaviours. Perhaps, as with the Helbing et al. studies, models can even provide means of optimising market regulation for the benefit of market participants. NASDAQ is unique in its application of agent-based simulations to explore the impact of proposed changes to market institutions in a controlled environment. However, it seems plausible that the approach will become more wide-spread in the future. The increasing impact of the world's financial markets on real economies, and the enhanced awareness we now have of the risks associated with extreme market volatility suggests such an aim, although ambitious, should be pursued as a clear objective of applied economics.

Darley et al. also advocate the possibility of using agent-based simulations in financial trading and research settings. Farmer (2001) agrees, claiming agent-based technologies may be used in investment strategies in the near future. Although it should be noted that Farmer's paper was written almost 10 years ago, agent-based models have not yet become widely used in investment settings (although there are, of course, exceptions: www.whodrivesthemarket.com). By calibrating simulation models in real-time using live data, models could provide market forecasting techniques similar in principle to the traffic forecasting models of Treiber et al. (2001). However, this level of sophistication is beyond the majority of most market observers. As Darley et al. themselves acknowledge: “it may well be possible to build simpler models than ours which bring the results down to a more fundamental set of criteria" (2007, p. 14). The amount of time required to develop a model similar to Darley et al. (taking them over 3 years, for example), in addition to the proprietary data and market access necessary to accurately calibrate models, makes the approach prohibitive for a broader user group. Ideally, an agent-based model would find a satisfactory middle ground between the realism required to validate the approach and the practical ease of implementation necessary to make a model usable and replicable. A model with this objective in mind is described in the next chapter of this thesis.

Various agent-based models, then, have been able to reproduce characteristics in common with real markets. As Darley et al. acknowledge (2007, p. 58), "statistical characteristics of market prices are highly robust emergent features". Indeed, Darley et al. struggled to find a scenario within their modelling framework in which prices did not have distinctive and realistic characteristics such as fat-tailed distributions. It may well be that these characteristics relate closely to ubiquitous situational constraints in financial markets, such as the nature of the order book and the double auction process, in addition to interaction effects between agents. Other details, such as whether agents are considered rational or irrational, or whether herding is considered explicit or implicit, may be less relevant in reproducing realistic collective behaviours.

If success at replicating the statistical features of market prices is readily achievable, what is next for agent-based models of markets? Alfarano, Lux, and Wagner (2006) suggest the natural next step for researchers in the area is to move towards parameter estimation for relating agent-based models more closely to real-world markets. This level of calibration could allow models to represent particular markets rather than just broader similarities common to many different markets. Attempting to calibrate a model to specific markets can test the validity of an approach closely, and if successful, offer insight into unique differences between markets.

The model developed by Alfarano, Lux, and Wagner (2005) claims to offer insight into individual differences between markets, providing a relatively simple and replicable model that can be calibrated towards the behaviour of specific financial markets. The approach combines principles common to many agent-based simulations, such as interactions between agents, changes in group sizes, and fundamental and noise traders. The model also has a very limited number of parameters; or in the words of Darley et al. (2007, p. 14), it brings “results down to a fundamental set of criteria”. This approach is demonstrated in detail in the following section.

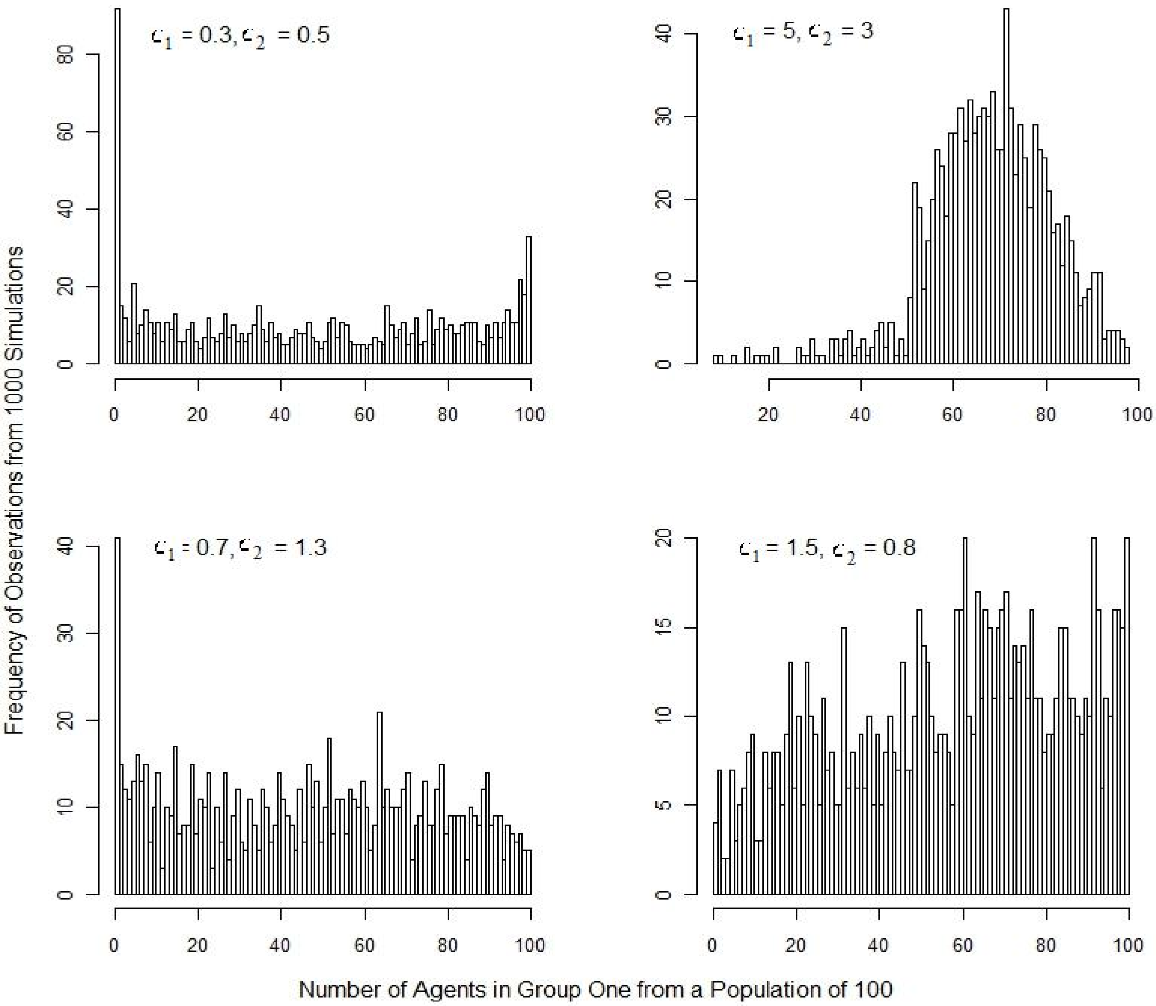
3.7 Alfarano, Lux, and Wagner's (2005) Model

Alfarano, Lux, and Wagner (2005) extend upon research by Lux and Marchesi (1999) and Alfarano, Lux, and Wagner (2004) to propose a version of Kirman's (1991) original formulation of a financial market. In the by now familiar framework, a finite population of traders move between two groups of noise traders (group 1) and fundamental traders (group 2). Fundamental traders buy and sell on the basis of deviations of price away from fundamental value. However, following the different approach of Lux and Marchesi (1999), noise traders are further sub-divided into optimists and pessimists. If noise traders are optimistic they are buying the market, if pessimistic, they sell the market. In this model, market sentiment, in addition to group composition, contributes to how market prices evolve.

As with Kirman's original formulation, the number of participants in group 1, corresponding to noise traders, changes over time. The probability of joining or leaving the group is similar to Kirman, but described here via two separate herding functions. The first function determines the probability of joining the noise trader group whilst the second describes the probability of leaving. Therefore, as there are only two groups, the probability of a trader joining the noise trader group can be different from the probability of a trader joining the fundamental trader group. An example of a time series generated by this process, representing the number of fundamental traders over time, is shown in the third panel of Figure 3.6. Superficially, this time series resembles that of Kirman's in Figure 3.4 above, but, as discussed subsequently, the use of two functions offers more flexibility. For Alfarano et al., this asymmetry in herding between the two groups introduced with the use of two functions is crucial for modelling unique differences between markets.

The parameters and describe the level of herding asymmetry between the groups. (Note for Kirman's original model is equal to). The model is implemented and Figure 3.5 demonstrates the distribution of the agents in group 1 as a result of specific parameter combinations at the end of a simulation involving 1000 steps. Note, if both parameters are less than 1, a bi-modal distribution arises (top-left panel of Figure 3.5); whereas if greater than 1, the distribution forms a unique mode (top-right panel of Figure 3.5). If is lower than 1 and is greater than 1, the distribution increases monotonically; if is greater than 1 and lower, the distribution decreases monotonically (remaining panels in Figure 3.5). Alfarano et al. note that the flexibility permitted with only two parameters contributes to the power of the model in describing idiosyncratic differences between individual markets.

Figure 3.5 Distribution of Agents in Group One Resulting From Specific Parameter Combinations at the End of Simulations Involving 1000 Steps



Other parameters in the model are also important for explaining a market's behaviour, including parameters for the total population of traders, an overall propensity to herd (as separate from an asymmetric herding propensity between groups, represented with parameters and), and a scale factor for the impact fundamental traders have on the price formation process. In total, then, only 5 free parameters are employed to explain a particular market’s behaviour.

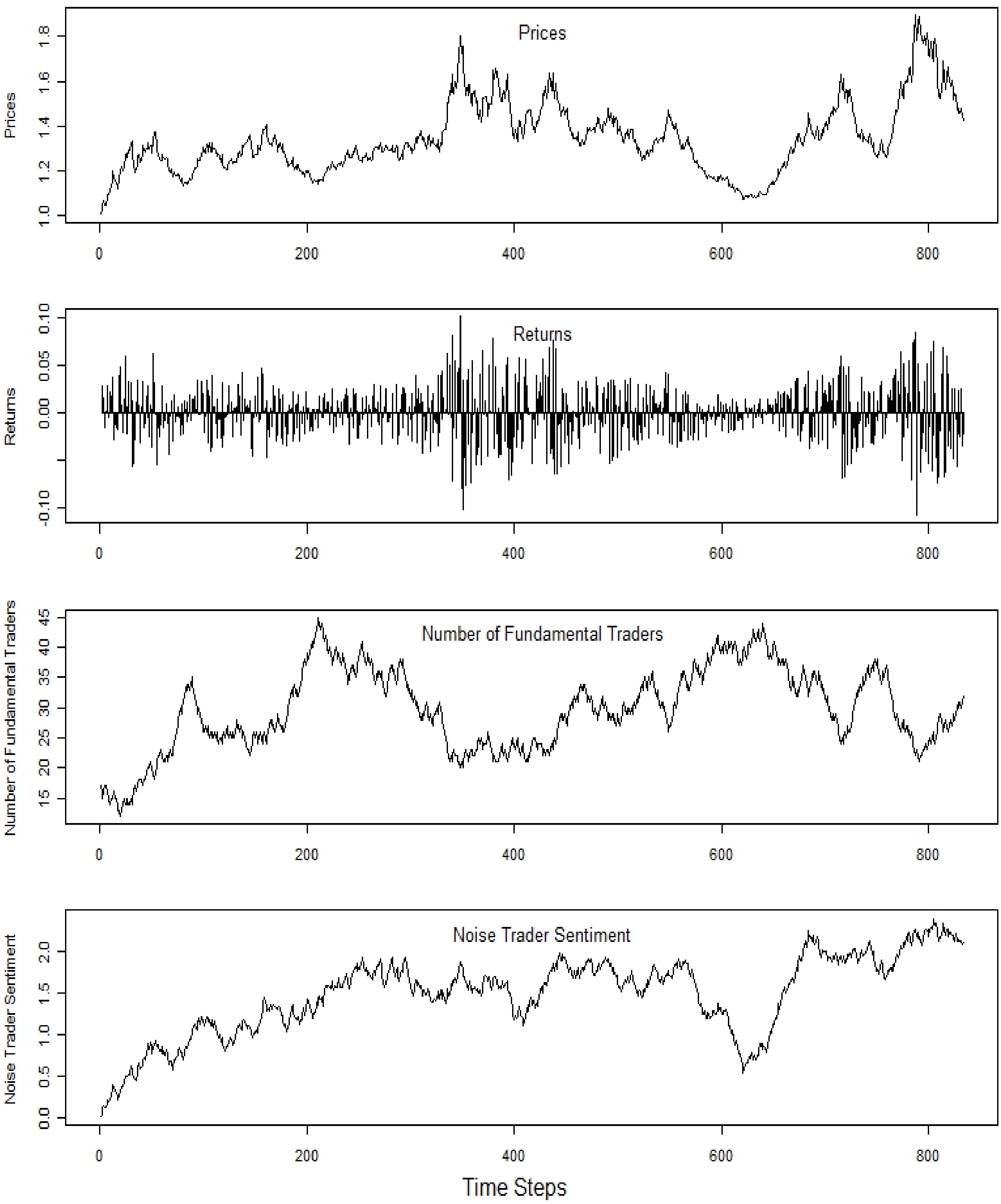
From these components a market price series is generated. Change in noise trader sentiment is represented as a random walk over time; the log price series for a market is derived from the proportion of fundamental traders , noise trader sentiment and a scale factor (the impact fundamental traders have on price formation) in the following way:

Equation 3.1 Simulating Market Prices According to Alfarano, Lux, and Wagner (2005)

$$Price_t = \rho\zeta_t / (-\zeta_t)\xi_t$$

Figure 3.6 presents, in descending order from top-panel to lowest-panel, simulated prices (specifically, the exponent of simulated prices), simulated returns, change in the number of fundamental traders, and change in noise trader sentiment. The fundamental valuation of the market is held constant at 1. If noise trader sentiment is greater than 0 it is optimistic, and noise traders are buying; if less than zero, pessimistic, and noise traders as selling. Figure 3.6 presents the model solved over 833 time steps. An account of why this number of time steps is selected follows below.

Figure 3.6 Example Simulation of a Financial Market, Alfarano, Lux, and Wagner (2005)



The interrelationship between the model components and the evolution of prices can be described in the following way. Noise traders buy and sell on the basis of (a random walk in) overall market sentiment. Fundamental traders respond to chartists' supply and demand to determine prices. Major trends in prices therefore result from consistent directional moves in market sentiment, coinciding with a reducing number of fundamental traders. With a lower number of fundamental traders, the impact of noise trader sentiment on the price development process increases. This abstraction of market dynamics into these theoretical components is simple and, at a broad level, plausible. In alignment with Keynes's observation, changes in overall market sentiment is central to how prices evolve, and, in keeping with Kirman's observation, the relative concentrations of different types of participants contribute to market price behaviour.

The validity of the model is supported by the alignment between the statistical characteristics of simulated prices and actual prices. As Figure 3.7 documents, the distribution of simulated returns has fat-tails when compared to a normal distribution; specifically, the kurtosis of the simulated return distribution is 4.632 (whereas a normal distribution has a kurtosis of 3). The simulated market returns in Figure 3.6 also vary in size over time. Note also the clustering in the amplitude of the size of returns. This is realistic market behaviour. Figure 3.8 demonstrates that for absolute returns, or market volatility, the autocorrelation for the first lag in the series is 0.407. For returns themselves, no obvious autocorrelation is apparent.

Figure 3.7 Distribution of Simulated Returns (top-panel) and a Comparison of Simulated Returns with a Normal Distribution (lower-panel)

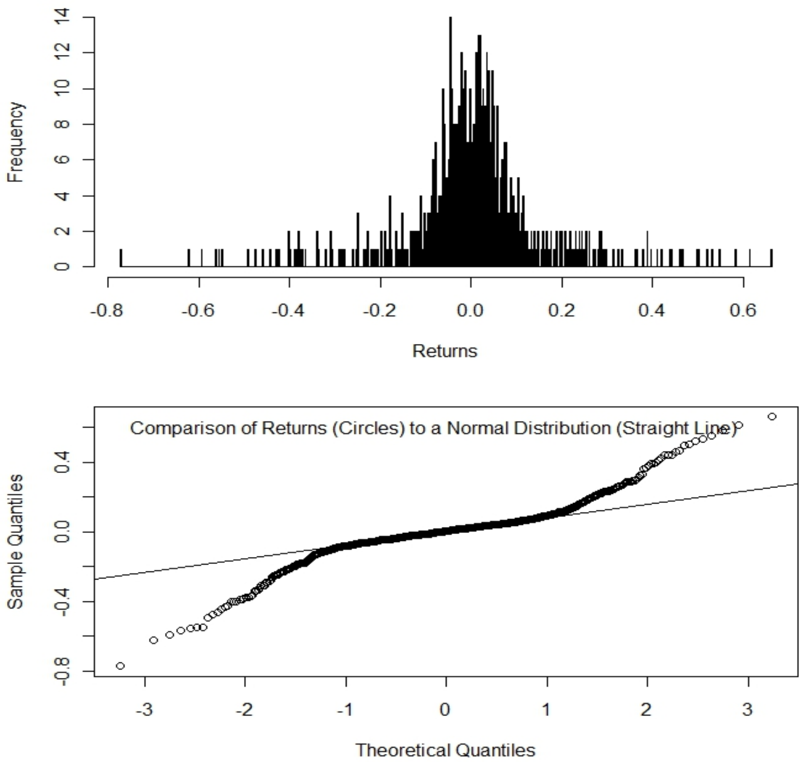
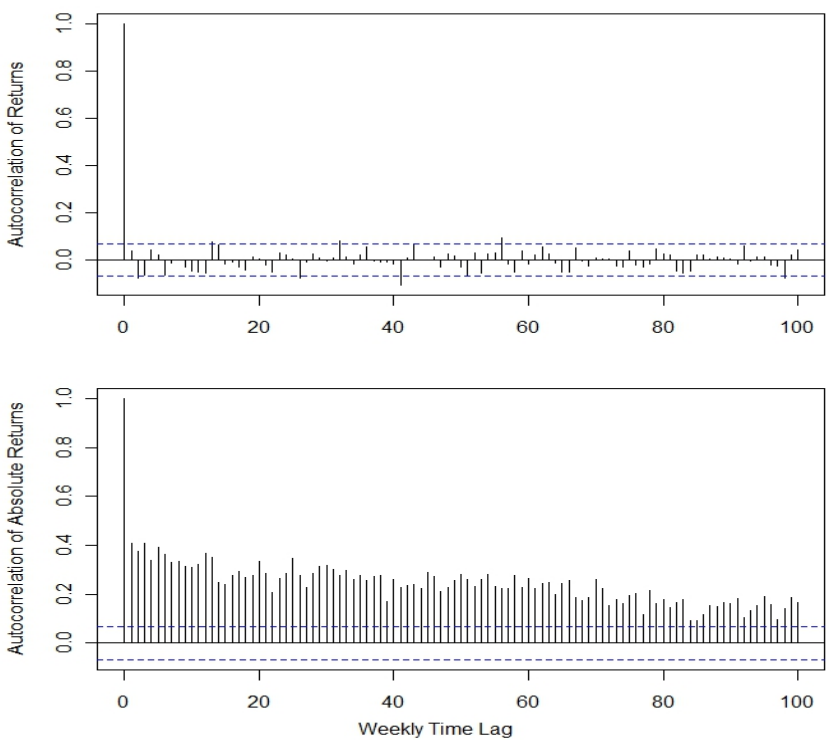


Figure 3.8 Autocorrelation of Simulated Returns (top-panel) and Simulated Absolute Returns (lower-panel)



In addition to replicating real-world market price behaviour successfully, the Alfarano et al. model can be calibrated to represent the price characteristics of a specific market. The above simulation is consistent with the Oil market and its statistical behaviour. I optimised the parameters for the model with a search algorithm employing a similar method to Gilli and Winker (2003). The fit between actual price characteristics and simulated price characteristics was evaluated by relating the absolute value of the mean real kurtosis to the mean simulated kurtosis , and the absolute value of mean first lag autocorrelation of absolute returns for the real market series to the mean simulated first lag autocorrelation of absolute returns , as determined by solving the model 100 times for each parameter combination (to reduce the stochastic element to the results). Future research could incorporate the Anderson-Darley test as a means to formalise differences in the non-normality of distributions as a further component. The fitness function is represented in Equation 3.2 (note the relative weighting of the two components is arbitrary):

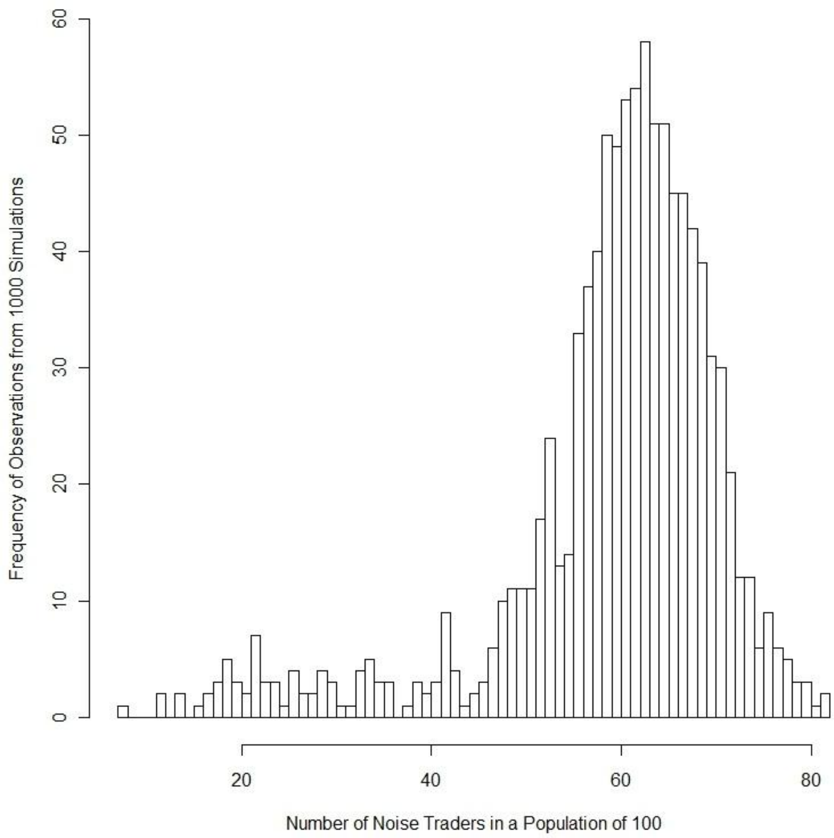
Equation 3.2 Fitness Function to Compare Simulated Characteristics to Real Characteristics

$$ff = |T - \tau| + |\Psi - \psi|$$

Each simulation has 833 time steps, the number of weeks in the Oil dataset. The upper panels of Figure 3.6 (simulated Oil prices) and actual Oil prices over the period 1991-2008 therefore have similar statistical properties as a result of the fitness function minimising the difference between the kurtosis of the return distribution and autocorrelation of absolute returns over the same time steps.

The parameters in this above simulation, where = 5.148, and = 9.116, therefore explain the Oil markets' behaviour as a result of an asymmetric herding between groups of fundamental and noise traders. This parameter combination (where <) specifies fundamental traders are more likely to switch to being a noise trader than noise traders are to switch to being a fundamental trader. Using these parameters, Figure 3.9 documents the distribution of traders in group 1 (noise traders) after 1000 simulations of the process over 833 time-steps. Note the higher frequency of observations around the 60-70 group size (out of a total population of 100). According to Alfarano et al., the Oil market tends towards a larger population of noise traders over time.

Figure 3.9 Distribution of Final Number of Noise Traders in 1000 Oil Market Simulations; = 5.148 and = 9.116



Alfarano et al. claim to provide a behavioural account of market dynamics, where model components are supposedly analogous to those found in real markets. The results of the model are indeed validated based on the statistical consistency of simulated prices with real-world prices. However, the underlying group dynamics proposed in the theory have not yet received similar levels of empirical scrutiny, despite their importance in accounting for the price behaviour. Just how realistic is the behaviour of traders and changes in group composition postulated by the Alfarano et al. model? The following section addresses this question by comparing theoretical group behaviour to actual group behaviour in the Oil market, as documented in COT data.

3.8 Assessing Behavioural Realism in a Financial Market Model

In keeping with other approaches reviewed in this chapter, central to the Alfarano et al. theory of market behaviour is the movement of a population of traders between two groups. The movement between groups modulates the random effect of sentiment (in noise traders) on market prices. This gives rise to the intermittent periods of more volatile price changes. In the Oil market, more specifically, the Alfarano et al. theory proposes group fluctuations via herding that tend to increase the numbers of noise traders relative to the number of fundamental traders. This asymmetry is considered important for explaining particular characteristics associated with the Oil market. We have seen that the Alfarano et al. theory is successful at representing characteristics of market prices, however, the purported underlying group behaviour has not yet been tested.

