THE INTERACTION BETWEEN INFORMED AND UNINFORMED AGENTS IN SECURITIES MARKETS

Brad Wong

A dissertation submitted in fulfilment
of the requirements for the degree of

Doctor of Philosophy

Discipline of Finance
Faculty of Economics and Business
University of Sydney

CERTIFICATE

I certify that this thesis has not already been submitted for any degree and is not being submitted as part of candidature for any other degree.

I also certify that the thesis has been written by me and that any help that I have received in preparing this thesis, and all sources used, have been acknowledged in this thesis.

Signature of Candidate

…………………….........

Brad Wong

Acknowledgements

I would like to extend my sincerest gratitude to my supervisors, Alex Frino and Andrew Lepone. I thank both of them for their intelligent advice, expert guidance and friendship throughout the course of my candidature. I also thank Alex for giving me the opportunity to pursue the type of Ph.D. which I have undertaken these last three years. The unique combination of both academic and industry focussed study has been invaluable, and I cannot overstate the worth of this experience towards my long term personal and professional development. I thank Andrew for his incredible dedication to my learning and his unwavering willingness to help me in every facet of my study, no matter how small or mundane. I would not have made it this far, if not for his day-to-day oversight of my work. Stephen Satchell and Reuben Segara have also provided useful counsel for Chapters 4 and 5 of this thesis respectively, and I thank them for their contribution. I thank Kate McCawe, Theo Voronov and Rizwan Rahman for their great research assistance. Finally, I would like to acknowledge the support and friendship of my fellow students: Jennifer Kruk, Hamish Malloch, Abhishek Das, Imon Palit, James Cummings, Angelo Aspiris, George Li, Steve Lecce, Brian Yang, Jeff Wong, Mitesh Mistry, Kiril Alampieski, Danika Wright, Elisa Di Marco and Talis Putnins. The most rewarding experience of my candidature has been getting to know these exceptional people and I am happy to have shared with them the challenging experience that is completing a doctoral dissertation.

Table of Contents

List of Tables

Preface

The work presented in this thesis is derived from three joint studies which have been published in refereed journals or are currently under review.

Chapter 3 is published as:

Frino, A., A. Lepone and B. Wong, 2009, 'Derivative use, fund flows and investment manager performance', *Journal of Banking & Finance*, 33, 925-933.

Chapter 4 is a working paper currently under review:

Frino, A., S. Satchell and B. Wong, 2009, 'How much does an illegal insider trade?', *Working paper* of the *Capital Markets Co-operative Research Centre.*

Chapter 5 is a working paper currently under review:

Lepone, A., R. Segara and B. Wong, 2009, 'Does broker anonymity hide informed traders?', *Working paper* of the *Discipline of Finance, University of Sydney*.

Synopsis

This dissertation contains three essays that examine the interaction between informed and uninformed parties in securities markets. Given the influential role that informed traders have in shaping securities prices, trading activity, market-wide and even economy wide outcomes, this research provides empirical evidence on significant and important issues. Each essay addresses a topical, yet under-developed research strand to ensure that the results of this dissertation are relevant to both academic and non-academic parties. The conclusions drawn from the three essays have the potential to influence the decisions of fund managers, regulators, market designers and, direct and indirect investors in securities markets.

The first essay examines the interaction between mutual fund managers and the investors that seek their services. Fund managers often incur significant adverse selection, transaction and opportunity costs when executing investors' liquidity requests. Prior research hints that index futures are able to mitigate these costs, though no research has provided convincing empirical evidence, primarily due to the fact that existing data on fund managers' use of derivatives is imprecise. Using unique survey data which indicates whether a fund manager uses index futures to manage investor flows or not, this essay is the first to provide conclusive empirical evidence on this issue. The results indicate that fund managers who trade index futures in this manner are unencumbered by investor flows and have superior fund flow conditional alpha and market timing measures of performance relative to their non-derivative trading peers. Informed fund managers are able to maintain their advantage even when their trading decisions are partially dictated by uninformed parties.

The second essay in this dissertation examines the interaction between illegal insider traders and the regulatory body that prosecutes these individuals. Drawing upon insights developed in the literature which describes crime through the prism of economic thought, the essay develops a model which predicts the intensity of an illegal insider's crime: their traded volume. The predictions of the model are tested using data drawn from case files of the Securities and Exchange Commission (SEC). As such, this essay is the first empirical study of illegal insider trading to investigate the behaviour of the insider, with all previous empirical research instead examining the market's response to insider trading. The study hypothesises that insider volume is a function of two factors in control of the regulatory body and associated law makers: the expected return and expected penalty from the insiders' trades. Furthermore, insider volume is hypothesised to be negatively related to the variance of the stock traded. The results, which validate the hypotheses and are robust to sample selection bias, have important policy implications for regulators seeking to detect illegal insider trading.

While the first two essays consider specific examples of informed traders, the final essay in this dissertation examines informed traders in general. In particular, the study investigates whether broker anonymity in electronic order driven markets obscures the presence of informed traders during the lead up to a significant information event. This research is important given the prolific changes to this feature of market design in recent years across electronic exchanges globally, and the fact that all prior research in this area has yet to consider the effects of broker anonymity on information transmission during periods of large information asymmetry. The study presents three pieces of evidence that informed traders are better camouflaged when the identity of the broker intermediary is hidden *vis-à-vis* when the identity is visible. Naturally, this suggests that uninformed traders suffer at the expense of informed traders during the periods examined in this study. This finding has important policy implications for exchange officials deciding whether or not to reveal broker identifiers surrounding trades, especially considering that almost all prior research suggests that broker anonymity is correlated with improved liquidity in the form of lower bid-ask spreads.

Chapter 1. Introduction

Information plays an important role in the function and dynamics of securities markets, a fact evinced by the number of prominent economic and financial theories underpinned by information. The efficient markets hypothesis describes how security prices are determined by information and the extent to which market participants can successfully profit from it (Fama, 1970). The process by which prices become informationally efficient is modelled extensively in the rational expectations literature (Grossman and Stiglitz, 1980; Brown and Jennings, 1989; Grundy and McNichols, 1989). Differences in the precision of private information possessed by individuals is hypothesised to influence trading activity (Wang, 1994), while the release of information into the public domain also generates trading (Kim and Verrechia, 1991). Uncertainty about whether a trader is informed or uninformed creates volatility and dramatic market movements (Gennotte and Leland, 1990; Jacklin, Kleidon and Pfleiderer, 1992). The extent of volatility, in turn, influences the likelihood of an option market being established for a particular asset (Mayhew and Mihov, 2004). The extent of information uncertainty influences the spread setting behaviour of intermediaries such as specialists and dealers (Bagehot, 1971; Copeland and Galai, 1983; Glosten and Milgrom, 1985; Kyle, 1985; Easley and O'Hara, 1987) as well as the amount of stock they are willing to offer (DuPont, 2000; Caglio and Kavajecz, 2006). Information influences prices, price changes, volume, volatility, trading costs and liquidity.

Beyond security specific outcomes, information influences a myriad of other important economic outcomes. Information costs determine the distribution of investable capital to fund managers (Huang, Wei and Yan, 2007). Heterogeneity in the types of information used by participants in markets is hypothesised to dictate the optimal structure of a market (Anufriev and Panchenko, 2009; Bottazzi, Dosi and Rebesco, 2005). The value of insider information shapes the optimal enforcement policy of illegal insider trading (DeMarzo, Fishman and Hagerty, 1998). The extent of informed (insider) trading can influence the cost of capital in an economy (Bhattacharya and Daouk, 2002).

A key feature of almost all information based models is the existence of an interactive element between two (or more) parties. For example, information based models of the bid-ask spread typically describe the interaction between informed traders, liquidity-motivated traders and the market maker. More precisely then, it is not information *per se* that influence prices, trading activity and other characteristics of the market and economy. Rather these characteristics are the observable outcomes of the interactions between economic agents who possess information and those that react to its presence. The primary goal of this dissertation is to examine the behaviour of informed individuals, and in particular, their interaction with some other (uninformed) participant in securities markets. Given the influential role of information in shaping security specific and economy wide outcomes, an understanding of these relationships is extremely valuable.

This dissertation consists of three essays. Each examines the interaction between an informed and uninformed party in securities markets. It is clear from the preceding exposition and the literature review in Chapter 2 of this dissertation that the topic of 'information in securities markets' is explored extensively in the academic literature.

To ensure that each essay provides a novel contribution to extant knowledge, each study is built around a topical, yet under-developed research niche to provide new insight into the behaviour of informed individuals in financial markets.

The first essay examines the interaction between mutual fund managers and the investors who seek their services. In particular, the essay examines how mutual fund managers use index futures to mitigate the negative effects of investor flows, such that informed fund managers can maintain superior returns even when their trading decisions are partially dictated by uninformed, external parties. In examining this interaction, the study also contributes to the under-researched area of mutual funds' use of derivative securities.

The second essay concerns the interaction between illegal insider traders (i.e. individuals with access to price-sensitive non-public information) and the regulatory body that prosecutes these individuals. The essay provides a model which describes the volume traded by an illegal insider as a function of two factors directly in control of the regulatory body and associated law makers: the expected profit and penalty of the insider's trades. While there are several studies which explain the volume traded by informed traders (e.g. Kyle, 1985; Easley and O'Hara, 1987), the second essay in this dissertation investigates the trading decisions of a peculiar class of informed traders – illegal insiders – whose decision process involves weighing up potential profit against a punitive risk. The study empirically tests this prediction using data drawn from SEC case files. As such, this essay is the first *empirical* study of illegal insider trading to investigate the behaviour of the insider trader, rather than the market's response to the presence of illegal insider trading.

While the first two essays consider specific types of informed traders (fund managers and illegal insiders), the final essay considers informed traders in general. This essay examines how broker anonymity in electronic limit order markets affects the ability of uninformed traders to detect informed traders in the lead up to a significant information event. This essay is the first study to examine how broker anonymity in electronic markets affects information transmission between informed and uninformed investors during periods of large information asymmetry. The following exposition introduces each topic in detail and explains the contribution of the work to the existing body of knowledge.

1.1. Derivative use, fund flows and mutual fund performance

The issue of mutual funds' use of derivatives appears to have attracted increased scrutiny in the financial press and other public channels. Several recent articles published in the *Wall Street Journal* comment on mutual funds' increasing investment in derivatives, often with headlines that draw upon the negative perceptions surrounding derivative investment[4] (Liase, 2007; 2006, Pollock, 2006). While less sensationalist in its delivery, this cautious sentiment was echoed in a recent speech by the SEC, which urged fund managers to appropriately manage the risk of increased

[4] The subtitle of one particular article went so far as to question whether derivatives represented "devil's spawn" (Pollock, 2006).

derivative exposure and to take a measured response towards investment in these securities (Gohlke, 2007).

Despite the attention this matter has gained in the financial press, very little academic research examines the use of derivatives by mutual funds. Koski and Pontiff (1999) attempt to infer mutual fund derivative trading behaviour by comparing the portfolio returns and their higher moments of derivatives users *vis-à-vis* non-users. Interestingly, there exists little difference in the (unconditional) distributional properties of several risk and return metrics between the two groups. While no significant difference is identified in unconditional risk, when conditioned on prior returns, Koski and Pontiff (1999) find that users of derivatives experience lower inter-temporal variation in risk between consecutive six month periods. They conclude that managers trade derivatives to minimise the impact of new fund flow on risk. The result is significant only for systematic risk (not idiosyncratic), suggesting that index futures feature prominently in the trading strategy of derivative users.

While a significant first step, their research is unable to further explore the effects of this particular derivative trading strategy, or indeed any other strategy that managers may decide to employ using derivatives. This is due to imprecision in their data with respect to the allocation of the derivative user characteristic. All mutual funds that use derivatives are aggregated into a single group and effectively no distinction is made between different types of derivative trading strategies. This broad classification method is also employed in studies of derivative use by investment managers in the U.K. (Fletcher, Forbes and Marshall, 2002), in Canada (Johnson and Yu, 2004) and Australia (Fong, Gallagher and Ng, 2005; Pinnuck, 2004). As such the analyses contained in Koski and Pontiff (1999), as well as these other studies, are only able to provide insight into 'average' derivative trading behaviour. Indeed Koski and Pontiff (1999) note that due to the limitations associated with their method of data collection (telephone survey) they are 'unable to obtain more in-depth information about the choice and purpose of specific instruments' (p. 796). The aim of the essay in Chapter 3 is to fill this gap in the literature by examining a particular and well-defined derivative trading strategy implemented by investment managers. Building upon the initial findings of Koski and Pontiff (1999), this study investigates further the use of stock index futures for managing cash flows. In industry, this process is often referred to as 'cash-equitisation' of investor flows.

To perform this analysis, this study has access to unique survey data compiled by the Sydney Futures Exchange on Australian managed funds, the equivalent to U.S. mutual funds. This data is superior to that used in previous studies since the data indicates which funds use index futures for the purposes of cash equitisation of investor flows and which funds do not use derivatives for this purpose. Due to greater precision in the allocation of the derivative user characteristic, it is possible to provide additional and deeper insight into the use of derivatives by investment managers. Since this study analyses a particular derivative trading strategy, it is possible to identify *ex ante* the instances when returns might differ between 'users' and 'non-users' and direct the research accordingly. Chapter 3 of this dissertation outlines a simple model of cash-equitisation. The model predicts that funds which engage in this behaviour experience superior alpha and market timing measures of performance, but only when fund flows are significant. When fund flows are negligible the model predicts little difference, on average, between equitisers and non-equitisers. Given the size and sophistication of the Australian investment management industry, this research is relevant to fund managers in other prominent economies in North America, Europe and Asia. At the end of 2007, the dollar value of funds under management in Australia reached approximately 1.2 trillion USD. This places Australia as the fourth largest investment management industry in the world behind the U.S., Luxembourg and France and the fourth largest in the world per capita of population[5] behind Luxembourg, Ireland and Hong Kong (Investment Company Institute, 2008, p157).

Why would an investment manager decide to manage fund flows using index futures? Theory and empirical evidence suggest that fund flows are a significant impediment to wealth creation in mutual funds. Edelen (1999) shows that fund flows are negatively related to funds' alpha performance. The result is based upon the hypothesis that fund flows force otherwise informed managers to engage in trading that is essentially liquidity motivated. In the rational expectations model of trade (e.g. Grossman and Stiglitz, 1980), equilibrium is only achieved when these traders sustain losses to the informed. Additionally, if fund flows cause managers to increase the (uninformed) turnover of securities, then the fund's alpha performance will suffer as a result of transaction costs such as the bid-ask spread, market impact costs and commissions. For example, Chan and Lakonishok (1995) provide evidence that investment managers with higher turnover rates experience significantly greater round trip market impact costs.

[5] Population data used to calculate each economy's per capita funds under management are sourced from the United States Census Bureau International Data Base.

Edelen (1999) also shows that mutual funds' market timing performance, under certain conditions, is hindered when experiencing large investor flows. If managers delay the investment of new funds, this causes temporary dilution of the fund's beta. Since there is a strong positive correlation between fund flows and market returns (Warther, 1995), fund managers exhibit reduced portfolio betas at exactly the point when they should be increasing them, hence negative market timing. The negative relationship between fund flow and portfolio betas is also documented at the aggregate level by Ferson and Warther (1996) and Ferson and Schadt (1996).

The results from Edelen (1999) and related studies indicate that managers face a trade-off when determining how to manage their fund flows. On the one hand, immediate and rapid investment of fund flows is costly in terms of adverse selection and transaction costs. This ultimately reduces the alpha performance of mutual funds. The alternative course of action for fund managers, patient trading, results in sub-optimal portfolio betas and negative market timing skills. Essentially, managers trade off the costs of accessing risk against the opportunity costs of not accessing that risk. The underlying rationale for using index futures to manage fund flow is that the security provides an inexpensive mechanism to access market risk, thereby alleviating both problems simultaneously.

It is apparent that this research is not only relevant to the literature on the use of derivatives by investment managers, but is also related to studies that examine the interaction between fund flows and concurrent or subsequent performance.[6] As a by product of the framework in which the analysis is constructed, the essay in Chapter 3

[6] This is in contrast to the literature that examines the reverse, how performance affects subsequent fund flows (e.g. Ippolito, 1992).

provides a mechanism for re-examining, in a different experimental setting, the hypotheses contained in Edelen (1999), Ferson and Warther (1996) and Ferson and Schadt (1996). In the most general terms, the methodology employed in these studies is to examine fund performance as fund flow varies and to draw inferences from this analysis. For example, to test the hypothesis that fund flows cause negative market timing by diluting fund betas at periods of higher expected returns, Ferson and Warther (1996) regress changes in fund flows against changes in mutual fund (public-information conditional) betas. Their results indicate that fund flows are negatively *correlated* with fund betas, but cannot definitely determine if fund flows *cause* the reduction in portfolio beta. Complementing this approach, this study examines the scenario where two funds experience large, material fund flows but one fund uses index futures to mitigate the costs of these flows while the other does not. If the hypotheses contained in the aforementioned studies are true (and index futures are an effective means of alleviating the costs associated with increased fund flow), then the manager that trades index futures under these conditions should experience superior performance relative to the other manager. Through investigation of this very question, this study provides additional insight into the relationship between fund flow and performance. Importantly, the analysis does not solely rely on examining the *correlation* between fund flow and performance. By examining the return differential associated with the use of index futures, given a fixed level of fund flow, additional evidence is presented as to whether fund flows *effect* negative fund performance or merely *covary* with it.

1.2. How much does an illegal insider trade?

Insider trading remains an important concern of regulators despite almost two decades of innovation in enforcement since the prominent scandals of the 1980s.[7] For example, in the 2008 fiscal year, the SEC initiated the largest number of insider trading cases in the Commission's history (SEC, 2008). Indeed, a recent action brought against employees of several well-known Wall Street firms and hedge funds (*SEC v Guttenberg et al., 2007*) reveals that the scale of insider trading schemes remains as large as they were during the era of Boesky, Milken and Levine.

While there is considerable academic interest in insider trading, only a handful of studies provide empirical evidence on the issue.[8] Meulbroek (1992) uses data sourced from SEC case files and finds that trading by illegal insiders is correlated with abnormal price movement and volume. Cornell and Sirri (1992) examine illegal insider trading before the 1982 acquisition of Campbell Taggart by Anheuser-Busch and conclude that insider trading leads to more informative prices, but does not impair liquidity. Chakravaty and McConnell (1997) reach similar conclusions but use data from Ivan Boesky's trades in Carnation prior to the company's takeover by Nestle. However, Chakravaty and McConnell (1999), using the same data set, find that Ivan Boesky's trades did not move prices any more than normal buyer-initiated trades, casting doubt over the proposition that insider trading, *per se*, moves prices. Finally, Fishe and Robe (2004) examine a sample of 30 stocks featured in an influential *Business Week* column and find that illegal insider trading is associated with wider

[7] Seyhun (1992) documents the changes in enforcement policy over time. See *re Ivan F. Boesky Sec. Litig.*, 957 F.2d 65, 69 (2d Cir. 1992) which is one of the most famous insider trading cases prosecuted.
[8] Academic interest towards insider trading primarily addresses the debate as to whether insider trading should be made illegal or not. See for example, Manne (1966), Carlton and Fischel (1983), Cox (1986), Demsetz (1986), Manove (1989), Ausubel (1990), Leland (1992), Georgakopoulos (1993) and Manne (2005).

spreads and lower depth in specialist markets. Clearly, the empirical literature to date has focussed on the effect of illegal insider trading on market behaviour.[9] The essay in Chapter 4 extends this literature by examining the behaviour of the insiders. Specifically, the study builds on the seminal work of Becker (1968), who developed an economic theory to explain criminal behaviour, and provides a model which identifies the factors which affect the intensity of an illegal insider's crime – i.e. the volume that they trade. The model supposes that illegal insiders act in a manner consistent with Becker (1968) crime utility maximisers and Markowitz (1952) return mean-variance optimisers. As such, traders respond to both the expected gains and costs of the crime as well as the expected return and variance of the stock for which they have sensitive information. This is a novel contribution to the illegal insider trading literature. These predictions are tested using data drawn from publicly available SEC litigation reports.

The behaviour of illegal insiders is important to regulators. An understanding of the factors that influence the volume traded by insiders can assist in building better detection mechanisms. To this end, one contribution of the essay is to show that insiders behave as normal investors insofar as the size of their position in the security is negatively related to the volatility of its returns. This is an interesting result because it suggests that, despite what one might expect, insiders do not possess information (or *believe* that they posses information) that is completely precise.[10] Furthermore, this research question is important from a policy formation perspective. DeMarzo,

[9] Rather than using actual insider trading data, a related strand of empirical literature uses the date of initiation and first enforcement of insider trading laws to make inferences regarding the efficacy of insider trading laws (Bhattacharya and Daouk, 2002; Bris 2005; Beny, 2005, 2007; Fernandes and Ferreira, 2009). The research presented in Chapter 4 is also distinct from these studies.

[10] This might occur for example, when an individual knows that a company is the target of a takeover attempt but does not know the exact offer price.

Fishman and Hagerty (1998) develop a model to determine the optimal regulation of illegal insider trading. They show that it is optimal to only investigate information events for which pre-announcement volume exceeds some threshold which is dependant on the value of the non-public information. Upon detection, an insider is then levied the maximum penalty. In developing their model, the authors assume that insiders set volume to maximise their expected profit, where profit (and hence volume) is a function of the expected return from the illegal behaviour, the probability of detection and the expected penalty (DeMarzo, Fishman and Hagerty, 1998, p 611). The essay in Chapter 4 explicitly tests this assumption with empirical data.

1.3. Broker anonymity and the detection of informed traders

One of the most prominent market design issues considered by exchange officials of electronic order driven markets in recent years is the decision regarding whether to reveal broker identifiers surrounding trades. Between 1999 and 2005 no fewer than seven exchanges made changes to their respective broker identification regimes and the high incidence of such changes has led to an equally high incidence of academic studies investigating the effect of the transparency change on market quality. Foucault, Moinas and Thiessen (2007) investigate the switch to pre-trade broker anonymity on the Paris Bourse in April 2001 and find that quoted bid-ask spreads decrease after the change and that spreads become less informative about future volatility. Comerton-Forde, Frino and Mollica (2005) examine the affects of broker identification changes on the Paris Bourse, the Tokyo Stock Exchange and the Korean Stock Exchange and find that improved market quality, in the form of reduced relative and effective bid-ask spreads, is correlated with pre-trade broker anonymity. Finally, Comerton-Forde and Tang (2009) document decreased bid-ask spreads, increased depth and greater order flow after the Australian Stock Exchange (ASX) removed pre-trade broker identifiers and delayed the reporting of post-trade broker identifiers on 28 November 2005. Table 1.1 summarises the recent broker identification changes implemented by electronic exchanges and related academic studies.[11] The focus of such studies has been broad in nature, with an emphasis on the effects of the transparency change on general market quality indicators.

Table 1.1
Recent changes to broker identification rules and related literature

This table summarises recent changes to broker identification rules that have occurred on electronic order driven markets since 1999. All exchanges, except for the Korea Stock Exchange, removed broker identifiers surrounding trades on the date listed. The Korea Stock Exchange added broker identifiers to trading screens on 25 October, 1999. Studies which investigate the respective transparency change are presented in the final column.

Exchange	Date of change	Academic Literature
Korea Stock Exchange	25 October, 1999	Comerton-Forde et al. (2005)
Paris Bourse	23 April, 2001	Foucault, et al. (2007); Comerton-Forde et al. (2005)
Brussels Stock Exchange	21 May, 2001	Maher et al. (2008)
Deutsche Boerse	27 March, 2003 to 10 April, 2003	Hachmeister and Schiereck (2006)
Tokyo Stock Exchange	30 June, 2003	Comerton-Forde et al. (2005)
Borsa Italiana	21 January, 2004	No academic literature
Australian Stock Exchange	28 November, 2005	Comerton-Forde and Tang (2009)

Despite the extensive literature on broker identification, no studies in this area examine how a change in broker anonymity affects market participants during periods of large information asymmetry. This is an important distinction since one would naturally expect that anonymity is more relevant during periods of high information

[11] Theoretical work by Foucault, Moinas and Thiessen, (2007) and Rindi (2008), and a study conducted in an experimental market by Perotti and Rindi (2006) support these empirical results. The overwhelming consensus amongst published literature is that pre-trade or post-trade broker anonymity reduces bid-ask spreads.

asymmetry *vis-à-vis* periods when no information event is pending. Intuitively, broker anonymity impairs the ability of uninformed traders, followers and dealers to discern the advent of some significant price-sensitive announcement from the pool of liquidity-motivated trades.[12] The hidden nature of broker identifiers is not as problematic (beneficial) for uninformed (informed) traders when no information event is about to occur. Furthermore, the interpretation of market quality statistics can be fundamentally altered depending upon the level of informed trading across the period analysed. For example, during periods when no information event is pending, tight bid-ask spreads represent lower transaction costs for uninformed traders, whereas tight bid-ask spreads before unanticipated material announcements with active informed traders, imply that liquidity providers are not adequately engaging in price protection. It is not possible to disentangle the two scenarios by examining, as previous studies have, market quality statistics averaged across all market conditions.

The purpose of the essay in Chapter 5 is to investigate whether the removal of broker identifiers camouflages the presence of informed traders prior to a significant information event. To perform this analysis, the study investigates pre-announcement trading in a sample of 258 takeovers, announced between 28 November 2003 and 28 November 2007, corresponding to a time period two years either side of the aforementioned transparency change that occurred on the ASX on 28 November 2005. As recognised by Cao, Chen and Griffin (2005), takeover announcements provide an ideal setting to test hypotheses related to information transmission in markets. The magnitude of potential returns provides a strong incentive for informed traders to trade and indeed it is well established that informed traders are active prior

[12] This reasoning is in the same spirit as Pagano and Röell (1996). However, their paper concerns the effects of order book price and depth transparency rather than broker identifiers.

to takeover announcements (Keown and Pinkerton, 1981; Jarrel and Poulson, 1989; Meulbroek, 1992). Furthermore, unlike earnings announcements, the timing and occurrence of takeover announcements is completely unknown to uninformed traders. As such, if abnormal volume or price activity occurs before these announcements, it most likely coincides with trading by informed participants. This study, therefore, explicitly addresses the issue of broker anonymity effects in the context of large information asymmetry. This is important given the frequency of changes to broker transparency that have occurred in financial markets in recent years and the fact that almost all studies to date suggest that improved liquidity (in the form of smaller bid-ask spreads) is correlated with an anonymous regime. The results indicate that informed traders are better off after a switch to anonymity, a finding which needs to be considered together with previous studies when assessing the implications of broker anonymity changes on market quality.

This study benefits significantly from access to a proprietary data set provided by the ASX which contains the broker counterparties to every trade executed on the exchange. Prior studies, including all those listed in Table 1.1, which investigate changes in the transparency of broker identifiers have yet to utilise data of this nature, resorting instead to broad trade and quote level data. While this can be suitable, and indeed two of the hypotheses in the essay require only trade and quote level data, one could argue that the most natural observational unit for a study of broker identifier transparency is the individual broker. This is the first study of broker transparency to incorporate within its analysis, research directed at the level of the individual broker.

The data set provided by the ASX allows for the calculation of the average permanent price impact of each broker's trades and the dispersion of this variable *across brokers*. The rationale for examining this metric is that, all other things being equal, the dispersion of permanent price impact across brokers provides an indication of the extent to which the market utilises the identifier to distinguish informed from uninformed trades. For example, all other things being equal, if the dispersion of average permanent price impact across brokers is zero, then the market places no informational weight on the identifier. Clearly in the anonymous broker regime it is impossible for the market to extract any information from the broker identifier. A comparison of the dispersion of broker price impact before and after the change, allows one to determine if the identifier has incremental signalling value in the transparent period in the lead up to takeover announcements. If it contains value, then by definition, its absence suggests that the informed traders are less detectable after the change to anonymity.

The analysis also investigates the extent to which liquidity suppliers adequately price protect themselves as well as the ability of the market to correctly interpret the information content of order imbalances in the 40 days prior to takeover announcements. Bid-ask spreads are examined since they provide a natural indication of whether informed traders are being detected by liquidity providers (Bagehot, 1971; Copeland and Galai, 1983; Glosten and Milgrom, 1985; Easley and O'Hara, 1987). The analysis also involves using the strength of the order imbalance to price relationship in the days leading up the announcement as another indicator of how well informed traders can disguise their status.[13] Studies show that informed trading is likely to manifest itself as an imbalance between buyer and seller initiated trades (Easley, Kiefer, O'Hara and Paperman, 1996; Easley, Kiefer and O'Hara, 1997). Since the periods being analysed in this study are likely to coincide with informed trading, the extent to which the market reacts to order imbalances during this time is another measure to assess the ability of informed traders to remain hidden from the market.

1.4 Summary

The three research essays contained in this dissertation each examine the interactive relationship between an informed agent and some other significant, but uninformed, party. The insights provided by these essays are important given the influential role that informed traders have in financial markets. Each essay incorporates a topical, yet under-developed research area within the analysis, ensuring that these studies are relevant for practitioners and academics alike. The empirical evidence provided in this dissertation shows that informed traders affect the decisions of direct and indirect investors, regulators, law makers and market designers.

The rest of this dissertation is organised as follows: Chapter 2 provides a review of prior literature pertaining to the relationships examined in the three essays (fund manager and investor; insider trader and regulator; informed and uninformed traders). Chapters 3, 4 and 5 present the three research essays discussed in this chapter. Each

[13] Another data-related advantage arises from the fact that the market being analysed is a centralised electronic limit order market. Therefore trade classification algorithms, such as the Lee and Ready (1991) algorithm commonly adopted in studies of U.S. markets, are not required to discern trade direction. Since all trades (excluding upstairs trading) must be executed at either the best prevailing bid or ask, it is possible to classify with certainty whether a trade is buyer or seller initiated. This facet of the data allows for accurate calculation of order imbalances for all firms in the sample.

chapter contains sections describing hypotheses, data and sample, research design, empirical results, additional tests and conclusions reached. Chapter 6 concludes by highlighting how the results presented in this dissertation provide insight into the behaviour of informed traders in financial markets.

Chapter 2. Literature Review

2.1. The interaction between fund managers and investors

To understand the vast literature on investment management it is useful to begin with a simplified description of the investor-manager relationship. In the most basic terms, the role of an investment fund is to trade on behalf of the funds' investors in securities markets permitted by the investors. The process of investment in mutual funds can be described in two steps. Firstly, investors provide capital to a manager. Secondly, the manager determines how that capital is allocated within or across asset classes with the returns of that allocation directed back to the investor. Despite the simplicity of this exposition, much of the research on the investment management industry can be classified as an attempt to understand the processes and outcomes of these two steps.

The first step is characterised by the decision process of the investor, while the second part is that of the manager. While the decision processes of investors and managers are (likely) complex and unobservable, the outcomes of those decisions are quantifiable, readily available and possess intuitive economic interpretation. Investor decisions are manifested by the flow of capital into mutual funds, whereas the decisions of fund managers are revealed in the returns of their portfolios. A large body of literature is therefore directed at examining the determinants of mutual fund flows and the performance of investment managers.

Moving beyond the initial description of the investor-manager relationship additional complexities arise. It is important to note that the two steps of the relationship are not necessarily independent of each other nor treated as such in the literature. For example, from the earliest studies, it has been noted that the prior performance of a manager is a prominent determinant in the allocation of new capital to that manager (e.g. Ippolito, 1992; Gruber, 1996; Sirri and Tufano, 1998). Due to the ubiquity of this finding, studies have taken to not only uncovering those variables which determine the level of investor flows but also investigating whether those variables influence the strength of the performance-flow relationship. Section 2.1.1 reviews the literature on the determinants of fund flows. Less explored, though no less relevant, is an analysis of how the timing and magnitude of flows into a fund affects the subsequent performance of the manager (e.g. Edelen, 1999). Section 2.1.2 provides an overview of research which investigates how investor flows can (negatively) affect the performance of fund managers.

The above exposition suggests that the interaction between investor and manager is unidirectional. That is, investors react to managers and their performance whereas managers, while being affected by investor capital flow, do not fundamentally alter their behaviour because of it. This is an incorrect assertion. Research suggests that fund managers are aware of both the impact performance has on subsequent investor flows (Chevalier and Ellison, 1997) and the affect investor flows have on subsequent performance (Koski and Pontiff, 1999; Greene, Hodges and Rakowski, 2007). Section 2.1.3 reviews the literature on how managers respond to investors.

Finally, since the focus of Chapter 3 is how investment managers trade stock index futures, Section 2.1.4 provides a review of the papers that investigate the use of derivatives by investment managers.

2.1.1. The investor decision process and the determinants of investor flows

Ippolito (1992) represents one of the first papers to model the optimal response of rational investors to managerial performance. In his model there are only two types of managers. Low quality managers do not generate risk adjusted returns and simply levy expenses on their fund holders. High quality managers generate positive risk adjusted returns net of expenses. Any given return provides only a noisy signal of whether the manager is high or low quality. Nevertheless, the model shows that it is optimal to invest in the most recent best performer even if there is only one observation to assess the pool of available managers.[14] From a Bayesian updating perspective, the probability of picking a high quality manager conditional on a large return is greater than the probability of picking a high quality manager unconditionally. An empirical analysis of yearly returns and investor flows of 143 open end mutual funds over a twenty year period (1965-1984) confirms the prediction of his model. Investor flows are positively related to prior performance, whether measured as annual returns from the previous three years or as the average of returns over the last five years.

Interestingly, Ippolito (1992) also shows that the response to performance is asymmetric. The inflow of funds to better performers is stronger than the outflow of funds from poorer performers. That investors condition their investment decisions on prior performance and react more strongly to positive performance is confirmed by numerous studies and appears robust to different time periods, sampling frequencies

[14] The model of Berk and Green (2004) modifies this relationship by allowing investors to condition future performance on both prior performance and the number of observations already observed. The basic relationship remains the same. However, the marginal information content of an additional observation decreases with the number of observations already observed. This prediction is confirmed by Chevalier and Ellison (1997) who find that investor flows respond less strongly to prior performance as the age of the fund (i.e. the number of observations) increases.

and measures of prior performance.[15] Gruber (1996), examining 227 mutual funds over the period 1985 to 1994, documents an asymmetric relationship between investor flows and prior year's performance, where performance is measured as the alpha from his 4-factor model. Chevalier and Ellison (1997) use yearly data for 449 mutual funds that operated during 1983 to 1993 and find a similar result. In their study, performance is measured as the simple difference between raw and market returns. Goetzmann and Peles (1997) analyse a survivorship-bias free sample of funds that existed between 1978 and 1988. They document a significantly positive relationship between raw returns and investor flows for the best performing quartile and a weaker negative flow-performance relationship for the bottom half of funds. Sirri and Tufano (1998) examine yearly data for 670 mutual funds over the period 1970 to 1991 and show that the top performing quintile of funds attracts a statistically significant amount of new money, whereas investor flows are insensitive to the performance of the bottom quintile of funds. The authors use a swathe of raw and risk-adjusted measures of prior returns to rank funds (see Table III, p1602 of their paper). More recently, Huang, Wei and Yan (2007) analyse the quarterly returns and flows of at least 3,446 funds over the period 1981 to 2001.[16] They find a similar non-linear relationship between flows and prior performance where prior performance is measured as the alpha from Jensen's (1968) one-factor model or Carhart's (1997) 4-factor model.

[15] Several studies find that prior performance is an influential factor in determining to which funds investors allocate their capital, but they do not document or test for the asymmetry in the flow-performance relationship. These studies include Spritz (1970), Smith (1978), Kane, Santini and Aber (1991), Patel, Zechkhauser and Hendricks (1994), Capon, Fiztsimons and Prince (1996) and Wilcox (2003).

[16] The authors do no explicitly state how many funds they analyse in total, but provide the amount of funds available for analysis in each year. The largest yearly value is 3,446 which represents the amount of funds operating in 2000 (see Table 1, p1290 of that paper).

Lynch and Musto (2003) provide an explanation for the convex flow-performance relationship which is consistent with the idea that investors rationally use past performance as a signal of unknown future performance.[17] They argue that asymmetry of investor response arises when investors, who usually condition future performance on prior performance, are able to disconnect the two variables under certain circumstances. One such circumstance is a change of manager or strategy. Since funds typically replace managers and strategies only after poor performance, investor flows are less responsive, on average, to the information content of poor performances. Using data on managerial changes and proxies for strategy changes the authors confirm the predictions of their hypothesis.

Besides prior performance, another determinant of fund flows investigated extensively in the literature is the 'salience' of a given mutual fund. Salience refers to factors such as marketing, investor search costs and presentation, that increase the probability of an investor choosing a particular fund amongst the vast universe of available options. In terms of the direct impact that marketing has on investor flows, Jain and Wu (2000) provide evidence that advertising in investment magazines attracts more money into funds compared to similar non-advertised peers. Confirming this result, Barber, Odean and Zheng (2005) show that funds which spend more resources on marketing (as indicated by the level of 12b-1 fees levied) attract greater fund flows. Cooper, Gulen and Rau (2005) suggest that not even advertising is necessary, showing that name changes towards current popular styles are enough to warrant additional capital from investors.

[17] Goetzmann and Peles (1997) and Huang, Wei and Yan (2007) offer different theories to explain the asymmetry in the flow-performance relationship. These papers are discussed elsewhere in the literature review.

Del Guercio and Tcak (2002) document the importance of an external, influential rating agency on fund flows. They show that Morningstar ratings subsume the incremental explanatory power provided by Jensen's alpha in describing investor flows. This result is confirmed by Capon, Fitzsimons and Prince (1996) who, in a survey of 3,386 individual mutual fund investors, find that the most important information source for decision making are published performance rankings of mutual funds.

Studies also investigate the role that the family fund structure plays in increasing the salience of a fund. Nanda, Wang and Zheng (2004) show that having one star performer[18] within a fund family induces investor flow externalities to other funds within that family. They also show that affirmation of star performance by Morningstar increases the flow of new money into other funds within that family. Their results suggest that salience by association can be a prominent determinant of mutual fund flows. Following on from this finding, Kempf and Ruenzi (2008a) show that being in the top decile of performers within a given fund family attracts additional capital (beyond that which would have been received due to its performance ranking relative to all funds in the sector). They argue that this could be the result of increased prominence for the top funds within a fund family and greater advertising spent on promoting these funds.

Complementing these studies, Sirri and Tufano (1998) examine how fund salience, specifically the role of investor search costs, can influence the strength of the flow-performance relationship. They use three measures to proxy for the search cost of the

[18] The authors classify a fund as a star performer if the fund performs in the top 5% of all funds within their sample in the previous 12 months. Funds are ranked according to their Fama and French (1993) 3-factor alpha performance.

investor – the size of the fund complex within which the fund resides, the amount of fees levied on investors (which is a proxy for resources spent on marketing) and the amount of media coverage the fund receives. Their results indicate that funds that belong to larger families enjoy greater fund flows, but it does not have a discernable bearing on the flow-performance relationship. Levying higher than normal (i.e. greater than the median) fees doubles the amount of investor flows received by the best performing quintile of funds, but has no statistically significant effect at the 5% level for the remaining funds. Media attention does not influence the strength of the flow-performance relationship.

The literature has identified another set of determinants which influence the decision process of mutual fund investors. These determinants can be broadly categorised as 'investment costs' and include one off costs such as front-end or back-end load fees[19] and switching costs, or continuous charges such as expense ratios and taxes.

In terms of direct fees charged by managers, Sirri and Tufano (1998) find a negative relationship between total fees incurred by the investor (calculated as the annual expense ratio plus one-seventh of the up-front load fee) and the flow of new money into that fund. Ippolito (1992) finds that the strength of the flow-performance relationship is influenced by whether the fund charges front-end load fees or not. Funds which do not charge load fees attract 1.7 times more investor flows for a given level of return compared to funds that charge load fees. Barber, Odean and Zheng (2005), analyse a large sample of mutual funds over the period 1970 to 1999 and find that investors respond to up front costs by reducing investment in those funds with

[19] A load fee is a payment made by the investor that acts as a form of sales commission for brokers. Front-end load fees are paid at the time of initial investment, whereas back-end load fees are paid upon redemption of fund shares.

higher front-end load fees. They also document an unintuitive result that annual expenses have little influence on fund flows over this period for all funds, or perversely, have a positive impact on fund flows for certain funds. They provide evidence that this apparent anomaly is driven by the fact that a certain portion of fees are used for marketing purposes, such that the deterrence effect associated with an increase in fees might be offset by the increased salience of the fund.[20] Using a sub-sample of their data they find some evidence to support this claim. The magnitude of management fees (which are not used for marketing purposes) has a negative impact on new money flows for most funds except the top 50 largest funds and those funds greater than five years old. The results of these studies suggest that mutual fund investor, like typical consumers of goods and services, are influenced by the explicit costs associated with their purchase.[21]

Taxes represent another form of investment cost. Several studies examine the role that taxes play in the demand for funds management services. Barclay, Pearson and Weisbach (1998) examine a particular tax effect associated with capital gains. Like other investors, mutual funds incur a tax liability when they sell shares which have appreciated in value. Unrealised gains in a fund's portfolio act as an indirect cost for any new investors since those investors are liable for the tax when the gains are

[20] The authors also note that this anomaly could be caused in part by behavioural biases. Building upon the results of Wilcox (2003), they hypothesise that investors respond more strongly to load fees because they are more salient compared to annual fees, which are subsumed by the natural volatility of returns. The authors also hypothesise that investors learn slowly about fees in general and the difference in distaste between load fees and annual expenses becomes more apparent after the first fund purchase made by an individual. They test for this effect by comparing purchases of funds by first time investors versus non-first time investors. They find that non-first time investors have a tendency to avoid load fee funds, consistent with their hypothesis.

[21] The work of Massa (2003) also supports this conclusion, though he does not directly examine the role of fees on investor flows. Massa (2003) hypothesises that being part of a large mutual fund family can increase the demand for a given fund because funds often allow investors to switch between funds at low cost. This provides a valuable option to investors – a value which is attributable in part to a reduction in switching fees. Therefore, his hypothesis naturally assumes that investors are sensitive to transaction costs. The results of his study confirm his hypothesis.

realised, without sharing in any of the benefits. This is referred to as 'capital gains overhang'. The authors show that for two years in their sample, 1994 and 1995, where they have access to appropriate data, inflows into equity mutual funds are negatively related to the size of the overhang. Expanding these findings, Bergstresser and Poterba (2002) investigate the effect that taxes in general have on investor flows. After making certain assumptions, the authors construct the tax burden for each fund implied by the form of its observed payouts. The authors show for a given level of return, investor flows are lower for funds with greater tax burdens, suggesting that investors are influenced by after-tax returns more than pre-tax returns.

From the papers discussed so far it is apparent that investors allocate their capital to fund managers according to three factors: prior performance (in an asymmetrical manner), fund salience and investment costs. A recent paper by Huang, Wei and Yan (2007) links these three factors into one coherent framework of investor behaviour. Their model revolves around a utility maximisation problem, where potential investors trade off the gains made from investment (returns) against the costs associated with making that investment (which they term 'participation costs'). To make their allocation decisions, investors use prior performance as a (noisy) signal of future performance. Fund salience enters the model as the cost required by the investor to become more familiar with the fund, that is, to reduce the variance of the signal (information costs). Investment costs are incorporated in the model as transaction costs associated with investing in a given fund. *Ceteris paribus*, funds with greater salience are more likely to be investigated by potential investors and upon investigation, funds with lower transaction costs are more likely to attract investor capital. These two aspects of the model lead to well documented asymmetrical response of inflows to prior returns. Specifically, funds that have high participation costs will attract increased capital only when the returns are sufficiently high to offset those costs. When returns are in the medium range, inflows are less sensitive to prior returns because the returns are not sufficiently large to warrant investors to investigate the fund (i.e. pay the information costs) or if they choose to investigate the fund, to pay the transaction costs. If a fund chooses to lower its participation costs (i.e. through attaining greater salience or decreasing transaction costs), the flow-performance relationship is still kinked, but at a lower threshold. The authors test the implications of their model using a large sample of equity mutual funds over the period 1981 to 2001. Utilising various proxies for information and transaction costs they examine the sensitivity of inflows to prior performance conditional on the level of participation costs. The results confirm the predictions of their model and are broadly consistent with previous studies which examine the influence of prior returns, salience and investment costs on inflows.

Finally, several papers investigate the effects of behavioural biases on the investment decisions of individual investors. Goetzmann and Peles (1997) examine the extent of cognitive dissonance in a sample of sophisticated and non-sophisticated mutual fund investors. Cognitive dissonance is the tendency of individuals to alter current beliefs to retrospectively justify their own past decisions. The individuals were surveyed about several features of their mutual fund investments. Part of this sample included a control subgroup of investments chosen by an external party for the non-sophisticated investors. The results are consistent with the respondents exhibiting cognitive dissonance with respect to their investments. All respondents overstated the success of their investments, with non-sophisticated investors overstating the returns of the funds they chose themselves by a greater magnitude than the funds chosen for them. These investors also expressed greater satisfaction with funds they chose relative to funds chosen for them. The authors use these results to explain the observed convex response of investor flows to returns. Cognitive dissonance implies an inability to recognise or act upon poor performance,[22] hence investor flows will be less sensitive to substandard performance. The authors show that a convex relationship exists but do not provide any evidence that their hypothesis better explains the data relative to other competing hypotheses.

Building on the early work of Patel, Zeckhauser and Hendricks (1991), Kempf and Ruenzi (2006) investigate the behavioural phenomenon known as status quo bias, which induces individuals to irrationally select an outcome merely because it was chosen before. To test the extent of the bias, the authors estimate the explanatory power that previous year's investor flows have on the current year's flows. Given that status quo bias is positively related to the number of available options (Samuelson and Zeckhauser, 1988), the relationship between year to year flows should be greatest for funds that exist in large segments of similar, substitutable funds. The results indicate that the size of the coefficient on previous year's flow increases monotonically with the number of available alternatives, and flattens after the investor has approximately 100 options to choose from. The results of this analysis and Goetzmann and Peles (1997) indicate that besides rational factors, behavioural factors influence the decision processes of investors when deciding where to allocate their capital. This is not entirely surprising given the survey results of Capon, Fitzsimons and Prince (1996)

[22] This result is also consistent with Shefrin and Statman (1985) who find weak evidence that investors irrationally ride their mutual fund losses (i.e. the disposition effect).

which reveals that a large number of investors are naïve and uninformed about their investment decisions.

2.1.2. The effect of fund flows on fund manager performance

Fund managers attempt to generate incremental wealth for their fund holders by allocating investors' capital across a set of securities which the manager believes is underpriced relative to some benchmark. Managers with skill are those that generate positive incremental wealth. In general, studies of fund manager performance implicitly accept this stylised framework of managerial evaluation.[23] Several articles however, recognise that investor flows represent an exogenous and costly distortion to the process of funds management. The basic premise of these articles is that investor flows compel managers into actions they might not otherwise undertake. As such, the observed performance of managers arises from some combination of their own decisions (skill) and the net cost associated with behaviour outside of their control (trading attributable to flow). This section reviews the literature which quantifies and examines the different types of costs attributable to fund flow.[24] It also surveys studies that attempt to assess the performance of asset managers in light of this externality.

[23] The general literature on fund manager performance is extensive. Several important papers include Jensen (1968), Lehman and Modest (1987), Ippolito (1989), Grinblatt and Titman (1989a, 1992, 1993), Gruber (1996), Carhart (1997), Daniel, Grinblatt, Titman and Wermers (1997), Wermers (2000) and Pinnuck (2003).

[24] Several theoretical papers utilise the intuition that investor flows impose general negative externalities on fund managers, without outlining the types of costs involved or specifying the mechanism by which costs are generated. For example, in Nanda, Narayanan and Warther (2000), the presence of flow induced costs is used to explain why managers set load feeds (load fees deter redemptions and therefore reduce flow costs). In Berk and Green's (2004) model of fund growth and performance, fund managers experience diminishing marginal returns as the size of the fund increases. Part of this is attributable to the increasing marginal costs of managing a larger portfolio. Since one way for a fund to grow is through investor flows, by implication his model utilises the idea that flows generate significant costs.