COT data, introduced in the previous chapter, and many models of financial markets (including Alfarano et al.'s outlined above), specify broad groups of traders. It has been suggested that these groups are comparable. Noise traders, or chartists, have been seen as analogous to large speculators documented in COT data, whilst fundamental traders are considered analogous to commercial traders (see, for example, Wiley and Daigler, 1998, p. 95). If this analogy between the groups is valid, the Alfarano et al. model (and other market models reviewed above) can be evaluated formally based on their behavioural realism; that is, the hypothesised group behaviour can be tested against real-world sources. However, if the analogy is not valid, then such models are empirically unfalsifiable: it is not realistic to test the rationality of different market participants. For the purposes of analysing the Alfarano et al. model, let us assume for now that the analogy between commercials and fundamental traders, and between large speculators and noise traders, holds true. Both offer, after all, a separation of market composition into two broad yet discrete groups. And, as the previous chapter documents, in real-markets, as in the Alfarano et al. model, the trading behaviour of these two groups is very different. Perhaps there is meaningful overlap between the categorisations presumed in theories and those found in real-world financial markets?

This analogy between the groups is strengthened if we assume that, rather than noise trader's miraculously changing into rational fundamental traders, or vice-versa – which would seem unrealistic – changes in group composition correspond to the replacement of an old trader by a new one who does not necessarily share the same strategy (where the total number of participants in the market is held constant for convenience). This permits a comparison between the information contained in COT data and the changing sizes of groups of traders in market models – after all, the number of large speculators and commercial traders also varies over time and across markets. COT data can provide verification for the claims made by Alfarano et al. on group behaviour.

Our analysis of the Alfarano et al. simulation begins with a comparison of the buying and selling of simulated noise traders to the actual buying and selling of large speculators in the Oil market. The lower-panel of Figure 3.10 presents the simulated excess demand of noise traders, as formulated in the Alfarano et al. model. This measured at each time step by multiplying the current number of noise traders by the current market sentiment (simulated with a random walk) by – a parameter representing the scale of impact noise traders have on the price formation process. We can see, therefore, the number of noise traders regulates the excess demand noise traders exert, which in turn corresponds to the overall impact of a random walk on the price formation process. The measure of noise trader excess demand is, based on the above analogy, comparable to real-world net-positions (long open interest minus short open interest) of large speculators, as presented in the lower-panel of Figure 3.11.

It is interesting to note a qualitative resemblance between noise traders' excess demand in Figure 3.10 and the net-position of speculators in Figure 3.11, both series fluctuate continuously. A more quantitative comparison, however, shows the kurtosis of speculator net-positions to be 0.06 whilst noise trader excess demand has a kurtosis of -0.61. The autocorrelation is also different. As shown in Figure 3.12, both series have significant autocorrelation although the lags for speculator net-positions decay more rapidly. The excess demand of noise traders is also proposed to relate to swings in market sentiment between optimism and pessimism (middle-panel of Figure 3.11). This theoretical component to the model could be tested with reference to real-world market sentiment measures such as consumer and investor surveys. However, this may well be straining an already unsupported analogy too far, so, for our purposes, the focus remains on a comparison of the model to COT data.

Figure 3.10 Oil Market Simulation: Prices, Noise Trader Sentiment and Excess Demand

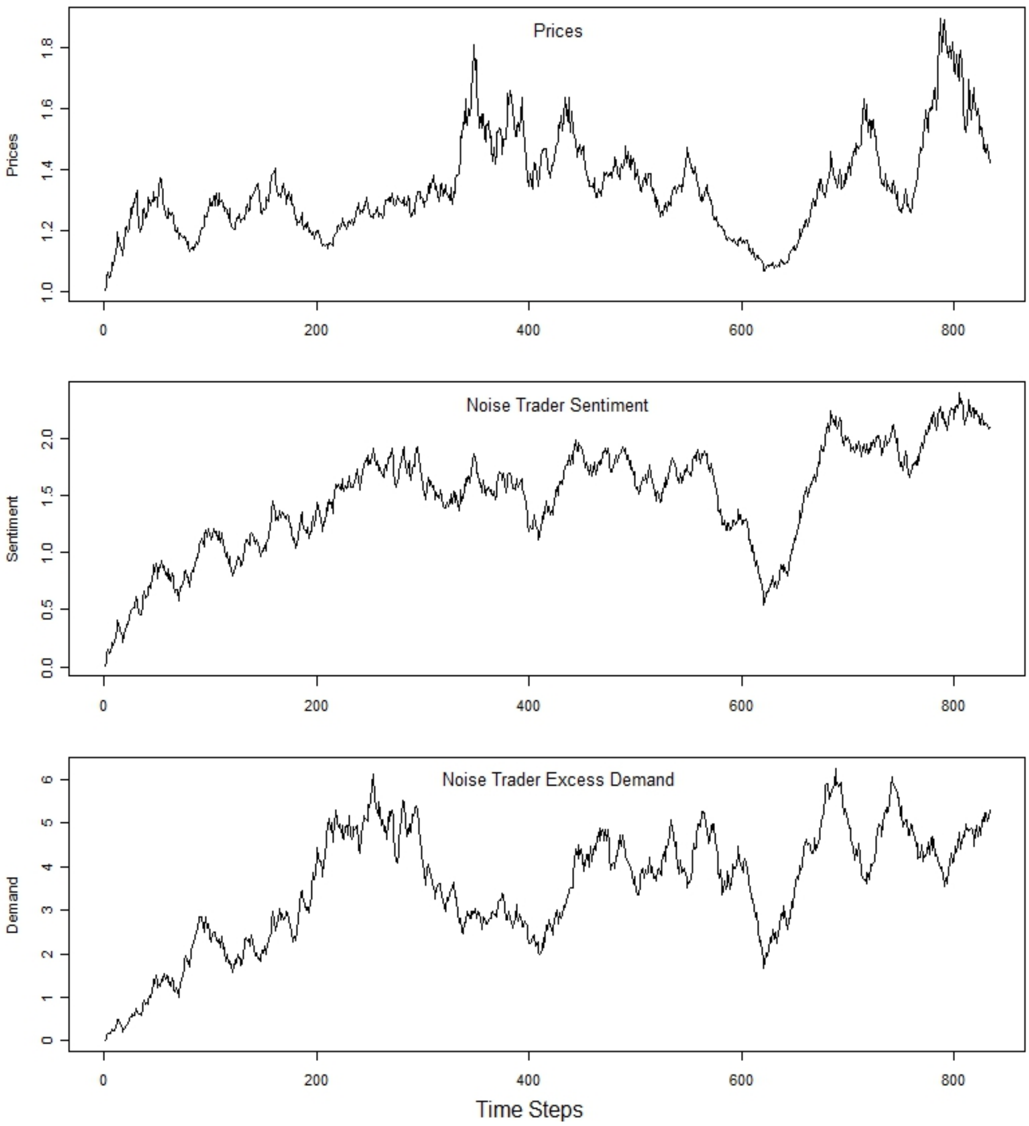


Figure 3.11 Real Oil Market: Prices and Net-position of Large Speculators, 1991-2000

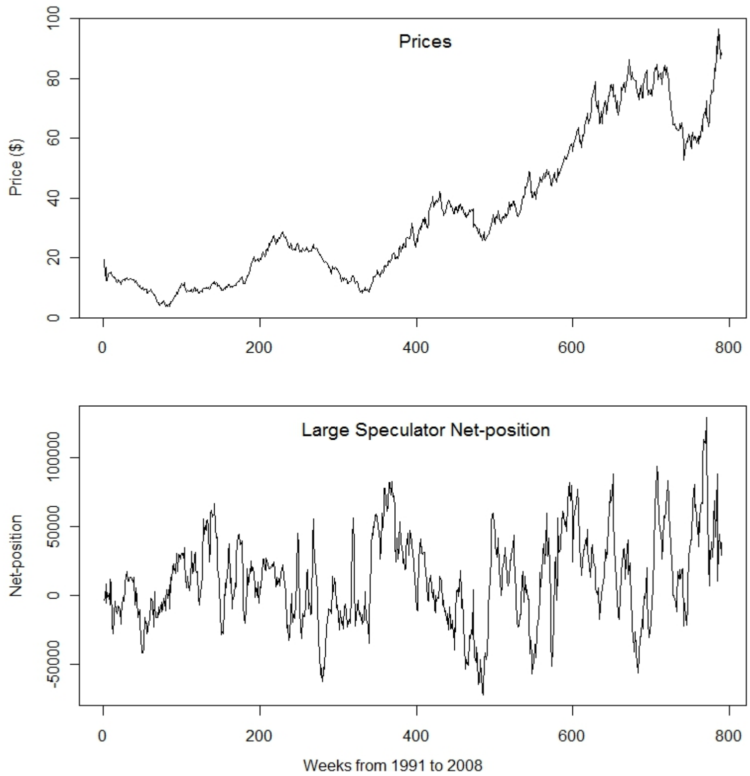
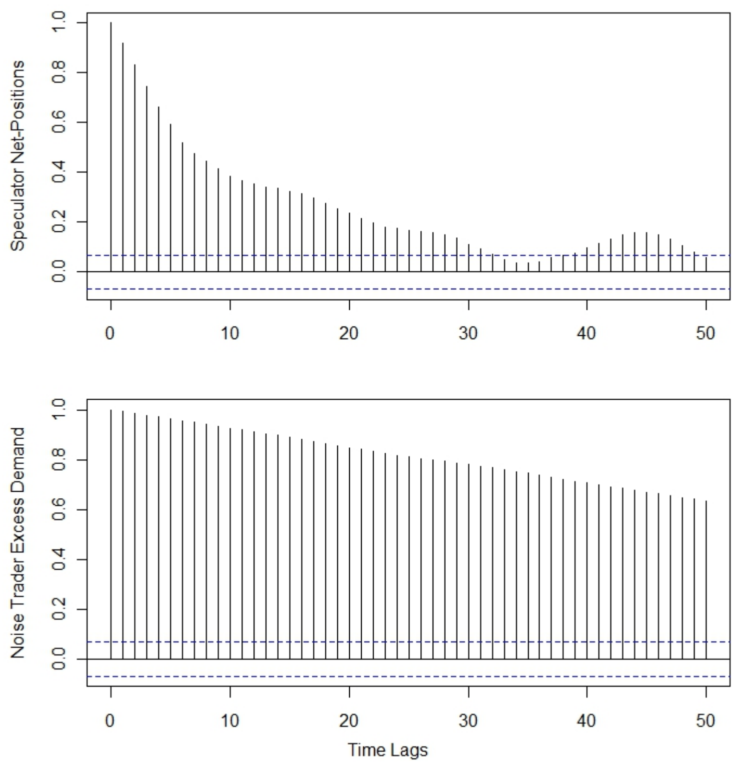
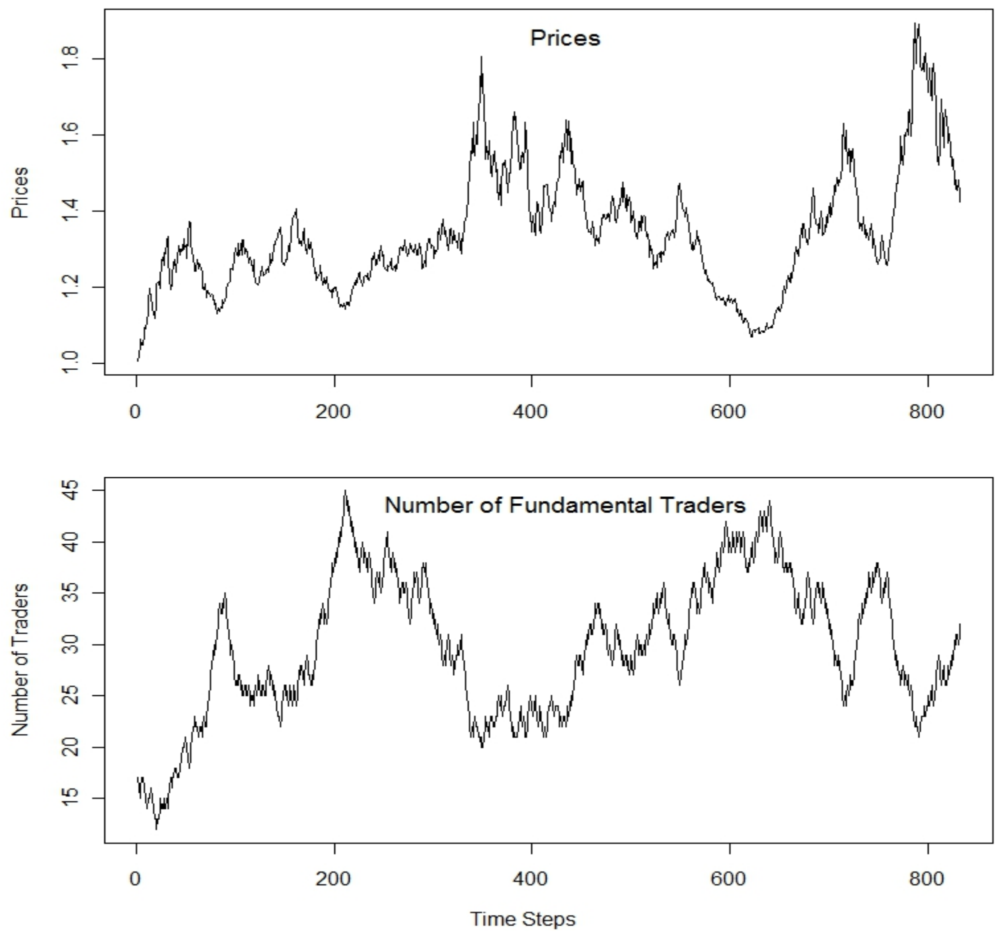


Figure 3.12 Autocorrelations of Speculator Net-Positions in the Real Oil Market, and Noise Trader Excess Demand in a Simulation of the Oil Market



In keeping with the other market models reviewed above, Alfarano et al. stipulate important changes in market composition over time. According to the particular parametrisation of the model for the Oil market, the variation in market composition tends towards larger concentrations of noise traders than fundamental traders over time. The lower-panel of Figure 3.13 displays changes in the number of fundamental traders based on the simulation of the Oil market. Note the overall number of fundamental traders tends to be below 50, a typical outcome in the model. In the real-world Oil market, it should be possible to see similar changes in participant composition over time: based on our analogy, the Oil market should observe a trend towards increased participation of large speculators over the sample period. This is a hypothesis that can be tested directly.

Figure 3.13 Simulated Oil Prices and Changes in Number of Fundamental Traders



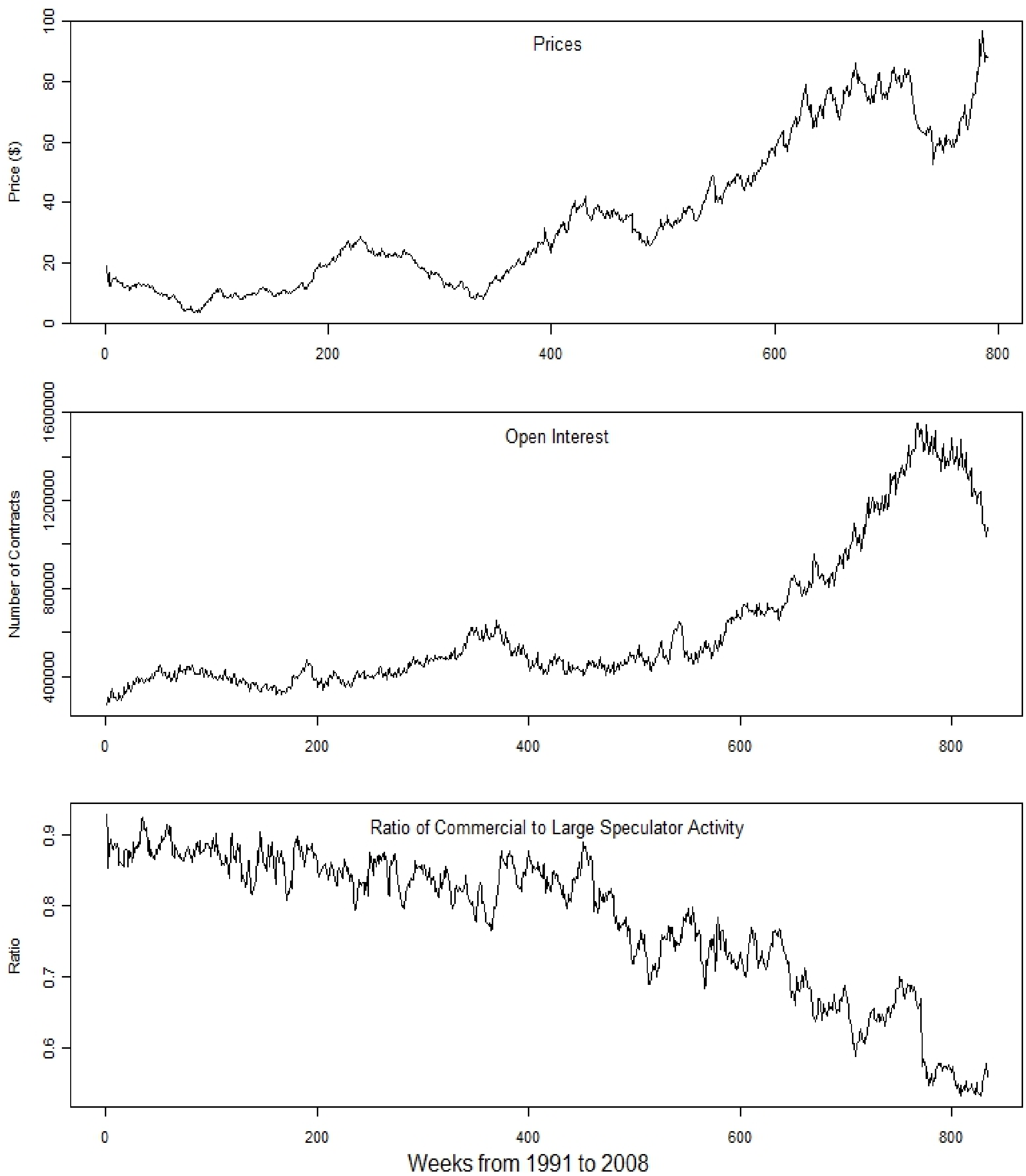
COT data is used to investigate changes in market composition in the following way. A metric is constructed of the concentration of commercial to speculator activity by representing the open interest (both long and short) held by commercials as a ratio of commercial plus large speculator open interest (again, both long and short positions). This ratio therefore relates the total participation of commercial traders to that of large speculators, incorporating both long and short positions to fully reflect how much of the market is taken up by each group (see Equation 3.3).

Equation 3.3 Concentration Ratio, Commercial Activity to Speculator Activity

$$conc = \frac{P_{Commercial,Long} + P_{Commercial,Short}}{P_{Commercial,Long} + P_{Commercial,Short} + P_{Speculator,Long} + P_{Speculator,Short}}$$

The lower panel of Figure 3.14 documents the change in market composition between commercials and large speculators in the Oil market. A high value for the ratio represents a larger amount of commercial activity, and a low value, a larger amount of speculator activity (where a value of 0.5 would represent equal proportions between the two groups). Note there is a general decline in the amount of commercial participation over the sample period, and conversely, an increase in speculation. Presuming the analogy between the groups and COT data holds true, this finding is relevant for two reasons. Firstly, it provides support for a major theoretical assumption typically made in agent-based market models: change in market composition, or the size of groups of traders, occurs over time. Secondly, the finding supports the more specific claim made by the Alfarano et al. model: in the Oil market, speculators (or noise traders) increase in concentration relative to commercials (or fundamental traders) over time. The Alfarano et al. model is therefore apparently valid for generating realistic price characteristics with, at least qualitatively, accurate representations of the underlying group dynamics involved.

Figure 3.14 Oil Market Prices and Changes in the Ratio of Commercial to Large Speculator Composition, 1991 to 2008



There is further evidence against the validity of the Alfarano et al. model, however. The increase in large speculation in the Oil market is not an isolated phenomenon. COT data documents, across almost all futures markets, a broad increase in the relative concentration of large speculator activity to commercial activity over recent decades. There are many possible ways to quantify this general increase in speculation. The simple approach adopted here is to take the median market participation ratio (see Equation 3.3) during the first 12 months and compare it to the median taken from the last 12 months, for each market in the sample. Table 3.1 documents these results across the 31 different futures markets sampled in the previous chapter. The final column in Table 1 compares the ratio at the start of the sample period to the ratio at the end. Note the majority of markets have seen an increase in large speculation. Presuming the analogy between the COT and Alfarano et al. groups holds, this suggests the discriminatory power of the Alfarano et al. model is inadequate: if the concentration of large speculation increases for almost all futures markets, how can it be a source of idiosyncratic differences between markets?

In addition, a related observation of real-world markets is a broad increase in total open interest (the number of contracts outstanding in a market) over the sample period. As the second from right column in Table 3.1 documents, most of the financial markets surveyed have increased in the overall size of participation during the last 17 years, often quite dramatically. The Alfarano et al. model, as is the case with all other agent-based markets reviewed here, fails to account for this behaviour, postulating instead a constant number of traders, or tradable float, over time.

Participation levels in all financial markets change, as does the amount of floated product being traded. For example, public limited companies regularly buy-back or issue more stocks and shares; new interest-rate products and currencies are often issued by governments; and in the futures markets, the number of outstanding contracts (as measured by open interest) changes continuously. A model of a market unable to account for often dramatic changes in the size of participation and floating product, and the more recent trend towards heightened activity in many financial markets, is not adequately representing one of the most prominent observations of real-world markets.

Table 3.1 Comparison of Commercial to Large Speculator Activity and Open Interest

Market	12 Month Period Beginning	Median Open Interest	Median Ratio of Com to Large Spec Activity	12 Month Period Beginning	Median Open Interest	Median Ratio of Com to Large Spec Activity	Increased Open Interest?	Increased Speculation?
U.S. 30 year bond	15 January 1991	337229	0.82	09 January 2007	941732	0.76	TRUE	TRUE
U.S. 10 year note	15 January 1991	190585	0.91	09 January 2007	2542149	0.72	TRUE	TRUE
U.S. 5 year note	15 January 1991	126503	0.92	09 January 2007	1613462	0.75	TRUE	TRUE
U.S. 2 year note	15 September 1992	15431	0.94	09 January 2007	991318	0.72	TRUE	TRUE
Eurodollar	15 January 1991	1485629	0.93	09 January 2007	10595158	0.78	TRUE	TRUE
S&P500	16 September 1997	14162	0.23	09 January 2007	2000172	0.71	TRUE	FALSE
Nasdaq100	29 June 1999	17322	0.68	09 January 2007	568845	0.71	TRUE	FALSE
Dow Jones Industrials	21 May 2002	14763	0.64	09 January 2007	102444	0.51	TRUE	TRUE
Russell 2000	13 October 2002	6400	0.45	09 January 2007	421054	0.61	TRUE	FALSE
Corn	06 January 1998	332895	0.7	09 January 2007	1234082	0.63	TRUE	TRUE
Wheat	06 January 1998	117025.5	0.61	09 January 2007	405465	0.58	TRUE	TRUE
Soybean	06 January 1998	145371.5	0.67	09 January 2007	501872	0.61	TRUE	TRUE
Sugar no.11	15 January 1991	90233	0.87	09 January 2007	678454	0.7	TRUE	TRUE
Coffee	15 January 1991	58584	0.78	09 January 2007	158302	0.58	TRUE	TRUE
Cotton no.2	15 January 1991	40306	0.78	09 January 2007	214731	0.63	TRUE	TRUE
Live Cattle	15 January 1991	67723	0.65	09 January 2007	245789	0.55	TRUE	TRUE
Lean Hogs	02 April 1996	13269	0.41	09 January 2007	176941	0.54	TRUE	FALSE
Oats	06 January 1998	15820.5	0.77	09 January 2007	15245	0.74	FALSE	TRUE
Rough Rice	04 October 1994	2839	0.76	09 January 2007	16104	0.68	TRUE	TRUE
Cocoa	15 January 1991	56898	0.83	09 January 2007	148172	0.67	TRUE	TRUE
Gold	15 January 1991	106734	0.73	09 January 2007	394090	0.48	TRUE	TRUE
Silver	15 January 1991	76501	0.7	09 January 2007	117498	0.52	TRUE	TRUE
Copper	15 January 1991	45871	0.8	09 January 2007	77528	0.63	TRUE	TRUE
Platinum	15 January 1991	13733	0.72	09 January 2007	13881	0.56	TRUE	TRUE
Brent Crude	15 January 1991	317914	0.88	09 January 2007	1404428	0.66	TRUE	TRUE
Natural Gas	15 January 1991	71249	0.92	09 January 2007	773909	0.49	TRUE	TRUE
British Pound	15 January 1991	29628	0.75	09 January 2007	133035	0.55	TRUE	TRUE
Euro	15 January 1999	44090	0.68	09 January 2007	214561	0.56	TRUE	TRUE
Japanese Yen	15 January 1991	48995	0.69	09 January 2007	276995	0.63	TRUE	TRUE
Canadian Dollar	15 January 1991	25486	0.68	09 January 2007	140722	0.56	TRUE	TRUE
Swiss Franc	15 January 1991	42202	0.69	09 January 2007	83803	0.55	TRUE	TRUE

This particular criticism of the Alfarano et al. model, and other models reviewed here, relates to the argument of Gallegati, Keen, Lux, and Ormerod (2006) for whom econo-physicists (researchers with a background in physics involved in economics) are often pre-occupied with modelling systems where exchange is conserved. In certain physical systems, a finite quantity of energy or matter exists and moves around a system without being increased or decreased in aggregate. In contrast, real economic systems, such as financial markets, are typified by dissipation, growth and change. Gallegati et al. note the increase in real-world per capita income over the 20th century, and highlight that many econo-physicists have conserved wealth in their economic models in place of this crucial feature of real-world economic dynamics. The Alfarano et al. model also assumes conservation in the form of market participation: a finite number of traders change states between two groups. Although this is deliberate, to maintain simplicity in the model, and is by no means fatal to the overall approach, more behaviourally realistic theories must acknowledge the change and growth common to real-world economic systems and include these features in their modelling objectives.