One type of cost directly related to investor flows is the cost of switching between cash and securities whenever investors redeem or purchase shares in the fund. Such costs include the bid-ask spread, market impact costs and brokerage. Surprisingly, while many studies analyse the transaction costs of asset managers in general[25], relatively few studies directly examine the relation between fund flows, transaction costs and fund manager performance.

The only study of fund flows and transaction costs at the micro-level is Johnson (2004). Utilising a proprietary data set, he examines the attributes of individual investors in a particular mutual fund family to ascertain which characteristics can predict the length of their investment period. He finds that the characteristics which provide information about the duration of holding period are also correlated with simulated measures of liquidity costs. Specifically, short term investors impose greater transaction costs on fund managers than longer term investors. Part of the reason why shorter term investors create larger transaction costs is that they have greater liquidity needs, as manifested in larger gross fund flow, and therefore require the fund manager to trade on their behalf more often. Using transaction costs estimates of general trading from Jones and Lipson (2001), Johnson (2004) calculates that the gross fund flows of investors contributes between 67 to 195 basis points annually in transaction cost underperformance, depending on the investment style of the fund.

Several studies investigate the relationship between fund size and performance. These studies show that, all things equal, as fund size increases managerial performance

[25] See for example Grinblatt and Titman (1989, 1993), Chan and Lakonishok (1993, 1995), Keim and Madhavan (1997), Jones and Lipson (1999), Chalmers, Edelen and Kadlec (1999), Wermers (2000), Bollen and Busse (2006) and Kacperczyk, Sialm, Zheng (2008).

deteriorates (e.g Chen, Hong, Huang and Kubik, 2004; Bris, Gulen, Kadiyala and Rau, 2007; Yan, 2008; Pollet and Wilson, 2008). Out of these studies, Chen, Hong, Huang and Kubik (2004) and Yan, (2008) show that the magnitude of underperformance is negatively related to the liquidity of the portfolios they hold. Since liquidity is inversely proportional to transaction costs, the results of these studies suggest that transaction costs play a significant role in the underperformance of large funds. Intuitively, performance should worsen as size increases due to the difficulty of investing even greater capital amongst the pool of investable and desired securities. To the extent that investor flows contribute to fund growth, these studies provide insight into how flows affect performance due to transaction costs. For example, Yan (2008) shows that for funds that hold stocks with low spreads, the largest quintile of funds underperform the smallest quintile of funds by 35 basis points a month (see Table 6, p758 of his paper).

Bris, Gulen, Kadiyala and Rau, (2007) investigate the relationship between fund size, fund flows and performance. Interestingly, they show that the negative relation between fund size and performance hinges on the concurrent level of fund inflows. Specifically, when fund inflows are low, size does not affect performance. As fund inflows become larger, the performance differential between large and small funds increases. The results suggest that it is not size *per se* that generates underperformance, but rather, the effect of large inflows is amplified as fund size increases. In light of the results of Yan (2008) and Chen, Hong, Huang and Kubik (2004), this suggests that fund inflows generate significant transaction costs for fund managers. For example, large inflows contribute 21 basis points per month in underperformance for the largest quintile of funds relative to the smallest quintile of funds (see Table 4 of their paper, p966).

Several studies examine the relationship between aggregate fund flows and market movements at short intervals. Since short term movements in securities markets are related to the magnitude of market impact costs (see for example, Kraus and Stoll 1972), such studies provide insight into macro-level effects of investor flows and transaction costs. Edelen and Warner (2001) examine the daily relation between aggregate flow of funds into U.S. equity mutual funds and stock market returns. The authors find evidence that unexpected flows into mutual funds cause stock prices to move within a given day. Furthermore, they also document that these price movements are reversed somewhat by the end of the next day, suggesting that the trading caused by flow generates price impact costs at the aggregate level. For days with extreme inflow (outflow) the magnitude of this temporary price impact is substantial measuring 20 (38) basis points.

Goetzmann and Massa (2002) analyse the relation between daily flows and intraday returns for three S&P500 index funds covering a four year sample period, 23 March 1994 to 31 December 1997.[26] They find that daily investor flows are positively related to afternoon returns on the S&P500 index, but not morning returns. This finding suggests that at higher frequency levels, fund flows cause short term market movements. However, the results of their analysis also show that prices are not reversed by the next day, making it difficult to infer the extent of fund flow induced market impact costs (if indeed any exist at all in their sample). Their result is

[26] Two of the funds only have data starting 4 January 1993. However, their analysis of returns and fund flows (Table 4 of that paper) only considers the common period.

consistent with there being no transitory market impact effects, and therefore no market impact costs. Alternatively, actual price reversals may occur at intervals longer or much shorter than that examined in the paper, making proper identification of the price reversal problematic.

Apart from transaction costs, the provision of liquidity services to mutual fund shareholders gives rise to significant uninformed trading costs, also known as adverse selection costs. As argued by Edelen (1999), when investors utilise the liquidity services of open-end mutual funds, the flows of capital to, or from, a fund cause the fund manager to engage in uninformed liquidity-motivated type trading. In rational expectations models of trade (e.g. Grossman and Stiglitz, 1980) equilibrium is reached when liquidity-motivated traders suffer losses to compensate informed traders for the costs associated with becoming informed. As such, the liquidity-motivated trades of fund managers are, on average, value destroying. To test this hypothesis, Edelen (1999) constructs a proxy for liquidity-motivated trading using fund flow and turnover data and assesses the alpha performance of mutual funds conditional on this metric. The results indicate that the level of liquidity-motivated trading exhibits a negative relationship with fund alphas, consistent with the idea that the provision of liquidity services contributes to underperformance in open-end mutual funds. Unconditional assessment of performance indicates that managers underperform their benchmarks by about 1.6% per year. Importantly, when conditioned on liquidity-motivated trading, the average abnormal return after fees is not significantly different from zero. In a rational expectations framework, these results suggest that fund managers act as informed traders generally, but also act as uninformed traders when they experience fund flow.

The effects of liquidity-motivated trading are further explored in a study by Alexander, Cici and Gibson (2007). They utilise a much larger sample of mutual funds[27] and a different proxy for liquidity-motivated trading *vis-à-vis* Edelen (1999). The authors argue that the direction and magnitude of trading, conditioned on the concurrent level of investor flows, provides insight into the motivation of a fund manager's trades. Specifically, when a fund manager experiences large net outflows (and is therefore compelled to disinvest) but sells only a small dollar value of shares and distributes that selling over a large amount of securities, such trades are likely to be liquidity-motivated. Conversely, if the fund manager experiences large net outflows, purchases a large dollar value of stock and concentrates that buying in a small number of securities, such trades are likely to be value-motivated. An equivalent argument is made for large net inflows. Using a combination of monthly fund flow data and quarterly portfolio holdings to infer trade direction and magnitude, the authors examine the returns on portfolios conditioned on their motivation. The annual excess return on a portfolio motivated by liquidity based purchases is an insignificant -0.41%. The annual excess return on value-motivated purchases is a significant 2.79%. Taken together, these results suggest that managers are skilled and have the ability to generate positive excess returns. However, when forced to engage in liquidity-motivated trading their excess returns drop to zero. Similar results, of an opposite sign, are documented for liquidity and value-motivated sell portfolios. These results are entirely consistent with Edelen (1999) when one notes that the returns in Alexander, Cici and Gibson (2007) are implied from the portfolio holdings of mutual funds and are therefore on a before fee basis, whereas Edelen's (1999) returns are on an after fee basis. The results of this study and Edelen's (1999) suggest that investor

[27] Edelen (1999) analyses the semi-annual fund flows and monthly returns of a sample of 166 mutual funds over the period 1985 to 1990. Alexander, Cici and Gibson (2007) use a sample of 1,400 mutual funds with a sample period ranging from January 1980 to December 2003.

flows are detrimental to fund manager performance when they cause managers to engage in substantial amounts of liquidity-motivated trading.

The two types of flow related costs examined thus far occur when the fund trades to meet the liquidity demands of the fund's shareholders. However, the performance of fund managers can also be hindered if the manager does not trade, or does not trade fast enough in response to the instructions of investors. Underperformance arises because delays in trading distort the portfolio from its optimal level of systematic risk (Edelen, 1999). When a manager receives net positive flow, but delays trading, the portfolio holds a greater relative weight in cash *vis-à-vis* if the manager trades immediately. Similarly, when a manager receives net negative flow and delays trading, the portfolio holds a greater relative weight in stock. Being overweight cash or stock does not hinder the *risk-adjusted* performance of the fund in and of itself.[28] Underperformance arises because investor flows and market returns are contemporaneously correlated (Warther, 1995). Therefore, in the above scenarios, it is more likely that the fund will be overweight cash when the market is rising and overweight stock when the market is falling. In terms of market-timing performance metrics introduced by Treynor and Mazuy (1966) and Henriksson and Merton (1981), managers will exhibit perverse market timing skills, holding low (high) beta portfolios while the market is rising (falling).

Ferson and Schadt (1996) provide preliminary evidence for this effect. They find that public information conditional betas of their sample of mutual funds are negatively correlated with aggregate net flows of money into funds of that investment style.

[28] Though this may give rise to agency costs if the manager systematically deviates from risk levels desired by investors.

Building upon this finding, Ferson and Warther (1996) show that public information betas are negatively correlated to fund flows and fund flows are positively correlated with indicators that point towards rising markets (i.e. high dividend yields and low treasury yields). Finally, Edelen (1999) directly measures the effects of investor flows on the market timing performance of mutual funds using fund flow adjusted versions of the classic market timing models of Treynor and Mazuy (1966) and Henriksson and Merton (1981). His results indicate that fund managers exhibit perverse market timing only when they experience fund flows. Otherwise, the market timing performance of managers is neutral. Each of these studies provides evidence that fund flows impair the performance of managers by moving portfolio systematic risk away from levels that would be optimal given the expected return on the market.

The previous exposition explains how post-flow optimal risk levels of the fund are affected by material investor flows. A related concept is the effect of *anticipated* fund flows on pre-flow risk levels. If a manager expects volatile or large fund flows, she may hold a greater proportion of cash to reduce the need to constantly trade in and out of position. Chordia (1996) provides evidence that there is a correlation between the expected volatility of fund flows and the amount of cash held by a fund. His paper though makes no comment on the performance effects of holding cash. Theoretically, a greater proportion of cash reduces the overall absolute performance of the fund since the return to cash is lower, on average, than the return to risky assets. This does not impair the risk-adjusted performance of the fund, but it does give rise to agency costs if the manager does not deliver a level of risk expected by the investors.

Another strand of literature examines the costs that arise when investors opportunistically take advantage of purchase (or redemption) prices offered by open-end mutual funds, for which the future short run returns are predictable, but the prices are currently 'stale'. Bhargava, Bose and Dubofsky (1998) represent one of the first studies to explore this phenomenon, which they explain using the example of international equity mutual funds domiciled in the U.S. To avoid confusion in the following exposition, the prices at which mutual fund units can be bought or sold are referred to as net asset values per share or 'NAVs', while the prices of securities in the fund's portfolio are referred to as 'prices'. Generally, a fund's current NAV is calculated using the last traded prices for the securities in the portfolio. However, because investors in the U.S. can submit orders to trade mutual fund units as late as 4:00pm EST, the last traded prices for international securities are several hours old depending on the location of the market where the shares trade. At 4:00pm EST, these prices are stale insofar as they do not reflect any information made available since the close of the foreign market. The fund's NAVs are, therefore, also stale. Due to the correlated nature of asset returns worldwide, the future movements of stale share prices might be predictable. In such circumstances investors can trade units in the fund at stale NAVs and reap a benefit when the prices (and NAVs) update to their full information values. While the profitability of such strategies has been investigated by several papers with respect to international equity mutual funds,[29] it is applicable generally to any mutual fund with mispriced NAVs. For example, domestic (U.S.) equity funds which hold illiquid securities are another candidate for stale price arbitrage. Chalmers, Edelen and Kadlec (2001) document significant positive daily returns for domestic small cap equity funds while Zitzewitz (2003) documents

[29] See for example Bhargava, Bose and Dubofsky (1998), Chalmers, Edelen and Kadlec (2001), Goetzmann, Ivkovic and Rouwenhorst (2001), Boudoukh, Richardson, Subrahmanyam and Whitelaw (2002), Greene and Hodges (2002) and Zitzewitz (2003).

profitable returns for small to mid cap domestic equity funds, specialty equity funds and several classes of bond funds.

While this type of behaviour confers a benefit to the investor making the trade, it imposes several costs on existing fundholders (Gastineau, 2004; Ciccotello, Edelen, Greene and Hodges, 2002). Firstly, as outlined previously in this review, excessive fund flows lead to significant transaction and uninformed trading costs. Because this strategy operates on daily mispricing, in order to capture substantial absolute profits without incurring market risk, flows of funds must be both large and transitory, exacerbating the extent of trading costs.[30]

Secondly, this strategy causes existing fund holders to subsidise the trading shortfalls of short-term arbitrageurs. Specifically, mispriced NAVs allow arbitrageurs to effectively purchase (sell) assets at prices less (more) than that obtainable in actual markets. This occurs because the manager, upon the receipt (redemption) of funds from an arbitrageur, cannot subsequently trade securities at stale prices, because the very act of trading is likely to bring prices to their full information values. However, the arbitrageur still pays (receives) the stale price. The shortfall is borne by existing shareholders. Goetzmann, Ivokovic and Rowenhorst (2001) estimate the wealth transfer brought about by daily fund flows in a sample of 166 international open-end equity mutual funds operating in the U.S. in the period 2 January 1990 to 24 July 1998. The authors find a very small percentage loss to existing shareholders as a result of this wealth transfer effect, measuring 0.006% per year at the median.

[30] Charski (1999) provides anecdotal evidence that excessive transitory fund flows lead to significant underperformance. Her article recounts the story of Montgomery Emerging Asia Fund which received $7million USD in one day, a substantial portion of the fund which at the time only managed $30 million USD. The flow was subsequently reversed, forcing the manager to sell good investments and incur substantial costs.

However, certain funds experience material underperformance due to this effect with the worst affected quartile of funds experiencing losses between 0.539% and 0.035% annually.

Zitzewitz (2003) estimates wealth transfer effects[31] on a sample of 1165 open end mutual funds spanning a suite of fund categories including international equity, international bond, domestic small and mid cap equity and domestic bond funds. His sample spans February 1998 to September 2001. He finds a modest average annualised cost of 14 basis points across all funds in his sample. However, for regionally focused international equity funds (the funds most vulnerable to arbitrage activity) the wealth transfer effects measure 1.60% per year. For general international equity funds the costs borne by long term fundholders is 81 basis points per year. Specialty equity funds, Latin American and global equity funds and U.S. small and mid cap equity funds also posses significant, albeit smaller, annualised wealth transfer losses of 33 basis points, 23 basis points and 12 basis points respectively.

The third type of cost attributable to mispriced NAVs arises when the flows of arbitrageurs dilute the returns of existing shareholders (Greene and Hodges, 2002). This cost occurs concurrently with the wealth transfer effect, but arises from the temporary cash holdings caused by the inability to trade, rather than the shortfall incurred upon trading. Consider the case where stale prices are expected to increase. An arbitrageur that provides money to the fund immediately has a proportional claim

[31] Zitzewitz (2003) uses the term 'dilution' effect when referring to the wealth transfer effects documented in Goetzmann, Ivkovic and Rowenhorst's (2001). Both terms describe conceptually the same phenomenon and are calculated in a similar manner (see p259 of Zitzewitz and p307 of Goetzmann, Ivkovic and Rowenhorst). In this review, the term wealth transfer effect is used to distinguish it from Greene and Hodges' (2002) 'dilution' effect, which is a fundamentally different type of cost imposed by arbitrageurs of mispriced NAVs.

to the returns on the existing asset pool. However, managers often cannot allocate arbitrageurs' funds before the stale prices update, either because the trades would be prohibitively costly or in the case of international funds, it is impossible to trade the shares. As such, existing investor returns are diluted, because the new money is still held as cash, but the arbitrageur that provided the cash has claim to a proportion of the subsequent positive portfolio returns.[32] Greene and Hodges (2002) estimate the daily dilution costs for a sample of 833 open end mutual funds over the period 2 February 1998 to 31 March 2000. They find that the average dilution effect causes a reduction in performance of -0.06% per year. This result is statistically significant but of questionable economic significance. However, for international equity funds, the dilution impact measures -0.48% per year, which is both economically and statistically significant. Furthermore, international funds which receive above median fund flows experience a dilution cost of 94 basis points a year. The results of this study as well as Zitzewitz (2003) and Goetzmann, Ivkovic and Rowenhorst (2001) indicate that investors who attempt to take advantage of mispriced NAVs represent a significant impediment towards long-term wealth creation in mutual funds.

The final fund flow related cost considered in this review is the affect of investor demands on the tax liability of all investors in the fund. As outlined in Dickson, Shoven and Sialm (2000), investors' tax liabilities are accelerated when a manager experiences significant investor redemptions and is forced to sell appreciated securities. Furthermore, the effect of redemptions on tax liability is asymmetric. The

[32] Interestingly, this cost is conceptually similar to the risk distortion effects of fund flow explored in Ferson and Schadt (1996), Ferson and Warther (1996) and Edelen (1999). Both costs arise due to a delay in trading new flow which, due to subsequent increases in the prices of assets, dilutes the returns of long term investors. The main difference between these two processes is that the mechanism which causes positive correlation in returns and flows is fundamentally different. Furthermore, the dilution effect operates over shorter horizons relative to the risk distortion effect.

selling of depreciated securities does not confer an immediate capital loss benefit to existing fundholders. Therefore net negative investor flows can potentially increase, in present value terms, fund holders' tax liability.[33] Dickson, Shoven and Sialm (2000) simulate the net effect of fund flow on the overall tax liability for a hypothetical passive fund comprising the largest 50 stocks, by market capitalisation, in 1983. Their simulation estimates the fund's tax liability under various fund flows assumptions using actual returns of these 50 stocks over a 15 year period. The results indicate that when investor flows are assumed to be -1% per month, the monthly after-tax returns of an equal weighted (value weighted) passive fund are reduced by approximately 5 basis points (8 basis points), relative to zero fund flow. The authors also simulate the tax effects of a hypothetical actively managed portfolio which comprises at any one point in time 30 out of the 50 stocks held by the passive portfolio. Depending on the inputs to the simulation, fund flows which average -1% per month (with a standard deviation of 4.5%) reduce monthly after tax returns by as much as 10 basis points per month relative to zero fund flow. The results of this study confirm that net negative fund flows can increase the tax liability of existing investors in a fund, therefore affecting their after tax returns.

2.1.3. Fund manager response to investor flows

Fund managers are typically compensated with respect to two criteria - the value of assets under management and performance. Direct compensation to managers is based on the value of assets in the fund, while performance determines whether the manager retains employment (Khorana, 1996). Performance also directly affects the value of

[33] Dickson, Shoven and Sialm (2000) also note that investor flows into a fund confer a tax benefit to existing shareholders. As explained previously, new money into a fund dilutes the liability associated with unrealised capital gains (Barclay, Pearson and Weisbach, 1998). Their simulation also investigates the positive tax benefits associated with fund inflows.

assets under management, since superior performance grows the value of assets and attracts additional capital into a fund. It is apparent that features of the flow-performance relation outlined in this review provide complex and potentially conflicting incentives for managers. For example, managers have an incentive, through superior performance or other means, to attract investor flows to the fund. Greater investor flows, however, create a drag on performance. The section reviews how managers respond to the salient features of the flow-performance relationship. Specifically, it examines the actions managers take to attract additional capital into a fund (besides improving risk-adjusted performance), especially in light of the non-linear relationship between performance and flow. Also reviewed are studies which examine how managers attempt to minimise the costs associated with investor flows.

Brown, Harlow and Starks (1996) are the first to investigate how the non-linearity in the performance-flow relationship influences the behaviour of asset managers. They recognise that, since the flow of money into superior funds is greater than the outflow from underperforming funds, managers face an option like payoff structure with respect to their performance. They hypothesise that this convexity induces underperforming (or 'losing') managers to augment the risk of their portfolios, since the value of this implied (out-of-the-money) option is maximised as risk increases. Furthermore, they argue that overperforming (or 'winning') mangers have an incentive to 'lock in' profits by indexing their portfolios. To refine their hypothesis they draw on aspects of economic tournament literature, which emphasises the importance of relative, rather than absolute performance, against other 'competitors' in the tournament. The authors contend that since investors pay most attention to annual performance rankings the appropriate length of the tournament is one year, beginning in January and ending in December. Their analysis, therefore, examines the correlation between relative performance in the first part of the year, with changes in risk between the first and second parts of the year.[34]

Utilising a sample of 334 growth funds in the period 1976 to 1991, the authors find that managers who underperform (overperform) relative to their peers in the first part of the year are more likely to have the greatest (smallest) increases in risk over the second part of year. They also demonstrate that certain characteristics influence the strength of this relationship. Underperforming younger funds and underperforming smaller funds tend to implement riskier strategies in the second part of the year rather than older or larger funds. Consistent with the insights uncovered in the fund salience literature, the authors provide indirect evidence that the media plays an important role in informing consumers about the performance of managers. For example, the results are most pronounced when the interim period is measured from January to July, consistent with the idea that managers change their strategies after second quarter results are reported by the financial press. Furthermore the results also indicate that the tendency for underperforming managers to alter risk increases over the course of their sample period. They attribute this to the advent of publication of fund manager performance rankings in investment magazines such as *Business Week* or *Money* during the late 1980s.

Chevalier and Ellison (1997) investigate a similar research question though add additional insight not provided by Brown, Harlow and Starks (1996). Using semi-parametric analysis, the authors first generate the shape of the performance-flow

[34] The first part of the year is defined as January to month M, where M = April, May, June, July or August. The second part of the year is defined as month M to December.

relation for funds of a given age. Using these functions as implied incentives for fund managers, the authors calculate optimal risk changes for a given interim level of performance. Consistent with intuition that was only assumed in Brown, Harlow and Starks (1996), the authors show that underperforming funds have an incentive to increase risk and superior funds have an incentive to wind back risk during the last quarter of the year. Using a sample of 449 mutual funds that operated during 1983 to 1993, they authors show that managers, in general alter their final quarter risk in line with these incentives. This holds whether risk is measured as total portfolio risk or idiosyncratic portfolio risk. The result is marginally insignificant when beta risk is considered. Furthermore the authors show that the tendency for managers to increase risk after underperformance decreases with the age and size of the fund.

Subsequent research has extended the insight developed in these early studies. Taylor (2003) develops a model which shows that in certain circumstances it is optimal for the superior funds to undertake risky strategies (rather than lock in performance) as an anticipatory move against underperforming funds. The incidence of winner funds undertaking risky strategies is directly proportional to a number of factors, including the volatility of the market, since high volatility increases the chance that a risk taking loser fund will overtake a passive winner over the last part of the year. His empirical results provide evidence that the incidence of well performing funds taking on greater risk is related to market volatility.

Kempf and Ruenzi (2008b) extend the analysis to the level of the fund family, providing evidence that similar risk shifting behaviour exists in intra-family tournaments. This research builds upon work by Kempf and Ruenzi (2008a) which documents convexity in the flow-performance relation at the family level. The authors show that in large mutual fund families, winning and losing funds behave as they do in Brown, Harlow and Starks (1996). Losing funds increase risk to get to the top of the mutual fund family, whereas winning funds lock in performance. However, they also show that for small mutual fund families, Taylor's (2003) strategic behaviour effect becomes more pronounced. Winning funds anticipate the behaviour of rival funds within a family such that overperforming funds subsequently increase their year-end risk relative to underperforming funds.

While Kempf and Ruenzi (2008b) investigate intra-family tournaments, Nanda, Wang and Zheng (2004) examine inter-family tournaments. Since the presence of a star performer provides positive fund flow externalities to other funds in the complex, a family has the incentive to produce at least one star. The authors show that one indicator of the *ex ante* probability of producing a star is high standard deviation of returns across the funds in the family. They also show that families with high standard deviation across member funds have inferior performance relative to other families. Put together, these results suggest that poorly performing families appear to undertake behaviour consistent with trying to produce a star and reaping the benefits of increased fund flow. In the context of their sample, this implies engaging in strategies to increase the standard deviation of returns across all funds in the family.

The studies reviewed thus far examine how managers act to take advantage of the features of performance-flow relation. Complementing these studies, the literature also examines how fund managers react to the reverse relation – the effect of flow on performance. This research examines the actions managers take to either deter fund flows or minimise the cost of those flows.

Managers have several mechanisms at their disposal to dissuade frequent trading in and out of a fund. These include levying load fees (or entry/exit fees)[35], enforcing minimum holding periods or minimum investment restrictions or, permitting only a set number of redemptions in a given year. In extreme cases, the manager can completely close the fund to new investors. Out of all these mechanisms to deter fund flows, the literature has investigated only two in detail – load fees and fund closures.

Chordia (1996) develops a model of the mutual fund which provides insight into why mutual funds set load fees and the benefits that accrue from this decision. In his model investors are either long or short term investors. They are identical except that short term investors have a greater probability of redeeming their investment. Redemptions impose two costs on existing investors – a liquidation cost and an opportunity cost. The liquidation cost arises when the fund is forced to sell shares. The opportunity cost arises because, as the *ex ante* probability of liquidation increases, the fund holds a greater proportion of cash as precautionary measure against redemption. Load fees impose a higher expected cost on short term investors, while conferring a benefit to long term investors. A fund sets load fees to reduce the number of short term investors or in some cases to completely discriminate between the two classes of investors. As a result, the model predicts that funds with load fees have less need to hold cash and other liquid assets to facilitate the liquidity demands of fund holders. His empirical

[35] The distinction between load fees and entry/exit fees is that load fees are primarily designed to pay for marketing costs, whereas entry/exit fees are designed to discourage rapid trading into and out of a fund. Functionally they are very similar since both require the investor to pay a fee upon entry and/or exit from a fund.

results provide support for this prediction, though are not statistically significant at conventional levels.

Nanda, Narayanan and Warther (2000), extending the insights of Chordia (1996), develop a theoretical model to predict which factors cause funds to use load fees as a means of minimising fund flows. In their model, load and management fees are set endogenously in a competitive setting by managers who are aware that fees deter fund flows and that fund flows impair performance. Due to the lower costs they impose, managers prefer long term investors over short term investors. Since load fees are set endogenously, such fees can be set such that they always deter short term investors. When a manager chooses such an action they must compete with other managers for the remaining pool of long term investors. As such, better performing managers set load fees since they have a comparative advantage in attracting long term investors. Importantly, their model also predicts that as the costs attributable to fund flow increase, the need for load fees decrease. Taken together these predictions suggest that funds which face the greatest comparative disadvantage with respect to fund flows – that is managers with superior performance or managers with poor transaction cost management – have the greatest incentive to impose load fees.

Greene, Hodges and Rakowski (2007) empirically test the intuition underlying the models of Chordia (1996) and Nanda, Narayanan and Warther (2000) – that fees levied on investor flows deter frequent redemptions. They test this issue using daily fund flow data for a sample of international equity, domestic growth, domestic income and domestic bond funds and investigate specifically the use of redemption fees by the fund managers to curb the short term arbitrage activity documented in

Section 2.1.2 of this review. The authors show that after initiating a redemption fee, the volatility of signed flows and the absolute value of daily flows decrease for all categories except domestic income funds. The authors also show that the initiation of redemption fees reduces arbitrage activity of the kind documented in Greene and Hodges (2002) and Zitzewitz (2003). The study, therefore, provides evidence that managers rationally impose redemption fees to reduce investor activity that impinges upon their assessed performance.

Several papers investigate the role of fund closures on investor and manager behaviour. After a fund initiates a closure, any further investment comes only from existing investors. In theory, closures present a way for managers to reduce flows and their associated costs. Bris, Gulen, Kadiyala and Rau (2007) investigate whether closures indeed represent an effort by managers to reduce the effect of flows on performance or whether there are ulterior motives for closure. They present three hypotheses. First, managers initiate closures to reduce flow and maintain good performance. Second, managers use closures to justify increasing management fees. Third, fund families close a well performing fund to attract attention to other funds within a family. Investigating a sample of 140 closures, the authors find that, despite the fact that closures lead to a significant reduction in fund flows, the returns of closing funds deteriorate relative to pre-closure levels. Furthermore, the performance of closing funds is comparable to their non-closed peers after the fund is shut off to new investors. This result suggests that while closures have the desired effect on fund flows, they do not have the desired effect on performance. Further analysis indicates that closures seem to be motivated by their second hypothesis – fund closures are correlated with statistically significant fee increases. The results of this study confirm earlier work by Zhao (2004), Manakyan and Liano (1997) and Smaby and Fizel (1995) which find that closed funds do not maintain their performance after initiating the investment restriction. Taken together, this suggests that fund closures do not seem to provide the expected performance improvement associated with lower fund flow.

Most managers choose not to use restrictions or fund closures to curb investor flows. Summary statistics in Greene, Hodges and Rakowski (2007) show that out of their sample of 4569 international equity, domestic equity and domestic bond funds that operated during the years 2000 to 2003, only 190 or 4.16% charge redemption fees. Their paper also documents that the use of other restrictions such as minimum investment amounts (34.96%), front-end load fees (30.05%), deferred load fees (37.37%) and purchase constraints (28.33%) is not common for funds in their sample. Fund closures appear to be even rarer. Bris, Gulen, Kadiyala and Rau (2007) use multiple news sources to hand collect a sample of 140 closures of equity funds over a twelve year period, 1993 to 2004. Zhao (2004) uses a sample of 139 closures of equity and bond funds over a ten year period, 1992 to 2001. Given that funds appear reluctant to use restrictions and closures to dissuade fund flows, managers wishing to avoid flow related performance effects can instead directly target the costs attributable to flow.

Derivatives represent one manner to reduce flow related costs. Koski and Pontiff (1999) provide the first evidence that portfolio managers use derivatives to minimise the risk distortion effects studied in Ferson and Schadt (1996), Ferson and Warther (1996) and Edelen (1999). The authors argue that since derivatives provide a mechanism to manipulate portfolio risk, these securities can be readily used to rebalance the portfolio after fund flows distort its risk characteristics. Furthermore, they also note that investor flows are directly proportional to past performance. The hypothesis that follows from these arguments is that the negative relation between past performance and risk should be weaker for funds which use derivatives compared funds that do not. Analysing a sample of 679 equity mutual funds partitioned into 'derivative user' and 'derivative non-user' groups, the authors estimate the relationship between six monthly performance and subsequent risk measures. The results indicate that the relationship between performance and risk is negative, but the relationship is non-existent or weaker amongst the derivative user group. Importantly, the study shows that managers are only able to repair changes to beta risk, suggesting that index futures or index options feature prominently in the execution of this strategy.

Chincarini (2004) explores the issue further, examining the extent to which four prominent index futures contracts – the S&P500, Nasdaq-100, Russell2000 and S&P400 Midcap – can be used to minimise fund flow related risk costs for various sector funds. The effectiveness of a futures contract in reducing risk effects is directly related to the extent to which the derivative can be used to mimic the typical returns on the managed portfolio. For all four index future contracts, the author estimates over a 30-day period the position required to mimic the sector fund's benchmark and then tests this estimated value on the next day's returns. The results indicate that for most sectors (all except precious metals, commodities, real estate and utilities) using index futures in this manner produces returns that are closer to the sector fund's benchmark than holding cash. Averaged across all sector benchmarks, the strategy reduces tracking error by 9 basis points per day. While offering important insight, the results of this study presents only the hypothetical savings of using index futures to minimise risk effects of fund flows. It does not test whether these benefits are actually realised by fund managers.

Besides dampening the risk distortion effects of fund flows, derivatives can also generate transaction cost savings for fund managers. Since futures markets are generally more liquid than equity markets (Fleming, Ostdiek and Whaley, 1996), funds that require transaction of large flows might find it more cost effective to engage in futures markets. Deli and Varma (2002) examine the factors that underscore the permission to invest in derivative securities and provide indirect evidence that fund managers use derivatives to reduce transaction costs. The authors find that the permission to trade derivatives is only provided to funds where transaction cost savings are likely to be large. There is a greater chance derivatives will be permitted for funds that hold less liquid portfolios and for funds that have greater turnover of shares. Furthermore, only those derivatives relevant to the portfolio are allowed to be traded. For example, equity funds can only trade equity derivatives and not bond derivatives. While this study provides evidence that derivatives are used to generate transaction cost savings, as in Chincarini (2004), these findings are only hypothetical. Without examining actual mutual fund return data, it is not possible to determine if fund managers actually realise these savings.

2.1.4. The use of derivatives by mutual fund managers

This section reviews all studies that investigate the derivative trading behaviour of investment managers. It covers the specific research questions examined in these papers, the effects of derivative trading on performance and risk and the methods used to classify funds into derivative user and non-user groups.

Koski and Pontiff (1999) is the first study to investigate the use of derivatives by investment managers. Their sample covers 679 equity mutual funds operating in the US over the period January 1992 to December 1994. Derivative user and non-user groups are classified according to the results of a telephone survey conducted by the authors. The paper first examines the characteristics that are correlated with the use of derivatives. Though it is not explicitly mentioned in the study, the results are consistent with the idea that derivatives are used to mitigate the costs of fund flows. Consistent with Deli and Varma (2002), funds with greater turnover are more likely to use derivatives. Funds which do not charge load fees or are part of fund family are more likely to trade derivatives. Both of these factors have been shown to increase the flow of money into a fund (Barber, Odean and Zheng, 2005; Kempf and Ruenzi, 2008a). In a largely exploratory analysis, the authors also investigate the distributional properties of return and risk metrics for the mutual funds in their sample. The results indicate that there is little statistical difference in the unconditional distributional properties of derivative users compared to non-users. Finally, as mentioned previously, the authors find that derivative users have lower intertemporal variation in beta risk (conditioned on prior performance) between consecutive six month periods relative to non-users. The authors use this result to suggest that a decrease (increase) in portfolio risk after strong (poor) performances is the result of fund flows, rather than incentive gaming as hypothesised in Brown, Harlow and Starks (1996) and Chevalier and Ellison (1997). If gaming was the true cause of the intertemporal variation in risk, the authors argue that derivative users should have a higher sensitivity of risk to prior performance rather than lower as they find.

Johnson and Yu (2004) replicate aspects of the analysis of Koski and Pontiff (1999) using data of derivative investment by Canadian domestic equity, foreign equity funds and fixed-income funds. Their sample covers 221 users and 777 non-users of derivatives which operated during the period September 1995 to September 1998. To classify funds, the authors have access to mutual fund holdings data. The data provide the amount of investment in three derivative categories – warrants, index futures and 'other derivative securities'. As with Koski and Pontiff (1999), the authors find that the factors correlated with derivative usage indicate the derivatives might be used to dampen fund flow related costs. Derivative use is associated with the absence of load fees and indicators which describe large, high turnover funds, though this result is only apparent for domestic equity funds. In terms of risk and performance, the study finds that there is no difference between users and non-users of derivatives in the domestic and foreign equity income category, while fixed income funds have higher risk and return measures.

Fletcher, Forbes and Marshall (2002) also replicate Koski and Pontiff (1999) on a sample of UK investment trusts investing in UK equities. Their sample consists of 98 funds that operated between January 1995 and December 1997. Through a written survey, 22 funds are classified as users of derivatives. As with Koski and Pontiff (1999) and Johnson and Yu (2004) the authors show that there is no statistical difference in the performance metrics of user compared to non-user funds. The results show no difference in mean risk values, but indicate that the distribution of risk metrics is more disperse for user funds. Finally the authors document that derivative users have lower intertemporal variation in conditional risk across consecutive six month periods. This is technically consistent with Koski and Pontiff (1999). However, the study also reports the incongruous finding that risk is *positively* related to prior performance. This is not consistent with the idea that fund inflows (outflows) accorded to strong (weak) performance bring about undesired dilution (concentration) of risk and provides considerable difficulty in adequately interpreting the results. The authors do not investigate the source of this incongruous finding.

Three studies examine the use of derivatives by Australian equity managed funds. Pinnuck (2004) examines the use of options by investment funds. In general he finds that investment in options is small, and averages only 1.76% as a percentage of total portfolio value. Option usage does not appear to be correlated with performance, risk or turnover. The author states there is weak evidence that option usage is correlated with fund size. Fong, Gallagher and Ng (2005), undertaking a similar analysis to Koski and Pontiff (1999), note that unconditional risk and return metrics are not correlated with the use of derivatives. Despite this lack of difference in performance between the groups, the authors also find that fund managers tend to use options to initiate momentum strategies in rising stocks. Investment in options is accorded more strongly towards underlying stocks with recent good performance. Finally, the authors show that option trades by fund managers are not correlated with price moves in the underlying security, suggesting that options trades by fund managers are not informationally motivated or are not perceived as such by the market. Finally, Benson, Faff and Nowland (2007) investigate the risk shifting behaviour of derivative using managed funds. The authors find some evidence that the behaviour of fund managers is consistent with the gaming hypothesis provided in Brown, Harlow and Starks (1996) and the active competition hypothesis of Taylor (2003). However, the results overall are mixed and not robust to the time period studied.

The salient features of the data sets, sample periods and results of the studies reviewed in this section are provided in Table 2.1. The results summary reveals a general consensus that, in unconditional analyses of risk and performance, derivative users are not significantly different to non-users. Secondly, the classification of mutual funds into user and non-user groups varies in terms of data sources and data precision. Some data sets allow the researcher to determine which derivatives are traded – options or futures and some data sets allow the extent of derivative investment to be determined. None of these data sources, however, allow the researcher to determine the purpose of the manager's derivative trading, e.g. is the manager hedging or speculating by trading a particular option? The purpose of derivative trades is inferred from comparisons of derivative users and non-users.

The study of derivative trading behaviour in Chapter 3 extends the literature in this respect since it utilises unique survey data which provides detail as to whether fund managers trade index futures for the purposes of fund flow management or otherwise. The results of the study also challenge the consensus that derivatives do not seem to hinder or enhance performance of fund managers.

Table 2.1
Summary of literature on the use of derivatives by investment managers

This table summarises studies that investigate the derivative trading behaviour of investment managers. The table describes features of the sample used in each study – the number of user and non-user funds, the period analysed and the method used to classify user and non-user funds. The table also summarises results of analyses which examine whether users and non-users of derivatives differ in terms of unconditional risk and return metrics. The final column presents other findings documented in the respective study.

Study	**Sample Features**			**Summary of Results**	
	Description	Period	Classification Method	Unconditional risk/return	Other findings
Koski and Pontiff (1999)	US equity mutual funds 141 users, 538 non-users	Jan 1993 to Dec 1994	Telephone survey indicates whether fund uses derivatives or not	No difference	1. Derivatives usage is correlated with turnover, the absence of load fees and the membership of a family 2. Users have lower variation in risk, conditioned on prior performance.
Fletcher, Forbes and Marshall (2002)	UK equity investment trusts 22 users, 71 non-users	Jan 1995 to Dec 1997	Written survey indicates whether fund uses derivatives or not	Users have greater dispersion in risk metrics. No difference otherwise	Users have lower variation in risk, conditioned on prior performance.
Pinnuck (2004)	Australian equity managed funds 21 user funds, 16 non-users	Jan 1990 to Dec 1997	Confidential portfolio holdings indicate whether funds hold options	No difference	Options play an economically insignificant role for funds.

Johnson and Yu (2004)	Canadian equity and fixed-income mutual funds 211 users, 777 non-users	Sep 1995 to Sep 1998	Portfolio holdings data reveals whether funds use warrants, index futures or other derivatives.	No difference for equity funds. User funds have greater risk and return in fixed-income category	Derivatives usage is negatively correlated with age (foreign equity and fixed-income) and positively correlated with size and factors attributable to growth funds (domestic equity).
Fong et al. (2005)	Australian equity managed funds 17 users, 17 non-users	Jan 1993 to Dec 1993	Confidential portfolio holdings indicate whether funds hold options or futures	No difference	1. Options are purchased to gain exposure to recent winner stocks 2. The options trades of fund managers are not informationally motivated.
Benson et al. (2007)	Australian equity managed funds split into two samples S1: 34 users, 68 non-users S2: 20 users, 10 non-users	S1: Jan 2002 to Dec 2005 S2: Jan 1994 to Dec 2003	S1: Data obtained from fund annual reports S2: Data obtained from Russell Investment Group	No difference	Evidence that funds in the sample behave in a manner consistent with gaming or active competition. Results are not robust to time period analysed.

2.2. The interaction between insider traders and regulators

Understanding crime and punishment through the prism of economic thought began with the pioneering work of Becker (1968). In his analysis on the supply of offences Becker notes that the expected utility of crime depends upon three variables – the expected gain from the crime (expressed as its monetary equivalent, *Y*), the probability of getting caught (*p*) and the punishment levied if caught (expressed as its monetary equivalent *f*). The expected utility from a crime is defined as:

$$EU_j = p_j U_j(Y_j - f_j) + (1 - p_j)U_j(Y_j) \tag{2.1}$$

In the context of illegal insider trading this relation can take a slightly altered form, if one recognises that, given that an individual decides to commit insider trading, both the expected income from the crime and the probability of getting caught is a function of the volume traded. Furthermore, unlike crimes with more esoteric concepts of 'gain' (e.g. sexual assault or vandalism), the gain from insider trading is predominantly monetary in nature and can be defined easily. The expected utility from insider trading is:

$$EU_j = p(s,x)_j U_j(s\delta - f_j) + (1 - p(s,x)_j)U_j(s\delta_j) \tag{2.2}$$

where s is volume traded by the individual, δ is the incremental value, in dollars per share, of the insider's information and x represents any other factors which influence the probability of detection. This idea parallels the insight developed in Stigler (1970), which allows for the probability of punishment to be directly proportional to the gain incurred by the criminal. In the equation presented above, the factor that drives this correlation is the volume traded by the insider. The consequences of Equation 2.2 are more formally explored in Chapter 4, but at first instance it is worthwhile noting that a utility maximising illegal insider trader chooses s to maximise EU given the other parameters, f, p and δ.

This intuition provides the motivation for exploring the interactions between illegal insiders and regulators, since the decisions of the regulator play a large role in determining these three factors. In essence, the regulator governs the behaviour of insider traders. Clearly, f and to a large extent, p are determined by the regulator. Not as clear is the influence of the regulator on the incremental value of the insider's information, δ. At first glance, it would seem that the acquisition of information by insiders is a process independent of the regulator's actions. Even if one accepts this to be true, it is nevertheless possible to argue that the *incremental* value of that information, once acquired, is affected by the regulatory and legal environment in which the insider operates. This is because the regulatory environment (e.g. disclosure laws, insider trading laws and corporate governance standards) has a strong bearing on the efficiency of the market (Fernandes and Ferreira, 2009; Beny, 2005; Bris, 2005). By definition the efficiency of the market determines the value and longevity of inside (non-public) information.

This part of the literature review summarises studies which examine the interaction between illegal insiders and regulators. Section 2.2.1 reviews studies which investigate how insiders respond to factors which increase the punitive side of Equation 2.2 – i.e. increases in fines or probability of conviction. Section 2.2.2 reviews the literature which investigates factors that influence the gains of insider trading. Finally, because Chapter 4 presents an empirical study of illegal insider trading, Section 2.2.3 reviews the general empirical literature on insider trading not included in Section 2.2.1 or 2.2.2. The entirety of Section 2.2 surveys literature on illegal insider trading, though where it is relevant literature on legal (reported) insider trading is also included.

2.2.1. Illegal insiders and expected penalty

The expected penalty of a crime is the product of two factors – the probability of conviction and the penalty upon conviction. To investigate the effect of expected penalties on the behaviour of insiders, the literature naturally turns to the legislative and enforcement environment in which insiders operate. Studies tend to divide the legislative environment into several regimes of increasing severity – no insider trading laws, insider trading laws with zero or very poor enforcement of those laws and finally, enacted and enforced insider trading laws. Further to this, studies also examine how insiders react to changes in the punishment levied upon transgressors.

Banerjee and Eckard (2001) examine a period in US history before the existence of insider trading laws to determine how insiders behave under complete impunity. Analysing a sample of mergers from the 'Great Merger Wave' of 1897-1901, the authors find evidence of substantial insider trading. For a selection of firms for which the first announcement of the merger is a notice indicating the merger is nearing completion,[36] the results indicate that insiders appropriate all the pre-announcement

[36] In this period, disclosure requirements and takeover laws were not as they are in modern times. It was possible to have a merger de facto completed before announcing it to the market.

returns. This study shows that insiders trade to realise the maximum profit when the threat of prosecution is non-existent.[37]

The results of Madison, Roth and Saporeschenko (2004) suggest a similar phenomenon – that insiders act readily to utilise information if there is no punishment attached to the behaviour. Their analysis however, is different to Banerjee and Ekard (2001) and indeed most studies in this area, in that it examines insider *non-trading*. Purchasing shares in a yet-to-be-announced takeover target produces the same terminal wealth effects as delaying the sale of shares already held. Only the former is illegal. Examining reported share sales of upper management of commercial banks, the authors find evidence that insider selling activity drops to zero, at the median, in the last two months prior to a merger announcement. Consistent with Banerjee and Eckard (2001), this study suggests that insiders act to capture 100% of the gains if the threat of prosecution is absent.

What happens if insider trading is illegal but the activity is not enforced? Bhattacharya, Daouk, Jorgenson, Kehr (2000) investigate stock price run-ups in a sample of Mexican news announcements. In Mexico insider trading laws exist but are not enforced. Insiders act with a technical, but not real, threat of prosecution. The results of the study indicate that there is no significant abnormal return on the day of news announcements in the Mexican Bolsa de Valores. Other factors which are

[37]Bris (2005) examines the same research issue in a modern context. As part of his broader analysis of the efficacy of insider trading laws, he documents a significant but modest cumulative abnormal return of 1.37% at announcement for a sample of mergers picked from a pool of 43 countries that first passed insider trading laws in the 1990s. The reliability of this part of his analysis, however, is questionable, given the sample size (27 – less than one per country) and includes countries with under developed markets. Furthermore the average premium associated with the mergers (100 days pre to 1 day post announcement) is an insignificant 0.52%, which appears completely at odds with typical researched mergers.

typically associated with levels of information asymmetry – increased volatility, greater bid-ask spreads, increased volume – are also absent on the announcement date. The authors find evidence of complete information leakage prior to the event, suggestive of insider trading. The results of this study show that the mere presence of insider trading laws does not appear to prevent insiders from being active in markets prior to sensitive news announcements. Wisniewski and Bohl (2005) provide contributing evidence from the Polish market, where insider trading laws are also poorly enforced. Their study shows that reported insider trades predict significant abnormal returns on the Warsaw Stock Exchange.

Studies suggest that it is the enforcement, rather than the presence, of insider trading laws that changes the behaviour of insider traders, though the evidence is only indirect. Bhattacharya and Daouk (2002) find that the company cost of equity decreases in a sample of 103 countries after the first enforcement of insider trading laws but not after the enactment of the laws. The authors speculate that this reduction in the cost of equity could occur in one of two ways. Firstly, liquidity providers tighten bid-ask spreads as adverse selection costs decrease under stricter enforcement. This improves prices for investors and hence reduces their required rate of return. Alternatively, under strict enforcement the behaviour of large shareholders is tipped towards greater scrutiny of management. In a regime of lax enforcement, management could 'bribe' large shareholders from undertaking costly monitoring through sharing of insider information. The shift towards greater monitoring under enforced laws makes investment more attractive and thus decreases the required rate of return. Importantly, both scenarios are associated with a lower incidence of insider trading. Beny (2005; 2007) provides evidence that ownership dispersion in an economy is positively correlated with whether enforcement in that economy occurred by 1994. Beny offers several reasons why greater ownership dispersion suggests lower insider trading and they are similar to those mentioned in Bhattacharya and Daouk (2002). Both these studies therefore, provide (indirect) evidence that the enforcement of laws has a real effect on the behaviour of insider traders.