A further criticism of the Alfarano et al. model is its failure to generate realistic measures of group trading behaviour. Such measures could enable more direct analogies to the real-world and therefore more falsifiable theoretical accounts. COT data documents long and short positions of groups, and not just a net-position or 'excess demand' as produced by noise traders (Figure 3.10). A related observation is that measures of buying and selling by groups of traders in real-markets may produce typical patterns of activity. These patterns of group behaviour are the subject of chapter 2 and can be targeted in market simulations alongside the more common objectives of generating realistic price characteristics. Although there are individual differences between markets, a broad pattern of group-specific trading behaviour is documented across a wide range of futures markets in the previous chapter, and may help to further constrain theoretical accounts of market behaviour.

Table 3.2 presents the slope coefficients and associated p-values from the time-series analysis for the Oil market, also presented in chapter 2, where changes in COT variables are regressed on concurrent changes in prices and significant lags of both COT variable and price. The analysis is carried out across a range of time-horizons to reveal consistent trading behaviour. Large speculators change in long and short positions is positively correlated with prices, whereas commercial traders are negatively correlated; a pattern of behaviour typical of a wide-range of markets.

Table 3.2 Oil Market, Group Trading Behaviour, Slope Coefficients and Significance at $p < 0.05$

Time Horizon	Commercial Short		Commercial Long		Speculator Short		Speculator Long	
	Slope Coefficient	P < 0.05	Slope Coefficient	P < 0.05	Slope Coefficient	P < 0.05	Slope Coefficient	P < 0.05
1 Week	0.30	*	-0.18	*	-1.49	*	1.84	*
2 Week	0.34	*	-0.17	*	-1.42	*	1.95	*
4 Week	0.29	*	-0.17	*	-1.2	*	1.67	*
8 Week	0.16	*	-0.13		-0.81		1.15	*

Although the Alfarano et al. model is parsimonious and succeeds in generating realistic price characteristics, the model fails as underlying dynamics are derived from theoretical notions of group behaviour that lack empirical foundations. The model does not aim explicitly to replicate the group categorisations provided in COT data, nor focus specifically on behavioural realism of groups of traders. However, it does make claims on how participants actually behave in financial markets, claims that underlie a theory of market behaviour and individual differences between markets.

If we assume the group categorisations in the Alfarano et al. model are not analogous to those documented in COT data, the model makes apparently unfalsifiable predictions. It is not feasible to assess how closely fundamental or noise trader group categorisations relate to real participants, or how changes in the relative dominance of these groups impact the market at any given moment in time. Alternatively, if the groups are a valid analogy to those in COT data, as the above analysis assumes, the model lacks discriminatory power and also fails. Alfarano et al.'s groups are simplifications, of course, permitting a parsimonious theory of how markets behave. But are these group categorisations the most valid and useful simplifying assumptions available? The answer to this question depends on the research being undertaken. But if the future agenda for agent-based models of financial markets is to be calibrated accurately for specific markets, and to be used in answering specific questions about specific scenarios that might be useful for practical objectives, behavioural realism must be achieved at a level higher.

3.9 Improving Behavioural Realism in Market Models

The underlying problem in fundamental and noise trader categorisations is a lack of empirical foundations. As discussed in section 3.5, typical groups relate to theoretical precedents rather than empirical evidence on how traders actually behave. This problem can be addressed directly with alternative group categorisation presented in COT data, which documents the historical trading record of three groups of financial traders, each with different business objectives: commercial, large speculator, and smaller (non-reportable) traders.

These groups are empirically grounded and relate to fundamental principles of financial markets, as discussed in chapter 1. This is presumably why the U.S. Government considers it pertinent to go to the considerable expense and effort to assemble daily trading positions of the three groups. It makes sense to align group categorisations used in market models with those that have direct real-world analogues. This would offer new and meaningful constraints on those developing theories on market behaviour, and additionally, making theories more directly applicable to the real-world.

However, the use of COT data for group categorisations in models of financial markets is not without its difficulties. Derivative markets are unique in that no underlying product is being vended. Stocks or bonds are not issued, nor currencies floated, rather, a derivative product explicitly relates to an underlying product – but it is derived. Derivatives are used in industrial settings by commercial traders, who produce and distribute products and therefore require derivatives to managing their cash-flow and risk. This activity by commercial traders does not necessarily extend to non-derivative markets, such as stock-markets, and would suggest that the group categorisations in COT data are limited in their application.

Whilst the group categorisations used in COT data do not apply ubiquitously, participants with different business objectives do operate in all markets. In stock markets, for example, it is possible to segregate participants in terms of their business goals; for example, there are companies issuing stocks to raise capital, market makers pursuing profits from small intra-day price changes, and pension funds investing large positions for dividend yields and returns that span many years. Each participant has unique objectives for being active in the marketplace and, in many cases, these objectives apply across a larger group. Although the specific COT data group categorisations do not apply universally, the broader dimension is universal: business objectives are important measures of trading behaviour that impact on groups of participants. COT data therefore offers a starting point for providing broad, yet empirical, categorisations that apply across a large number of participants.

To summarise, behavioural realism can be improved in agent-based models by ensuring simulated agents correspond more accurately to empirical evidence on actual market participants. Additionally, by ensuring detailed measures of trading activity for participant groups are generated, and reflect realistic patterns of trading behaviour (such as those documented in chapter 2), new and important constraints on theories of financial markets are provided. Furthermore, although of lesser relevance, models can increase their behavioural realism by allowing the overall size of a simulated market to fluctuate over time, to correspond to this characteristic of real-world markets.

3.10 Conclusion

This chapter has reviewed a number of agent-based models developed in the social sciences, noting necessary conditions and requirements that can apply to the modelling of financial markets. These include the existence of a large amount of non-arbitrary empirical data on a phenomenon, to assist in the development and evaluation of simulation results, and separately, adequately specified representations of the situational constraints and agent characteristics involved in a system.

On the first of these points, a substantial amount of historical price data is available for financial markets, although information on trader behaviour and market composition is much more limited. On the second point, whilst more recent modelling approaches incorporate realistic situational constraints associated with trading in financial markets (as reviewed in the following chapter), agent representations typically stem from theoretical rather than empirical precedents. This is a serious weakness associated with many approaches, such as the model developed by Alfarano et al. (2005) analysed in detail in this chapter. The inclusion of non-empirical trader representations as central theoretical components for many models can be associated with low levels of validity (LeBaron, 2000).

By utilising empirical sources on the behaviour of different groups of traders, however limited, and ensuring theories accurately represent the characteristics of different participants, new constraints on theoretical accounts and higher levels of realism can be achieved. An agent-based model with these objectives is proposed in the following chapter.

4. BEHAVIOURAL MODEL OF A FINANCIAL MARKET

Contents:

Abstract:

The agent-based model developed here proposes order-type preferences amongst groups of market participants with different business objectives. Commercial traders are considered less aggressive and therefore tend towards limit orders, buying as prices decline and selling as prices increase; speculators are considered more aggressive, utilise relatively more market orders and aggressive limit orders, trading in the direction of prices changes. These behavioural preferences, in the absence of deeper strategic considerations or a distinction between 'informed' or 'uninformed' decision-making, are sufficient to account for empirical regularities in trading behaviour identified in chapter 2. The market model presented here captures essential elements of the dynamics involved at two separate levels, the order-flow level and the level of group behaviour. In combination, the model offers a high level of behavioural realism and a powerful tool for exploring market dynamics.

“Market participants make decisions in an extremely complex environment, but in the end these decisions are reduced to the simple actions of placing and cancelling trading orders.”

Mike and Farmer (2008, p. 201)

"Models need to be judged by what they eliminate as much as by what they include -- like stone carving, the art is in removing what you do not need.”

Miller and Page (2007, p. 43)

4.1 Introduction

The late American economist, Robert Heilbroner (1999), believed that the study of economics has lost its way, and offered two objections to the current state of the discipline. Firstly, economics should be more socially aware, concerned with improving capitalism and moving towards a more responsible and sustainable society. This was, after all, the motivation of the 'worldly philosophers' that preceded modern-day academic economists. Secondly, Heilbroner rejects “the increasing tendency to envision economics as a science” (1999, p. 317). The concepts of volition, human consciousness, and individual free-will all separate human beings in economic systems from the unconscious well-behaved particles found in physical systems. The claim is that economics cannot be modelled as mechanical and deterministic, as physical systems can be, and many academics are in danger of “confusing economics with mathematics” (Nelson, 2004, p 211).

Heilbroner's criticism applies to the agent-based modelling of social economic systems reviewed in the previous chapter -- that pursue coherent explanations via computational simulations of agents and their interaction rules. However, as Nelson (2004) notes, recent scientific developments have moved away from the more deterministic, clock-work image that Heilbroner considered, towards a wider appreciation for randomness, interrelationships, and the fundamental role of unpredictability and adaptation in social systems (Miller and Page, 2007). This shift in thinking is well represented in agent-based modelling techniques that focus on interaction processes and collective emergent behaviour patterns. In keeping with Heilbroner's objective of moving towards more socially-aware economic research, agent-based models can also offer useful applications to real-world problems. Examples reviewed in the previous chapter include the

Sugarscape model of economic growth (Epstein and Axtell, 1996).

According to Ball (2004), Heilbroner overlooks a crucial aspect of social systems that permits meaningful scientific models to be constructed. In certain contexts, choices available to people are inherently constrained. That is: situations, economic or otherwise, may limit possible expressions of free-will, and the behaviour of a large number of people may inevitably converge. This does not neglect Heilbroner's original observation of the importance of human volition, but rather, places it within context. Free-will can, at times, be sufficiently bounded for useful modelling and theory building to take place. With this in mind, a plausible scientific study of social phenomena requires an associated appreciation for the impact of situational constraints on human behaviour. As reviewed in detail in the previous chapter, the particular form and consequences of situational constraints can often be effectively represented within agent-based models.

Research into traffic flows discussed in the previous chapter offers a useful example. Individuals driving cars on roads inevitably have very limited expressions of free-will; essentially they can change speed or change direction, and as a result, behaviour is similar across a large number of people. The behaviour of drivers also relate to similar objectives. Drivers typically occupy vehicles in order to arrive somewhere else; they wish to do so as quickly, safely and as comfortably as possible. Situational factors therefore give rise to meaningful agent-level representations, resulting in effective modelling of the collective behaviour involved (see literature review in previous chapter). A parallel exists in the study of human behaviour in many economic systems, where expressions of free-will may be constrained and objectives shared across a population.

This chapter continues with a review of research into the role of situational factors and its impact on economic behaviour. This is followed by a more detailed overview of the role of institutional constraints in financial markets and on traders' behaviour. Related models are discussed, and the Mike and Farmer (2008) simulation of a financial market is implemented. My own agent-based model presented in this chapter extends Mike and Farmer's and adheres to many of the suggestions put forward at the end of the previous chapter on how to achieve higher levels of behavioural realism. As discussed subsequently, I use this model to test a hypothesis developed in this chapter to account for the systematic group trading behaviour documented in chapter 2.

4.2 Situational Constraints on Economic Behaviour

Negatively inclined demand curves are an important theoretical component of many theories of economic behaviour. Household spending, for example, is considered to respond to changes in the relative prices of different products as demand for a given product is negatively related to its price. This simply states, as products get relatively cheaper we buy more, as they get more expensive we tend to buy less. Traditional economic theories assume economic agents respond to such changes in supply and demand as a result of rational, utility maximising behaviour. However, researchers have proposed that assumptions on rationality may not be required for such economic theories to retain their explanatory power. In contrast, literature reviewed in this current section argues that situational factors alone can play an important role in observed economic behaviour, due to changes in the opportunity set or the options available for an economic agent.

Becker (1962) shows negatively-inclined demand curves can persist even if agents behave irrationally. If household spending is limited to products costing no more than available income, a change in relative prices will impact on the distribution of products available. For Becker, across a large number of households, the average product chosen must tend towards the centre of the distribution of products-by-cost available. Even if the sampling of products were done randomly, or 'irrationally', this overall aggregate outcome would still be similar to that predicted by the existence of rational agents: it would tend towards the centre of the distribution of available options, resulting in a systematic aggregate response in household spending. Becker demonstrated theoretically how a change in the opportunity set associated with the situation can have an important impact on behaviour regardless of the decision-making rule being employed.

Gode and Sunder (1993) empirically demonstrate similar findings. A traditional view held by economists is that competitive markets lead to allocative efficiency, where available gains from trade are fully exhausted (Hayek, 1945; 1968). This competition is associated with individuals using information in an intelligent way, and the aggregation of all this rational behaviour leading to effective market responses. However, as Gode and Sunder (1993) demonstrate, a market can sustain high levels of allocative efficiency even if agents do not seek profits or deliberately maximise their utility.

Gode and Sunder explore continuous double-auction markets – where buyers submit bids and sellers submit offers simultaneously – in an experimental setting. A market can be composed of different participants: 1) profit-motivated graduate students, 2) zero intelligence computer programs, or agents, submitting random bids and offers (independent and identically distributed across a range of prices), and 3) zero-intelligence agents with budget constraints, that is, unable to submit a bid above redemption value or an offer below cost. The allocative efficiency of experimental markets is measured as total profits earned by traders divided by the maximum total profit that could have been earned (sum of producer and consumer surplus). Experiments with these different participants demonstrate that a market composed of the third category, zero-intelligence agents restricted to prices that satisfy a no-loss constraint, is almost indistinguishable in terms of efficiency from markets with human agents. For Gode and Sunder, access to information and sophisticated decision-making is not essential; as Beckers (1962) also observed, the narrowing of an opportunity set alone can result in rational market responses.

Gode and Sunder test the convergence of experimental markets to equilibrium prices, as defined by the intersection of a market's supply and demand curves. With budget-constrained zero-intelligence agents, prices converge almost as precisely to equilibrium as a market composed of human, profit-maximising traders. Gode and Sunder relate these counter-intuitive findings to the structure of a double-auction market, noting the powerful constraining force it exerts on individual behaviour. Sunder (2003) describes the efficiency of a double auction markets as primarily a function of two rules: 1) traders abiding with their proposals (that is, their bids and offers), and 2) priority for proposals being disadvantageous to their originators: higher bids and lower asks increase the probability of trading but are disadvantageous to the trader initiating the order. For Sunder, some features of market outcomes are therefore robust to the decision-making rules of agents; sophistication and access to information may not be necessary for aggregate outcomes, such as equilibrium prices and allocative efficiency, to approach optimal levels.

For Gjerstad and Shachat (2007), however, such claims are too onerous: the behaviour of budget-constrained zero-intelligence agents can be considered as very similar to individual rationality. If agents do not place any orders that directly result in a negative pay-off, this is a form of deliberate intelligence and reasoning. Othman (2008) agrees that budget constraints, for all intents and purposes, are equivalent to rationality, but suggests Gode et al.'s research still highlights the value of what should be considered as a new approach to economics. Zero-intelligence agents, or rather, 'zero-intelligence-plus' agents (e.g. Cliff and Bruten, 1997) have restricted attributes of intelligent behaviour, and can therefore provide important insights where other approaches are unable to do so. If realistic models of economic situations involving such agents differ from the real-world, these differences inevitably relate to what is lacking in the agent's cognitive or behavioural repertoire, such as human reasoning, learning, and developing strategies (Othman, 2008). As Othman notes, human agents can only act in ways that are general restrictions of the random behaviour of zero-intelligence agents, and, therefore, this provides a benchmark, or null hypothesis, for the role of different features in economic behaviour.

For Othman, more heavily descriptive models, for example, where financial traders are classified as fundamentalists or chartists, proceed without a clear null-hypothesis. These typical groupings of market participants are considered behaviourally realistic from the onset, and therefore meaningful a priori, but it is unclear what market behaviour would exist without such descriptive features and relatively detailed decision-making rules. The alternative, zero-intelligence approach to economics enables researchers to quantify the impact of different theoretical components and build more gradually towards theories that inevitably have stronger validity.

Farmer, Patelli, and Zovko (2005) also advocate the zero-intelligence, or rather 'low-intelligence' approach to studying specifically financial markets, proposing that research be divided into two parts. Firstly, the characteristics of markets that result from situational constraints, such as the nature of order placement and order flow in financial markets, must be understood as a foundational for further research; and separately, descriptions of agent behaviour, such as their strategic considerations and interactions, can be considered. This is in contrast to the traditional economic approach that involves working downwards from canonical assumptions of human behaviour and rational decision-making, towards institutional and situational considerations. For Farmer et al., these situational factors must come first. The following section of this chapter reviews how situational factors can restrict trading behaviour in financial markets, where the term 'situational constraints' relates to the environment in which individuals or organisations operate, which includes market institutions and exchange rules.

4.3 Situational Constraints in Financial Markets

Chapter 1 and 2 document how different organisations may have different objectives for participating in financial markets. For example, in derivative markets, commercial traders are involved in order to hedge exposure to underlying markets where they have business dealings. Speculators, in contrast, are involved to anticipate and profit directly from price changes in the derivative market. These objectives relate to different institutional constraints placed upon the dealing behaviour of different agents, and these constraints can lead to very different trading behaviour, as demonstrated empirically in chapter 2.

Business objectives may impact on trading behaviour more generally, however, when applied to other group categorisations apart from commercial and speculative traders. Peters (1994) supports this proposition, suggesting market participants typically have different time-horizons for their trades. These different time-horizons may also correspond to institutional constraints placed on trading behaviour. For example, pension-funds often hold positions in financial markets for long periods of time. This relates to the size of their investment pools and the associated high transaction costs involved in changing positions. In contrast, market makers provide liquidity to markets and are therefore involved in markets over intra-day time-horizons, profiting from small spread between bid and offer prices; they are trading much more frequently and with less trading size than pension funds. Peters argues that heterogeneous objectives and trading characteristics must be represented in financial markets for liquidity and price stability to be present – and are therefore crucial to the healthy functioning of markets. This subject is discussed in detail in the following chapter.

In addition to the constraints arising within business organisations, exchange protocols also introduce important situational constraints relevant for understanding economic behaviour. Modern financial markets mostly operate as a continuous double auction where buyers and sellers can submit two basic kinds of orders. Impatient traders submit market orders, to buy or sell immediately at the best available price, whereas more patient traders submit limit orders, bids to buy or offers to sell at a given stated price. Often limit orders do not result in a quick transaction and are therefore stored in a queuing system known as the limit order book until transacted or cancelled. Market orders to buy are transacted against limit orders to sell, whereas market orders to sell transact against limit orders to buy. There are typically other sub-types available, such as stop-loss orders, but, for all intents and purposes, all order-types can be considered fundamentally similar to either market or limit orders. This distinction between order-types is directly relevant for the hypothesis developed in this chapter to account for the patterns of trading behaviour identified in chapter 2.

From a general agent-based modelling perspective, traders in financial markets are restricted to either buying, selling, or doing nothing. (This level of situational constraint parallels the constraints of individuals driving in cars, for example, as reviewed previously: there are a very limited number of available expressions of individual free-will.) From a more precise perspective, however, the trading behaviour of agents in financial markets can be viewed in relation to the institutional constraints associated with their business objectives. Participants' behaviour varies in terms of the order quantity of a trade, which relates systematically to institutional constraints associated with particular trading organisations. For example, pension funds will trade much larger positions (and typically hold those positions for longer) than market makers. Participants' behaviour also varies in terms of selecting different order-types, that is, either market or limit orders – a choice, as the following literature review demonstrates, that is also related to their trading organisations.

The theory developed here builds on the relationship between institutional constraints and order-type preferences to account for the empirical findings on traders' behaviour presented in chapter 2. Before outlining this hypothesis in more detail, the following section reviews existing research that considers a wider range of factors that impact the traders' choice of market or limit orders.

4.4 Choice Between Market or Limit Order

The choice of order-type inevitably corresponds to a trade-off between immediacy of execution (and the use of a market order) and improving execution price (and the use of a limit order). Traders can choose to place limit orders and supply liquidity (or 'depth') to the market, or place market orders and consume liquidity. Parlour (1998) shows the probabilities involved in this trade-off relates fundamentally to the existing market depth (or number of limit orders held) on either side of the limit order book. An increase in buy-side market depth reduces the probability of a new buy-side limit order being executed, and vice versa for sell-side orders; which, in turn, encourages an incoming trader to submit a market order. Therefore, an increase in buy-side market depth also makes limit orders to sell more attractive, as a market order in the opposite direction is more likely, and vice-versa. A positive relationship between increases in limit order book depth and increases in the use of market orders is supported empirically (Griffiths, Smith, Turnbull, and White, 2000; Ranaldo, 2004; Hall and Hautsch, 2006; Duong, Kalev, and Krishnamurti, 2009).

An area explored further in the following chapter is the relationship between market price volatility and the choice between market or limit orders. Foucault (1999) suggests higher volatility increases the probability of limit orders becoming executed at an unfavourable price. The appropriateness of a particular limit order price may change as prices fluctuate, but, due to the costs of monitoring the market, the limit order price is not adjusted and gets 'picked-off' unfavourably during more volatile periods. For Foucault, when price volatility is high, traders placing limit orders will therefore demand a higher pay-off for the increased risk of being 'picked-off', and will place more limit orders relative to market orders (as limit orders provide more competitively prices). This theory is also supported empirically (Bae, Jang and Park, 2003; Ranaldo, 2004; Beber and Caglio, 2005).

The time of day may also affect the choice of limit or market orders. Harris (1998) proposes informed traders become more aggressive as the trading day progresses as a result of the potential for information to be more publicly available at the end of the trading day. This finding is supported by Bae et al. (2003) and Anand, Sugato, and Terrence (2005) who find institutional traders on the New York Stock Exchange are less likely to submit limit orders when there is little time left until the market closes. Duong, Kalev, and Krishnamurti (2009) document time-of-the-day effects as they relate to different groups of market participants. Institutional investors, who are considered better informed, use more aggressive orders in the opening hour of the trading day, whereas individual, or 'retail' investors are found to use more limit orders at the start of the day and increase order aggressiveness during the day. These results are interpreted to support Harris's hypothesis, that the wider dissemination of information throughout the day encourages an increasing use of aggressive orders amongst retail traders.

Other possible influences reviewed in the literature include the size of the spread between the best bid and best offer (known simply as the 'spread' in finance parlance). Limit orders are found to increase when spreads are high, reflecting the decreased attractiveness of market orders (Biasis, Hillion, Spatt, 1995; Chung, and Van Ness, 1999; Foucault, 1999; Duong et al. 2009). The size of the order may also be a contributing factor. Bae et al. (2003) analyse a proprietary NYSE dataset and find traders are more than twice as likely to submit a large order as a limit order rather than a market order. As Zovko and Farmer (2002) propose, the choice of order-type may relate to the time-horizon of the trading strategy being employed; larger traders are obliged to trade longer time-horizons and therefore pursue the use of more patient, limit orders. This returns us to the relationship between order-types and the business objectives associated with particular types of traders; a number of empirical studies demonstrate how institutions with particular trading approaches have different order-type preferences.

Kein and Madhavan (1995) analyse a large number of equity trades made by different institutions during the period from 1991 to 1993, the total market value of which was \$83billion. There is considerable heterogeneity across the sampled institutions, including investment managers, index funds and pension funds. These institutions are broadly categorised into three groups according to their trading strategies: 1) value-based investing (considered as using fundamental information); 2) technical or momentum strategies (considered as relying on chartist information and also, possibly, fundamental information); and 3) index strategies (who mimic the behaviour of a benchmark index). Kein and Madhavan find order-type preference strongly link to group categories, proposing more active managers, such as momentum and index traders, trade on information that is short-lived and therefore prefer to use market orders to assure quick execution. In contrast, value managers trading on the basis of longer-term information tend to have longer-term trade durations and use more limit orders. These managers also trade larger positions, where the negative price impact for using market orders would outweigh the opportunity costs associated with non-execution.