Once insider trading laws are passed and are well enforced, what factors affect the probability of detection? Due to the inherent data-related difficulties in answering this question[38], the literature offers only scant empirical evidence. Park, Jang and Loeb (1995) develop a model of insider trading before earnings announcements where the probability of detection is a decreasing function of the days until the news is released. Their model predicts that, conditional on the insider having sensitive information and choosing to trade on it, insider trading activity should decrease as the information event approaches. To test their hypothesis the authors investigate reported insider trading activity in the 40 days prior to earnings announcements. The results indicate that insider trading activity is greater than normal 40 to 21 days before the information event and significantly lower than normal 10 to 1 days before the information event. While the analysis is conducted only on reported insider trades, the findings suggest that insiders are aware that trading immediately before a material announcement is likely to draw attention to the activity. This suggests that the proximity to the announcement date is a determinant of the detection probability.

Ke, Huddart and Petroni (2003) provide contributing evidence for this conclusion. They examine reported insider trading activity before earnings announcements, in

[38] In order to determine the factors which relate to the probability of detection, one needs to have data on illegal insiders who were not detected. Such data is generally unavailable.

which reported earnings decrease compared to the corresponding quarter of the previous year. Such events, which the authors term a ‘break’, are shown to involve significant abnormal negative price reactions on announcement day. The authors find an absence of insider selling activity in the two quarters prior to a break. However, there is evidence of significant selling activity between seven to three quarters prior to the break. This is consistent with detection minimisation behaviour on the part of insiders and like Park, Jang and Loeb (1995) suggests that the probability of detection is lower the further away an insider trades from the event.

Finally, several papers investigate the effect that increases in penalties have on the behaviour of insider traders. Seyhun (1992) investigates the change in insider trading behaviour surrounding the introduction of two key laws that increased the maximum punishment levied on insiders. These statutes were the Insider Trading Sanctions Act (1984) and the Insider Trading and Securities Fraud Enforcement Act (1988). In the appendix of Seyhun (1992), a simple model of insider trading is developed which predicts that greater penalties upon conviction result in lower volumes of insider trading. Investigating all reported insider open market transactions in 8,856 firms over the period January 1975 to December 1989, the author finds mixed evidence for his hypothesis. Specifically, insider trading volume in general increases after the enactment of harsher regulations. However, in the 30 day period prior to earnings announcements insider trading decreases substantially after the enactment of new laws. These results complement those of Ke, Huddart and Petroni (2003), and suggest that at the very least, the regulations caused insiders to reduce their trading at times when the regulators were most likely to scrutinise their behaviour.

Garfinkel (1997) finds corroborating evidence with respect to earnings announcements and the passing of the Insider Trading Securities and Enforcement Act (1988). Examining reported insider trades in 13,862 quarterly earnings announcements between January 1984 and March 1991, the author finds that after the passing of the act, the frequency of insider trading before the announcement decreases. Specifically, insiders postpone liquidity motivated trades to after the announcement and the incidence of pre-announcement trades which are in the same direction as the earnings surprise (buys for positive surprises and sells for negative surprises) decreases substantially. The results suggest that insiders respond to increases in expected penalties by reducing their traded volume 30 days prior to earnings announcements. A caveat with respect to the results of Seyhun (1992) and Garfinkel (1997) is that both studies use data on insider trades reported to the SEC. By their very nature, such trades are unlikely to be as motivated by information as covert insider trades. These studies only provide limited insight into the effect of greater sanctions on the behaviour of illegal insider traders.

2.2.2. Illegal insiders and expected gains

Regulators and legislators establish the rules and laws that govern exchanges and related financial systems. Their actions help determine, amongst other things, the efficiency of the market (Fernandes and Ferreira, 2009; Beny, 2005; Bris, 2005). As such, regulators play a large role in influencing the expected returns to insider trading, since by definition, the extent of market efficiency determines the value and longevity of inside (or price-sensitive) information. The exact relationship between insider trading laws and market efficiency is the subject of debate. Several studies investigate how the enactment and enforcement of insider trading laws influences the information environment of the markets in which illegal insiders operate. Prominent critics of insider trading laws, such as Manne (1966), suggest that the insider trading should improve the price efficiency of the market since there is a strong incentive to trade on information to the point that stock prices are at their full-information values. However, Fishman and Hagerty (1992) suggest that the presence of insider trading might reduce the informational efficiency of a market since it crowds out other information seekers. Furthermore, the ability to profit from insider trading might create incentives for corporate insiders to withhold information from the market, thereby reducing efficiency (Benabou and Laroque, 1992).

The extant literature on the relationship between informational efficiency and insider trading laws is sparse and inconsistent. Fernandes and Ferreira (2009), in a cross-country study of 48 economies, empirically test whether the enforcement of insider trading laws improves or worsens market efficiency. Using several metrics for information efficiency, the authors show that market efficiency improves after the enforcement of insider trading laws, but only for developed economies. In developing economies, they suggest that the lack of appropriate legal safeguards acts as a deterrent for market professionals to fill the gap left by insider traders. Therefore, these economies do not exhibit improvement in market efficiency after the first enforcement of insider trading laws.

Beny (2005, 2007) performs a similar analysis, however only utilises one measure of market efficiency – the extent of stock price synchronicity between firms – and investigates the effect of insider trading laws in only 33 economies. Her results indicate that the harsher insider trading laws are correlated with greater information efficiency, but unlike Fernandes and Ferreira (2009) she does not test for differences between developed and non-developed countries.

In a related study of 100 countries, Bushman, Piotrowski and Smith (2005) investigate how the first enforcement of insider trading laws affects the extent of sell-side analyst coverage of firms. Investigation of analyst coverage is interesting because this group of individuals represents one prominent source of non-insider information-based traders. The results indicate that the first enforcement of insider trading laws is correlated with a subsequent increase in analyst coverage, with greater percentage increases for emerging, non-liberalised markets. This result is somewhat at odds with the finding in Fernandes and Ferreira (2009), although the two papers can be reconciled if one believes that analysts in emerging markets do not contribute substantially to the informational efficiency of those markets (Chan and Hameed, 2006).

Finally Bris (2005) examines the stock price run-up prior to 4,541 takeover announcements before and after the first enforcement of insider trading laws in 52 economies. His study indicates that the announcement day return contributes a greater percentage of the total takeover premium (defined as the pre-announcement run-up plus announcement day return) after the first enforcement of insider trading laws. In an environment where insider trading laws are not enforced, announcement day returns contribute to 39.27% of the takeover premium. This compares to 44.44% after the first enforcement. This study provides evidence inconsistent with Fernandes and Ferreira (2009) and Beny (2005, 2007) since it suggests that markets become less strong-form efficient and more semi-strong form efficient after the first enforcement of insider trading laws.

While there is no consensus on the effect of regulator action on market efficiency, it is nevertheless important to discuss how changes in market efficiency might affect insider trading behaviour. Put differently, how do insiders behave if the value of their information changes? This question is difficult to address in the context of the enforcement of insider trading laws because the change in the value of their information associated with changes in market efficiency are also accompanied by a change in the expected penalty for the use of that information. Bris (2005) suggests that while insider trading laws might deter overall illegal trading activity (leading to greater announcement day returns for his sample of takeovers), those insiders that choose to trade capture greater profits. In terms of standard economic theory, the presence of insider trading laws creates less competition amongst the suppliers of crime, thereby increasing their rents. This provides little indication however, as to how an individual insider acts when the value of their information increases, *ceteris paribus*.

Economic theories of crime provide some insight into how insiders might behave when the value of their information increases. An inspection of Equation 2.2, which is drawn from Becker (1968), suggests that as the potential gain from crime increases insiders supply more of their crime – i.e. take a greater position in the security – since the return is more likely to offset the expected penalties of transgression. In other words, there is greater incentive to act on insider information when the value of that information is larger. The only study that provides evidence for this assertion is

Seyhun and Bradley (1997). Their study investigates the selling behaviour of insiders prior to corporate bankruptcy. Their results indicate that insiders begin selling shares as early as five years before the onset of disaster. Importantly, as the event becomes imminent (and presumably the probability of disaster increases), selling by insiders reaches a peak. This suggests that as the expected value of the information rises[39], insiders trade more stock.

2.2.3. Other empirical studies of illegal insider trading

Empirical studies using illegal insider trading data focus exclusively on the effect of insider trading on the broader market. This section summarises the nature of the data sources, the research questions and related findings of these studies.

Meulbroek (1992) uses data gleaned from SEC litigation reports and confidential prosecution case files to ascertain the effect of illegal insider trading on price discovery and volume. Her data set comprises all insider trading cases initiated by the SEC from 1980 to 1989 and covers the illegal trading activity of 320 defendants. Her unit of observation is an 'insider trading episode' which involves all trading by defendants in a security before a material information announcement. There are 183 of these episodes in her sample.

To ascertain the effects of insider trading on price discovery, Meulbroek (1992) estimates a modified market model regression using daily price data before the announcement date. She incorporates a dummy variable into the regression, which equals one if her data indicate an illegal insider traded on that day, to ascertain the

---

[39] $E(value) = P(bankruptcy) * Cost$. So as the probability of bankruptcy increases the value of the information also increases.

effect of insider trading on price discovery. Her results show that on days in which illegal insiders trade the abnormal return on the stock is on average 3.06%. Furthermore the average pre-announcement cumulative abnormal return of all insider trading days is 6.85%, which is 47.56% of the total information content of the announcement. This suggests that insiders contribute significantly to price discovery in the days leading up to information release. Meulbroek (1992) also shows that volume on insider trading days is 64% larger than normal (excluding the insiders' trades).

Cornell and Sirri (1992) access criminal and civil judgements of cases regarding illegal insider trading in the 1982 acquisition of Campbell Taggart by Anheuser-Busch to identify trades conducted by 38 illegal insider traders. The authors conduct a daily analysis of the effect of insider trades on price, volume and liquidity in Campbell-Taggart. Their results indicate that on days when the insiders trade, the abnormal return of the stock is significantly positive consistent with Meulbroek (1992). Interestingly, the authors also note that bid-ask spreads did not increase during the period when insiders were active, a result inconsistent with adverse selection models of the bid-ask spread (e.g. Copeland and Galai, 1983; Glosten and Milgrom, 1985). Furthermore, market impact costs marginally improved during the period when the insider traders were active. The authors attribute this to increased volume in the security during the pre-announcement period.

Chakravaty and McConnell (1997) investigate similar research questions to Cornell and Sirri (1992) but instead use case files regarding Ivan Boesky's trading in Carnation, before its subsequent takeover attempt by Nestlé in 1984. The authors conduct both a daily and an hourly analysis of the affect of Boesky's trades on the price of Carnation stock. Consistent with Meulbroek (1992) and Cornell and Sirri (1992), the trades conducted by the insider are contemporaneously correlated with abnormal returns. In their hourly analysis, the authors also provide evidence that Boesky's trades caused prices to move, rather than the reverse (i.e. Boesky waited for large price movements to trade). Like Cornell and Sirri (1992), Chakravaty and McConnell (1997) also show that market liquidity – bid-ask spreads and depth – were not adversely affected by the trades of superiorly informed individuals.

Chakravaty and McConnell (1999) challenge the findings of the previous three studies that suggest that insider trading contributes to improved price discovery. Using the same data set of Ivan Boesky's trades analysed in Chakravaty and McConnell (1997), the authors undertake a methodology which compares the price impact of insider trading against non-insider trading of the same direction. The results indicate that Ivan Boesky's trades in Carnation are statistically indistinguishable from non-Boesky trades in Carnation in terms of their impact of returns. These results suggest that some caution is required in asserting that insider trading promotes improved price discovery.

Finally, Fishe and Robe (2004) analyse trades conducted by brokers who had advance access to an influential *Business Week* column entitled 'Inside Wall Street', for their effect on bid-ask spreads and depth. The authors take advantage of the fact that of 116 stocks featured in the column during the period of the insiders' trading, the brokers took positions in only 40 securities. This allows the authors to compare the liquidity effects of insider trading on the traded stocks, with the non-traded stocks forming a control group. The results indicate that bid-ask spreads widen and depth falls when insiders trade, but only for trades conducted in the specialist market (i.e. NYSE). These results are inconsistent with the findings of Cornell and Sirri (1992) and Chakravaty and McConnell (1997).

Chapter 4 of this thesis takes the empirical literature on insider trading in a new direction. Instead of focusing on the affects of insider trading on market quality and price discovery, this chapter examines the behaviour of insider traders as inferred by the position they take in the securities for which they have sensitive information. The work builds upon the insights developed by Becker (1968) and models the decision process of insiders as an economic problem of utility maximisation.

2.3. The interaction between informed agents and uninformed agents in securities markets

The first two essays of this thesis examine two specific relationships of informed agents (fund managers and insider traders) and another party (investors and regulators). In the final essay, the general relationship between informed traders and uninformed traders is explored, with a particular focus on how broker transparency affects the ability of uniformed traders to detect and protect themselves from informed trading in stock markets.

Section 2.3.1, 2.3.2 and 2.3.3 provide a review of selected literature on how uninformed agents respond to the presence of informed traders in stock markets. These sections focus on three prominent indicators of informed trading – permanent price impact, the bid-ask spread and order imbalances, respectively. These particular metrics are examined in Chapter 5 of this thesis. In each of these sections, the theory underpinning how these metrics relate to informed trading is discussed. Following this, each section reviews prominent empirical studies which utilise these metrics to make inferences regarding informed trading or the detection of informed trading in markets. Since Chapter 5 concerns broker anonymity, Section 2.3.4 reviews the literature on the effects of broker anonymity in securities markets.

2.3.1. Permanent price impact and the detection of informed traders

The total price impact of a trade can be divided into two components: transitory and permanent (Kraus and Stoll, 1972). The transitory component measures the price impact associated with temporary liquidity constraints and microstructure effects (such as minimum tick size) at the time of the trade. In contrast, the permanent component measures the longer lasting price impact of the trade. Importantly, this metric can be used to ascertain the market's assessment of the information content of the trade, under the basic rationale that long term price movements are primarily caused by the incorporation of new information into security prices by market participants (Hasbrouck, 1991).[40] As such, several studies examine permanent price impact to make inferences regarding the level of informed trading (as assessed by the market) associated with a particular class of trades or a particular event or even a particular type of trading platform. The traditional measure of permanent price impact is to examine the simple return from a benchmark equilibrium price prior to the trade (for example, the opening price on the day of the trade or the closing price the day before) to a point after the trade (Holthausen, Leftwich and Mayers, 1987). This approach is utilised in many studies.

Early studies in this area investigate the price effects and information content of large block transactions. Block transactions are particularly relevant for investigation since it is reasonable to assume, at least in the first instance, that informed investors would trade large quantities to extract the most value from their information. Kraus and Stoll (1972) represents one of the first papers to investigate the information content of block trades. The authors estimate the permanent price impact as the simple return from the close on the previous day of the trade to the close on the day of the trade. The authors find significant positive permanent price impact for buyer initiated trades (1.42%) and significant negative permanent price impact for seller-initiated trades (-1.148%). This result allows the authors to make two important conclusions regarding the information content of block trades. Firstly, block trades are perceived to contain

[40] Indeed a recent study by Chung, Li and McInish (2005) shows that permanent price impact is positively related to the Easley, O'Hara, Kiefer and Paperman (1996) measure of the probability of informed trading.

information not otherwise incorporated into the price before the execution of the trade. Secondly, the information content of buyer-initiated trades is perceived by the market to be larger than the information content of seller-initiated trades. These two findings are confirmed in numerous subsequent studies on the information content of block trades and are robust to different sample periods, stock markets and types of trades analysed.

For example, Holthausen, Leftwich and Mayers, (1987) examine the information content of block trades on the NYSE executed during 1982 and find a permanent price impact of 1.610% for block buys and -1.180% for block sales. In a follow up study, the same authors find a permanent price impact of 0.500% for block buys and -0.340% for block sales for NYSE block trades executed during 1982 to 1984 (Holthausen, Leftwhich and Mayers, 1990). Qualitatively similar (though quantitatively different) results are documented for block trades on the ASX (Aitken and Frino, 1996a; 1996b), the LSE (Gemmill, 1996), and the upstairs market of the NYSE (Madhavan and Cheng, 1997). Rather than examining block trades in general, Chan and Lakonishok (1993) examine trades executed by a sample of 37 fund managers during the period 1986 to 1988. They also document an asymmetry in buys and sells for block trades. Finally, Chan and Lakonishok (1995) examine the permanent price impact of trade packages of institutional investors (rather than individual trades) and document positive permanent price impact of block buys which is larger than the permanent price impact of block sales.[41]

[41] The permanent price impact of block sales in Chan and Lakonishok (1995), however, are positive rather than negative as per the previous studies.

For the purposes of this dissertation, the magnitude of the permanent price impact documented in these studies is not as important as the underlying approach exhibited in their interpretation of this metric – namely, that permanent price impact is a direct indication of the market's assessment of the information content of a trade and can be used to infer the presence of informed traders (assuming the market is, on average, adept at detecting informed trading). As an example of this, several of the aforementioned studies seek to explain the asymmetry in the permanent price response of block purchases and sales as a product of asymmetry in the information content of purchases versus sales. Kraus and Stoll (1972) suggest that the block purchases exhibit greater price response because of the information content of their trades is not only rich, but also biased upwards due to inclusion of many takeover targets in their sample. Chan and Lakonishok (1993, 1995) and Keim and Madhavan (1995) also suggest that block purchases possess greater information, since a purchase indicates a direct preference for one particular firm over all other firms in the market. As such, the decisions of these investors are more likely driven by positive information concerning the stock in question. In contrast, block sales are more likely attributable to portfolio rebalancing considerations since sellers are typically restricted to selling only those stocks they own.

Beyond investigating the information effects of block trades, Barclay and Warner (1993) utilise permanent price impact to ascertain which trade size is most often used by informed traders. The authors examine the 30 day lead up period to a sample of 108 selected tender-offer announcements, and attempt to infer which trade size causes the greatest permanent price impact. Their results indicate that medium sized trades, where the trades are 500-9900 shares, are associated with 92.8% of all permanent price movements during this period. Furthermore, the study finds that medium sized trades are associated with the greatest price movements during normal trading periods (though the results are not as strong as during tender offer pre-announcement periods) and therefore, concludes that medium sized trades are most likely to be used by informed traders. Chakravaty (2001) reconfirms this finding using a different sample of NYSE stocks which exhibit at least 5% price movement over the three month period, November 1990 to January 1991. The results of the study indicate that medium sized trades account for 79% of the permanent price movement for this sample of securities consistent with the idea that informed traders use medium sized trades. Furthermore, the data in that study allows for identification of the initiating party of all trades. Additional tests show that almost all of the trades that account for 79% of the price movements originate from institutional investors. Put together these results imply that the market places large informational weight on medium sized trades of institutional investors.

Several papers examine the permanent price impact of trades around information events to determine the extent of informed trading associated with these announcements. Barclay and Dunbar (1996) examine the permanent price impact of block trades around quarterly earnings announcements to ascertain whether informed trading is significant during these periods. Their sample of quarterly earnings announcements is from 1984 and consists of 2,567 buyer initiated block trades and 2,624 seller initiated block trades. The authors find that block trades exhibit positive (negative) permanent price effects for buyer (seller) initiated trades of between 0.64 and 0.67 (-0.72 and -0.68) %. However, the results are not materially larger than a control group of block trades executed during normal trading periods, suggesting that it is the block trades rather than the forthcoming information announcement that generates the price effect. Daley, Hughes and Rayburn (1995) investigate a similar question, but instead examine a slightly different series of quarterly earnings announcements (October, 1984 to April, 1985) and compare pre-announcement price impact to post-announcement price impact. The results indicate overall a significant difference between the two which suggests, in contrast to Barclay and Dunbar (1996), that informed traders are active before these information announcements. The results are particularly strong for a sample of small firms, which indicates that these securities have the greatest levels of information asymmetry before quarterly earnings announcements.

Koski and Michaely (2000) provide a comprehensive analysis of permanent price impact during three information environments: pre-dividend announcements periods, regular periods and ex-dividend periods. The authors argue that these three periods correspond to decreasing levels of information asymmetry and examine permanent price impact of trades to test their hypothesis. Their sample consists of all trades in 378 firms listed on the NYSE that paid dividends during 1987 and 1988 and were present in the S&P500 during those years. The authors measure permanent price impact for trades of various sizes, where permanent price impact is the cumulative excess return from the five trades either side of the trade of interest. The results indicate that for block purchases (trades of 50,000 shares or more) the permanent price impact is positive and increases with the level of information asymmetry as proxied by the information environment. This result adds nuance to the already established link between permanent price impact and the information content of the trade – specifically, block purchases signal new information to the market, but the strength of that signal depends on the information environment in which the trade is executed. In contrast, the permanent price impact for block sales, while negative and significant, does not differ according to the information environment.

The papers cited above use a simple cumulative return to ascertain the permanent price impact of a trade. Another method of estimating the price impact of trades is outlined in Hasbrouck (1991) which explicitly models the dynamic relationship between permanent price impact and informed trading as a vector autoregressive system (VAR). In his model a market maker sets initial bid and ask quotes. The purpose of the paper is to explain how these initial quotes are revised to incorporate the information contained in 1) new trades and 2) non-trade public information (i.e. news announcements). The model assumes that quote revisions are determined by three components: previous quote revisions, the size and sign of current and previous trades and new non-trade public information. The inclusion of previous quote revisions suggests an autoregressive function of revisions. Furthermore, the time *t* trade is itself a function of previous quote revisions, previous trades and an unexpected component of trade (i.e. all that cannot be described by the other determinants)[42]. These two equations create a vector autoregressive system in which important new information resides in the public information term or the unexpected component of trade term. The relevant term for the purposes of this review is the unexpected component of trade. When the VAR is estimated, the coefficient on this variable is an indication of not only the permanent price impact of the trade but also its information content. As such, Hasbrouk's (1991) model creates a link between trading, permanent price impact and information. A handful of papers utilise

[42] Both the non-trade public information component and the unexpected component of trade have zero means and are jointly and serially uncorrelated.

Hasbrouk's (1991) model to explore hypotheses related to price impact and information.

Dufour and Engle (2000) examine the relationship between permanent price impact and the time between trades to draw conclusions regarding the temporal nature of the trading environment when informed trading occurs. They generalise Hasbrouck's (1991) model of quote revisions and trade to incorporate the time between trades and find that as trading intensity increases, the price impact and the autocorrelation of signed trades increase. They use this finding to conclude that informed traders are particularly prevalent during periods of very active trading.

Pascual, Escribano and Tapia (2004) estimate the information content of each trade in IBM during the period February to June 1996 using the permanent price impact coefficient from Hasbrouck's (1991) VAR model. In the paper the model is modified to include variables related to current market conditions: the bid-ask spread, depth at the best quotes, volatility, the hour in which the trade is conducted and following Dufour and Engle (2000), the time since the last trade. The results indicate that larger trades sizes executed during more illiquid and volatile periods are positively related to price impact. Confirming Dufour and Engle (2000), rapid trading also creates a larger price impact. Finally, trades executed during the first and last half hour of the day have greater price impact on average compared to other trading periods. The authors use the results from the estimated VAR to simulate adverse selection costs for IBM. To accomplish this, the paper draws upon the intuition that price impact is a measure of the market's perception of the probability of informed trading and can therefore be used to estimate the magnitude of adverse selection costs.

Finally, Barclay, Hendershott and McCormick (2003) investigate order flow competition between market makers on the NYSE and NASDAQ against electronic communication networks (ECNs). As part of their analysis the authors examine where informed traders choose to execute their trades. Like Dufour and Engle (2000) they utilise Hasbrouk's (1991) VAR model to estimate the price impact associated with trades in various trading venues to infer the presence of informed trading. They find that the price impact is 50% greater on ECNs compared to other trading venues and thus, conclude that informed traders use ECNs to execute their trades. The authors hypothesise that this occurs because market makers on the NYSE and NASDAQ are adept at recognising informed traders and route their orders to other venues. Furthermore, informed traders are able to execute their trades cheaply on the anonymous ECN order book and therefore, tend to gravitate towards this platform.

2.3.2. The bid-ask spread and the detection of informed traders

Bagehot (1971) is one of the first articles to propose the idea that the bid-ask spread set by a market maker incorporates the risk of trading with informed traders. His central argument is that there are (at least) two types of traders – specifically, traders with superior information who trade to take advantage of uninformative prices, and second, traders who trade for liquidity purposes only. The market maker always makes a loss when trading with informed traders – since these traders only engage with the market maker when it is to their advantage and not otherwise. In contrast, the market maker makes a positive expected return when trading with liquidity-motivated traders, since their demand for the security allows for continuous turnover of the stock, through which the market maker earns the bid-ask spread. Bagehot (1971) argues that to succeed as a market maker, the spread needs to be set such that the losses made to informed traders are offset by the gains made from liquidity-motivated traders. This implies that the size of the spread is directly proportional to the chance of trading with an informed trader. This initial intuition is formalised in a series of papers that model the spread setting behaviour of market makers.

Copeland and Galai (1983) develop a one period model that follows the broad outline of Bagehot (1971) and presents the setting of the spread as an optimisation problem for the market maker. A larger spread reduces the risk that a given quote will be 'in-the-money' for an informed trader and therefore reduces the losses to these individuals. However, the model also allows for liquidity-motivated traders to have price-sensitive demand for the security, and for competition to exist between market makers, such that excessively large spreads might lead to a reduction in uninformed demand for the security. Therefore, the market maker sets the bid-ask spread to balance these two competing factors and maximise revenue. An important implication of the model is that as the percentage of informed traders in the market increases, the bid-ask spread widens.

The analysis in Copeland and Galai (1983) details only the *equilibrium* spread setting behaviour of the market maker. Glosten and Milgrom (1985) extend this analysis by providing a sequential trade model which describes the evolution of the spread towards the equilibrium value. They posit that market makers act in a Bayesian manner – setting the price of a quote conditional upon the quote being taken. Furthermore, unlike in Copeland and Galai (1983), each trade against the market maker does not fully resolve the information asymmetry and instead, the market maker uses each trade to Bayesian update the probability that the current quotes are informationally efficient. Like Copeland and Galai (1983) a key implication of the model is that the bid-ask spread is proportional to the percentage of informed traders in the market, *ceteris paribus*. Easley and O'Hara (1987) expand the analysis to account for stochastic information arrival and the ability of individuals to trade different sized lots. While more complex than Glosten and Milgrom (1985), the same fundamental result remains: the bid-ask spread is proportional to the market maker's assessment of the rate of informed trading.

Several papers utilise this prediction to make inferences with respect to the level of information asymmetry around particular information events. Morse and Ushman (1983) represent one of the first studies to examine bid-ask spread changes around an information event. They examine daily closing bid and ask quotes for a sample of 25 NASDAQ stocks that traded between 1973 and 1976 and in particular examine spread behaviour around quarterly earnings announcements. The authors do not find evidence that bid-ask spreads change significantly around these events. This result is inconsistent with subsequent studies that examine a broader cross-section of securities, utilise multivariate analysis and examine finer data.

Chiang and Venkatesh (1986) examine daily closing bid-ask spreads in the days prior to earnings and dividend announcements for a random sample of 75 NYSE listed stocks. The authors consider instances when the announcements are made simultaneously and when the announcements are separated by at least ten days. They hypothesise that a delay between the announcements (which are usually announced jointly) signals that the second announcement has a greater likelihood of being a non-routine, price-sensitive information event. As such, bid-ask spreads should be wider around the second announcement relative to the first announcement or relative to joint announcements. After controlling for the inventory cost component of the spread, the authors find evidence that bid-ask spreads are on average wider before the second announcement, consistent with the idea of greater information asymmetry around this information event.

Lee, Mucklow and Ready (1993) provide one of the first studies to examine *intraday* bid-ask spreads around earnings announcements. The authors examine bid-ask spread values (taken at half hour intervals throughout the day) for a sample of 230 NYSE listed firms that traded in 1988. The authors find that in the 26 half hour intervals (equivalent to two full trading days) before an earnings announcement, bid-ask spreads are significantly larger than expected. Specifically, bid-ask spreads are 1.28% larger two days before the announcement and 1.44% larger one day before the announcement. Multivariate analysis, which controls for volume and autocorrelation in returns, confirms these initial univariate results. Interestingly, the authors also note that spreads tend to be largest for a sub-sample of firms which have the largest price changes on the announcement day. This suggests that specialists are adept at identifying those particular firms with the largest amount of information asymmetry, and adjust their spreads accordingly to reflect this fact.

Rather than examining the total bid-ask spread, Krinsky and Lee (1996) analyse the components of the bid-ask spread in advance of earnings announcements. By focusing on the adverse selection component of the spread, this study is able to better ascertain whether the increased spreads documented in previous studies are linked to increased information asymmetry around the announcement date. The authors examine intraday data (half hour intervals) for a sample of 511 quarterly earnings announcements made for NYSE and AMEX traded securities during 1989 and 1990. The results indicate that the adverse selection component of the spread is significantly larger during the 26 half hour intervals before the announcement, at 59.5% of the percentage spread, compared to 46.6% during a non-information benchmark period. This suggests that market makers are sensitive to the presence of informed traders prior to earnings announcements. Incidentally, the other components of the spread (order processing and inventory holding) are significantly smaller during the pre-announcement window, which the authors attribute to greater transactional volume during this period.

Besides earnings announcements, other prominent market sensitive announcements examined in the literature are merger and takeover announcements. Conrad and Niden (1992) examine daily closing bid ask spreads in the ten days leading up to 37 takeover announcements on the NYSE during 1983. They find that the bid-ask spreads significantly *decline* on the day before and the fourth day before the information announcement. There is also weak evidence that closing spreads increase two days before the announcement date on average. In cross-sectional tests using regression analysis, the authors find no abnormal changes to bid-ask spreads before or after the takeover announcement.

Jennings (1994) examines a sample of 168 takeovers on NYSE listed firms during 1987 and 1988. In contrast to Conrad and Niden (1992), the authors use intraday spread data and analyse, in particular, the five quotes before and after the announcement of the takeover. The results indicate that bid-ask spreads are not significantly larger prior to the information event in this short window, however there is some evidence that the adverse selection cost component of the effective spread rises, if not the overall quoted spread.

Apart from merger and earnings announcements, the behaviour of spreads around other information events is also considered. Rao, Tripathy and Dukes (1991) examine bid-ask spread changes on a firm's equity around the commencement of option listing for that same firm. They find that spreads decrease after the options listing date, which they attribute to reduced adverse selection costs for equity market makers. The authors argue that adverse selection costs decrease since informed traders migrate to the options market where trading is cheaper and potentially more profitable for them, and also because market makers can utilise options to hedge information risk. Tripathy and Rao (1992) examine the temporal behaviour of bid-ask spreads around the announcement dates for seasoned equity offerings and find that bid-ask spreads are larger than expected in the 80 days leading up to the announcement. Franz, Rao and Tripathy (1996) analyse bid-ask spreads after the announcement of director open market share repurchases. These events typically signal positive private information about the company, and therefore the authors hypothesise that this should resolve any existing information asymmetry. The results suggest the bid-ask spreads decline following the announcement, consistent with this hypothesis.

While not made explicit, the previous papers imply that market makers are successful at detecting informed traders in the market. When this assumption is made, it is possible to infer the extent of information asymmetry around a particular event by examining the behaviour of bid-ask spreads. Put differently, the ability of market makers to detect informed trading is considered certain, whereas the existence of information asymmetry is uncertain. Under these assumptions, the bid ask spread then becomes an indicator of information asymmetry, if any. Alternatively, it is possible to assume the reverse – that information asymmetry is certain and market makers are imperfect with their detection of informed trading. In this case, the bid-ask spread is an indicator of how successful market makers are at detecting informed traders. Such an approach is used in a handful of empirical papers, with a particular focus as to whether a non-anonymous, floor traded, monopolist market maker structure (e.g. NYSE or AMEX) is better able to detect informed trading relative to an electronic, anonymous, multiple market maker system (e.g. NASDAQ).

Garfinkel and Nimalendran (2003) focus on a class of trades which they hypothesise to contain a greater proportion of informed trading than normal – namely, medium sized trades (500-9900 shares)[43] conducted by corporate insiders – and examine market maker's spread setting behaviour around these trades. In particular, their research examines whether the different market structures on the NYSE and NASDAQ allow for greater anonymity of informed trading in the competitive dealer market. The authors find that effective bid-ask spreads are significantly larger (relative to a control sample) on days in which insiders trade for NYSE listed shares, but are not significantly larger for NASDAQ listed shares, suggesting that specialists can detect informed trading better than dealers in a competitive market. This result is consistent with the theoretical model of repeated broker-specialist interactions of Benveniste, Marcus and Wilhelm (1992). Their model supposes that specialists are better able to detect informed trading because the nature of repeat interactions

[43] This definition follows Barclay and Warner (1993) who find that medium sized trades are more likely to be utilised by informed traders.

between floor brokers and the specialist provides incentives for brokers to be candid about whether their client is informed or otherwise. These repeated face-to-face interactions are not possible on the electronic NASDAQ market.

Fishe and Robe (2004) analyse trades conducted by brokers who had advance access to an influential *Business Week* column entitled 'Inside Wall Street'. These traders were indicted by the SEC for insider trading and so it is fair to assume that in this scenario informed trading occurred with certainty. The authors analyse the intertemporal behaviour of bid-ask spread in the time leading up to the trades. The authors show that bid-ask spreads widened but only in the specialist market (i.e. NYSE). This finding suggests that informed traders are more readily detectable by monopolist market markers (i.e. specialists) compared to market makers acting competitively and is consistent with the empirical evidence in Garfinkel and Nimalendran (2003) and the theoretical predictions of Benveniste, Marcus and Wilhelm (1992).

Gleason (2007) investigates to what extent market maker competition affects the ability of dealers to respond to informed trading. She examines a sample of reported open market purchases of NASDAQ shares by corporate insiders, and ascertains the relationship between the size of the bid-ask spread, the intensity of insider trading and the number of market makers for that security. The results indicate, as expected, a positive relationship between bid-ask spread and insider trading intensity. Interestingly, this result is twice as strong for a sub-sample of securities with below the median number of market makers, indicating that market maker competition dampens market-wide ability to detect informed trading. This research is important because it provides additional insight into what drives the different rates of informed trading detection between exchanges. Benveniste, Marcus and Wilhelm (1992) suggest that the non-anonymity of brokers leads to greater detection of informed trading in floor-traded exchanges. However, besides anonymity, exchanges differ in numerous ways – market maker competition is one such difference – and it is entirely possible that the results of studies which compare NYSE/AMEX to NASDAQ are driven by one of these other differences. Gleason’s (2007) results indicate that market maker competition might indeed be another factor driving this distinction in informed trading detection.

Finally Heidle and Huang (2002) examine changes in bid-ask spreads when firms switch their listing between the three prominent U.S. exchanges (NYSE, AMEX and NASDAQ) to ascertain which structure can best detect informed trading. The authors utilise the probability of informed trading measure (PIN) developed by Easley, Kiefer, O’Hara and Paperman (1996) as a proxy for the level of information-based trading for a given security. The authors find that when a stock shifts to the NASDAQ from the NYSE or AMEX, the PIN for that stock rises. Similarly, the PIN falls for the reverse switch and remains statistically similar for changes between the two monopolist market maker exchanges (NYSE and AMEX). Interestingly, the authors also find that bid-ask spreads are positively related to the probability of informed trading, indicating that market makers across the three exchanges are adept at ascertaining the level of informed trading and adjusting their bid-ask quotes effectively. Their work is the only paper which concludes that NASDAQ dealers respond appropriately to information based trading.

Much of the development of information-based theories of the bid-ask spread concern markets with designated market makers. Does the same theory apply to electronic limit order book markets with no designated market makers? In other words, is the risk of trading with an informed trader proportional to the size of the bid-ask spread when all traders are free to post limit orders? Glosten (1994) develops a model that describes investor behaviour in an anonymous electronic limit order market and how such a market fares against competing market structures. While the article considers issues beyond the relationship between bid-ask spreads and information, part of the theoretical development assumes that liquidity suppliers factor in the probability of trading with an informed trader (see Glosten, 1994, p1140). The model shows that no matter how small the tick size, a bid-ask spread will exist as long as there is the risk of trading on private information. Interestingly, the analysis also shows that the electronic limit order book mimics a monopolist market maker insofar as adverse selection costs are averaged out against returns from liquidity motivated traders. This insight is fundamental to all the aforementioned theoretical models of bid-ask spread and information in dealer markets.

Foucault, Moinas and Theissen (2007) provide a model of an electronic limit order book where informed traders possess information about a stock's future volatility and act as liquidity suppliers. They compete for order flow with uninformed liquidity suppliers, who behave according to the participation rate of informed dealers in the market. Nature decides whether an information event occurs, and if so, informed dealers enter the market and act first by posting limit orders which maximise their expected profit. If there is no information event, a pre-committed dealer acts first. Uninformed liquidity suppliers post orders after the initial round. By definition, uninformed liquidity suppliers cannot tell whether an information event has occurred, but they can infer the presence of informed traders by the state of the order book when it is their turn to post orders.[44] The authors consider two scenarios: one in which informed dealers are known to others as signalled by their broker identity (transparent market) and one in which informed dealers are unknown (anonymous market). The anonymous market is the only scenario relevant to the discussion of informed trader detection since in a transparent market, uninformed dealers behave as if they have perfect information as to whether an order book is set by an informed dealer or otherwise. For an anonymous market, when the participation rate of informed dealers is low, uninformed liquidity suppliers never assign a large enough probability of an information event (even when the order book looks like it has been set by an informed dealer), such that the profit maximising response is to provide price improvement (i.e. reduce the spread). Similar reasoning leads the authors to conclude that, when the participation rate of informed dealers is large, spreads widen such that there is a positive correlation between bid-ask spreads and the participation rate of informed dealers.

Foucault, Moinas and Thiessen (2007) assume that uninformed traders are able to accurately assess the participation rate of informed dealers and act accordingly. In reality however, the behaviour of uninformed dealers is not determined by the participation rate of informed dealers, but rather the uninformed dealers' *beliefs* about the participation rate of informed dealers. The bid-ask spread is therefore an indicator of such beliefs and prior to significant information events the bid-ask spread is an

[44] A wide bid-ask spread indicates a greater probability that an information event has occurred.

appropriate measure of the extent to which uninformed liquidity suppliers can discern the presence of informed liquidity suppliers in an electronic limit order book market.

2.3.3. Order imbalance and informed trading

Order imbalance is a measure of excess buyer over seller initiated trading in a given period, where trading can be defined by the total number of shares traded, the total dollar value of trades or simply, the total number of trades (Chordia, Roll and Subrahmanyam, 2002). While not as widely utilised as permanent price impact and the bid-ask spread, there nevertheless exists a small body of literature which recognises order imbalance as an indicator of informed trading. The basic theory underlying the use of order imbalance in this way is that informed traders trade only in one given direction, moving the price until it reaches its full information value. In contrast, it is assumed that the combined preference of liquidity and other uninformed traders is directionless (i.e. no preference for buying versus selling). As such, when informed investors trade they exert pressure on one side of the market, manifesting itself as an order imbalance. Early theoretical studies on the spread-setting behaviour of market makers draw upon this basic framework to explain how specialists use order flow to update their beliefs on the true value of their security (Kyle, 1985; Glosten and Milgrom, 1985; Admati and Pfleiderer, 1988).

Extending these early studies, Easley, O'Hara, Kiefer and Paperman (1996) formalise the intuition that order imbalances are inherently linked to the presence of informed traders. They develop a mixed discrete-continuous time model of market making, with a particular focus on the mechanics that determine the arrival rate of buys and sells to the market maker. The market contains both informed traders and liquidity motived investors. For informed traders, their arrival rate to the market maker is determined by the existence of an information event and whether that information event is good or bad news. Specifically, when an information event occurs (which is a stochastic process) and the news is good (bad), the informed buy (sell) arrival rate is μ. The arrival rate of noise traders is constant regardless of the information environment and is termed ε in their paper. The result of these assumptions is that on days in which informed traders are active, there exists an imbalance between buy and sell orders. This imbalance is proportional to the arrival rate of informed traders, μ. On days with no information event, and hence no informed traders, the arrival rate of buys and sells is equal and there is no imbalance. This simple exposition outlines the link between order imbalances and informed trading.[45] If one accepts that order imbalances arise due to informed trading[46], then the market's response to the existence of an order imbalance is an indication of how well the market can assess the presence of these traders. A handful of studies empirically examine the relationship between informed trading and order imbalances.

Lee, Liu, Roll and Subrahmanyam (2004) examine order imbalances in an electronic limit order book setting, using all trades in the largest 30 stocks on the Taiwan Stock Exchange during the period September 1996 to April 1999. The study benefits from a unique data set which enables identification of the trader type (domestic institution, domestic individual and foreign institution), and therefore a more nuanced analysis of

[45] The authors extend the analysis, after applying several more assumptions, to develop the well-known probability of informed trading measure (PIN). Their paper examines the relationship between order imbalance, via PIN and the bid-ask spread. In contrast, the study in Chapter 5 examines the relationship between order imbalance and returns.

[46] Order imbalances can also reflect temporary liquidity shocks. If that is the case, then the response of the market is characterised not by the adverse selection paradigm, but rather the inventory control paradigm. Chordia, Roll and Subrahmanyam (2002) investigate the relationship between order imbalances and returns on an aggregate (i.e. market) level. Their analysis, therefore, is devoid of information asymmetry considerations and instead focuses on inventory control effects of order imbalances on returns.

order imbalances. The authors first investigate which agents cause the greatest price pressures and find that domestic and foreign institutions have persistent order imbalances. The source of the persistence for institutions is due to both herding by multiple agents within the trader class and order splitting by the same institution over several days. Importantly, analysis of the price impact and profit of the marketable limit orders executed by domestic institutions reveals that these traders appear to be most informed, providing evidence consistent with the theoretical predictions of Easley, Kiefer, O'Hara and Paperman (1996) that those traders which initiate the greatest order imbalances are also those which have superior information.

Cao, Chen and Griffin (2005) investigate the respective roles of options and stock markets in the price discovery process prior to takeover announcements. The authors examine a sample of 78 option-listed firms which were the subject of a takeover during the period 1986 to 1994. The study hypothesises that the options market replaces the stock market during periods of extreme information asymmetry, such as the period before a takeover announcement, as the main market for price discovery. This occurs because the inherent leverage in options securities attracts informed traders to this market. To test this hypothesis, stock returns are regressed against lagged and contemporaneous daily order imbalances in shares, puts and calls with the implication being that the market's assessment of the information content of order imbalances should be reflected in the returns on the security. The analysis is split into whether the period is a pre-announcement period (days -30 to -1) or a 'normal' period (days -200 to -100). The results indicate that returns are positively related to call imbalances and share imbalances, though the coefficient on call imbalances is larger during pre-announcement periods. During periods when a takeover is not pending only share imbalances are positively related to stock returns. These results support the paper's main hypothesis that price discovery occurs in the options market prior to an important information announcement (i.e. a takeover). While not made explicit in the paper, the result also implies that traders and market makers in stock markets are adept at interpreting the information content of order imbalances in options markets, particularly when significant information asymmetry exists.

Brown, Walsh and Yuen (1997) represents one of the very few studies to examine order imbalances in the context of an electronic limit order book. The paper investigates the relation between daily, semi-daily and hourly order imbalances and returns for 20 stocks that traded on the ASX during the period January 1994 to December 1995. The lack of designated market makers on the ASX removes the possibility that adjustments in price or volume after order imbalances are driven by inventory control considerations. As such, the authors argue that any relation between order imbalances and returns are probably driven by information considerations. The authors conduct causality tests on their data and find, in their intraday analysis, that excess buy orders correlate with future positive returns for up to 3 hours. Similarly, excess sell orders lead to negative stock returns for up to 3 hours. Given the structure of the ASX, this result suggests that order imbalances are perceived to contain information by participants in this electronic limit order book market.

Finally, Lee (1992) examines order imbalances around earnings announcements for a sample of 230 NYSE-listed firms which traded during 1988. The paper investigates the nature of order imbalances in the lead-up to both good news and bad news announcements. The analysis considers the order imbalance deriving from both large and small trades. The study finds that prior to the announcement, order imbalances are uninformative regarding the eventual outcome of the announcement. Good (bad) news is not preceded by excessive buying (selling) activity. The author uses this result to conclude that informed traders are inactive prior to earnings announcements, and therefore, there is little information leakage. Unfortunately, the paper does not investigate further the connection between order imbalances and informed trading and instead focuses on the post-announcement properties of order imbalances.

2.3.4. Broker anonymity

Changes to broker identification rules have occurred on at least seven electronic exchanges since 1999 – the Korea Stock Exchange, Tokyo Stock Exchange, Australian Stock Exchange, Paris Bourse, Deutsche Boerse, Brussels Stock Exchange and the Borsa Italiana. The high incidence of such changes has led to an equally high incidence of empirical studies on the issue, with the primary research question being the effect of the transparency change on market quality of the relevant exchange.

Foucault, Moinas and Thiessen (2007) examine the change to bid-ask spreads on the Paris Bourse after the removal of broker identifiers from the trading screens on 23 April 2001. The authors develop a model (reviewed in Section 2.3.2 of this literature review) of an electronic limit order book which predicts that the removal of broker identifiers leads to a change in bid-ask spreads. The model does not indicate which direction the change occurs (thinner or wider bid-ask spreads), but does predict that if spreads are thinner (wider), the bid-ask spread becomes less (more) informative of future price volatility. All trades in a sample of 39 stocks are examined to determine the validity of their hypothesis. The results indicate that the quoted euro spread, the quoted percentage spread and the effective spread decrease after the change to broker anonymity. The quoted euro spread and the effective spread decrease by approximately 0.02 euros. Importantly, the results also indicate that bid-ask spreads are informative about future price volatility prior to the change, but this relationship is weaker after the change to an anonymous broker market. These results confirm the predictions of their model.

Comerton-Forde, Frino and Mollica (2005) examine the affects of broker identification changes on the Paris Bourse, the Tokyo Stock Exchange and the Korean Stock Exchange. The first two exchanges removed pre-trade broker identifiers from their trading screens on 23 April, 2001 and 30 June, 2003 respectively, whereas the Korean Stock Exchange introduced pre-trade broker identifiers on 25 October, 1999. The paper examines a sample of the largest stocks by market capitalisation for each exchange. In univariate and multivariate analyses the results indicate that time weighted relative bid-ask spreads are correlated with the absence of broker identifiers for all exchanges. For the Paris Bourse and Tokyo Stock Exchange, the price impact from simulated market orders also declines following the removal of broker identifiers. These results suggest that trading costs decrease when there are no broker identifiers on the trading screens of electronic exchanges.

Comerton-Forde and Tang (2008) investigate the effects of broker identification removal on bid-ask spreads, immediacy costs, order aggressiveness and order flow competition. The subject market is the ASX, which removed broker identifiers on 28 November, 2005. The authors consider trading in a sample of 463 stocks and stratify their analyses according to whether the stock is in the top 200 by market capitalisation (large stocks) or outside this definition (small stocks). The results concerning market quality are consistent with the studies of Comerton-Forde, Frino and Mollica (2005) and Foucault, Moinas and Thiessen (2007). Multivariate analysis indicates that the reduction in bid-ask spreads for large (small) stocks is 5 (25) basis points after the removal of broker identifiers. The analysis also considers immediacy costs by simulating the market impact of trades of various sizes for both the transparent and anonymous regimes. The results indicate that the market impact of trades decreases in the anonymous regime for large stocks. For small stocks, market impact costs are lower for all trade sizes except for trades worth more than $500,000.

Besides market quality, the paper also investigates the order aggressiveness of stocks and the competition for order flow after the removal of broker identifiers. The results indicate that order aggressiveness decreases for all classes of stock. The authors attribute this finding to a greater willingness of informed brokers to submit limit orders, rather than market orders, since anonymity reduces the incidence of front running. Importantly, this explanation suggests that informed traders are more concealed in the anonymous broker regime. Finally, the paper investigates whether the change induces a shift in order flow from the transparent upstairs market to the anonymous downstairs market. The results indicate that the propensity to execute trades in the upstairs market is lower after the downstairs market becomes anonymous, though this result only holds for large stocks.