Similar findings are identified in a study by Aitken, Almeida, Harris, and McInish (2007) on limit orders held by various brokers in Australia. Institutions who trade through the brokers are grouped into two categorises: 1) proprietary trading desks and hedge funds (PTDH), and 2) mutual funds, index funds and insurance companies (MII). The study does not focus on the use of market orders or limit orders by either group, but, rather, on the level of aggressiveness in the use of limit orders, where the relative distance of the limit order price from the best bid or best offer at time of placement provides a measure of order aggressiveness. The dataset compiles the dealings of a number of brokers and provides a unique snapshot of limit orders held by each group of market participants every 20 minutes during the trading day, over the period from

January 2001 to June 2002. As with Kein and Madhavan, Aiken et al. find the level of aggressive order placement relates systematically to the type of institution. PTDH are more aggressive than MII, typically placing limit orders at, or closer to, the best bid and offer. Aitken et al. relate this finding to a model developed by Handa, Schwartz, and Tiwari (2003) that considers order-types in relation to the opportunity cost of non-execution. Active and passive institutional trading differs in the perceived cost of non-execution, and, therefore, leads to a consistent choice in the use of either market or limit orders.

This conclusion is also supported by qualitative evidence cited by Aitken et al. on how brokerage commission varies between the two groups examined. PTDH typically only pay 0.02-0.1 percent of the notional value of the trades being executed in commission, whereas PTDHs typically pay a higher 0.15-0.35 percent. This apparently reflects different levels of brokerage service. MIIs require minimal intra-day contact with brokers, typically relying on end-of-day benchmarks to evaluate the effectiveness of order entries. In contrast, PTDHs are “high service intensity clients” (2007, p. 154), requiring continual updates on the state of the market and access to order flow information not available to the wider marketplace; that is, details of the 'flow' of other trades going through the same broker. The two groups of institutions clearly have very different approaches to participating in the markets: the PTDH group profits by continuously monitoring the market and exploiting relatively fleeting real-time information based on market liquidity, news flow, and analysts' opinions; MIIs have longer time-horizons, and therefore, require less active order entry strategies.

The study by Aitken et al. suggests order-type preferences should not be considered as a strict, binary choice between market or limit orders, but rather, participants should be viewed on a continuum of order aggression. Certain participants will tend to be less aggressive, relying on limit orders that are not necessarily close to the current market prices, other participants will be much more aggressive, placing limit orders at the current market price and using market orders more heavily. The findings of Kein and Madhavan (1995) and similar findings over 10 years later by Aiken et al. (2007) support a proposition that such preferences are relatively stable behavioural traits of different groups of traders. These characteristics can be seen as fundamentally related to institutions and their associated business objectives. From a modelling perspective, whilst market participants can either buy, sell, or do nothing, participant behaviour can also be characterised by the choice of order-type, or rather, the level of aggression associated with orders. This characteristic can be considered linked to other dimensions of participant behaviour, such as the position-size and time-horizon of trades, in a relatively stable way.

4.5 Hypothesis of Group Order-Type Preferences

Institutional order-type preferences may relate to the patterns of group behaviour identified in COT data and outlined in chapter 2. To recap, COT data documents the long and short positions of large speculators, commercial traders, and smaller, non-reportable traders in U.S. futures markets. A very clear pattern of trading behaviour is identified in historic COT data and analysed in a variety of ways in chapter 2: speculators tend to increase long positions and reduce short positions during rising prices (that is, they increase their buying), whereas commercial traders increase short positions and reduce long positions during rising prices (or increase their selling). The reverse pattern of activity in both groups is typically found during declining prices. As documented in chapter 2, this trading activity is statistically significant across a range of tests, identified in a cross-section of markets and over an extended period of time. These findings suggest relatively stable and enduring underlying behavioural dynamics for many markets.

A typical economic account for these empirical findings would do so in terms of strategic or informational differences between groups of commercial traders and speculators. For example, Keynes (1930) proposed that commercial traders require futures markets to transfer risks and therefore effectively pay speculators a risk-premium for taking the other side of their trades. This proposed division of labour between the groups of participants could account for findings of asymmetric trading behaviour, but crucially, does not provide insight into the particular form or consistency of the trading behaviour observed. Theories of noise and positive feedback trading (e.g. Black, 1986; Shleifer and Summers, 1990) may offer a stronger account, suggesting that certain trading styles involve extrapolating past prices to predict future prices, and can therefore explain the tendency of certain groups to trade in the direction of price changes (for example, where speculators buy more as prices rise). Theories of noise and positive feedback trading also suggest particular groups may be more informed than others and therefore different types of traders can behave very differently. As demonstrated in chapter 3, however, theories involving a division of participants into uniformed and uninformed traders and informed traders may not adequately represent group-level dynamics in real-markets; and, whilst these typical economic accounts are clearly valid considerations, the degree of consistency in group behaviour argues for a more precise, behaviourally-orientated explanation.

Wang (2003) proposes that high levels of coherence in group trading behaviour corresponds to herding, where, as a group, certain participants tend to trade in the same direction over a lengthy period of time. Whilst studies support the role of herding in financial markets (e.g. Grinblatt, Titman, and Wermers, 1995; Irwin and Yoshimaru, 1999), this explanation neglects the observation that all groups in COT data typically have substantial long *and* short positions; that is, individual participants within each group have very different views on market direction. Directly opposing positions within a group suggests herding behaviour alone cannot account for the findings reported in chapter 2.

A more parsimonious explanation for the empirical results is provided by relating patterns of trading behaviour to order-type preferences. Whilst order preferences may possibly relate to strategic and informational differences, the related economic theories may not be required to account for the empirical results described in chapter 2. As Mike and Farmer (2008, p. 231) highlight, "going all the way from strategic motivations to prices is a much bigger step than moving from strategic motivations to regularities in order flow". That is, rather than trying to immediately derive a model based on strategic motivations, one can "empirically characterise behavioural regularities in the order flow and work backwards to understand the strategic motivations that give to the regularities in the first place". The following section of the chapter follows this recommendation by extending an agent-based model developed by Mike and Farmer. This model, described further in the following sections, is extended in order to test a hypothesis of order-type preferences amongst commercial and speculative traders. I propose that commercial traders tend to be less aggressive, using more limit orders, whilst speculators tend to be more aggressive, relying on more market orders, and that these simple preferences are powerful enough to account for the findings identified in chapter 2.

The following example helps to clarify this hypothesis. During rising prices, a tendency for limit orders to be held by commercial traders would result in more selling activity by commercials as prices trades higher; that is, prices rise into limit orders to sell, resulting in commercial traders increasing their short positions and decreasing long positions (depending on the original position being held). On the other side of the market, buyers using market orders or more aggressive limit orders (for example, adding more orders to the current bid price) cause prices to move higher; speculators initiating these trades would increase long positions and decrease short positions. In other words, speculators may trade more aggressively in the direction of price changes, whereas commercials are more passive, trading with limit orders against the direction of price changes. These order-type preferences may relate to different information sets, trading time-horizons, and overall strategic approaches; but, to para-phrase Mike and Farmer, investigating these more theoretical considerations of different strategies or information sets amongst groups of traders is made more concrete and plausible by first identifying behavioural differences between groups.

With this hypothesis of order-type preferences, large speculators reported in COT data can be considered analogous to the group of proprietary trading desks and hedge funds documented in Aitken et al. (2007), or, alternatively, institutions operating with momentum-orientated strategies as identified in Kein and Madhavan (1995). Both these group categorisations encompass institutions involved in markets in order to profit directly from price changes, including investment managers, hedge funds and proprietary trading desks – and both these studies find a preference for relatively aggressive order-types amongst these traders. These participants may use shorter-term information to make trading decisions associated with a high opportunity cost of non-execution and therefore make use of market orders or more aggressive limit orders (Handa et al., 2003). In contrast, commercial traders may be analogous to more value-orientated trading approaches (Kein et al., 1995) typical of mutual funds and insurance companies (Aitken et al., 2007), relying on longer-term information to make trading decisions where the value of the information decays relatively slowly. This information may relate to the production or distribution of commodities that commercial traders are typically involved in and relate to the hedging of relatively long-term risk exposures. These participants therefore have lower concern for 'picking-off' risk (Foucault, 1999) and the active monitoring of orders (Aitken et al., 2007) as they are trading larger, longer-term positions.

This hypothesis can be tested more formally via an agent-based simulation. The Mike and Farmer model introduced in the following section is well-suited for this experiment. The approach distinguishes between different order-types (market and limit) and is considered a 'behavioural' model. It is empirically derived from historical data to represent accurately the flow of orders in a continuous double auction of a typical financial market. By simulating the interaction of market and limit orders, the model uniquely reproduces many of the statistical properties of real prices, including the distribution of returns, the absolute level of volatility, and characteristics of the spread. The approach is also considered a 'zero-intelligence' model; buying and selling is simulated as a stochastic process with no underlying strategic or informational considerations on behalf of the agents. In the following section I extend on this zero-intelligence to include different types of traders with systematic order-type preferences and record details of their long and short positions over time. Trading is still driven by the same stochastic process as Mike and Farmer develop, but group-specific order preferences are also introduced. In this controlled environment, it is possible to assess whether, with no deeper strategic or informational considerations provided, order preferences in isolation are sufficient to account for the identified regularities in trading behaviour.

The remainder of this chapter proceeds as follows. Background research on the statistical characteristics of limit orders books is briefly reviewed, and the Mike-Farmer model and its implementation are discussed in more detail. My extension of this model is described, followed by results from the experiment testing the importance of group-specific order preferences. The chapter ends by discussing the implications of these results and potential applications to practical problems – a subject that is developed further in the following chapter of this thesis.

4.6 Mike and Farmer's (2008) Model

Chapter 1 reviewed empirical evidence on the statistical characteristics of market prices, where similar features are identified across a range of markets and time-periods. Research into the characteristics of the order flow involved in financial markets (that is, the placement and cancellation of orders) also reveals important consistencies. A crucial finding is that even the most liquid financial markets are, actually, not as liquid as one might imagine. The volume of buy or sell limit orders held in an order book at any point in time varies considerably, but is consistently small, often in the region of only 1% of the daily traded volume. For a stock, this may represent only a very small percentage of its total capitalisation. The limited available liquidity has important implications for the behaviour of traders – as the following describes in more detail.

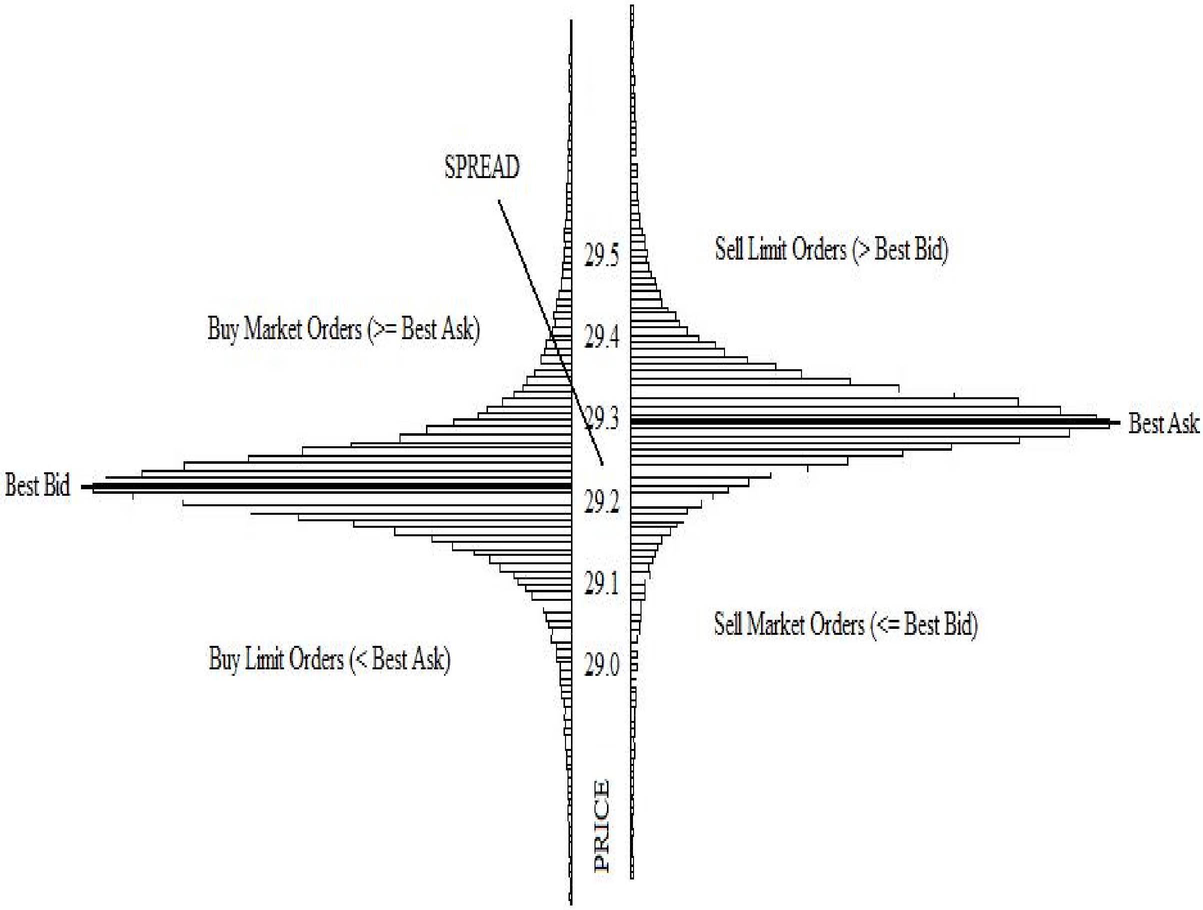
It is a well established fact that price returns are essentially uncorrelated over time (a finding typically associated with market 'efficiency' in the literature). However, more recent research identifies that order signs have a surprisingly high-level of autocorrelation; where the sign of an order corresponds to its status as either a buy or a sell order. Bouchaud, Gefen, Potters, and Wyart (2004) and Lillo and Farmer (2004) find evidence that the sign of an order has non-random levels of autocorrelation for periods as long as weeks into the future. Due to the limited liquidity available in a market at any given time, even fairly small orders must be broken up into smaller sub-orders. Therefore, large orders may take many days to get completed, and buy and sell orders have high levels of long-run dependence. For Lillo and Farmer (2005), the fact that market prices are not as predictable as order signs highlights the importance of limit order book dynamics in determining market prices: markets must continuously adjust other properties, such as the placement and cancellation of limit orders, to prevent price changes becoming correlated over time. These order book dynamics are a focus in the Mike-Farmer model and are modelled empirically to identify some other surprising regularity.

Mike and Farmer analyse the stock Astra-Zeneca during the period May 2000 to December 2002, where the high-frequency data includes tens of millions of trading orders and prices that allow the state of the market at each moment in time to be re-constructed. Analysis of this dataset identifies the frequency distribution for the placement of orders relative to the best corresponding price (the best bid for buy orders or best ask for sell orders) is well-described by a power-law. This finding is supported by previous research using historic data from the London Stock Exchange (Zovko and Farmer, 2002) and the Paris Bourse (Bouchaud, Mezard, and Potters, 2002), respectively. Zovko et al. finds a power-law with exponent of -1.5 describes the frequency with which orders are placed relative to the corresponding best price for stocks traded in London, whereas Bouchaud et al. find an exponent of -0.8 captures for placement of limit orders in Paris. As Zovko et al. proclaim, even for the placement of limit orders, "striking regularity can emerge when human beings are confronted with a complicated decision problem" (2002, p. 392).

The Mike-Farmer model uses the Student distribution, or t-distribution as it is often referred, to represent this finding as this distribution has a power-law tail. More specifically, the model involves sampling x from a Student distribution, parametrised to fit a particular market, in order to simulate the log price for a new order relative to the best corresponding price (best bid for buy orders, best ask for sell orders). For buy orders, the new price is the best bid + x, and for sell orders, the relative price is best ask – x. This process is easiest to conceptualise via two separate distributions corresponding to the buy-side and sell-side. Figure 4.1 demonstrates the centre point of a distribution aligned to the best bid and a separate distribution aligned to the best ask. The centre of the Student distribution is therefore equal to where the frequency of order-placement is highest.

New orders are sampled either side of centre and correspond to either a new limit order (if less than the asking price for a buy; or greater than the bidding price for a sell) or a new market order (if greater or equal to asking price for a buy; less than or equal to bidding price for a sell). Note the power-law tail results in a non-zero probability that new limit orders can be placed a substantial distance away from the current market prices – this is consistent with the empirical findings. The Mike-Farmer model therefore draws both limit and market orders from the same distribution.

Figure 4.1 Schematic of Mike-Farmer Method for Determining the Relative Price of New Orders



This method for simulating order placement captures important empirical features of the spread (between best bid price and best ask price) found in real markets. For example, when the spread is wide, simulated orders chosen at random are more likely to fall within the spread and less market orders are likely to be placed (Foucault, 1999). Also, when the spread is smaller, market orders become more likely – a process that helps to preserve stability in the number of orders accumulating in the order book (Bouchard, Farmer, and Lillo, 2009). Other statistical properties of the spread not directly modelled in the Mike-Farmer approach include a fat-tailed distribution and time correlations consistent with a long-memory process (Plerou et al., 2005; Gu, Chen and Zhou, 2007).

A final component to the Mike-Farmer model is the cancellation of limit orders, which is found to relate to a number of internal variables, including the total number of orders in the book, the imbalance in the order book between buy and sell orders, and the position of the order relative to the current opposite best price. The functional relationship between these variables described by Mike and Farmer effectively captures the increasing probability of a limit order being cancelled when it is further away from the current opposite best price, and the increasing probability of an order being cancelled when it is competing with more limit orders on the same side of the book (e.g. Duong, Kalev, and Krishnamurti, 2009).

The Mike-Farmer model follows a long lineage of previous research into the statistical modelling of financial market order flow. Approaches that precede Mike and Farmer (2008) include Bouchaud, Mezard, and Potters (2002); Challet and Stinchcombe, (2001); Daniels, Farmer, Gillemot, Iori, and Smith (2003); Chiarella and Iori, (2002); and Smith, Doyne, Gillemot and Krishnamurthy, (2003). The Mike-Farmer model is most closely related to Daniels et al. (2003), where the placement of limit orders, the placement of market orders, and the cancellation of limit orders are modelled as independent Poission processes. Farmer, Patelli, and Zovko (2005) test Daniel et al.'s model against real historical data and find, despite the zero-intelligence of the approach, it accurately predicts 96% of the spread variance and 76% of the variance for the price diffusion rate (the impact of market orders on prices) for a range of stocks. In line with the conclusions of Gode and Sunder (1993), Farmer et al. suggest that this finding highlights the important role of the statistical mechanics involved in the continuous double auction, in contrast to intelligent or conditional agent behaviour.

Mike and Farmer's (2008) approach relates closely to Daniel et al., but each component is modified further based on an empirical analysis of a particular stock, Astra Zeneca, traded on the London Stock Exchange. Based on this analysis, Mike and Farmer (2008) apply their model to a number of other markets (with similar tick sizes) and find the captured dynamics to be broadly representative. The degree of correspondence between unseen market data and the model provides strong evidence of consistent relationships between simple components of the order-flow in financial markets and more complex, or emergent features, such as levels of price volatility. (The model remains to be extended for other markets with different tick sizes where the functional relationships do not hold so accurately.) In terms of its relatively simple yet empirical orientation, and the array of different statistical characteristics represented, the model can be considered as amongst the most accurate simulations of a financial market currently available (Bouchard, Farmer, and Lillo, 2009).

The process involved in the Mike-Farmer simulation is now described in more detail. Each time-step in the simulation corresponds to the generation of a new order. An initial order sign is generated from a fractional Gaussian process (e.g. Beran, 1994) that represents the long-run dependence found empirically in order signs for both limit and market orders; the sign of the resulting random numbers corresponds to either a buy (1) or a sell (-1). The signed order is then allocated a relative price, and, as described above, determined as a limit order and placed relative to the corresponding best price, or a market order and traded immediately at the opposite best price. This relative price is rounded to represent a tick integer price and recorded as either a new limit order or as a transaction (market order) with an associated price.

During each time-step, multiple limit orders can be cancelled based on a function (see Mike and Farmer, p. 219, Equation 4) relating the number of orders in the book, the imbalance between buy and sell limit orders, and the position of the order relative to the current opposite best price (updated every time-step). This feedback between order book variables and the cancellation of limit orders is fundamental for the model to create realistic market behaviour. As identified in Farmer et al. (2004), gaps between limit orders relate closely to the volatility of market prices, as transacted prices jump between available limit orders. This interplay between new limit orders and the cancellation of existing limit orders is central to how prices evolve and represented accurately in the model.

Based on Mike and Farmer implementation, the volume of each order (limit and market orders) is held constant, this relates to the observation that the volume of orders does not materially impact on the order book dynamics (Bouchard, Farmer, and Lillo, 2009). Additionally, an ad hoc constraint is introduced: a minimum number of limit orders must be held in the order book before market orders or limit order cancellations can occur. This requirement ensures a relatively consistent price series, but, as acknowledged by Mike and Farmer, it highlights the failure of the model to capture all the dynamics involved in the order-flow – the model remains a highly simplified representation. Figure 4.2 provides a plot of a typical simulation over 100,000 time steps (or new order generations, that is, new market and limit orders) and Figure 4.3 offers a snap shot of the limit order book at the end of this simulation. The parameters employed here are for the default Astra Zeneca model described in the original text (see Mike and Farmer, 2008, p. 220, Table 2).

Figure 4.2 Simulated Prices from Mike and Farmer (2008)

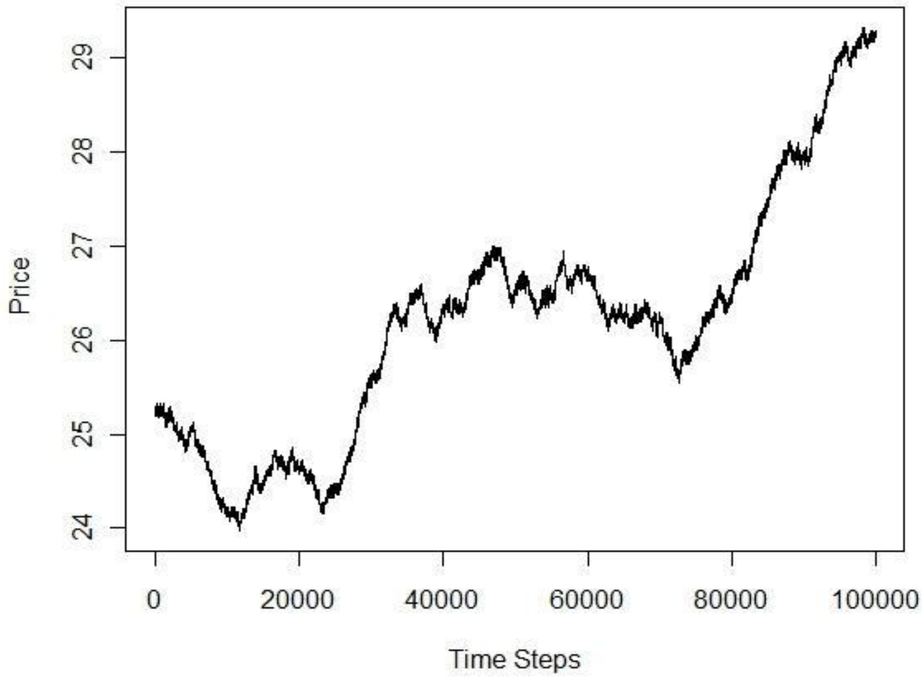
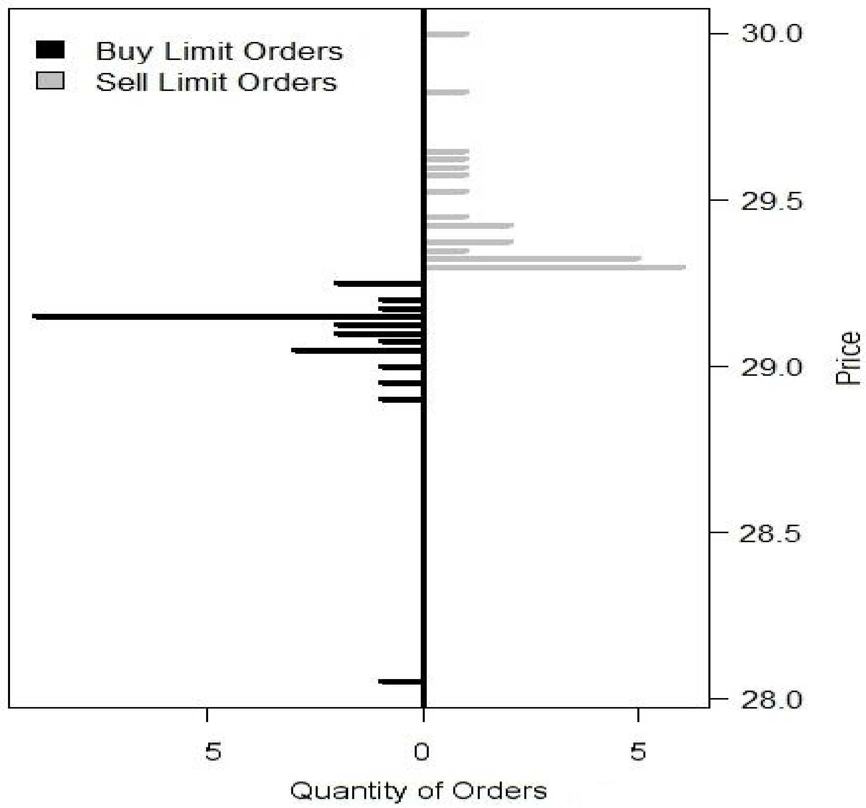