Hachmeister and Schierek (2006) analyse the change to market liquidity after exchange officials removed information concerning post-trade broker identifiers from the trading screens of the Deutsche Boerse in March 2003. The authors find that quoted effective spreads decrease and quoted depth increases for a sample of 30 DAX stocks after the removal of post-trade broker identifiers. These results are consistent with aforementioned literature which examines pre-trade broker anonymity. Taken together, the results suggest that broker anonymity of any form appears correlated with improved liquidity. Interestingly, the authors also investigate whether the Easley, Kiefer, O'Hara and Paperman (1996) measure of informed trading (PIN) changes after the anonymity switch. The results indicate that, contrary to expectations, PIN decreases after the change to anonymity. The authors attribute this finding to the fact that the PIN measure, developed in Easley, Kiefer, O'Hara and Paperman (1996) is only relevant in the context of a market maker setting, such that the imbalance of liquidity *demanded* determines the probability of informed trading. In an electronic market such as the Deutsche Boerse, informed traders are also free to provide liquidity, and thus PIN does not account for this phenomenon. If informed traders, due to the protection afforded by anonymity, change strategies to provide more liquidity this will reduce the PIN measure, though not necessarily the incidence of informed traders in the market.

As is apparent from the preceding literature review, the primary focus of studies on broker transparency in electronic limit order book markets is to examine the effect of transparency/anonymity on market quality. The overwhelming consensus is that broker anonymity, whether pre- or post-trade, is correlated with improved liquidity. These results are consistent with the theoretical predictions of Rindi (2008) and findings from an experimental market (Perotti and Rindi, 2006). Several studies have touched upon the information transmission effects of broker anonymity, though no study has explored it in great detail. The essay in Chapter 5 seeks to fill this gap in the literature.

Chapter 3. Derivative Use, Fund Flows and Investment Manager Performance

3.1. Introduction

Section 2.1.4 shows that there exists only a modest body of empirical studies on the use of derivatives by institutional investors. Furthermore, no study to date has sourced and analysed data on a specific application of derivatives by mutual fund managers. This essay seeks to fill this gap in the literature by examining a well-defined and often used trading strategy: the cash-equitisation of investor flows. To perform this analysis, this study uses unique survey data on Australian managed funds which describes whether a given fund manager uses index futures to manage investor flows or not. This study provides important insight into the relationship between fund managers and the investors who seek their services. It shows how informed investors can maintain superior returns even when their trading decisions are partially dictated by uninformed, external parties.

The rest of this chapter is organised as follows: Section 3.2 provides the theoretical background on the relationship between fund flow, derivative use and the two components of fund manager performance – alpha and market timing. Section 3.3 describes the data and sample selection criteria. Section 3.4 presents the results of the analysis. Section 3.5 summarises and concludes the chapter.

3.2. Hypothesis development

Section 2.1.3 shows that mutual fund managers are acutely aware of the effects that investor flows have on their assessed performance. Koski and Pontiff (1999) provide evidence that one method to dampen the extent of fund flow externalities is to trade derivatives. This section provides a model which links fund flows and performance. First, a simple model is developed which describes how fund flows affect performance when the fund manager does not undertake any form of fund flow management and simply allocates new money to replicate the returns of the existing portfolio. Second, the process of derivative-based fund flow management is explained and the hypotheses with respect to this process are outlined.

3.2.1. Fund flow and performance

If a fund receives no new cash flow at the start of the period, then the fund's performance is simply the return over the period, $r_{t,a}$, on existing assets at the start of the period, a_t. Equation 3.1 provides the benchmark with which to assess the impact of cash flows on fund return.

$$r_{t,a} = \frac{a_t(1+r_{t,a})}{a_t} - 1 \tag{3.1}$$

When a fund experiences fund flow the manager determines how much of this cash is invested in assets immediately, λ_t. Any part of new flow that cannot be invested (or the fund manager chooses not to invest) is held as cash, γ_t, to be invested later. When net fund flow is negative, λ_t, and γ_t are equivalent to the dollar value of assets sold and cash borrowed (or paid out from reserves), respectively, to meet redemptions of the fund's shares. Assuming that the fund experiences flow at the beginning of the period and the manager's allocation decision is also made at that time, the return on the fund is defined as:

$$r^*_{t,a} = \frac{(a_t + \lambda_t)(1 + r_{t,a}) - \theta_t^{\lambda} + \gamma_t(1 + r_{t,c})}{a_t + \lambda_t + \gamma_t} - 1 \qquad (3.2)$$

For ease of exposition, the return on the newly invested flow, λ_t, is expressed as the return on existing assets less some cost factor, θ_t^{λ} (in dollars). This 'catch all' variable represents the cost of obtaining immediacy in equity markets. The part of new flow held as cash earns a return, $r_{t,c}$, which can be zero or some nominal value.

The effect of fund flow on performance is therefore, the difference between Equation 3.2 and the zero fund flow benchmark, Equation 3.1:

$$r^*_{t,a} - r_{t,a} = \frac{-\theta_t^{\lambda} - \gamma_t(r_{t,a} - r_{t,c})}{a_t + \lambda_t + \gamma_t} \qquad (3.3)$$

From Equation 3.3 it is possible to discern the two factors which hinder performance in the presence of investor flows. The first factor is θ_t^{λ}, the cost of obtaining immediacy. The bid-ask spread almost certainly forms part of this cost, since immediacy is obtained using market orders. Market impact costs may also be a factor if the magnitude of λ_t is substantial. If new cash causes the manager to engage in liquidity motivated trading, then adverse selection costs are another component of θ_t^{λ}. This is an expected result of the rational expectations model of trade where trading equilibrium is only achieved if noise traders sustain losses to entirely compensate the informed for the costs associated with being informed (Grossman and Stiglitz, 1980). Empirically, Edelen (1999) shows that approximately 70% of gross fund flow is invested as liquidity-motivated trades, and approximately 1.5% (which is statistically significant) of the value of these noise trades is lost via adverse selection costs.

The other factor that hinders fund manager performance is the opportunity cost of holding cash, represented by the second term in the numerator of Equation 3.3. Several papers have speculated that the costs of holding cash are inherently linked to negative market timing results documented extensively in the literature.[47] Specifically, because there is a strong correlation between market returns and aggregate flow (Warther, 1995) and fund managers cannot or choose not to immediately invest the new cash, funds accumulate more cash during rising markets.[48] In the context of Equation 3.3 this represents a positive value for the opportunity cost of cash. In the context of market timing studies this represents a decrease in portfolio beta at exactly the time when a manager should increase beta, hence negative market timing. Therefore, opportunity costs of cash, fund flows and negative market timing are intrinsically related. Empirical evidence for this hypothesis is found in Ferson and Schadt (1996) and Ferson and Warther (1996). Both studies show that fund betas (conditional on public information) are negatively related to aggregate fund flows. Edelen's (1999) work reaches a similar conclusion, but his analysis is at the level of the individual fund. He estimates managers' market timing skills, conditional on the level of concurrent flow experienced by the manager. When conditioned on investors' liquidity demands, the market timing skill of the average manager in his sample is neutral.

[47] Papers that document negative market timing skills include Treynor and Mazuy (1966), Kon (1983) and Henriksson (1984).
[48] By parity of reasoning funds also accumulate more stock during falling markets. Funds pay out redemptions from their cash reserves in the short run, and thus increase the relative holdings of stock.

The relationship between fund flow and performance can be summarised succinctly. Fund flows reduce alpha when the manager rapidly converts new cash to stock, since this type of trading attracts adverse selection and other trading costs. Fund flows impair market timing when managers delay investment of their cash, because fund flows are positively correlated with market returns. The appropriate action to take in response to new fund flow is an unenviable decision for the manager. Both trading and non-trading can reduce fund assets through trading costs and opportunity costs respectively. A reduction in one type of cost is likely to increase the other.

3.2.2. Derivative-based management of fund flows

A simple fund flow management strategy might involve purchasing (shorting) stock index futures when faced with incoming (outgoing) fund flow. Exact synthetic replication[49] of index returns is possible by purchasing an appropriate amount of stock index futures and risk free assets (Frino, Wearin and Fabre, 2004; Miller and Meckel, 1999). Regardless of the particular strategy, the general aim of derivatives-based management of flow is to *rapidly* obtain risk exposure with derivatives in the first instance, and then unwind the position into stock or cash as required. Due to the leveraged nature of futures contracts, obtaining exposure to the desired position does not require complete investment of all flow and therefore the balance of funds remains as cash. The return on a fund that uses index futures to manage flow can be described by:

$$r^{**}_{t,a} = \frac{a_t(1+r_{t,a}) + \varphi_t(1+r_{t,i}) - \theta_t^{\varphi}}{a_t + \varphi_t} - 1 \qquad (3.4)$$

[49] Theoretically, an appropriate combination of long positions in the index futures and interest bearing securities exactly replicates the returns of the underlying security including dividends. Practically, there is a small degree of tracking error associated with this strategy (see Frino, Wearin and Fabre, 2004).

where the returns on the 'portfolio' of index futures (and residual cash) is $r_{t,i}$, and the magnitude of flow is φ_t .The affect of the initial investment in futures, relative to the zero fund flow benchmark (Equation 3.1) is similar to the form of Equation 3.3:

$$r{**}_{t,a} - r_{t,a} = \frac{-\theta_t^{\varphi} - \varphi_t (r_{t,a} - r_{t,i})}{a_t + \varphi_t} \tag{3.5}$$

The two terms in the numerator reflect the two costs of the index futures trading strategy. The first, θ_t^{φ} represents the cost of immediacy in the futures market. The second, $\varphi_t (r_{t,a} - r_{t,i})$, represents the amount of 'tracking error' associated with the strategy – that is, how closely the fund manager is able to replicate existing portfolio returns with index futures. Since investors seek funds with investment styles that match their individual risk appetites, agency problems are minimised when the manager trades futures in such a way that the fund flow achieves a level of risk exposure similar to existing assets.

How might trading derivatives in this manner improve performance relative to outright trading in stocks? With respect to alpha performance it is hypothesised that using index futures involves lower adverse selection and other transaction costs. Mathematically, $\theta_t^{\varphi} < \theta_t^{\lambda}$. Subrahmanyam (1991) develops a model which describes the adverse selection costs associated with trading a portfolio of individual securities versus a single security of multiple stocks (such as index futures). His model predicts that even when informed traders possess information about systematic factors, adverse selection costs are lower when trading index futures compared to trading the individual securities, because the directions of firm value signals tend to offset each other in a security representing multiple stocks.[50] Secondly, in terms of bid-ask spread and market impact costs, futures market transactions are considerably cheaper than the underlying market (Fleming, Ostdiek, Whaley, 1996; Berkman, Brailsford and Frino, 2005). Therefore, in the first instance, trading futures should deliver adverse selection and other transaction costs savings over trading underlying stock.

Using index futures to manage fund flow, however, involves two rounds of trading rather than one. It is worth exploring the trading returns and costs associated with the transition from futures to stock. Interestingly, it is possible that the second round of trading leads to positive alpha returns. Having 'parked' incoming cash in the futures contract, fund managers are free to shift their positions into stock when they receive private signals about firm value. These trades are completely discretionary and assuming fund managers are well informed, generate value for fund shareholders. In support of this, Edelen (1999) finds that in the absence of liquidity-motivated trading, fund managers exhibit positive alphas (before expenses) and fill the role of informed traders in the rational expectations model of trade. In terms of costs, trading out of the futures position involves another set of brokerage costs and potentially bid-ask spread and market impact costs, depending if the manager uses market or limit orders.

The extent to which derivative-based fund flow management reduces the costs of liquidity-motivated trading (if at all) is an empirical question. The first set of hypotheses can be stated as:

---

[50] Empirically Frino, Kruk and Lepone (2007) document complete price reversals after transactions in futures markets, suggesting that the market does not perceive trades in index futures to be informationally motivated.

Hypothesis$_{3.1}$: *The alpha performance of non-user funds is negatively related to fund flow.*

Hypothesis$_{3.1a}$: *The alpha performance of user funds is not materially affected by fund flow.*

The first hypothesis is the same hypothesis tested in Edelen (1999), though Edelen's analysis does not focus on the distinction between users and non-users of derivatives. The second hypothesis reflects the reduction in adverse selection costs associated with derivatives-based fund flow management. If both hypotheses are true, then *ceteris paribus*, user funds have higher fund flow conditional alphas than non-user funds.

Derivatives-based management of cash flows might also improve market timing performance of fund managers. Since new cash is rapidly exposed to market risk via futures, there should be minimal dilution of portfolio beta during rising markets. In terms of Equations 3.3 and 3.5, it is hypothesised that $(r_{t,a} - r_{t,i}) < (r_{t,a} - r_{t,c})$. This relationship will hold if managers are able to replicate existing portfolio risk with index futures, or choose not to manipulate risk to game incentive systems. Koski and Pontiff (1999) show that funds that use derivatives are able to alleviate undesired changes to fund systematic risk associated with increased fund flow. They therefore, provide indirect evidence for the hypothesis that fund managers use derivatives to access risk, though they do not specifically address the issue of market timing using the traditional specifications of Treynor and Mazuy (1966) or Henriksson and Merton (1981). Importantly, their results also indicate that fund managers who use derivatives do not tend to manipulate risk in order to game incentive systems. With respect to market-timing performance the hypotheses are:

Hypothesis$_{3.2}$: *Market timing performance measures of non-user funds are negatively related to fund flow.*

Hypothesis$_{3.2a}$: *Market timing performance measures of user funds are not materially affected by fund flow.*

In summary, stock index futures allow funds to achieve sufficient risk exposure at low cost, alleviating the dual problem that managers experience when faced with fund flows – specifically, investment of flows is costly, but non-investment increases opportunity costs of cash. Section 3.4 investigates the extent to which fund managers achieve transaction cost savings and improved market timing with index futures.

3.3. Data and sample selection

This section describes the two primary data sources used in this essay. The first data source is Morningstar Direct, from which general information concerning fund returns, fund size and fund age are sourced. The second data source is a unique survey conducted by the Sydney Futures Exchange which describes whether a fund uses index futures for the purposes of fund flow management or otherwise.

3.3.1. Fund data

An initial search of Morningstar Direct for active, large-cap, long-only Australian investment trusts yields a preliminary sample of 471 funds. The period of analysis is

31 July, 2003 to 31 July, 2006, representing three years of monthly fund data before the survey was completed. This study encounters a similar problem to that experienced by Koski and Pontiff (1999). A longer time frame potentially improves the precision of the parameter estimates and the generalisability of the results. However, increasing the length of analysis increases the time between the date of information on derivative trading behaviour and the date of the fund returns. This has the potential of lowering the accuracy of the survey data. Following Koski and Pontiff (1999), three years of monthly fund data are also examined.

Monthly data on fund size and returns is acquired for all funds in the sample. Returns are net of expenses, but do not include entry and exit fees. Standardised net fund flows (*SFF*) are calculated as follows:

$$SFF_t = \frac{Size_t - Size_{t-1}(1 + r_{a,t})}{Size_{t-1}} \tag{3.6}$$

This calculation is based on the intuition that any change in fund size not attributable to fund returns must be due to (net) fund flow. Data on gross flows of funds are not available.

Certain features of the funds management industry in Australia present complications that might affect the analysis contained in this study. Firstly, a number of institutions establish funds which pool money, mainly from retail investors, in order to directly purchase units in a single wholesale fund of an external manager. These 'funds' are not unique entities in themselves and including them in the analysis has the affect of double counting the returns of the underlying wholesale manager. Secondly, several firms offer ‘fund of funds’ products, whose inclusion also results in a double counting of the constituent investment managers. Finally, a number of institutions outsource all or part of their funds management operations to external managers, making it difficult to identify the manager responsible for each fund. While this does not represent double counting, correct identification is necessary in order to properly allocate the characteristic of user, or non-user, of derivatives to a particular fund.

To resolve these issues, each prospectus (also known as the Product Disclosure Statement) of the 471 funds in the preliminary sample are sourced and read. There are 144 funds that indirectly invest in equities through purchasing units in another fund and 53 funds of funds. After removing these from the sample, the number of remaining funds is 274. Where a fund outsources its operations the name of the external manager is noted.

3.3.2. Derivative use

These 274 funds are matched to their responses in the survey data compiled by the Sydney Futures Exchange on Australian fund managers. The survey was conducted over the course of six weeks via telephone interview. Respondents were asked whether they traded SPI 200 index futures for the purposes of cash equitisation, and whether they traded any other derivatives.

The data indicate that of the 274 funds a very high proportion of managers engage in some form of derivatives trading. Twenty-eight funds indicate that they do not trade derivatives at all. Of the total, 246 indicate that they trade index futures to manage fund flow. Nineteen funds in the sample did not have information on their derivative trading behaviour. Information provided by the Sydney Futures Exchange indicates that these funds did not wish to participate in the survey. Twenty eight funds indicate that they do not use derivatives at all. In total, almost 90% of funds manage fund flow using index futures.[51]

Of the 246 funds that use derivatives for cash-equitisation, 79 funds indicate that they also trade derivatives (index futures and options) for reasons unrelated to fund flow management such as for portfolio insurance and tailored trading strategies. Since the purpose of this study is to identify the incremental benefit of using index futures to manage cash flows only, these 79 funds are removed from the sample. While their inclusion potentially reduces the standard error of the coefficient estimates, in the interests of experimental design, these funds should be removed to provide a cleaner test of the affects of this particular derivative trading strategy and avoid the aforementioned issues of aggregating across different types of derivative trading strategies. Therefore the final sample of funds used in this study is 175 – of which 147 (84.1%) are derivative users and 28 (15.9%) are non-users. In terms of monthly fund data, there are 3738 monthly fund observations for users and 674 for non-users.

[51] Several structural factors contribute to this high rate of cash equitisation amongst Australian investment funds. Every year since 1993 employers in Australia are compelled to contribute to each employee's superannuation (retirement savings) the equivalent of 9% of the employee's annual salary. Nationwide, almost all of this cash is invested with superannuation managed funds. Therefore, investment management companies in Australia have had experience dealing with significant and constant fund flows for almost fifteen years. While we can only speculate, it is not unreasonable to believe that this fact has contributed to the high rate of index futures trading by fund managers. This is probably even more the case given that the market for exchange traded index funds (ETFs), an alternative security that can be used to manage fund flows, is not well developed. Trading ETFs attracts very high transaction costs. We calculate daily closing percentage bid-ask spreads for these substitutable securities during 2006 and find that ETFs attract on average a 51.56 basis points round trip transaction cost compared to only 6.52 basis points for index futures.

Table 3.1
Summary statistics of mutual funds

Sample of 175 Australian investment funds from Morningstar Direct. *SFF* is the monthly standardised net fund flow as defined in Equation 3.6 and |*SFF*| is its absolute value. *Size* refers to the value of assets under management in dollars. The variable is first averaged across the time series of values for a given fund. The summary statistics are based on these mean values. Autocorrelation of *SFF* is calculated by measuring the correlation between consecutive *SFF* per individual fund. The values presented below are summary statistics of these correlations.

Panel A: All Funds (n=175)	**Mean**	**Median**	**Standard Deviation**
SFF (%)	2.41	0.82	5.01
|*SFF*| (%)	4.79	3.20	4.45
Size ($ millions)	286.11	46.92	643.32
Autocorrelation of *SFF*	0.09		
Panel B: Non-users of derivatives (n=28)			
SFF (%)	2.63	1.37	4.66
|*SFF*| (%)	4.87	3.33	3.46
Size ($ millions)	96.17	21.46	184.38
Autocorrelation of *SFF*	0.02		
Panel C: Users of derivatives (n=147)			
SFF (%)	2.59	0.58	6.22
|*SFF*| (%)	4.77	3.20	4.62
Size ($millions)	280.24	34.64	631.88
Autocorrelation of *SFF*	0.10		

Table 3.1 provides descriptive statistics on several fund characteristics. Both users and non-users of derivatives receive on average similar amounts of fund flow, whether measured as the signed or absolute value of *SFF*. Non-users experience mean fund flow (absolute fund flow) equivalent to 2.63% (4.87%) of assets under management. For users of derivatives, this value is equal to 2.59% (4.77%). The period of analysis corresponds to a rising market and so it is unsurprising that funds experienced positive fund flow at the mean and median. As in Pinnuck (2004), funds that use derivatives have greater assets under management than non-users of derivatives. The average non-user has $96 million under management while the average user manages almost three times as much at $280 million. However, this is due to the fact that several very large funds use derivatives. The median value of funds under management is reasonably similar between the groups.

3.4. Empirical results

3.4.1. Alpha returns

This section investigates the extent to which investor flows affect fund abnormal returns. The results of this section provide insight into the validity of Hypotheses 3.1 and 3.2. The following cross-sectional regression is estimated:

$$\alpha_{jt} = \beta_0 + \lambda \left| SFF_{jt} \right| + \sum_{i=1}^{9} \beta_i \alpha_{jt-i} + \varepsilon_t \tag{3.7}$$

Each α_{jt} is calculated using the actual fund return (in excess of the interbank cash rate) in that month less the predicted fund return, estimated from either a univariate market model or quadratic market model. The two specifications are (respectively):

$$R_{jt} = \psi_{0\,jt} + \psi_{1\,jt}\, R_{mt} + \varepsilon \tag{3.8}$$

$$R_{jt} = \psi_{0\,jt} + \psi_{1\,jt}\, R_{mt} + \psi_{2\,jt} (R_{mt})^2 + \varepsilon \tag{3.9}$$

Where R_{jt} is the return on fund *j* in month *t*, less the return on the Australian interbank cash rate and R_{mt} is the return on the ASX200 Accumulation Index in month *t* in excess of the interbank cash rate.

Since many studies document short-term serial correlation in mutual fund performance (e.g. Grinblatt and Titman, 1992; Hendricks, Patel and Zeckhauser, 1993; Carhart, 1997; Huij and Verbeek, 2007), nine lagged values of α_{jt} are included in the regression specification (Equation 3.7).[52] This specification is in the spirit of Edelen (1999). However, unlike Edelen, this study does not have access to gross flow or fund transaction data. Therefore, it is not possible to decompose flow into components of liquidity motivated and discretionary trading. This is not a material problem, since Edelen finds a strong relationship between *gross* flow and incremental liquidity-motivated trading activity. This implies that fund flow is a reasonable proxy for liquidity motivated trading and probably more so when *net* flow is considered. Gross flow will not lead to trading when it is netted against gross flow of the opposite sign during the fund's cash accumulation period. By definition, this cannot happen to net flow and therefore the incidence of net flow should be more closely correlated to liquidity motivated trading than gross flow. With respect to the discretionary trading component, its omission is not likely to lead to specification bias. The coefficient on the discretionary trading component in Edelen's analysis is not significant for almost all of his regression specifications (pp. 458-459).

Edelen (1999) points to a number of econometric issues that need to be considered in a regression of this nature. Firstly, literature shows that fund returns can influence subsequent flow into the fund as investors engage in return-chasing behaviour (Ippolito, 1992; Friesen and Sapp, 2007). This essay examines the opposite scenario – the impact of flow on fund returns. This represents a problem of endogeneity, and leads to inconsistent estimators if not properly addressed. A second problem relates to cross correlated residuals. As Edelen (1999) points out, fund returns are likely to possess cross correlated errors, which biases any standard error estimates.

---

[52] Using six lags of alpha does not seem to control for all the autocorrelation and places a positive bias on λ. Utilising twelve lags of alpha involves problems of micronumerosity since each cross-sectional regression for non-users of derivatives only has at a maximum 28 observations and we are concerned about having sufficient degrees of freedom in each regression. A specification involving nine lags of alpha is chosen as a compromise.