Figure 4.3 Snap shot of Simulated Limit Order Book



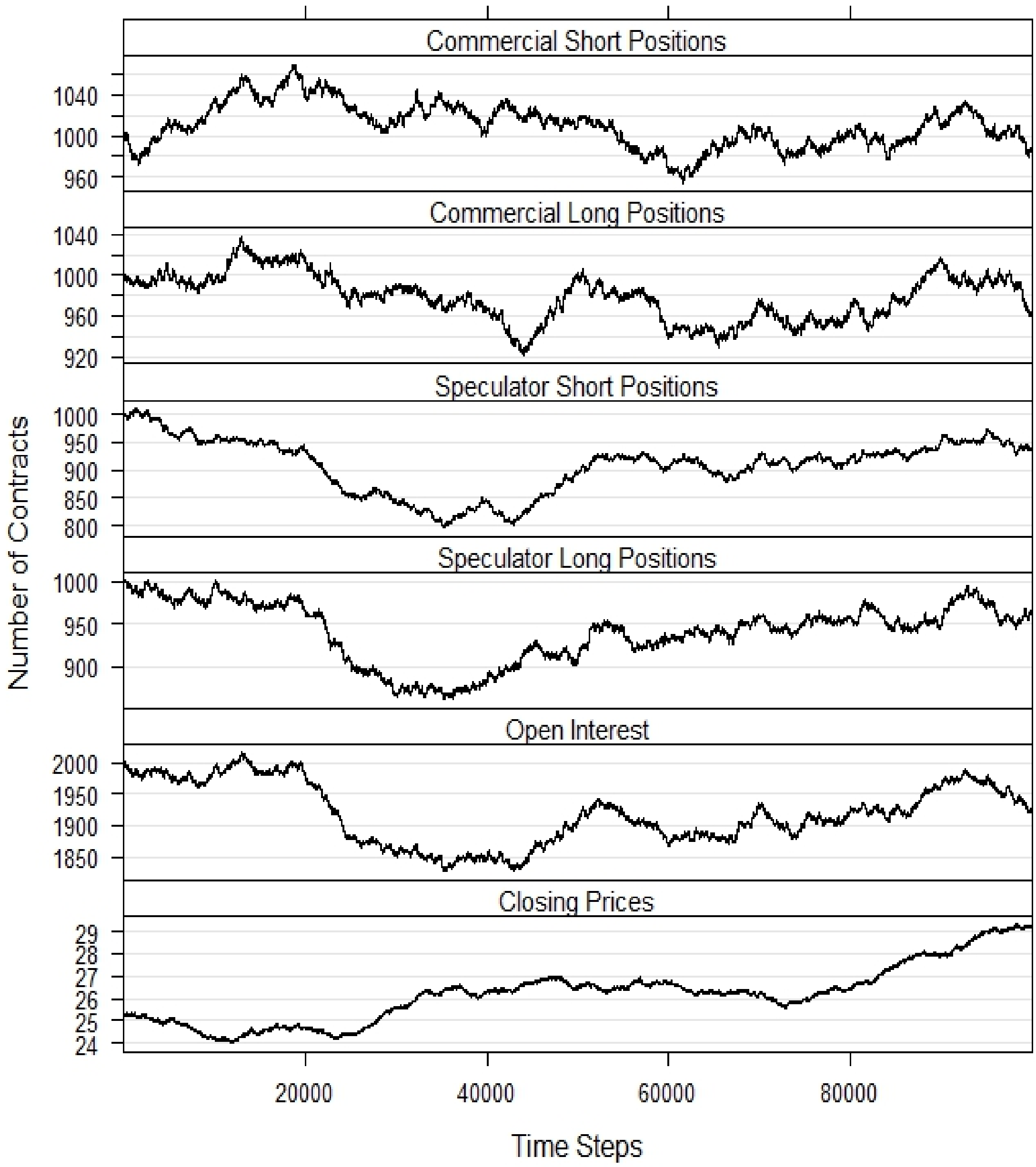
4.7 Extending the Mike-Farmer Model

Chapter 3 reviewed possible ways of improving the behavioural realism in financial market simulations and agent-based models. This included, crucially, agents that correspond more closely to empirical data on actual participants and their trading behaviour. To facilitate this, models can ensure measures of trading activity for different participants are produced, namely, changes in long and short positions over time. Based on these measures, group behaviour patterns can also be reproduced, such as those identified in chapter 2. Furthermore, the overall size of the market can be permitted to fluctuate over time to correspond to this ubiquitous characteristic of real-world markets. These additions can introduce new and important constraints on existing theories of financial markets and move newer models towards higher levels of validity.

The Mike-Farmer model is extended here to accommodate these recommendations, incorporating different types of traders and their associated long and short positions over time. In the simplest version of the extended model, 2 groups of traders are included to correspond to commercials and speculators as reported in COT data and documented in chapter 2. An initial arbitrary long and short open interest of 1000 contracts is allocated to each group. As with real-markets, the total long and short open interest must be equal at all times, representing the total open interest in the market (1000 contracts in this case). As described subsequently, the simulated measures of long and short positions also vary over time as the different types of traders buy and sell in the simulation.

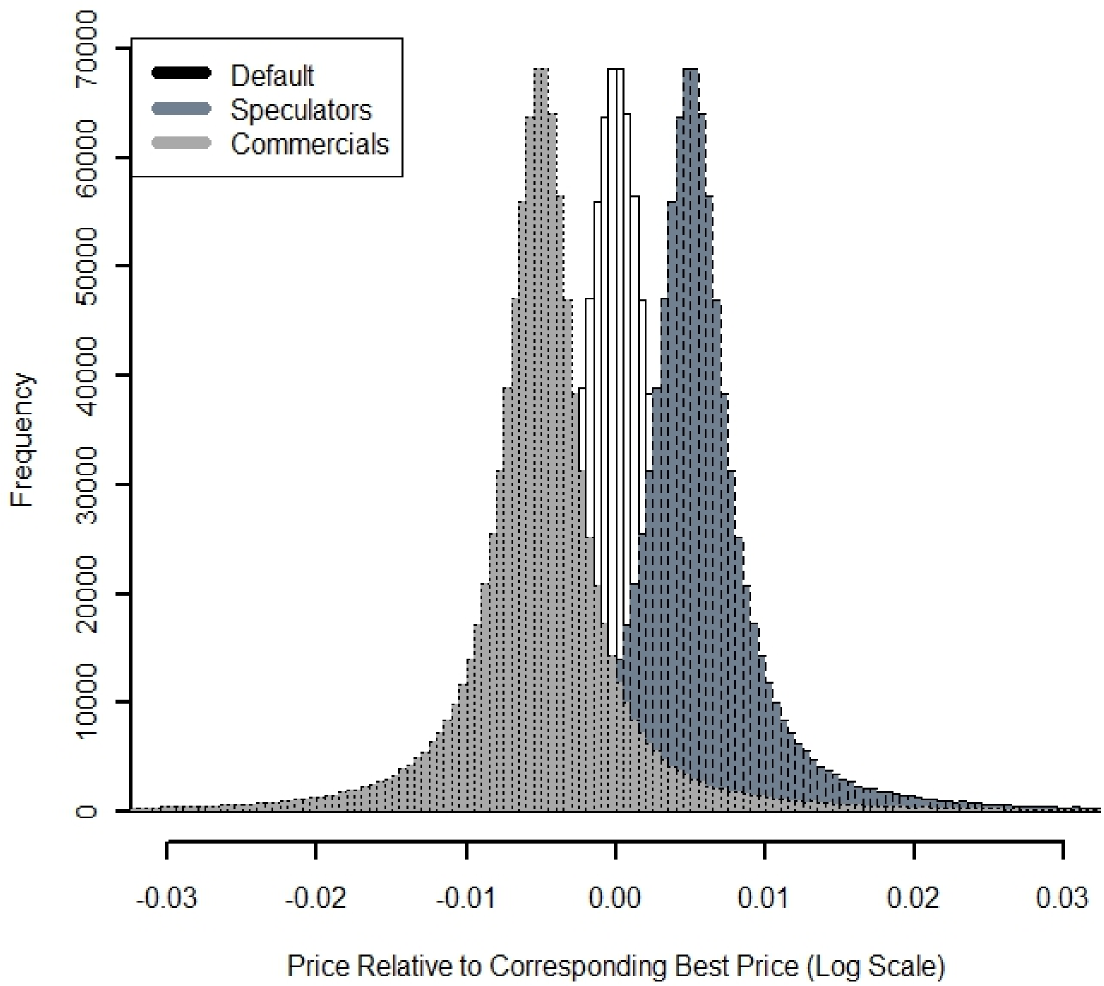
The extended model proceeds in the following way. As each new order is generated, it is randomly allocated to a type of trader with equal probability. As a transaction occurs, it updates the groups corresponding long or short open interest. However, each new order of a particular sign may alter either the long *or* short open interest for the given group. For example, a new buy order made by speculators can increase long open interest (as speculators are buying more) or decrease short open interest (as speculators are buying back an existing short position). This allocation to either increase or decrease open interest is determined randomly with equal probability. Figure 4.4 provides a plot of simulated market prices and the corresponding changes in commercial and speculator long and short open interest, and total open-interest, over 100,000 time-steps. This plot is analogous to Figure 1.1 in chapter 2 depicting the same variables for the Oil market over the 1991 to 2008 period.

Figure 4.4 Simulated Positions for Commercials and Speculators, Open Interest, and Prices



This new, extended model can be used to test the hypothesis of group order-type preferences outlined above. Speculators are hypothesised to have a preference for more aggressive orders, including market orders, whereas commercial traders are hypothesised to typically use less aggressive limit orders. These preferences can be simulated by varying the Student distribution used to generate the relative price for a given order, as described above, for a particular group. Figure 4.5 demonstrates this approach. The default Student distribution used by Mike and Farmer is incremented and decremented by a given value to represent different levels of order aggression, or a preference for market or limit orders. In Figure 4.5, speculators have a distribution skewed to the right, meaning new orders are more likely to be implemented as market orders or more aggressively-priced limit orders (for example, placed within the spread). In contrast, the commercial distribution skews to the left, meaning market orders are correspondingly less probable, and limit orders away from the current best price are more likely.

Figure 4.5 Representing Order Aggression with Different Student Distributions



The econometric methodology outlined in chapter 2 involved estimating the relationship between group positions and changes in market price with a regression model, where the slope coefficient for each group position represents its contemporaneous relationship to changes in market prices. Table 4.1, taken from Table 2.10 in chapter 2, represents the relationship between group positions and market prices across all 31 markets analysed (as described in chapter 2, Equation 2.2, this is achieved with a categorical variable assigned to each market and includes significant lags of both prices and positions).

Table 4.1 demonstrates the clear pattern of trading behaviour described previously: commercial long positions and speculator short positions are negatively correlated with price changes whereas speculator long positions and commercial short positions are positively correlated. According to the hypothesis outlined above, a similar pattern should emerge in the simulated group positions from the extended version of Mike and Farmer's model once different levels of order aggression are introduced.

Table 4.1 Real Market Data, Slope Coefficients for Change in Group Positions and Concurrent Change in Prices, Significance at $p < 0.05$

	Commercial Short	Commercial Long	Speculator Short	Speculator Long
Slope Coefficient	1.24	-1.04	-2.55	2.61
P Value	*	*	*	*

The level of increment or decrement applied to the Student distribution represents the level of order aggression and is a central parameter in this new, extended version of the Mike-Farmer model. This order aggression value is referred to as *oA* henceforth and applied symmetrically to both groups in order to maintain the original shape of the Student distribution as closely as possible. This is negatively in the case of commercials (corresponding to lower levels of aggression) and positively in the case of speculators (corresponding to higher levels of aggression).

In the following experiment to test the hypothesis of group order-type preferences outlined above, the *oA* parameter varies between 0 and 0.00217 at levels equal to the percentiles 50, 55, 60, 65, 70 and 75th of the default Student distribution. For each *oA* level, the model is run across 1,000,000 time steps and a regression model fits the change in group positions to changes in market prices – the same methodology as applied to real data and described in chapter 2, Equation 2.1. The resulting slope coefficients for the simulated data are reported in Table 4.2.

Table 4.2 Simulated Market Data, Slope Coefficients for Change in Group Positions and Concurrent Change in Prices

oA	Commercial Short	Commercial Long	Speculator Short	Speculator Long
0.00000	0.00136	0.00052	0.00133	0.00208
0.00036	0.02113	-0.02387	-0.02455	0.02075
0.00073	0.08612	-0.03759	-0.02964	0.04556
0.00114	0.15190	-0.03818	-0.03820	0.19223
0.00161	0.05829	-0.09108	-0.09454	0.06001
0.00217	0.09150	-0.23311	-0.09790	0.05796

From the *oA* level of 0.00036 onwards, changes in commercial and speculator long and short positions follow the same qualitative pattern as identified empirically in historical COT data: changes in commercial short positions and speculator long positions have a positive sign; changes in commercial long positions and speculator short positions have a negative sign. This result is consistent with the hypothesis of group order-type preferences outlined above. Different levels of order-aggression, in the absence of more involved strategic or informational considerations, can account for the patterns of trading behaviour identified in historical COT data.

It is interesting to note in Table 4.2 that only a relatively small level of group-preference is required for a clear pattern of behaviour to emerge; at the *oA* level of 0.00156 (the 55th percentile of the default distribution) speculators are only 10% more likely to use market orders than commercials, who are 10% more likely to use limit orders. As the level of *oA* increases, the size of the slope for each group inventory also generally increases. This suggests that inter-market differences may relate to different levels of group-preferences within a particular market. (Note, efforts have not been made to align the absolute value of the coefficients extracted from the simulated data to those found for the real markets; although, in principle, it would be possible to equalise the relative change in variables to achieve this level of realism – a point discussed in more detail in chapter 6.)

This model can be extended further to include the third group of participants reported in COT data and analysed in chapter 2: non-reportable, or smaller, traders. Typically, these participants have a similar pattern of group behaviour as speculators, although less pronounced (chapter 2, Table 2.5), and implies a slight preference for more aggressive orders. This third group can be introduced into the model and provided with an *oA* value less extreme than speculators (whilst ensuring the *oA* values across all the groups nets to 0 in order to match the original distribution as closely as possible). Example coefficients from a simulation involving three groups is provided in Table 4.3.

Table 4.3 Simulated Slope Coefficients with 3 Groups and Open Interest

	Commercial Short	Commercial Long	Speculator Short	Speculator Long	Other Short	Other Long	Open Interest
Slope Coefficient	0.01899	-0.02681	-0.02558	0.01409	-0.00575	0.00613	-0.00049

4.8 Opportunities for Future Research

Whilst inevitably increasing its complexity, the model can be extended in a variety of ways to explore a wider array of research questions. For example, currently, there is no direct feedback between group buying and selling and market prices; the group-level dynamics in the model operate in isolation from the order-flow dynamics. In the real-world, inevitably, important relationships exist between group and order-flow behaviour. Exploring how these two levels interact, how group behaviour impacts price and order-flow, and vice-versa, is an interesting area for future research.

For example, the analysis in chapter 2 demonstrates changes in open interest as being positively correlated with changes in market prices across a wide-range of markets (see chapter 2, Tables 2.5 to 2.8). However, as shown in Table 4.3, this relationship is not adequately represented in the current simulation. A positive relationship between open interest and market prices implies a feedback effect whereby increasing prices involve new transactions that increase long and short open-interest rather than decrease it. Currently in the model, this is determined via a random sampling with equal probability of a transaction increasing or decreasing open interest. Feedback effects could be specified by changing this probability to be a function of recent price movement, for example, as prices increase, the probability of new transactions expanding total open interest also increases.

More accurate econometric descriptions of group trading behaviours could also be explored in the model. Chapter 2 documents significant autocorrelations in changes in long and short open interest of the different groups (see chapter 2, Table 2.4). These characteristics are not currently represented in the model; new orders are assigned to each group based upon a uniform sampling with equal probability for each group. This allocation could occur differently, via, for example, a fractional Gaussian process similar in mechanism to the generation of order-signs. The impact of long-run dependence in group behaviour on market price behaviour could then be explored more formally. This point is returned to in more detail in chapter 5.

Another area for further research is the impact of different concentrations of trader types, or particular participant ecologies, on market price behaviour. Currently, the relative concentration of different groups of participants is equal in our simulated marketplace. However, the relative concentration of different participants could be varied and the impact on lower-level market behaviours, such as market liquidity, and higher-level market behaviours, such as price volatility, could be studied in a controlled environment. This new strand of research may be relevant for more practical issues. Chapter 3 documents an increase in the concentration of large speculators in most futures markets. The impact of these shifts in market composition could be explored more formally with versions of this model – this is a subject returned to in the following chapter.

4.9 Conclusion

The agent-based model developed here to account for patterns of trading activity identified in historic COT data does so on the basis of order preferences amongst different groups of participants. Commercial traders are considered less aggressive and therefore tend towards limit orders, buying as prices decline and selling as prices increase; whereas speculators are considered more aggressive and therefore utilise more market orders and more aggressive limit orders, trading in the direction of prices changes. These behavioural preferences, in the absence of deeper strategic considerations or a distinction between 'informed' or 'uninformed' decision-making, are sufficient to account for empirical regularities in trading behaviour reported in chapter 2.

Research reviewed in this chapter identifies that situational constraints often impact on economic behaviour broadly and in important ways. Existing literature focuses on how institutions, such as the continuous double auction process found in most financial markets, can restrict trading behaviour and result in consistent statistical characteristics in prices and order-flows in the absence of trader strategies or information processing (e.g. Farmer et al., 2005). This current research contributes to the existing literature by demonstrating how constraints imposed by different business institutions and their associated objectives may also have important effects on behaviour. Commercial traders may have less time-sensitive information and thus lower opportunity cost of non-execution leading to a preference for non-aggressive orders. In contrast, large speculators may rely more on time-sensitive trading strategies and utilise relatively aggressive orders due to the high opportunity cost of non-execution. Relatively stable business objectives may therefore correspond to relatively stable patterns of trading behaviour as a natural consequence.

This work can therefore be considered part of a broader, zero-intelligence approach to studying economic phenomena that places situational factors as the starting point for building more complex explanations of economic behaviour. Rather than invoking top-down and theoretically driven notions of human behaviour at the on-set, as is typical of many traditional economic theories, this approach involves studying economics from a bottom-up, empirical perspective, assuming zero-intelligence and using computerised simulations to test the contribution of different factors. A natural starting point in this process is the role of situational factors. For the study of financial markets, these include the behavioural constraints associated with the double auction process and, as introduced here, the business objectives associated with different groups of participants.

The agent-based model presented in this chapter therefore permits a minimum of theoretical assumptions, being almost entirely empirically derived to capture a wide-variety of features associated with the behaviour of financial markets. These include the properties of the spread, the distribution of returns, and trading patterns of different groups of market participants. Based on the uniquely empirical orientation of this model, it can also be calibrated to represent a particular market where two sources of data are available: higher-frequency, order-flow level data; and lower-frequency, COT data. The level of realism and calibration has been lacking in previous market simulations, and, whilst alternative approaches have been put forward (e.g. Darley and Outkin, 2007) they are typically proprietary and much more computationally expensive.

The model introduced here therefore captures essential elements of market dynamics involved at two separate levels, the order-flow level, and at the level of group behaviour. In combination, this is a powerful tool to explore questions related to the interaction of different levels of market dynamics, for example, how changes in the relative concentration of different types of traders can impact on price behaviour. This topic is of relevance to regulators charged with maintaining the effective functioning of financial markets and is explored in more detail in the following chapter.

5. BEHAVIOURAL ECONOMICS AND MARKET REGULATION

Contents:

Abstract:

Recent debate on financial market regulation has included calls for the restriction of speculators' positions in order to limit market volatility. This chapter reviews related evidence with the use of the behavioural market model developed in the previous chapter and of the analysis of historic COT and price data. The results generate mixed conclusions, highlighting the need to extend the market model to include new relationships that link group behaviour and order-flows more closely, and more broadly, to re-direct regulatory debate towards the role of liquidity in causing market volatility. Overall, the research presented here suggests the net-effect of increased speculation is to provide more liquidity to a market, and therefore, to lower market volatility, even if speculators prefer more aggressive orders. A discussion considers the possibilities for new financial market regulation focused on orders preferences amongst traders, and, thus, on influencing the available liquidity in a market.

5.1 Introduction: the Regulation of Speculators

The relationship between the activity of speculators and the volatility of financial market prices has long been an area of interest and concern to those involved in financial markets, including regulators, academics and practitioners. As far back as the 1850s, there are records of farmers and various legislative representatives calling for speculators to be eliminated from futures exchanges to avoid excessively high or low prices (Chicago Mercantile Exchange (CME), Discussion Paper, 2009). Tobin (1978, p. 154) famously proposed that taxing speculators and their transactions would introduce “sand in the wheels” to reduce the level of noise in financial markets. With the recent credit crunch period being attributed, in part, to excessive speculation in derivative markets (Bernanke, 2010), the role of speculation in the healthy functioning of the economy continues to be an ongoing area of political debate, applied academic research, and focus for legal reform. This chapter extends the findings presented previously to explore the relationship between speculators and market behaviour.

In July 2010, the Dodd-Frank Act was enacted by the U.S. Government with a number of far-reaching reforms to the U.S. financial system to be phased in over the coming decade. These include a number of new regulatory bodies to impose severe limits on financial market speculation, or 'proprietary trading', by banking entities. There is to be a re-structuring of the Over-the-Counter (OTC) derivative markets (customised transactions between counter parties in the absence of an organised exchange) to enable the government directly to oversee operations. Also heralded is a new Office for Financial Research empowered to collect vast amounts of data from financial firms, including long and short positions and the identity of counter parties – thereby effectively widening the scope to include international markets (Lester and Bovenzi, 2010). The new legislation gives regulators broader powers and mandates higher prudential standards, aiming to reduce the risk of financial crisis occurring in the future.

One area of reform still under debate is the permitted size of positions held by speculators in particular markets. During the Great Depression, the U.S Commodity Exchange Act (CEA) was enacted to impose position limits on net-long and net-short positions held by speculators in Grain futures markets for the purpose of protecting against the burdens of 'excessive speculation'. This notion of excessive speculation considers two separate types of risk. The first is the risk arising from market manipulation, where an individual or group of participants takes control of a large concentration of a market and sets prices in the absence of realistic supply / demand conditions. The second is the risk associated with extreme volatility of market prices not reflective of underlying economic conditions. Position limits are considered to be relevant for both these types of risk and are therefore applied in a wide range of U.S exchange traded derivative markets. More recent regulatory debate has focused on whether position limits should increase in severity and apply more broadly (Commodity Futures Trading Commission (CFTC), Discussion Paper, 2010).

The distinction between these two separate types of excessive speculation is an important one. The first risk issue is relatively straightforward – market manipulation involves the accumulation of a commodity by a particular party that effectively monopolises supply and provides control over market prices. There is one notorious example of such 'cornering' of a market. The Hunt brothers were charged by the CFTC in 1985 with manipulating the silver market. At one stage, towards the end of the 1970s, the Hunt brothers allegedly controlled 77% of the total silver supply (Tuccille, 2004). This episode led to the bankruptcy of the Hunt brothers and the application of new position limits by the CFTC to the metal markets. The second type of risk, as outlined above, relates to market volatility, and is more subtle and non-linear. The application of position limits to constrain market volatility raises questions of how different types of participants interact to generate emergent market characteristics, such as increased price volatility, and whether a particular market can suffer from too much speculation. It is research related to this second question that is the primary focus of this chapter.

The standard theory for the impact of speculation on financial markets underlies the current regulation-by-type-of-trader (RTT) approach, where position-limits are applied to speculators. The standard theory proposes that a relationship between trading activity and market price volatility depends uniquely on the information that different types of traders possess (see sections 2.2 and 3.5). The theory argues that prices in financial markets change as new information emerges and participants revise their estimates of the fundamental value of a market. But, crucially, some subset of participants are considered less informed (Frankel and Froot, 1986; Shalen, 1993) and trade on the basis of more noisy measures of information (Black, 1986) or positive feedback strategies (Shleifer and Summers, 1990; Shleifer, 2000). These traders possess a wider dispersion of expectations for future prices and their trading activities are therefore associated with higher levels of market volatility. This view is also related to the strong correlation between trading volume (or the number of market order transactions) and market volatility that has been known for a long-time (Tauchen and Pitts, 1983; Karpoff, 1987; Gerety and Mulherin, 1989; Stephan and Whaley, 1990; Gallant, Rossi, and Tauchen, 1992). This relationship has also been interpreted as causal, that is, volume is seen to drive volatility (Ane and Geman, 2000). It follows that speculators can cause prices to move excessively because of the wide dispersion of beliefs underlying their buying and selling, and, therefore, that their actions need to be restricted in order to reduce the impact of noisy trading on market prices.

An immediate issue with the standard theory and the associated RTT approach is the operational problem of measuring 'information'. Notions of information and informed / uninformed participants are highly abstract, and, as discussed in chapter 3, models derived from this viewpoint may not be falsifiable or offer empirical validity. However, this approach also neglects empirical research into the causes of market volatility. It is now well-established that volatility in financial market prices relates closely to available liquidity, rather than the total volume of transactions or their size (Farmer, Gillemot, Lillo, Mike and Sen, 2004; Weber and Rosenow, 2006; Joulin, Lefevre, Grunberg and Bouchaud, 2008). Mike and Farmer (2008) define liquidity as the difference between the current midprice (the price between the best bid and best ask) and the price where an order of a given size can be executed. However, it can be defined more broadly as the relative balance between market and limit orders; that is, if a market is considered 'liquid' it has a sufficient number of limit orders to offset new market orders without dramatic changes in price.

Alongside an enhanced understanding of the underlying causes of market volatility, evidence of order-type preferences amongst groups of participants also offers a new perspective. If speculators rely on more aggressive order-types, their increased participation may naturally coincide with higher levels of volatility. Limit orders supply liquidity to the market whereas market orders remove limit orders, and thus, remove liquidity (Foucault, Kadan, and Kandel, 2005). If speculators typically rely on more market orders their activity may naturally coincide with lowering levels of liquidity, and therefore, more volatile prices – as there are less resting limit orders at current prices to offset new market orders. Crucially, with this explanation, no abstract theory of informed or uninformed trading is required to understand a positive relationship between the activity of speculators and increases in market volatility.

This remainder of this chapter is outlined as follows. The next section reviews existing research on the impact of speculators on financial markets. This has tended to focus on specific markets and events and therefore overlaps with both areas of risk from increased speculation that are outlined above. This review is followed by a more focused analysis on the second area of risk – that of price volatility and its relationship to the activity of speculators. Predictions made by the market model introduced in the previous chapter are presented, and similar research questions are also addressed using historic COT and price data, as introduced in chapter 2. This analysis finds inconclusive results and highlights the need to extend the existing modelling framework with new relationships between the group and order-flow levels that are not currently specified. The chapter closes with a discussion on possibilities for a new perspective on market regulation that incorporates an empirical view on price volatility, an awareness of behavioural characteristics of different groups of traders, and the use of more sophisticated models of financial markets as pragmatic tools for research.

5.2 Research on the Impact of Speculation in Futures Markets

The CFTC has recently issued a proposal to introduce speculative position limits in a wider range of markets (CFTC, 2010). Numerous hearings on the issue of excessive speculation and the RTT approach in derivative markets have been held in the U.S House of Representatives and Senate. The debate is also ongoing in other developed economies. In the UK, a commentary on the issue of limiting speculation has been published (Financial Services Authority (FSA), 2009), although currently position limits in U.K domestic markets are not considered by type of trader, but apply to all market participants. Research papers and commentaries on the subject have also been released by major exchanges (e.g. CME, 2009) and international regulatory bodies (Domanksi and Heath, 2007; International Monetary Fund (IMF), 2008a; Mayer, 2009; United Nations Conference on Trade and Development (UNCTAD), 2009b; Irwin and Sanders, 2010). As discussed in more detail below, academics have also increased their efforts to clarify the impact of speculation on financial market behaviour.

This increased interest in the subject is largely a result of the extreme price volatility seen across a range of markets over the last decade. Although stock market bubbles and crashes are the crises most notorious in the public mind, extreme market moves have occurred in many other asset classes. During the period from January 2006 to June 2008, the Commodity Research Bureau Index of a basket of commodity prices increased by a dramatic 71%. Oil futures reached a high of $147 in mid-2008, only to reverse direction dramatically over the following 6 months. This level of volatility is unprecedented in the Oil market and has been associated with an influx of new, speculative money into commodity markets. The following section reviews research related to this recent volatility in commodity prices and its relationship to the activities of speculators. This is a subject that has stimulated substantial academic research and the following literature review provides a broader context for appreciating concerns regarding excessive speculation.

Irwin and Sanders (2010) clarifies that new money entering the commodity markets over the recent decade has come in a number of different forms, including: Index funds (where investors hold a basket, or 'Index', of different commodities), exchange traded funds (where investors can gain exposure to a basket or particular commodity by holding a fund traded on a stock exchange), and over-the-counter (OTC) Swap agreements (where customised transactions between counter parties are hedged in exchange traded futures markets). These relatively new investment products can provide investors with long positions (that is, profits if prices rise) in a basket of different commodity markets, and the interest in these products has been substantial. According to a Barclays report (see Irwin and Sanders, 2010), during the period from 2006 to the end of 2007 Index fund investment increased from $90billion to $200billion. Current estimates suggest $320billion of retail and institutional money is now devoted to commodities (The Economist, 2010). Irwin, Sanders, and Merrin (2009) suggest the increase in speculative capital flowing into commodity markets is a result of influential studies demonstrating the value of commodities in investment portfolios and poor returns from more traditional investments, such as stock markets during the early 2000s.

Many commentators claim new legislation in the year 2000 also had an important impact on speculation in derivative markets (e.g. Masters, 2008). The Commodity Futures Modernization Act (CFMA) was intended to maintain the competitive position of the U.S in OTC derivative markets, but has been criticised for allowing speculators to enter derivative markets en-masse. Specifically, the CFMA excludes OTC derivative transactions from regulation under the same government body as exchange traded derivatives, the CFTC. This legislation effectively reduces speculative position limits when positions are considered across both exchange and OTC venues; and provides a loop-hole for increased speculation in derivative markets via unregulated markets (an oversight that has largely been addressed in the more recent Dodd-Frank act). Furthermore, the CFMA treatment of Swap positions has also come under criticism. Swaps, often held by large financial institutions, do not represent an outright speculative position, but are considered commercial transactions and therefore not subject to position limits. However, according to Masters (2008), these transactions are often placed by large brokers who are hedging OTC positions with speculators. Swaps may therefore correspond indirectly to speculative trades and can allow speculators to exceed their designated position-limits. New provisions on Swap dealers enacted under the Dodd-Frank act include the public reporting of trades to increase levels of transparency and accountability.

The CFTC responded to increased interest in the new money flowing into commodity markets by issuing extended reports. The weekly Supplemental Commodity Index Traders (CIT) report, started in 2007, disaggregates positions of Index traders in 12 agricultural markets. Complaints followed the release that the report was too narrow in scope. As a result, the Disaggregated Commitment of Traders (DCOT) report began its weekly release at the end of 2009, including information for agricultural, energy and metal markets (excluding other asset classes, such as currencies, stocks and interest-rates, as analysed in chapter 2). The DCOT classifies all reporting traders as either swap dealers, managed money, processors and merchants, and other reporting traders (rather than commercial, large speculators, and non-reportable traders). The report increases the transparency of dealings of particular groups of traders, but is limited by the low number of markets covered and the restricted historical data, extending only 3 years prior to first release. Despite limitations, the data has been used by researchers to investigation the impact of specific participants on commodity markets.

Masters (2008) analyses CIT data and the sums of money tracking specific Commodity Indexes to infer the total dollars allocated to a given market based on the weight it holds in an Index. From these calculations, Masters infers precisely the new demand entering specific markets over time as a result of increased participation in Index funds. Masters argues Index speculators have had a severe and negative impact on market liquidity. Whilst more traditional speculators will typically buy and sell futures and hold substantial long and short positions, Index funds are long-only, may never sell their positions, and thus offer little liquidity to the markets. Notably, Masters highlights international stock markets, traditionally the venue for large institutional investors, are approximately 240 times larger than traditional commodity markets (excluding financial-orientated derivatives). Masters claims a direct link between large investments from institutions into smaller commodity markets and the dramatic increase in food and energy prices seen over the period – and highlights the adverse consequences for the wider economy.

A similar position is taken by the U.S. Senate Permanent Subcommittee (USS/PSI, 2009). This U.S. Senate report labels the activities of Index funds in the Wheat futures market as constituting 'excessive speculation' under the CEA and advocates a number of reforms. These include: 1) the replacement of position limit exemptions applied to certain Index funds; 2) the imposition of tighter position limits, such as 5000 contracts per trader, in the Wheat futures market; 3) an investigation into Index funds operating in other agricultural markets; and 4) higher levels of data collection on the levels of Index fund participation across all derivative markets. Debate continues as to the appropriateness of these recommendations.

Aside from the appreciation of commodity prices associated with higher levels of speculation, other negative implications have been suggested by various studies. Historically, commodity prices have had a relatively low correlation with prices in other asset classes and a relatively high correlation with inflation (Gordon and Rouwenhorst, 2004). However, as Index strategies involve linking a large number of different markets into a single portfolio, researchers have found new inter-market relationships have emerged that do not necessarily reflect economic fundamentals. For example, Tang and Xiong (2010) identify that agricultural commodities have begun to trade more closely with energy commodities, and a United Nations discussion paper shows commodity futures becoming more closely correlated with the stock market (Mayer, 2009). Additionally, according to Medlock and Jaffe (2009), negative implications from higher Oil prices (associated with increased Index speculation) has contributed to the $331billion spent on Oil imports in the U.S in 2008 (representing 47% of the trade deficit; compared to only 19% in 2002). This has strained the U.S. economy and weakened the value of the Dollar over the period. (Medlock et al. note that Oil and the Dollar had a negative correlation of 0.82 between 2001 and 2008, evidence of the importance of Oil prices to the economy). Domanski and Heath (2007) also provide evidence that the relationship between futures and the underlying commodity market prices has degraded in recent years, with negative implications for commercial traders using derivative markets to hedge their business dealings.

Not all researchers agree with this viewpoint, however. Irwin, Sanders, and Merrin (2009) analyse DCOT data and note that, if Index funds are driving commodity prices higher, then markets without Index fund investments should not advance. But there is evidence that this is not the case. Markets without Index investments, such as fluid milk and rice futures, and those commodities without corresponding futures markets, such as apples and edible beans, have also shown large price increases along with various other agricultural and energy markets. Other evidence supports this viewpoint. The livestock market, which had the highest concentration of index fund positions during the first half of 2008, also experienced the smallest price increase relative to other commodities. This suggests that Index buying is not the primary causal influence on price increases and indicates legitimate changes in the fundamental value of many commodities may be driving prices.

Irwin and Sanders (2010) test the causal relationship between speculator activity and market price volatility more directly, via a series of econometric tests. Irwin and Sanders use DCOT and CIT data and apply Granger causality tests to determine whether past values of trader positions are useful in forecasting price volatility. Irwin and Sanders (2010) find no statistically significant relationship to indicate changes in Index fund and swap-trader positions increase market volatility over future periods. In contrast, they find evidence that increases in Index fund positions are associated with declining volatility in certain markets. They advocate further research to understand this effect. However, for Frenk (2010), the Granger causality tests conducted by Irwin and Sanders are inappropriate for the given context. Research demonstrates Granger causality to be ineffective when applied to volatile financial time series (Pagan and Schwert, 1990; Phillis and Loretan, 1990) and therefore, researchers using this technique may reach inappropriate conclusions as to the role of speculation in commodity market volatility.

A brief review of research into the impact of speculation in commodity futures markets paints a mixed picture, but demonstrates the level of interest and controversy surrounding the subject area. The recent Dodd-Frank act introduces important reforms to OTC derivative and Swap markets, with particular implications for Index funds and Swap dealers operating in commodity futures markets. These include higher levels of margin requirement and new transparency requirements for large positions. This new regulatory framework will contribute to new participant behaviours and market reactions and makes questions about the impact of specific participants on market prices, such as how the Swap trader loophole contributes to price increases, difficult to study scientifically as research is limited by available data. The analysis of specific questions inevitably relies on data reflecting specific conditions. These constraints may limit the value of highly focused, condition-dependent research.

However, as levels of speculation and overall trading volume continue to balloon in financial markets, broader questions as to the contribution of speculators and other core groups of participants to the behaviour of markets continue to be relevant to regulators. The pursuit of more general questions may offer longer-term value to regulatory debate, permitting more robust generalisations that are not limited to temporary conditions. Furthermore, analysis into broader questions may benefit from larger and less detailed datasets, such as the COT dataset introduced in chapter 2, due to the less focused scope of the research; additionally, benefits may arise from the use of alternative research techniques, such as experiments with computational models, as introduced in chapter 4, due to the relatively coarse dynamics represented.

There is, of course, an underlying assumption to this line of research: that the behaviour of participants, and correspondingly, their impact on aggregate market behaviours, such as levels of market volatility, is relatively consistent and therefore meaningful to study. Chapter 2 provides evidence that certain behavioural characteristics in large groups of traders are markedly consistent in a majority of U.S. Futures markets over the last two decades, and therefore suggests the study of how group trading behaviour relates to market volatility is a valid area for further enquiry. Other researchers share this viewpoint and have carried out related research, as the following paragraphs review.

Daigler and Wiley (1999) investigate the relationship between core groups of traders and market volatility with the use of a dataset provided by the Chicago Board of Trade. The 'Liquidity Data Bank' provides historical trading volume (long and short trading volume) associated with 4 different types of traders. They are market makers (also known as floor traders, who are also exchange members), exchange members trading on their own account, floor traders operating for other exchange members, and the general public (corresponding to speculators, managed funds and small hedgers). Daigler and Wiley analyse these data across 5 different futures markets between June 1986 and June 1988 to study the impact of different groups on the volatility of returns across each market. They also find consistent results: the volume traded by the general public category (which includes speculators) is positively related to market volatility, that is, increases in activity by this category of participants co-occurs with increases the variance of prices; whereas, volume of exchange members and floor traders tends to be negatively associated with market volatility.

Daigler and Wiley interpret their finding of an asymmetric relationship between different categories of traders and market volatility in terms of the different quality and quantity of information possessed by these separate participants. The general public cannot adequately capture information related to changes in fundamentals, and therefore, trade more imprecisely with a greater dispersion of expectations; this leads to a positive relationship between their trading activity and market volatility. Alternatively, exchange members are considered better informed, and therefore, have lower dispersion of beliefs; thus, their activities are negatively associated with price volatility.

A similar finding comes from Wang's (2002) analysis of weekly COT data on currency futures markets over a more substantial period of time, from January 1993 to March 2000. Following a similar methodology as Bessembinder and Seguin (1993), market data is decomposed into expected and unexpected components using ARIMA models (or 'Autoregressive Integrated Moving Average' models) – general purpose models fitted to predict future values of a time-series based on previous values of the same series (e.g. Mills, 1990). Bessembinder et al. identifies that market data, such as trading volumes and open-interest, is serially correlated and therefore highly predictable. They demonstrate that unexpected activity (or the residual values from fitted ARIMA models) typically has more significant statistical relationships with other market variables than expected components (or predicted values). This approach is extended by Wang (2002) to study the relationship between group trading activity (which, as chapter 2 demonstrated, is also found to have significantly autocorrelations) and market volatility.

Wang separates net-positions (long minus short positions) of commercials and speculators into expected components and unexpected components. When controlling the effect of overall trading volume, open interest, and expected net-positions, he finds significant relationships between unexpected trading activity and market volatility that are not otherwise apparent. Unexpected activity by speculators is found to be positively associated to price volatility, and thus interpreted as having a destabilising impact on market prices. In contrast, unexpected activity by commercials is significantly and negatively associated with volatility, and therefore seen to stabilise market prices. As with the conclusions drawn by Daigler and Wiley, Wang supports a theory of uninformed and informed trading amongst speculators and commercial traders. Wang proposes that commercial traders possess private information and therefore buy and sell within a relatively small range of prices around the fundamental value. They thus dampen volatility. Speculators, however, are likely to be uninformed with a wider dispersion of beliefs, and therefore destabilise the market.

Findings of a broad relationship between activities of particular types of traders and levels of market volatility can be interpreted from a different, behavioural perspective. As discussed previously, more recent research demonstrates that the volatility of market prices over a given period reflects the relationship between market and limit orders over the same period. If different groups of traders have consistent order preferences, it follows that there may be systematic relations between the activity of different groups and market volatility. This behavioural explanation may account for the findings of Daigler and Wiley, and Wang, and not require more abstract notions of informational differences between groups of traders.

Daigler and Wiley acknowledge that “floor traders tend to reduce volatility as they take the opposite position of other traders and provide short-term liquidity” (1999, p. 2310) but fail to recognise that this behaviour might correspond closely to the use of limit orders. A common market-making strategy employed by floor traders is to place bids and offers simultaneously in the market, in order to profit from the spread (Lukeman, 2003). In line with findings from the previous chapter, this use of limit orders may account for a negative relationship between market makers' activity and market volatility. To paraphrase the above Daigler and Wiley quote, as more limit orders are placed in the order book, more liquidity is supplied, and price movements become more constrained or less volatile as a result. Equally, the general public, which Daigler and Wiley find to be positively associated with price volatility, may typically rely on market orders and thus be positively related with market volatility. These traders remove resting orders and reduce liquidity, thereby causing prices to become more volatile.

The same interpretation can apply to the findings of Wang on the activity of speculators and commercials in currency futures markets. Unexpected speculator activity is positively associated with price volatility due to the increased (or unexpected) use of market orders, whereas commercial activity is associated with decreased volatility due to an increased (or unexpected) use of limit orders. This interpretation of the studies' results is more concrete than invoking abstract notions of informed and uninformed trading to explain findings. The explanation can also be considered more parsimonious: the impact of different traders on market volatility relates to their order preferences.

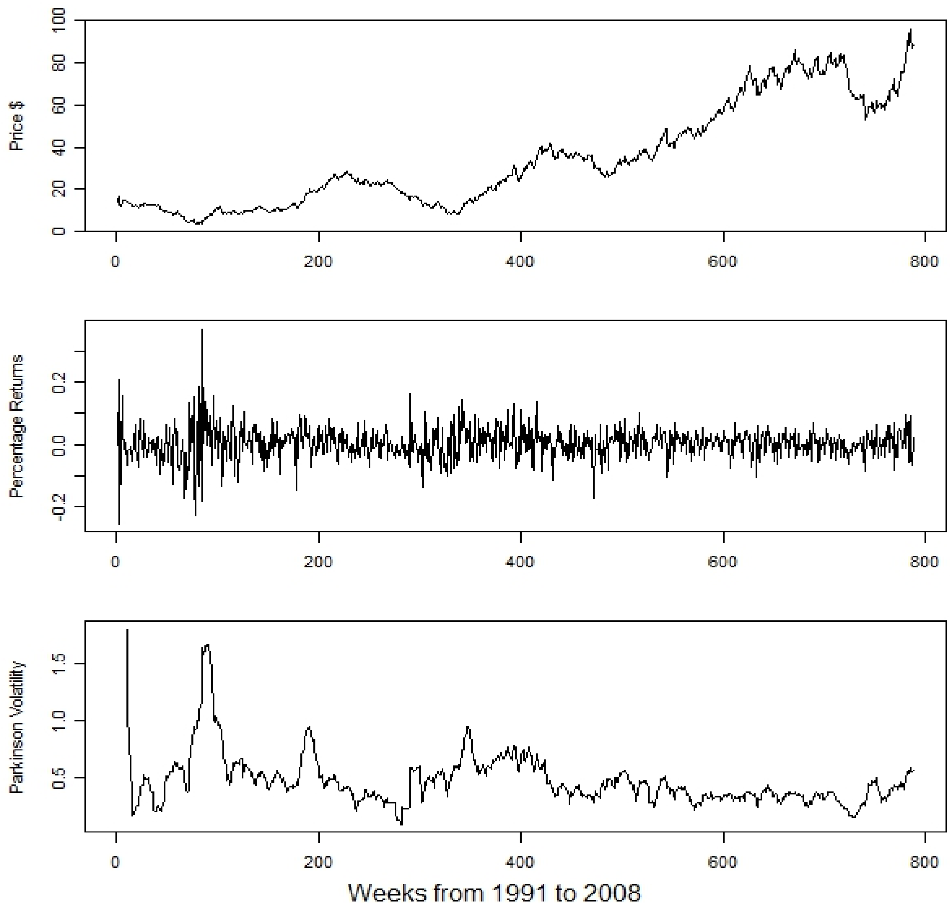
5.3 Relationship Between Groups with Order Preferences and Market Volatility

This section considers the relationship between group trading activity and price volatility by focusing on two research topics. Firstly, as explored by Wang (2002), a study is carried out on the relationship between unexpected changes in group net-positions and market volatility. Secondly, a study is carried out on the relationship between market composition, or the relative proportion of commercials and speculators in the market place, and market volatility. These research topics are addressed by generating predictions from the market model introduced in the previous chapter, and then comparing these predictions to an analysis of real-world market data.

5.3.1 Defining Volatility

There are various approaches to measuring price volatility, the most simple of which is taking the standard deviation of log returns (see, for example, Floros, 2009). An alternative, standardised technique is developed by Parkinson (1980) and applied here. It involves referencing the highest and lowest price in addition to the closing price for a given period. This volatility measure assumes an underlying geometric Brownian motion with no drift for prices (see Chan and Lien, 2003). Figure 5.1 shows the volatility measure for the Oil market from 1991 to 2008, using the default rolling-window of 10 periods to determine volatility (or 10 weeks as applied here). To apply this approach to the simulated COT data, in addition to the closing price for each period, the highest and lowest price is therefore also extracted from the simulated data.

Figure 5.1 Oil Market Prices, Returns, and Parkinson's Volatility Measure



5.3.2 Unexpected Changes in Group Net-Position

The objective of Wang's (2002) methodology is to document the concurrent relationship between unexpected changes in net-positions and market volatility, controlling for other measures of trading activity. In the following analysis, the methodology is applied to a larger number of markets than used in Wang's original study; additionally, the methodology is applied to simulated COT data, as generated by the market model introduced in the previous chapter. This analysis assesses how broadly Wang's original findings apply to markets outside of the currency futures he original tested; it, furthermore, enables the model's predictions to be scrutinised against real-world results and highlights discrepancies as areas for future development.

The measures of trading activity used in Wang (2002) include weekly net-positions (long minus short open-interest) of commercials and speculators, open-interest, and trading volume. Following the original methodology, these variables are included in the current study and represented as period-on-period percentage change (weekly returns) to ensure stationarity (see section 2.5). Significant autocorrelations are also incorporated by referencing 6 period lags of each variable. In order to separate group net-positions into expected and unexpected components, group net-positions are regressed from the previous lags in order to derive a predicted (or expected) component and a residual (or unexpected) component. With the data prepared in this way, price volatility is regressed on concurrent and 6-period lags of volume and open interest , and the expected and unexpected components of group net-positions (the same variable naming conventions as in the original text). Equation 5.1 represents the regression model.

Equation 5.1 Wang's (2002) Regression Model for Price Volatility

$$\sigma_t = \alpha + \beta ENP_t + \zeta UNP_t + \sum_{i=0}^{k} \gamma_i vol_{t-i} + \sum_{i=0}^{k} \delta_i oi_{t-i} + \varepsilon_t$$

To apply this methodology directly to simulated COT data, extensions are required to the model. The simulated data needs to be made more realistic in terms of 1) the time-windows between observations, which correspond to weekly periods in real-world COT data, and 2) the time-series characteristics of the simulated group trading activity (to permit expected and unexpected components to be derived). On the first issue, a weekly trading period is represented with a predetermined amount of trading volume (or number of market transactions). This is achieved in the following way in the simulation. Once a predetermined volume threshold has been exceeded, the high, low and closing prices, along with the long and short positions of each group, are recorded for that period (as is the case for COT data at the end of each week) and a new ‘week’ begins. The volume thresholds used are sampled from a normal distribution with a mean of 2000 and a standard deviation of 500. These values are arbitrarily chosen but enable the simulation to mimic variation in weekly volume as found in real markets. The model proceeds across 52 'weeks' recording market activity at the end of each period.

In the second required extension, the simulated trading activity is made more realistic by extending the model to permit autocorrelation in the buying and selling activity of each group. This is different from the model extensions introduced in chapter 4, where each new order was allocated randomly with equal probability to either speculators or commercials. Chapter 4 described how, based on the allocation of a new order to a particular group, the order is then assigned a relative price level which may correspond to a more aggressive limit or market order if a speculator, or a less aggressive limit order if a commercial. In the extensions to the model introduced here, autocorrelation in trading activity is introduced at the level of trade allocation, where, instead of allocating to each group based on a random sampling with equal probability, the sampling is derived from a fractional Brownian motion with a corresponding Hurst exponent (exactly the same technique originally applied by Mike and Farmer to determine trade signs – see section 4.6). This simple extension of the original methodology, when combined with the long-run dependence in trade signs already present in the Mike-Farmer model, results in the trading activity of each group relating to its trading activity in previous periods. With these modifications to the model in place, it is now possible to apply the Wang (2002) methodology to simulated COT data and determine the model's predictions regarding the relationship between group activity and volatility. To keep things as simple as possible, the number of groups in the market simulation is kept to two, corresponding to commercial and speculators with their particular order-type preferences, rather than including a third group as was carried out for chapter 4.

The Wang methodology is applied to different data sets of simulated market data, each derived from different model parameters in order to observe how the results vary under different conditions. The *oA* parameter introduced in the previous chapter represents different levels of order aggression amongst the groups of traders. The simulated COT data is generated for different levels of *oA* and additionally, for different levels of Hurst exponent (representing the long-run dependence in group trading activity). The regression model (see Equation 5.1) is applied to the simulated data and the Coefficients, representing the relationship between unexpected commercial net-positions and market volatility, are presented in Table 5.1. The results for speculators (not shown) are the inverse of Table 5.1 based on the constraint of only two groups being present in the market. Note in Table 5.1, the higher the *oA* value, the less aggressive the commercial order preferences.

Table 5.1 Simulated Market Data: Coefficients for the Relationship Between Unexpected Commercial Net-Positions and Market Volatility Across Different Levels of *oA* (Group Order Aggression) and Hurst Exponent (Long-Memory in Group Positions)

oA	Hurst Exponent				
	0.5	0.6	0.7	0.8	0.9
0.00000	0.003208	0.016662	0.000701	-0.016985	-0.000814
0.00036	0.046881	-0.001940	0.001344	-0.003096	0.001547
0.00073	0.002752	-0.015424	0.001958	0.002370	0.000478
0.00114	0.000692	-0.004518	0.002008	-0.002563	-0.000323
0.00161	0.000003	0.007837	0.021903	0.003388	-0.000900
0.00217	0.005377	0.001690	-0.002895	-0.000318	0.000859

Wang (2002) finds unexpected changes in speculator net-positions to be associated positively with market volatility (that is, positively signed coefficients) and vice-versa for commercial traders (negatively signed coefficients). The results of the Wang methodology applied to the simulated COT data do not show a clear effect, as Table 5.1 demonstrates. This inconclusive finding could relate to a number of factors, including the relative noise of the simulation, the two-group constraint, the limited sample size of the simulated COT data, or the particular methodology used to introduce auto-correlation into the group positions. These are potential areas for future research and are discussed further towards the end of the chapter.

Wang's approach is now applied to real-world data across the 31 markets analysed in chapter 2 with more conclusive results. Table 5.2 reports the coefficients for unexpected net-positions of both speculators and commercials (no longer symmetric as there are more than two groups). When accounting for open interest and trading volume, unexpected speculator net-positions co-vary positively with market volatility and unexpected commercial net-positions co-vary negatively. In many cases, a t-test shows the results to be significant (at $p < 0.05$). This clear inverse pattern of results across the two groups is consistent with Wang's findings. The results also support a claim that the activities of speculators are associated with destabilising market prices. Further research is required in order to replicate Wang's results within the existing modelling framework – offering a clear avenue to improve behavioural realism still further.

Table 5.2 Real Market Data: Coefficients for the Relationship Between Unexpected Speculator and Commercial Net-Positions and Market Volatility

Market	Speculator Net-Position Slope Coefficient	P < 0.05	Commercial Net-Position Slope Coefficient	P < 0.05
U.S. 30 year bond	0.0000007	*	-0.0000006	*
U.S. 10 year note	0.0087267		-0.0047485	
U.S. 5 year note	0.0000002		-0.0000003	*
U.S. 2 year note	0.0000005		0.0146592	
Eurodollar	0.0673496		0.0025737	
S&P500	-0.0000001		0.0000000	
Nasdaq100	0.0000003		-0.0000005	
Dow Jones Industrials	0.2078466		0.0000004	
Russell 2000	0.0602054		0.7730038	*
Corn	-0.0437117		0.1936386	*
Wheat	0.0000034	*	-0.0000026	*
Soybean	-0.4691055		-0.7458157	
Sugar no.11	0.0000005	*	-0.0000005	*
Coffee	0.0000059	*	-0.0000058	*
Cotton no.2	0.0000025	*	-0.0000023	*
Live Cattle	0.0000019	*	-0.0000007	
Lean Hogs	0.0000037	*	-0.0000012	
Oats	-0.1250549		-0.0000133	*
Rough Rice	-0.0017708		-0.0000153	*
Cocoa	0.0160628		0.1563608	
Gold	0.1150322		-0.0335137	
Silver	0.0000035	*	-0.0000029	*
Copper	0.0000015	*	-0.0000015	*
Platinum	0.0000120	*	-0.0000083	*
Brent Crude	0.0000013	*	-0.0000013	*
Natural Gas	0.0000015	*	-0.0000018	*
British Pound	0.0000019	*	-0.0000015	*
Euro	0.0074628		0.0377252	
Japanese Yen	0.0000023	*	-0.0000022	*
Canadian Dollar	0.0000021	*	-0.0000017	*
Swiss Franc	0.0000044	*	-0.0000034	*

Note: as discussed in chapter 4, the absolute values of slope coefficients cannot be compared meaningfully across markets as the relative size of changes in group positions differ.

5.3.3 Concentration of Different Groups

We turn now to the second research question: the relationship between the concentration of different groups in a market and the market's price volatility. Underlying the debate for the heightened regulation of speculators, as discussed in the introduction to this chapter, is the premise that increased speculation results in less-stable market prices (Masters, 2008). If speculators are considered as having more aggressive order preferences than commercial traders, these preferences may provide a causal link for a relationship between increases in speculation and increases in market volatility. This question is now explored by using the model to simulate market price volatility under different group-concentrations, and separately, by examining the relationship between group-concentrations and market volatility based on historic COT and price data.

Experiments with the original Mike-Farmer model show more aggressive orders correspond to more volatile prices. In the model, the relative price of a particular order (and therefore its status as either a market or limit orders) is determined by sampling randomly from a t-distribution (see Figure 4.1). The degrees of freedom parametrises the t-distribution and is referred to as   in the original paper. A default value of 1.31, taken from the original paper, has been used in all simulations thus far. Mike and Farmer use different values of   to describe the characteristics of different markets. Table 5.3 is derived from simulations involving 100,000 transactions. (Note, to maintain a consistent sample size, transactions rather than new orders-generated are held constant.) As decreases and the t-distribution becomes more peaked, more aggressive orders are placed (including relatively more market orders), and, more volatile prices result. Therefore, in terms of the model's predictions regarding the impact of speculators, to the extent that an increase in speculation shifts the overall value of lower, prices will become more volatile.

Table 5.3 Simulated Market Price Volatility at Different Levels of

α_x	Volatility
1.31	0.000988
1.20	0.000995
1.10	0.000999
1.00	0.001045
0.90	0.001120
0.80	0.001164

In the extended version of the Mike-Farmer model, introduced in the previous chapter, the t-distribution is manipulated with the *oA* parameter. This is found to have a similar effect on price volatility as varying . The *oA* parameter systematically shifts the mean of the t-distribution to increase (as is the case for speculators) or decrease (as is the case for commercials) the relative aggression of orders with a resulting effect on market volatility (results not shown). This extended approach therefore also suggests a link between speculators and price volatility.

However, a single t-distribution may not be the most effective way to represent the relative order placement of both commercials and speculators. As shown in chapter 4, by introducing a group-specific t-distribution (the *oA* parameter shifting the distribution differently for each group) we replicate more realistic patterns of group trading behaviour. It may therefore be more realistic to allocate separate t-distributions to each group and sample their relative prices independently from each t-distribution. Experiments with the model employing this alternative approach demonstrate a more complex relationship between speculators and market price volatility than is found when using a single t-distribution to represent both groups.

To demonstrate this, market volatility is again recorded across various simulations each involving 100,000 transactions. Separate t-distributions are allocated to commercials and speculators: speculators are granted more aggressive order preferences with a lower value; commercials have less aggressive orders with a higher value. In addition to using two separate t-distributions, the proportion of new orders allocated to each group is also varied across different simulations. This is achieved by changing the threshold where new orders are allocated to a particular group, which effectively changes the proportion of speculators to commercials in the simulation. The results, presented in Table 5.4, demonstrate the price volatility associated with different levels of for each group and different proportions of speculator to commercial trading.

Table 5.4 Simulated Market Volatility at Different Levels of and Proportion of Speculators

α_X		Proportion of Speculators in the Market				
Com	Spec	0.1	0.3	0.5	0.7	0.9
1.31	1.31	0.000970	0.000977	0.000976	0.000956	0.000965
1.60	1.20	0.000921	0.000938	0.000961	0.000976	0.000988
1.90	1.10	0.000887	0.000920	0.000961	0.000977	0.001036
2.20	1.00	0.000871	0.000910	0.000977	0.001010	0.001078
2.50	0.90	0.000866	0.000934	0.000992	0.001094	0.001106
2.80	0.80	0.000866	0.000973	0.000967	0.001125	0.001168

As Table 5.4 demonstrates, although speculators tend to increase volatility, the impact depends on the proportion of speculators in the market, and additionally, on the extremity of order preferences amongst commercials and speculators. The model predicts more volatile markets are typically associated with a higher proportion of speculators and more extreme order preferences; but, additionally, that extreme order preferences can result in lower volatility if the proportion of speculators is also low.

A separate experiment finds similar results by varying the extremity of order preferences amongst the two groups via the *oA* parameter (rather than using two t-distributions with separate values) whilst also varying the proportion of each group in the market. Results are in Table 5.5.

Table 5.5 Simulated Market Volatility at Different Levels of *oA* (Group Order Aggression) and Proportion of Speculators

oA	Proportion of Speculators in the Market				
	0.1	0.3	0.5	0.7	0.9
0.00000	0.00097	0.00096	0.00096	0.00096	0.00095
0.00036	0.00097	0.00099	0.00098	0.00098	0.00097
0.00073	0.00100	0.00101	0.00103	0.00103	0.00100
0.00114	0.00101	0.00108	0.00110	0.00107	0.00106
0.00161	0.00085	0.00118	0.00120	0.00119	0.00116
0.00217	0.00088	0.00133	0.00136	0.00134	0.00128

Overall then, the model predicts that higher levels of speculation should result in more volatile prices as a result of the heightened use of market orders and a proportionally lower number of aggressive limit orders. However, depending on the assumptions used to model the relative placement of orders amongst different groups, the relationship between the proportion of speculators and volatility may be affected by the existing number of speculators in the market and the extremity of order preferences. As described in the following paragraphs, the relationship between speculators and market volatility may also relate to a significant third factor, not currently incorporated into the modelling framework; namely, overall levels of market liquidity.

An analysis of historical market data identifies some broad trends in market behaviour across a majority of futures markets. These include a trend towards increased speculation over time (see Table 3.1), and, as Table 5.6 demonstrates, a trend towards increased trading activity (as measured by trading volume) and a trend towards decreased volatility (as measured by a standard deviation of returns over the relevant period). It is a reasonable assumption that increased speculation has also brought increased liquidity to most markets. As trading volume has increased, so has the size of limit order books, and, as a result, prices may have generally become less volatile (that is, more limit orders are available at current prices to offset new market orders). The predictions made by the model do not account for this important relationship. The model divides new orders between speculators and commercials, but does not increase the total volume of orders, and therefore, cannot simulate the increased liquidity that may accompany higher levels of speculation.

Table 5.6 Comparison of Volatility and Median Trading Volume During the First 12 Months of Available Data (1991 for Most Markets) to the Last 12 Months (2007-8 for All Markets)

Market	Volatility of Prices at Start of Dataset	Volatility of Prices at End of Dataset	Volatility Decreased?	Median Volume at Start of Dataset	Median Volume at End of Dataset	Volume Increased?
U.S. 30 year bond	0.7696	0.1130	TRUE	1291380	100067	FALSE
U.S. 10 year note	0.5394	0.0839	TRUE	266747	324283	TRUE
U.S. 5 year note	0.3012	0.0598	TRUE	127989	177626	TRUE
U.S. 2 year note	0.0316	0.0275	TRUE	5918	80939	TRUE
Eurodollar	0.0614	0.0084	TRUE	429162	1266265	TRUE
S&P500	0.2490	0.2024	TRUE	63919	7291588	TRUE
Nasdaq100	0.6498	0.2474	TRUE	43857	1640084	TRUE
Dow Jones Industrials	0.4256	0.1923	TRUE	97650	691256	TRUE
Russell 2000	0.3284	0.2648	TRUE	44378	1057127	TRUE
Corn	0.0945	0.3133	FALSE	160330	138643	FALSE
Wheat	0.0836	0.4120	FALSE	60479	46188	FALSE
Soybean	0.1971	0.2896	FALSE	136317	105366	FALSE
Sugar no.11	1.5305	0.2381	TRUE	44729	199018	TRUE
Coffee	0.3973	0.2836	TRUE	33750	53717	TRUE
Cotton no.2	0.2731	0.2488	TRUE	20089	78224	TRUE
Live Cattle	0.2787	0.1265	TRUE	31647	69887	TRUE
Lean Hogs	0.3350	0.1856	TRUE	18829	53112	TRUE
Oats	0.1944	0.2956	FALSE	4124	2402	FALSE
Rough Rice	0.1295	0.2215	FALSE	730	1850	TRUE
Cocoa	0.2305	0.3345	FALSE	17375	37361	TRUE
Gold	0.0746	0.2166	FALSE	83278	340877	TRUE
Silver	0.1363	0.3265	FALSE	34572	93452	TRUE
Copper	0.4237	0.3936	TRUE	22593	48860	TRUE
Platinum	0.4687	0.2169	TRUE	8643	6420.5	FALSE
Brent Crude	1.1257	0.4378	TRUE	230731	1188250	TRUE
Natural Gas	0.1284	0.4075	FALSE	22362	266013	TRUE
British Pound	0.3906	0.0855	TRUE	53134	367083	TRUE
Euro	0.1120	0.0839	TRUE	50830	774805	TRUE
Japanese Yen	0.1685	0.1131	TRUE	70677	508992	TRUE
Canadian Dollar	0.1155	0.1239	FALSE	21583	207411	TRUE
Swiss Franc	0.3048	0.0917	TRUE	109553	247109	TRUE

The assumption that increased speculation has also brought increased liquidity to most markets is also supported indirectly by the empirical modelling of Mike and Farmer (2008). As Figure 4.1 in Chapter 4 demonstrates, the t-distribution used by Mike and Farmer to model the relative placement of buy and sell orders is most dense at the corresponding best price (the best bid for buy orders and best ask for sell orders). This means that for a given sampling of new orders (both market and limit orders) there will typically be a higher number of limit orders than market orders. This higher proportion of limit orders suggests that increased levels of overall market activity (or an increase in new orders) may typically correspond to deeper limit order books, and therefore, less volatile prices, as more limit orders are available to offset new market orders.

A time-series analysis of historic market data also highlights this relationship between increased speculation and decreased volatility. A measure of the proportion of (long and short) commercial activity to (long and short) speculator activity in a given market over time, introduced in chapter 3, Figure 3.14 and Equation 3.3, provides a proxy for market composition. As described in Equation 5.2, a regression model relates this weekly measure of market composition to a market's volatility , whilst accounting for recent changes in trading volume and open interest in a manner similar to the Wang study outlined above. The resulting coefficients for market composition are reported in Table 5.7.

Equation 5.2 Regression of Price Volatility on Group Composition, incorporating Trading Volume and Open Interest and Lags

$$\sigma_t = \alpha + \sum_{i=0}^{6} \beta_i conc_{t-i} + \sum_{i=0}^{6} \gamma_i vol_{t-i} + \sum_{i=0}^{6} \delta_i oi_{t-i} + \varepsilon_t$$

In Table 5.7, although only a limited number of markets are found to have statistically significant relationships, the positively signed coefficients highlight a tendency for increased speculation to co-occur with decreasing volatility. The number of markets with positively signed coefficients is 25, and only 6 markets have negatively signed coefficients. Based on a Binomial test (e.g. Siegel, 1956), there are significantly more positive coefficients than would be expected under the null hypothesis that both positive and negative signs are equally likely to occur ($p < 0.001$, two-tailed). Although individual markets may not have statistically significant results, the overall trend across markets is significant.

Table 5.7 Coefficients for the Relationship between the Proportion of Commercial to Large Speculator Activity (Market Composition) and Market Volatility

Market	Proportion of Commercial to Large Speculator Activity, Slope Coefficient	$P < 0.05$
U.S. 30 year bond	0.1689	
U.S. 10 year note	0.0230	
U.S. 5 year note	0.1326	
U.S. 2 year note	0.0257	
Eurodollar	3.3049	*
S&P500	-0.0043	
Nasdaq100	0.1247	
Dow Jones Industrials	-0.0276	
Russell 2000	-0.2455	
Corn	0.6961	*
Wheat	0.2961	*
Soybean	-0.0356	
Sugar no.11	0.0537	
Coffee	0.2685	*
Cotton no.2	0.1920	
Live Cattle	0.0715	
Lean Hogs	0.0132	
Oats	0.2570	*
Rough Rice	0.1637	
Cocoa	1.0864	*
Gold	-0.0565	
Silver	0.3041	
Copper	0.2332	*
Platinum	0.0435	
Brent Crude	0.1423	
Natural Gas	2.1050	*
British Pound	-0.1374	*
Euro	0.0962	
Japanese Yen	0.2860	*
Canadian Dollar	0.0453	
Swiss Franc	0.0406	

These broad trends in the data contradict the claim that increased speculation always destabilises market prices (Masters, 2008) and demonstrates that predictions made by the market model, as it is currently specified, are ineffective. The model predicts that, for a constant level of market activity, an increase in speculation will tend to increase price volatility. But increased speculation is also associated with increased liquidity historically. This highlights that additional components need to be introduced to the model in order more accurately to represent the relationship between increased speculation and increased market liquidity, and therefore, between increased speculation and lower levels of volatility. The following section discusses possible extensions to the model in more detail.

5.4 Recommendations for Further Extensions to the Mike-Farmer Model

In Chapter 4, I proposed extending the existing market model by specifying new links between the group-level and the order-flow level. One area discussed, based on the analysis of the historic COT data in chapter 2, is a relationship between higher prices and increases in open interest. As Tables 2.5, 2.6, 2.7 and 2.8 demonstrate, a significant and positive relationship exists between changes in open-interest and changes in prices across a majority of markets. Currently in the model, as described in chapter 4, whether a transaction increases or decreases open interest is determined randomly with equal probability. I suggested in chapter 4 that a more realistic relationship could be introduced by raising the probability of a new order increasing open interest when prices have also been increasing – this would correspond to a positive coefficient between changes in open interest and changes in prices. A similar positive feedback relationship could relate to the activities of speculators, stipulating that speculative transactions have a higher probability of increasing open-interest than transactions carried out by commercial or other traders. This relationship could therefore link the increasing activity of speculators to increasing open interest, as seen historically across most markets in the sample (Table 3.1 and Table 5.6).

A further opportunity to extend the model is to specify that the size of the limit order book (the total number of limit orders available) changes in line with the total open interest. Currently, in the model, changes in open interest have no direct impact on the total number of limit orders held in the order book, although there is a logical connection between these two measures of activity: more open interest means more contracts waiting to transact, and therefore, a larger limit order book. This could be specified in the model by varying the lower-bound of limit orders required for any transactions or limit order cancellation to take place. An ad-hoc parameter to this effect is already present in the Mike-Farmer model to maintain realistic order book sizes (as described in chapter 4), but could be made more meaningful by relating it to changes in the overall size of open interest. By introducing these new relationships between the group and order-flow level, an indirect relationship between increases in speculation and liquidity, and therefore decreases in volatility, would result.

It is by disaggregating market behaviour into its different components that different dynamic relationships become apparent and can be incorporated more accurately into formal models. It is likely that new group to order-flow level relationships improve the model to generate more realistic predictions regarding group activity and market volatility. Additionally, they allow the model to be applied more meaningfully and generally to further areas of enquiry. This is a clear area for future research. As discussed in chapter 3, this incremental process of model development, empirical scrutiny of predictions and then refinement of theoretical components, is central to progressive science, and more specifically, well-suited to the use of agent-based modelling in understanding complex phenomena such as financial markets.

5.5 Regulating Order Preferences Rather than Speculators

Rather than regulating particular types of traders, it is potentially much more effective to regulate or encourage the use of particular types of orders, or levels of order aggression, and by doing so, enforce minimum levels of market liquidity and, thus, useful caps on market volatility. This line of thinking would represent a major shift away from the traditional view on the impact of speculators in financial markets – focused on informational differences between types of traders and imposing limits on the amount of speculation in a market – and involve adopting a new paradigm. This viewpoint is already gained credence, as Farmer highlights, “if it is considered socially desirable to lower volatility, this can be done by giving incentives for people who place limit orders, and charging the people who place market orders” (as quoted in Davis, 2005). This could be done in graded way, for example, during heightened market volatility fees associated with market orders could gradually increase to encourage more patient trading. This is in stark contrast to threshold limits placed on speculation in a given market, as advocated by the RTT perspective.

Whilst Farmer has suggested regulating trades not traders only speculatively, the research presented here can move this line of thinking forward more formally. Evidence presented in chapters 2 and 4 identifies that groups of traders in a large number of markets have relatively stable order-type preferences. Imposing fees on market orders and incentives on the use of limit orders will affect different groups of traders in profoundly different ways. Speculators, who tend to take liquidity from the market, would effectively be taxed by higher costs on market orders whilst commercials may not be affected as directly. There are other groups of participants to consider of course, for example, market makers who tend to use limit orders and trade over shorter time-horizons. It is crucial to have a deep understanding of the impact of regulatory change on different groups of market participants and anticipate both the local and emergent effects on market behaviour. This point was understood clearly by the NASDAQ Stock Exchange prior to the overhaul of its pricing structure and market tick-sizes, leading to a significant investment in agent-based technology to model the repercussions of their proposals prior to implementation (Darley and Outkin, 2007). Research conducted here on the behaviour of groups of traders, and the market model incorporating this knowledge, can move research forward with a more user-friendly and parsimonious representation of important group-level dynamics. Future versions of the model may offer regulators a cost-effective way to investigate the impact of regulatory changes.

As Goldstone and Janssen (2005) argue, with more empirical modelling techniques, direct intervention on the part of regulators could be a thing of the past. In large-scale systems of interacting agents, such as financial markets, changing the structure of the environment even slightly to facilitate certain forms of behaviour could induce major changes to a systems' emergent behaviour, in part due to the positive feedback effects involved. A style of regulation that leaned heavily on computational modelling could explore the impact of gradual changes to market structures – such as graduated changes to order fees in response to changing levels of market volatility. This would offer major gains to government bodies charged with controlling market crises and systemic risks. Indeed, controlling liquidity in the wider economy is a central part of government monetary policy. Interest rates are manipulated in the wider economy, often gradually over time, to influence consumers and businesses, to encourage savings with higher interest rates or spending with lower interest-rates. It may also be feasible to apply incentives in order to manipulate liquidity in more localised financial markets.

This approach to changing participant behaviour is not without precedent. Financial market trading platforms have started to employ pricing regimes to encourage liquidity or attract liquidity away from competing trading platforms by charging higher fees on market orders (taking liquidity) and rebates on limit orders (making liquidity). Table 5.8 provides example fees charged and rebates offered for different order-types across different U.S equity trading platforms, so called Make / Take fees (taken from Traders Magazine, July 2008). Similarly, Exchanges often operate with 'Designated Market Makers' who are obliged continuously to provide limit orders in return for a predetermined income from the Exchange. This process often occurs when a new product is launched, to guarantee liquidity, or some-other structural change takes place (see, for example CME, 2008).

Table 5.8 Example Make Fees (or Rebates for Limit Orders) and Take Fees (charged for Market Orders) Across a Selection of U.S. Equity Trading Platforms (in Cents per 100 Shares)

Trading Platform	Make Fee	Take Fee
AMEX	-30	30
NASDAQ	-20	30
NYSE Arca	-25	30
PHLX	-22	30

Make / Take fees have caused controversy within the financial community (see Citadel, 2008), pointing to the need for more detailed understanding of the effects of such regimes on different groups of market participants. The U.S Securities and Exchange Commission have acknowledged this controversy and recently imposed a cap of $0.003 per share in Equity markets (Rule 610(c) of Regulation NMS), with calls for similar caps on Options Exchanges. With these processes already in place commercially, it seems a logic area for regulators to consider in more detail as a means to influence participants and liquidity, and therefore, to control market volatility more effectively.

5.6 Conclusion

Regulators concerned with the economic impact of overly-volatile financial market prices have, in many cases, attributed blame to speculators and an increase in their activities (the so called regulation-by-type-of-trader, or RTT approach, as discussed in the introduction). This chapter has reviewed literature on the relationship between speculators and financial market behaviour and explored this relationship with the use of a market model and historical COT and price data. In line with the mixed conclusions drawn from the literature review, new research presented in this chapter also suggests the impact of speculators on market behaviour is not easily determined.

On one side of the debate, speculators may trade more aggressively and therefore extract liquidity from markets and increase volatility; a positive relationship is found in historical COT data between unexpected changes in net-positions by speculators and market volatility; additionally, the market model (as it is currently specified) predicts, for a given level of market activity, that increased speculation legitimately relates to increased levels of market volatility due to a preference for more aggressive orders.

On the other side of the debate, an alternative methodology applied to historic COT data demonstrates that increased speculation also accompanies higher levels of market activity, and therefore, higher liquidity. As a result, increased speculation is also associated with lower levels of market volatility in the real data. These conflicting results point to a crucial observation about the nature of market volatility seemingly overlooked by the RTT advocates: it is the balance between liquidity taking (the use of market orders) and liquidity provision (the use of limit orders) that is central to understanding market volatility. Speculators may contribute to both these sides of the market, despite a preference for more aggressive orders when compared to other participants such as commercial traders. This awareness should inform market regulators and enforce a shift away from the RTT approach.

For regulators, rather than focusing specifically on the role of speculators, an alternative framework that regulates types of trades rather than types of traders may be more effective. As discussed above, this new approach could influence market volatility via market liquidity – by incentivising the use of market or limit orders with variable fees and rebates. There is also precedence for such a regime, with the existence of Make / Take fees and Designated Market Makers already common on many exchanges.

6. CONCLUSION

Contents:

Abstract:

This chapter reviews the objectives and preceding research in this thesis, offering criticisms and areas for improvement and future research. The chapter closes by placing this work within the broader context of future developments in the study of financial markets. A movement towards a theory of ‘market morphology’ is proposed, that would encompass the mapping of different forms of emergent level price behaviour to the different participant ecologies operating in a market-place. Research in this thesis has assisted in the study of market morphology in three ways: by advocating a move beyond existing models of financial markets and their outdated representations of trader behaviour; by demonstrating empirical consistencies in trader-group behaviour that contribute to representations for more accurate market models; and by introducing a new market model achieving behavioural realism at multiple levels of analysis.

“Our view is that the enormous quantities of data that are now available fundamentally change the approach one should take to building economic theories about financial markets.”

Bouchaud, Farmer and Lillo (2009, p. 63)

6.1 Introduction

The primary research objectives for this thesis are to increase understanding of the behaviour of groups of traders in financial markets, and to develop a market model that incorporates more realistic group behaviour as a foundation for more practical, future research into market dynamics. With these objectives in mind, this chapter reviews how effectively the research presented in this thesis achieved these goals. Each chapter is briefly reviewed and potential successes and limitations of each step in the research process are discussed, with areas for future research highlighted. The chapter closes by placing the overall findings within a wider context to determine their significance and relevance for future work.

6.2 Chapter Review: Successes, Limitations and Areas for Future Research

Chapter 1 briefly reviews findings of statistical characteristics associated with financial market prices. When changes in market prices are measured in a standardised way to allow meaningful comparisons across different markets, research identifies certain observable features to be remarkably similar across a wide range of markets, such as the long-tailed distribution of returns and the relationship between the size of returns and their frequency. Specific parameters describing these statistical characteristics are even found to be directly comparable (see Figure 1.3). At a conceptual level, these are important findings. They suggest other consistencies in market behaviour may exist, and may have been overlooked by existing research. Additionally, these findings point intriguingly towards universal mechanisms underlying aspects of markets behaviour. These observations are the foundation for the research carried out in this thesis, which explores consistencies in financial markets at the level of group behaviour, rather than at the level of price behaviour; and is motivated by the awareness that the behaviour of traders inevitably relates to the behaviour of market prices – and their associated characteristics.

An empirical study into traders' behaviour with data spanning almost 2 decades across 31 different futures markets is carried out in chapter 2. This chapter represents the bulk of the empirical work carried out in this thesis and is therefore reviewed and critiqued at some length in the following paragraphs. Although the COT dataset used here has been analysed elsewhere, this has been primarily in economic settings. A thorough investigation into the behaviour of traders as a direct focus of the research has been lacking in the literature, as reviewed in chapter 2. The empirical work identifies a pattern of behaviour in historic COT data: speculators typically buy into rising prices whereas commercial traders typically sell into rising prices; the opposite pattern occurs during falling prices. This systematic behaviour of different groups of traders is apparently robust and applies across the majority of markets sampled. The remainder of the thesis explores the implications of this trading pattern for existing models of financial markets, provides a behavioural account of the phenomena in terms of order-type preferences and a market model incorporating these results, and investigates how these insights inform on the relationship between the activities of different groups and the volatility of market prices – with possible implications for market regulation.

I employ two separate research methodologies for chapter 2. An econometric approach demonstrates consistencies in group trading behaviour via standard time-series models. A time series regression predicts the change in a group's positions on each time step as a function of the current market returns, and the returns and change in positions on previous time steps. The coefficients describing the relationship between change in positions and returns have a significant and consistent pattern across markets: speculators' coefficients are positive whereas commercial traders' coefficients are negative (Table 2.5). This pattern is also shown to hold at longer-time-horizons and additional tests confirm that the coefficients associated with the groups are significantly different. I then explore this same pattern of behaviour using an alternative, more bespoke methodology. This approach employs a standardisation procedure to compare changes in traders' positions across different markets. (This is comparable to the approach adopted by other researchers to analyse statistical characteristics of market prices, as cited in chapter 1.) By comparing changes in positions associated with price changes of a standardised size and similar sign (positive or negative price changes), direct comparisons of behaviour under similar conditions are carried out across markets. This second approach produces results consistent with the econometric methodology, and also permits new studies of the phenomena. For example, a comparison of trading behaviour across markets demonstrates that relative changes in positions within groups – for a given relative price change – cannot be considered significantly different; that is, a high level of similarity may exist within groups and across markets (Tables 2.13 and 2.14).

The second research methodology is unorthodox and can be criticised for lacking direct parallels to previous research. It is my view, however, that, as a supplement to more standard econometrics, the methodology of standardising and categorising market behaviour is complementary, being both non-parametric (although non-parametric econometric techniques could certainly be explored for future research) and allowing for new research questions to be addressed. The primary contribution of the alternative methodology is to show that not only are commercial and speculators significantly different in their trading behaviour, but, additionally, behaviour *within groups* cannot be considered significantly different in many cases. These results indicate that intra-group behaviour is similar across a majority of markets – a new research finding. Additionally, the second methodology allows for a comparison of scaling in trading behaviour, finding evidence that certain group behaviours can be considered proportional at different relative scales of price changes. These are novel research directions most effectively supported by a novel research approach.

An additional critique of chapter 2 relates to the consistencies of the findings and the observation that interest-rate and stock index markets may show less consistent patterns of group behaviour than other markets, including currencies and more traditional agricultural, metal and industrial futures markets (see Tables 2.5 to 2.8). There are certainly important economic differences between the asset-classes that could underlie differences in results. Interest-rates and stock indexes are financial, rather than tangible, as is the case with a commodity, for example. It could be that the lack of a more tangible underlying product to these derivative markets results in different, or less pronounced patterns of behaviour. There has been no further study into these differences and additional statistical tests are required to assess whether they are meaningful.

A further criticism of the empirical work in chapter 2 applies to the choice of markets. I select 31 different futures markets covering 6 different asset classes as a comprehensive and diverse sample of different products. However, these markets were chosen on a discretionary basis, as being sufficiently liquid, economically relevant, and diverse. The selection criteria could have been more systematic here; for example, markets could have been selected strictly on the basis of liquidity or trading volume. Furthermore, in addition to futures markets, option markets are also reported in COT data. Including option markets in the study could have provided a larger sample size.

A final criticism of the empirical work presented in chapter 2 relates to the scope of the research. My research focuses very deeply on a particular pattern of trading behaviour; I analyse the consistency of a pattern of behaviour across markets and within groups. I do not explore, more broadly, other possible patterns of trading behaviour that may exist and be identifiable via new research techniques or datasets. One possible research direction overlooked, but strongly suggested by the findings reported in chapter 2, is a causal relationship between changes in positions and market returns. This area of research was partly avoided due to the existence of a number of other studies investigating this same subject using various datasets from stock exchanges (Choe, Kho, and Stulz, 1999; Nofsinger and Sias, 1999; Griffin, Harris, and Topaloglu, 2003). These findings generally suggest that market returns have some ability to forecast changes in traders' positions, but not the other way around. As reviewed in chapter 2, similar studies have also been conducted with the use of COT data (Buchanan, Hodges, and Theis, 2001; Wang, 2001). My intention in chapter 2 is to focus on concurrent relationships between market returns and group positions, and the surprising level of consistency found here – an area that has not been the subject of a comprehensive study using COT data.

As possible further research, it may be of interest to explore how the causal relationship identified by other researchers between market returns and traders' positions relates to order-type preferences. (That is, the theory of different levels of trading aggression associated with different types of traders that is explored in the following chapters of the thesis.) More broadly, future research could involve the study of alternative datasets and proceed with clearer hypotheses that extend from my own work. A recent paper by Lillo, Moro, Vaglica and Mantegna (2008) analyses the synchronous relationship between market returns and changes in the trading positions of firms in the Spanish stock market. The results of this study are very similar with my own, but span an entirely different set of markets and participant groups. Focusing on the four most highly capitalised stocks and approximately 70 of the most active trading companies in the Spanish stock market, Lillo et al. classify participants into three well-defined groups. Firms are characterised by changes in their positions as being either positively correlated with stock returns (similar to my findings on large speculators), negatively correlated (similar to my findings on commercial traders), or uncorrelated (with similarities to non-reportable traders). Lillo et al. (2008, p. 12) suggest these trading firms "self-organise in groups to the extent that in most cases it is possible to characterise a firm with a specific resulting strategy". Furthermore, Lillo et al. identify that firms typically stay in the same group over the 4 year sample period, indicating a long term specialisation. These findings are analogous to those in chapter 2, suggesting high levels of consistency in trading behaviour. Lillo et al. also argue their results offer an empirical basis for agent-based models of financial markets, as I have done throughout this thesis, but fail to explore possible links between patterns of trading behaviour and order-type preferences.

Moving on to Chapter 3, which reviews literature on computational and agent-based modelling in the social sciences, and more specifically, the application of this relatively new approach to modelling financial markets. The literature review in this chapter highlights that many existing models of financial markets incorporate unrealistic representations of groups of traders, relying on theoretical convenience rather than empirical evidence. For this chapter, I implement the Alfarano, Lux, and Wagner (2005) market model that generates realistic statistical characteristics of market prices and use the model to demonstrate weak group representations. The simulated group behaviour from this market model is unrealistic, yet a central theoretical component. This analysis leads to a number of suggestions on how to improve behavioural realism in future market models.

Whilst informative, the analysis of Alfarano et al. in chapter 3 can be criticised as being inappropriate given the model's intentions. The developers set out to replicate key price characteristics and develop a model that can be calibrated to represent a particular financial market's behaviour. To do so, they use highly stylized components that extended logically from previous literature, including the typical groups of fundamental and noise traders (see discussion in sections 2.2 and 3.5). These representations of groups of participants have a long heritage in academia and it is difficult to criticise Alfarano et al. for using these established components to develop a model that is broadly successful within the context of their objectives. However, as a relatively recent publication and representative of many other models in this area, the approach of Alfarano et al. demonstrates a misalignment between the research objectives and the established components used to derive the results. If an objective of such research is to calibrate a model to represent real financial markets more closely, other sources of empirical data, in addition to those on market prices, are equally valid measures of a model's success, and, should therefore be referenced as a tool for progressive research. The comparison of simulated to real-world group behaviour carried out in chapter 2 helps to demonstrate that the group representations upheld as the status-quo in modern market models do not adequately extend from empirical sources. With new objectives of moving towards higher levels of realism and market-specific calibration, the status-quo is in need of updating. My analysis here is intended to highlight this point as it applies to Alfarano et al. and, with equal merit, the broader research paradigm.

An alternative 'zero-intelligence' approach to modelling economic phenomena, including financial markets, is reviewed in chapter 4. It is named ‘zero-intelligence’ because of the focus on situational constraints in economic situations, rather than agents’ intelligence. The approach also advocates a bottom-up stance to model building that relies on using empirical data to develop models rather than theoretical assumptions. The market model developed by Mike and Farmer (2008) is implemented for chapter 4 and accurately calibrates its core components on real-world market data. The model, in the context of empirically derived components, demonstrates that the continuous double-auction – the standard trading institution of almost all financial markets – has a powerful constraining influence on traders’ behaviour. Via the accurate simulation of the placement and cancellation of market and limit orders, and, in the absence of any rational decision-making or conditional behaviour on behalf of agents, a number of statistical characteristics associated with financial market behaviour naturally emerge in the model. Deeper theoretical assumptions, including a division between fundamental and noise traders, are not required for the model to be effective.

Chapter 4 extends the Mike-Farmer model to include groups of traders with different levels of order-aggression as an account of the patterns of behaviour identified in chapter 2. Speculators are considered typically to rely on market orders whereas commercial traders typically rely on limit orders. These different levels of order aggression, when introduced into the Mike-Farmer model along with measures of trading behaviour amongst different groups (referred to as ‘simulated COT data’), give rise to the behaviour documented in historic COT data. This new layer of realism in the model is consistent with the original Mike and Farmer approach – it is derived from empirical data and indirectly captures global characteristics in the market place (in this case, the aggregate behaviour of different types of traders).

Introducing order-type preferences as an explanation for the behaviour documented in chapter 2 is an assumption, of course, and does not imply that such preferences actually produce the phenomena in real-world financial markets. This assumption can be adequately defended on two counts, however. Firstly, and most crucially, the approach is strongly supported by existing evidence of order-type preferences amongst market participants with different business objectives (see studies discussed in section 4.4 and 4.5); secondly, the theoretical assumption of group order-type preferences is introduced into the model at a low-level, applying to groups of traders that make up the market system, and is not crucial to the model's overall performance (the Mike-Farmer approach proceeds to simulate price behaviour accurately in the absence of order-type preferences). This is in contrast to focusing assumptions at the highest-level, and abstracting over the entire behaviour of the system, as typical of alternative modelling approaches (e.g. Alfarano et al. 2005; Miller and Page; 2007).

There are alternative explanations for the patterns of group behaviour and these are discussed in chapter 4. A more typical economic account would propose consistencies in trading behavior arise via strategic or informational differences, or via noise and positive feedback trading (e.g. Black, 1986; Shleifer and Summers, 1990), or herding behavior (Irwin and Yoshimaru, 1999). Whilst there may be merit in these theories, and, indeed, none are mutually exclusive from my own, the question posed in chapter 4 is: which account offers the most evidence-driven, parsimonious explanation? I consider a theory of order-type preferences to be the most powerful account, linking most naturally to differences in business objectives amongst market participants, and supported by evidence of varying levels of order aggression amongst different types of traders. As such, the extended Mike-Farmer model can be considered a constructive 'proof' of the proposition that order-type preferences contribute to patterns of group trading behavior across a broad range of markets.

The extended Mike-Farmer market simulation is unique in that it is empirically consistent at two separate levels of analysis: at the order-flow level, based on the modelling and empirical calibration conducted by Mike and Farmer, and at the group-level, based on my own research. Whilst other approaches have sought-out similar levels of realism (Darley and Outkin, 2007), the model presented here is relatively simple and easy to replicate. Indeed, it would be possible to take forward the simulations I have done analytically, and relate them more closely to previous mathematical models. For example, Parlour (1998) shows that the probabilities involved in the trade-off between the choice of market and limit order relates fundamentally to the number of limit orders currently held; Foucault (1999) suggests higher volatility increases the probability of limit orders becoming executed at an unfavourable price; Handa, Schwartz, and Tiwari (2003) demonstrate that participants who rely on shorter-term information have an associated higher opportunity cost of non-execution and therefore make use of more aggressive orders. All these models have some relevance to my own approach and offer potential frameworks for extension. As Miller and Page (2007) highlight, it is the norm in economics to derive mathematical models from first principles and, whilst the approach can yield valuable insights, it can also be limiting, applying most appropriately to homogeneous and equilibrating 'worlds', rather than complex and dynamic ones such as financial markets. I choose to extend the Mike-Farmer computational model due to its flexibility and its uniquely empirical focus that aligns with the objectives of this thesis. Additionally, this model is very recent and represents the current trend in the literature away from purely theoretical models. I consider the market model developed here to accommodate a number of realistic characteristics of market behaviour on a minimal number of theoretical components. It is sufficiently powerful to offer a strong foundation for future research. As Miller and Page (2007, p. 20) highlight, good models are often “designed to be just sufficient to tell a story that could be understood easily yet have enough substance to provide some insights into broader issues”. Some broader issues are explored in the next chapter of the thesis.

Chapter 5 addresses the relationship between the activities of particular types of traders, in particular speculators, and market volatility – a topical subject of relevance to financial market regulators. An analysis is conducted with historic COT and price data, and with the market model developed previously. Computational models are unique in that they provide a laboratory for research, an environment in which to test and develop key hypotheses for understanding emergent behaviour more accurately. In chapter 5, parameter values in the market model are varied to explore how the concentration of different groups may impact on market volatility. The model clearly predicts that increased use of aggressive orders from speculators leads to more volatile prices, but also demonstrates how important non-linearity can be introduced from changes in the relative concentration of different groups of traders (and their associated order-preferences).

The empirical research in chapter 5 finds conflicting results, however: over the sample period, the activity of speculators is often associated with reduced volatility (at least when using stark statistical tests – see section 5.3.2 on Wang’s methodology). Increased speculation may introduce more liquidity to markets and therefore be associated with reduced volatility. The empirical analysis in chapter 5 leads to a number of suggestions for future improvements to the market model, which include linking the size of the limit order book more closely to the total amount of open interest in the simulated market.

Additionally, the analysis leads to a discussion on new possibilities for market regulation: regulating types of trades rather than types of traders. By regulating market liquidity (the supply of limit orders relative to market orders) it is possible to regulate market volatility. I suggest this approach has not been adequately explored by market regulators.

A worthy criticism of the empirical research in this chapter applies to the sample period for the data analysed here, which extends until 2008 only. Although in most cases the data covers the preceding 17 years and is therefore substantial, for many markets, the period from 2008 onwards has been marked by periods of unusually extreme volatility. For example, the stock market effectively crashed in September-October 2008 with the bankruptcy and government bail-outs of a number of international companies. Economists may consider this time as characteristic of a ‘regime shift’ in market activity – and therefore unrepresentative of more typical market behaviour. Further research could compare and contrast findings on group behaviour from the period preceding the recent volatility and use subsequent data as an out-of-sample test of the findings.

One of the most interesting areas for future research is to continue to develop the Mike-Farmer model. In particular, it may be interesting to provide a clearer framework for emergence in the market model, whereby well-formulated aggregate behaviour can arise from localised, individual behaviour. To develop models that move beyond our initial understanding, flexible frameworks are required for new and unanticipated features to arise (Miller and Page, 2007). The current specification of the market model provides a framework for realistic group behaviour to arise from lower-level probabilistic specifications of order preferences, but more research in this direction is certainly possible. For example, it would be possible to demonstrate how different constraints associated with business objectives lead inevitably to participant behaviours. As Epstein (2007, p. 8) highlights, the motto of a new form of ‘generative’ social science is: “if you didn’t grow it, you didn’t explain its emergence”. Within the context of this modelling research, market agents could be provided with a range of position-sizes associated with their trading (which can be considered as related to their business objectives; for example, pension funds have much larger position sizes then market makers), whilst the time-horizons for investments and the associated order-aggression are optimisable parameters in the model and determined on the basis of agents’ performance. Agents could then evolve over time towards optimal behaviour given their unique business constraints, whilst other agent decisions (such as whether to buy or sell) are determined randomly so that the influence of business objectives on behaviour is isolated. Such a modelling specification may lead naturally to the emergence of the pattern of group behaviour identified in chapter 2.

6.3 Conclusion: Towards a Theory of Market Morphology

Given the above chapter review, I consider that the objectives of this thesis - to increase understanding of group behaviour in financial markets and to develop a market model incorporating more realistic behaviour - to have been broadly achieved. There is clear scope for improvements and future research and a number of options in this direction have been outlined in this chapter and elsewhere. This concluding section now briefly considers the broader significance and contribution of this work to new developments in the study of financial markets.

I consider this research to be increasingly important in connecting the behaviour of participants in financial markets, or what can be considered local level market dynamics, with higher level behaviour associated with financial market prices, or what can be considered the emergent level. By offering new evidence on the behaviour of groups of traders, this thesis contributes to more realistic models of market dynamics, and therefore assists in the process of mapping emergent level behaviours more accurately to local level components. This mapping process could be termed a theory of 'market morphology': connecting the form of market behaviour (or emergent behaviour) to its component parts (or local level behaviour, including relative concentrations of different types of participants). The goal of this area of research would be to understand broad similarities and idiosyncratic differences between financial markets, in liquidity, volatility, or more abstract notions of power-law scaling (as discussed in chapter 1), in terms of differences in local level components – such as unique participants and participant ecologies.

There are analogies for a theory of market morphology from other areas of science. Morphological diagrams are standard measurement tools in the study of bacterial colonies (Ball, 2004). Shapes form in agar gel, for example, as it develops depending uniquely on the amount of nutrients and the hardness of the gel during development. The resulting form of the bacteria is reliably related to its inputs so that maps of this relationship have been constructed. A more well-known example is the relationship between air temperature, humidity and the shape of snowflakes. For example, hexagonal columns of ice grow below -25c, whilst, between -5c and -22c, snowflakes form as flat plates in relatively dry air, and as more typical star shapes if air humidity is higher. For snowflakes, temperature and humidity can be considered control parameters that construct a 'morphological space'. Growth patterns for both bacteria and snowflakes can be divided into discrete classes based on the relationship between core control parameters, and the subsequent form of growth is repeatable, even if precise details differ.

In a similar way, local level quantities in financial markets, such as the relative quantity of participants with particular business objectives and trading characteristics such as order-aggression, may generate a morphological space for particular types of market behaviour to emerge. As Bouchaud, Farmer, and Lillo (2009, p. 145) highlight, "it would be extremely valuable to have a comprehensive empirical study that connects the heterogeneity of market participants with their strategy and with the properties of price dynamics". It is not suggested that this theory could offer a complete explanation of market behaviour, but it could forge new, broad insights into how the interactions of different types of participants influence the behavior of markets.

Whilst my research does not focus on exploring a theory of market morphological directly, it does provide insight into components that are required for such research. Chapter 2 provides empirical evidence demonstrating a clear pattern of behaviour amongst two very different types of market participants in large U.S future markets: speculators typically use more market orders, whereas commercial traders typically use more limit orders. These order-preferences may relate closely to fundamental types of market participants. As Bouchaud, Farmer and Lillo (2009) argue, there may be two broad classes of agents in financial markets: liquidity takers and liquidity providers. The impact these different types of participants have on a market system may relate to the positive and negative feedback effects they introduce via liquidity changes. This broad distinction between liquidity takers and providers could also be extended to encompass other market participants not documented in COT data, such as market makers, who are traditionally viewed as liquidity providers, although recent debate on the high frequency trading and automated market making has suggested otherwise (e.g. Grant, 2010). Lillo et al. (2008, p. 14) agree that there is “an interplay of at least two classes of traders, different with respect to their size heterogeneity and responding to price changes in different ways”. In moving towards a theory of market morphology, Lillo et al. (2008, p.14) support the possibility that “the fluctuation of price returns, i.e. the market volatility, is significantly affected by the fluctuations in the relative trading intensity of the two groups.”

Accurately calibrated market models and clear hypotheses from empirical research offer strong foundations for a theory of market morphology. But this area of research also faces numerous challenges. Empirical datasets are limited and markets are highly dynamic environments: models must be able to distinguish what is contingent from what is robust, via rigorous testing against empirical sources. Models must also successful locate a middle ground between excessively crude caricatures of a financial market and excessively complex ones. Within these important constraints, a theory of market morphology must also have realistic and pragmatic aims: to deliver much needed insight into differences between markets that can benefit those charged with regulating them. It is widely accepted that the severe economic downturn that began in 2008 was partly caused by the extreme behaviour of certain financial markets; a research agenda that increases our understanding of how market behaviour changes and evolves over time is of clear relevance at this time.

To continue the comparison with the natural world, there is an intriguing analogy for the potential in this new area of research found in the study of natural systems, suggestive of the important role of participant heterogeneity in understanding and effectively regulating financial markets. Honey bees have a dependence on the internal temperature of their hive, which must fall within a specific and narrow range in order for bees to reproduce and grow effectively (Fischer, 2004). To regulate this temperature, bees collectively vary their behaviour: to increase the heat, bees huddle together and rapidly flap their wings; to reduce the temperature, bees spread out and fan their wings. The temperature threshold that stimulates this behaviour is linked to a genetic trait. Hives with bees that lack genetic diversity are prone to extreme fluctuations in internal temperature. As bees react at similar temperature levels, extreme fluctuations in temperature and limited hive-productivity result. In contrast, hives with higher levels of genetic diversity amongst bees have more stable temperatures. The collective response of the bees to changes in temperature is more gradual, being graded at different thresholds to offer a more consistent hive environment. In a similar respect, the collective response of market participants creates aggregate fluctuations in market liquidity, volatility and prices. Sufficient diversity amongst traders and financial institutions – specifically, their order preferences, levels of trading aggression, or prices at which they are willing to buy and sell - may promote more stable economic environments. By developing a thorough understanding of the behaviours associated with participants, and an accurate mapping of how these behaviours interact and aggregate in market environments, it may be possible to mitigate related risks more effectively.

7. References

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