To overcome these problems, two-stage least squares regression technique is utilised, where the first pass regression is described by:

$$SFF_{jt} = \delta_0 + \sum_{i=1}^{9} \delta_i \alpha_{jt-i} + \delta_{10} SFF_{jt-1} + \varepsilon_t \qquad (3.10)$$

Both equations 3.7 and 3.10 are estimated cross-sectionally for each month to avoid cross-correlation of residuals. Summary statistics are calculated from the time series (n=36) of coefficient estimates and test statistics are generated using normal transformation. This procedure is consistent with the approach taken in Edelen (1999), though he uses a single variable – lagged flow – as the instrument of current flow. Lagged abnormal returns are additionally incorporated into the regression since the correlation between consecutive monthly fund flows in the sample is low (approximately 9% in the sample – see Table 3.1). Therefore, the use of lagged flow as the sole instrument of current flow is not appropriate for the sample. The use of prior abnormal returns as instruments is motivated by prior research which documents correlation between returns and subsequent fund flow (Ippolito, 1992).

The issue of small sample size requires consideration. The number of non-user funds is 28, which represents the maximum number of observations used to calculate Equations 3.7 and 3.10 for that class of funds. The number of parameters to be estimated is 10. A small sample size*, per se*, does not violate the assumptions of the classical linear regression model, though it does affect the precision of the standard errors and increases the likelihood of Type II error. Therefore, Equation 3.7 is re-estimated using maximum likelihood estimation with pooled cross-sectional data, which substantially improves the sample size for the class of non-user funds. The use of maximum likelihood estimation removes the need for two stage regressions.

Table 3.2
The effect of flow on abnormal returns

The following regression is estimated:

$$\alpha_{jt} = \beta_0 + \lambda\left|SFF_{jt}\right| + \sum_{i=1}^{9} \beta_i \alpha_{jt-i} + \varepsilon_t$$

α_{jt} is estimated from a time series regression of excess fund returns on i) excess ASX 200 Accumulation Index returns (univariate market model) or ii) excess ASX 200 Accumulation Index returns and its square (quadratic market model). |*SFF*| is the absolute value of the monthly standardised net fund flow as defined in Equation 6. The model is estimated cross-sectionally over 36 months using two stage least squares regression where the first pass regression is defined by:

$$SFF_{jt} = \delta_0 + \sum_{i=1}^{9} \delta_i \alpha_{jt-i} + \delta_{10} SFF_{jt-1} + \varepsilon_t$$

The figures presented represent the mean coefficient across 36 months, and t-stats are calculated by normalising the mean by the standard error of λ. T-stats are shown in brackets. Alternatively, the coefficient is estimated from pooled cross-sectional data using maximum likelihood estimation. The results are split between non-users and users of derivatives.

	Cross-sectional two stage least squares		Pooled cross-sectional maximum likelihood	
	Univariate market model	*Quadratic market model*	*Univariate market model*	*Quadratic market model*
Panel A: Non-user funds				
β_0	-0.002	0.001	-0.000	0.000
	(-0.67)	(0.55)	(-0.73)	(0.24)
λ	-0.022	-0.011	-0.012	-0.015
	(-1.89) ***	(-0.85)	(-2.25) **	(-2.72) *
Panel B: User funds				
β_0	-0.001	-0.002	0.000	0.000
	(-0.97)	(-1.51)	(0.20)	(0.38)
λ	-0.006	0.020	0.003	0.001
	(-0.11)	(0.61)	(1.16)	(0.48)

* Denotes significance at the 0.01 level
** Denotes significance at the 0.05 level
*** Denotes significance at the 0.10 level

The estimated values of λ under various estimation techniques are presented in Table 3.2. The results confirm Hypotheses 3.1, 3.1a, 3.2 and 3.2a. The alpha performance of funds that do not use derivatives to manage cash flow are negatively related to fund flow. When alpha returns are measured from a univariate market model, every 100 basis point increase in fund flow as a percentage of fund size, leads to a 2.2 (1.2) basis points reduction in abnormal returns in a cross-sectional (pooled cross-sectional) regression specification. For a quadratic market model the reduction in performance is

1.1 (1.5) basis points in a cross-sectional (pooled cross-sectional) regression specification. All of these figures are statistically significant at conventional levels, except for the cross-sectional regression where returns are measured from a quadratic market model. However, the coefficient obtained (-0.011) is economically significant and similar to the values obtained in other regression specifications. Interestingly, the losses attributable to fund flow documented in this study are comparable in magnitude to those obtained by Edelen (1999). Between 1-2% of new net investor flows are lost in the trading process.

Fund managers who use index funds to manage cash flows do not appear to be at all burdened by the liquidity demands of fund investors. Estimated values of λ under all regression specifications are not significantly different from zero. The distinction between user and non-user funds could not be clearer. Funds that manage cash flows with derivatives are not affected by flow, despite summary statistics indicating that the average monthly flow is similar between users and non-users of derivatives. These results indicate that the use of index futures to manage cash flows can significantly improve fund flow conditional performance.

When considered together, the results from both samples of funds strongly support Edelen's (1999) hypothesis that investor flows are the source of negative alpha performance. Firstly, the results show that the alpha performance of funds is negatively related to investor flows. This is consistent with the theory, but it does not preclude the existence in this study or his, of some statistical or sample specific anomaly driving the results. However, it is also shown that when fund managers take steps to limit the costs associated with investor flows, the negative relationship between alpha performance and flow disappears. This suggests that fund flows *effect* negative alpha performance, rather than merely *covary* with it.

Finally, the findings point to the parity of fund managers when all other things are equal. The intercept on Equation 3.7 represents the average alpha return controlling for fund flow and autocorrelation in returns. In a pooled cross-sectional regression and when alpha is measured from a univariate (quadratic) model of returns the intercept is equivalent to -0.51% p.a. (0.17% p.a.) for funds that do not use derivatives. For funds that use derivatives the intercept value represents a fund flow neutral alpha of 0.04%p.a. (-0.11%p.a.).[53] All of these values are insignificantly different from zero. This result is also consistent with Hypotheses 3.1, 3.1a, 3.2 and 3.2a. In the absence of flow, there is no *a priori* reason why the fund mangers from the group of funds that use derivatives should be any more skilled in stock selection than those that do not use derivatives. The relative superiority of the user group is inherently linked to the occurrence of fund flow and the fact that they manage this flow with index futures. It is not because these managers happen to be, on average, better at stock selection than the non-users. Furthermore these insignificant alpha returns (conditional on zero fund flow) indicate that the average manager is only able to achieve abnormal returns to the point that it covers fund expenses. This is the case regardless of whether the fund is a derivative user or not. As with Edelen's (1999) sample, the managers in this study fit the role of informed traders in the rational expectations model of trade. The only difference is that non-user funds also act as liquidity motivated traders in the presence of flow, whereas user funds do not.

[53] The unconditional alpha for user funds is very similar to the fund flow conditional alpha since the coefficients on fund flow are trivially small.

3.4.2. Market timing

Models of market timing measure time variation in managerial behaviour across different market conditions. During bull (bear) markets, managers should shift between high (low) beta portfolios to maximise returns. Models of market timing are generally of the form:

$$r_{jt} = \alpha_j + \beta_j R_{mt} + \gamma_j f(R_{mt}) + \sum_{i=1}^{n} \phi_i X_{it} + \varepsilon_t \qquad (3.11)$$

Where r_{jt} is the fund return in excess of the risk free rate, R_{mt} is the market return in excess of the risk free rate, $f(R_{mt})$ is the market timing variable and X_{it} represents any other factors that may describe returns. Prominent models of market timing include Treynor and Mazuy (1966 - hereafter TM) and Henriksson and Merton (1981 – hereafter HM). In the TM specification of market timing, $f(R_{mt}) = R_{mt}^2$, whereas in the HM specification $f(R_{mt}) = \max(-R_{mt}, 0)$, with no other factors beside the market return used to describe the model.

Both of these measures of market timing are known to suffer from several biases (Grinblatt and Titman, 1989b). In particular, Ferson and Schadt (1996) show that time variation in market risk and the market risk premium cause funds to exhibit negative market timing performance. The average fund in their sample exhibits statistically significant negative market timing skills using either the TM or HM model of market timing. Their result is consistent with a number of studies which show that managers exhibit perverse levels of market timing, that is, they hold low beta portfolios when markets are rising and vice versa.[54] However, after controlling for time variation using lagged public information variables, Ferson and Schadt (1996) show that the market timing performance of funds improves relative to regressions involving an unconditional benchmark. Edelen (1999) confirms that the time variation in expected returns documented by Ferson and Schadt (1996) is intrinsically linked to fund flows. Edelen (1999) estimates the following time series regression:

$$r_{jt} = \alpha_j + \beta_j R_{mt} + \gamma_{1j} f(R_{mt}) + \gamma_{2j} f(R_{mt}) * flow_{jt} + \varepsilon_t \tag{3.12}$$

where $flow_{j,t}$ is some measure of fund flow. This model is the same as Equation 3.11 with an interactive regressor on the market timing regressor to control for flow related timing performance (i.e. $X_{1_t} = f(R_{mt}) * flow_{jt}$). His results indicate that the market-timing coefficient, γ_1, is negative when Equation 3.11 is estimated but insignificantly different from zero when Equation 3.12 is estimated. Importantly, the coefficient on the interaction term is significantly negative. Taken together this shows that the causes of fund managers' seemingly negative market timing skill are exogenously determined liquidity shocks. Funds exhibit perverse market timing only when they experience fund flow.

---

[54] For example Treynor and Mazuy (1966), Kon (1983) and Henriksson (1984).

Table 3.3
The effect of fund flow on market timing

The following time-series regression is estimated:

$r_{jt} = \alpha_j + \beta_j R_{mt} + \gamma_{1j} f(R_{mt}) + \gamma_{2j} f(R_{mt}) * SFF_{jt} + \varepsilon_t$

Where $f(R_{mt}) = R_{mt}^2$ (Treynor Mazuy specification) or $f(R_{mt}) = \max(-R_{mt}, 0)$ (Henriksson Merton specification). The equation is estimated for each fund. The first two columns present the average coefficient values across the relevant sub-sample of funds (28 for non-user funds; 175 for user funds). T-stats are calculated by normalising the mean by the standard error of the coefficients and are presented in brackets. The final two columns indicate the percentage of funds with the indicated coefficient value greater than zero.

Treynor Mazuy specification				
	γ_1	γ_2	$\gamma_1 > 0$ (%)	$\gamma_2 > 0$ (%)
Non-user funds	-0.77	-30.73	43.5%	21.7%
	(-1.51)	(-2.45)**		
User funds	-0.39	0.94	45.8%	49.3%
	(-1.10)	(0.08)		
Henriksson Merton specification				
Non-user funds	0.02	-3.57	54.2%	37.5%
	(0.40)	(-1.74)***		
User funds	-0.06	0.29	40.3%	49.3%
	(-1.21)	(0.15)		

* Denotes significance at the 0.01 level
** Denotes significance at the 0.05 level
*** Denotes significance at the 0.10 level

To test the effect of derivative use on market-timing Equation 3.12 is estimated for each fund, where $flow_{j,t} = SFF_{jt}$, under both the TM and HM specifications. Results are presented in Table 3.3. The funds that do not use derivatives exhibit characteristics similar to Edelen's (1999) sample. In the absence of fund flow, the average fund in the sample does not possess superior nor perverse market timing skills, as indicated by the coefficient on γ_1. All negative timing ability is due to the effects of fund flow as indicated by the coefficient on γ_2 which is statistically significant at conventional levels. Tellingly, only 21.7% (37.5%) of funds have positive coefficient values for this variable in a TM (HM) model of market-timing.

For user funds, the coefficient on γ_1 indicates that this class of funds does not exhibit market timing significantly different from zero, in the absence of fund flow. The interesting result is that the coefficient on the interaction term is also not significantly different from zero, rather than being significantly negative. Slightly less than half of the funds have coefficient values on the interaction term greater than zero in either specification of the market timing model. This finding supports the hypothesis that cash equitising funds are able to mitigate the negative consequences of fund flow by rapidly exposing new cash to market risk via index futures. As in the previous section, the findings show that the average fund manager from each group is statistically equivalent, *ceteris paribus*. Upon controlling for investor flows, the average fund manager, whether derivative trader or not, is a neutral market timer.

At this point it is worth noting the results of Koski and Pontiff (1999) whose findings are closely linked to the findings in this essay. The results indicate that user funds do not exhibit negative market timing when they experience fund flow. It is hypothesised that these funds invest new cash in index futures to rapidly obtain market risk and this has the effect of keeping portfolio beta higher during rising markets. If this hypothesis is true then a natural corollary is that fund risk is not significantly altered by fund flows. Koski and Pontiff (1999) show that fund risk is affected by period to period fund flows but the effect is less pronounced for derivative traders. Furthermore this phenomenon is only apparent for fund *systematic* risk, not idiosyncratic. They note that this result is consistent with funds using index based derivatives to manage cash flows. It appears that the 'user' funds in both the sample used in this study and theirs exhibit similar derivative trading behaviour – the management of investor flows with index futures.

3.5. Conclusion

The results of this study indicate that using index futures to manage funds flow can significantly reduce the negative consequences of investors' desire for liquidity. Funds that choose not to use derivatives lose around 1.5% of flow in trading. These funds also exhibit negative market timing skills, a phenomenon which is directly attributable to investor flows. In contrast, funds that use index futures are not materially affected by the liquidity demands of investors. Alpha and market timing measures of performance are independent of flow. The average manager that uses index futures approximates the average manager that does not cash equitise *and* experiences zero fund flow. The results suggest that index futures are an important mechanism for enhancing performance, especially when a fund provides significant liquidity services to its investors.[55]

The conclusion of this study appears at odds with several others which state, for example, that 'funds that use derivatives have similar performance as funds that do not use derivatives' (Koski and Pontiff, 1999 – p813).[56] Statements such as this are often based on analyses of the unconditional performance of funds. This study, however, examines fund flow conditional performance. This difference in methodology and focus is a likely cause of the divergent conclusions. Using index futures to reduce the costs of liquidity-motivated trading can improve performance, but only at the margin and only when fund flow is substantial. The benefits of using index futures for cash flow management are likely to be subsumed by the natural

[55] It is possible that investment in derivatives for the purposes of cash equitisation has ancillary benefits for fund holders beyond enhancing returns. Since index futures are able to mitigate the costs of investor flows, funds that engage in this strategy may have less need to impose restrictive conditions, such as minimum holding periods or redemption fees, to deter costly redemptions. For a discussion on the use of redemption fees to deter short-run redemptions see Greene, Hodges and Rakowski (2007).
[56] Other studies take a neutral view of derivatives e.g. Johnson and Yu (2004); Gallagher, Fong and Ng (2005); Pinnuck, (2004); and Fletcher, Forbes and Marshall. (2002).

volatility of fund returns in an unconditional analysis of performance. This is an important consideration for future research into the relation between derivative trading and mutual fund performance.

Finally, the results provide some insight into the debate regarding whether mutual funds should be able to invest in derivatives. Deli and Varma (2002) show that the freedom to invest in derivatives is positively related to the likelihood of transaction cost savings associated with using derivatives. They note that these potential savings are likely to be weighed against the agency costs of using derivatives. The results of this study indicate that these potential savings are actually realised by managers that trade index futures and the magnitude of the savings is material, in the order of 1.5% of new cash flow. To maximise returns, fund managers should be permitted to trade derivatives when expected agency costs of using these securities are less than this value.

Chapter 4. How Much Does an Illegal Insider Trade?

(N.B. The mathematical model of insider trading described in Section 4.2 and the Appendix to this chapter was primarily authored by Stephen Satchell of Cambridge University. All other work contained in this chapter, including an outline of the hypothesis derived from Equation 4.4, empirical analysis and write up remains the work of the PhD candidate).

4.1. Introduction

Drawing upon the intuition developed by Becker (1968), this study provides a model which describes the volume traded by an illegal insider as a function of the expected profit and penalty from trade. The study uses data sourced from SEC case files to test the predictions of the model. The literature outlined in Section 2.2.3 shows that empirical studies of illegal insider trading to date focus on the effects of illegal insider trading on market behaviour. This essay extends this literature by instead, examining the behaviour of the illegal insider. Besides academic interest, this work is relevant to regulators who wish to better understand the behaviour of illegal insider traders.

The rest of this chapter is organised as follows: Section 4.2 describes the model of illegal insider trading and related hypotheses. Section 4.3 presents the data and sample selection criteria. Section 4.4 presents the empirical results, while Section 4.5 presents the results of additional tests. Section 4.6 concludes and summarises the chapter.

4.2. Hypothesis development – a model of insider trading

The literature outlined in Section 2.2 reveals that illegal insiders are sensitive to the expected returns and expected penalty of their crime. The purpose of this section is to describe a model that predicts the volume to be traded by an individual that has access to non-public price sensitive information ("the insider"). Traded volume is denoted by *s*. Let *z* be the event that crime is committed. Let *h* be the event that it is detected. Both *z* and *h* are Bernoulli variables.

In looking at transgressions, this essay explicitly conditions upon $z = 1$. In the case of *h*, $Prob\ (h = 1) = P(s)$. The transgressor has a utility function $U(sr)$ where *r* is the return of the risky asset. Transgressing implies that $r \mid z = 1 \sim N(\mu + \Delta, \sigma^2)$ whilst if there is no inside information, and therefore no crime, $r \mid z = 0 \sim N(\mu, \sigma^2); \Delta > 0$. It is possible to endogenise *z* by letting the investor choose the maximum of $E(U(sr)/z=1)$ *versus* $E(U(sr)/z=0)$. However, since the data are for transgressors only, this avenue shall not be pursued further and the analysis continues with the suppressing conditioning on $z = 1$. Thus the investor chooses *s* to maximise expected utility:

$$\begin{aligned} &\max E(U(sr)) = E(U(sr)/h=1)P(s) \\ &+E(U(sr)/h=0)(1-P(s)). \end{aligned} \tag{4.1}$$

This function is directly inspired by Becker (1968) who was the first to model the supply of crime using expected utility theory (see Becker, 1968, p177). In the analysis, it is assumed that the investor is concerned with expected utility over one period. Clearly, this is a simplification though an extension to a multi-period setting adds complexity without providing additional insight into understanding the total volume traded by illegal insider traders.[57] Denoting the left hand side of Equation 4.1 by *V(s)*, one needs to solve for $V'(s)=0$. That is:

$$\begin{aligned} V'(s) &= P'(s)(E(U(sr)/h=1)-E(U(sr)/h=0)) \\ &\quad +P(s)(E(U'(sr)r/h=1))+(1-P(s))E(U'(sr)r/h=0) \\ &= P'(s)[E(U(sr)/h=1)-E(U(sr)/h=0)] \\ &\quad +E(U'(sr)r)=0 \end{aligned} \tag{4.2}$$

The expectation is that *P(s)* is increasing in *s*, $P'(s)>0$. This is equivalent to saying that as traded volume increases, the probability of detection increases. Also the term $\varphi(s)=E(U(sr)/h=1)-E(U(sr)/h=0)$ should be negative since the utility of the investor of detection should be smaller than the utility associated with non-detection. This proves that for an interior maximum, $E(U'(sr)r)>0$. Now considering the second derivative, $V''(s)$, for this to be negative corresponding to a maximum, note that $V''(s)=P''(s)\varphi(s)+P'(s)\varphi'(s)+E(U''(sr)r^2)$. Sufficient conditions for a maximum are that $P''(s)$ is non-negative, that $U''()<0$, that is, the investor is risk-averse, and that $\varphi'(s)\le 0.$ The last assumption implies that:

$$E(U'(sr)r/h=1)\le E(U'(sr)r/h=0). \tag{4.3}$$

This means that the "marginal utility" from increasing *s* under detection must be less than the marginal utility of increasing *s* under non-detection.[58]

[57] In any case, summary statistics contained in Section 4.3 indicate that the median insider trades only once, consistent with a one period allocation decision.
[58] It is not implausible to consider a risk-loving transgressor. In this case, different sufficient conditions on $\varphi'(s)\le 0.$ and *P(s)* need to apply.

Particular choices of functional form for *U(sr)* and *P(s)* lead to particular solutions. For example, Seyhun's (1992) empirical work is motivated by $U(w) = w$ (risk-neutrality), where w is more generally wealth and $P(s) = \lambda s$ (a linear probability model in *s*). More complex forms can be computed but these in turn lead to complex first-order conditions that can only be solved by non-linear methods or approximation. Whilst this is certainly an area for future research, in this dissertation only potential solutions leading to closed-form or approximate solutions are considered.

Proposition 1. As an example, suppose that $P(s) = P(0)\exp(sv)$. $P(0)$ could be interpreted as the probability of detection of insider trading for trading one share (the smallest tradeable amount to be liable for insider trading). Furthermore, assuming $r \mid z = 1 \sim N(\mu + \Delta, \sigma^2)$ and $U(rz) = -\exp(-\lambda rz); \lambda > 0$, and c is the fixed detection penalty expressed as a return. Then the optimal traded volume, *s*, is given by:

$$s = \frac{(\mu + \Delta - P(0)c)}{\lambda\left(\sigma^2 + \frac{2P(0)cv}{\lambda}\right)} \tag{4.4}$$

Proof : see Appendix to this Chapter.

It is worth noting that the units of *s* and *r* have not been fully specified. The variable, *s* is referred to as the volume traded and *r* as the return. A number of interpretations here are possible. For example, *s* might be the proportion of wealth invested, whilst *r* might be the rate of return. An alternative version could be that *s* is the number of shares and *r* is the return i.e. the change in price associated with buying and selling the share. The hypotheses are equivalent whichever interpretation is taken, however, the estimation of parameters, especially those of the return distribution, will differ.

Proposition 1 leads to several hypotheses.

Hypothesis$_{4.1}$: *An increase in* $\mu + \Delta$ *(the sum of the unconditional expected return of the asset and the incremental return associated with the information event) will increase* s.

Hypothesis$_{4.2}$: *The volume transacted by the insider,* s, *is reduced by an increase in* c *(penalty rate per share) not just through the mean effect (numerator) but also via the variance effect (denominator).*

Hypothesis$_{4.3}$: *An increase in the variability of the asset (* σ^2 *) will also decrease* s.[59]

Hypothesis$_{4.4}$: *An increase in* v *(the sensitivity of the detection function with respect to volume) will decrease* s *as will an increase in* P(0) *(baseline probability of detection).*

Hypothesis 4.4 concerns changes to the two components which make up the probability of detection function, *P(s).* Unlike the other variables derived from Equation 4.4, this function is not directly observable. However, in the empirical analysis in Section 4.4, the following factors are considered as proxies for the detection function:

[59] This is driven by the model and the independence of *P(s)* from σ^2. It would be straightforward to extend the above analysis to make σ^2 a parameter of *P(s)* which decreases the probability of detection. This would then have a countervailing affect on the magnitude of *s* so that, in an extended model at least the impact of volatility could be ambiguous.

1. Specialist versus dealer markets – Several empirical studies examine whether specialist market makers are better at detecting informed trading than dealers in a multiple market maker environment. In an analysis of repeated illegal insider trading in 116 stocks, Fishe and Robe (2004) show that specialists on exchange-listed securities reduce depth and increase bid-ask spreads after illegal insiders begin trading. In contrast, for NASDAQ listed securities quoted depth decreases, but less so than for NYSE-listed stocks, and there is no appreciable reduction in bid-ask spreads. Garfinkel and Nimalendran (2003) show that effective bid-ask spreads for NYSE-listed stocks, are larger *vis-à-vis* NASDAQ-listed stocks on days when registered (legal) insiders trade. Rather than analyse particular incidences of informed trading, Heidle and Huang (2002) examine how the probability of informed trading in general differs as stocks transfer from dealer to specialist markets, and vice versa. Their results indicate a move to a multiple dealer environment coincides with a higher likelihood of informed trading overall, suggestive of the fact that this market structure is less able to constrain informed investors. Theoretical work also predicts that specialists might be better able to avoid informed trading.[60] Given the results of these studies, insiders wishing to conceal the fact they are trading illegally may choose to be less aggressive when trading in a specialist market such as the NYSE.

2. Days between trade and information announcement – the probability of being detected may be a function of the time between the trade by the insider and the date of the announcement. If insiders believe that trading immediately before an information announcement is more likely to attract a penalty then a rational insider will trade as

[60] For example, Benveniste, Marcus and Wilhelm (1992) model the repeated interactions between brokers and specialists on the floor of the exchange. Their model predicts that floor brokers have an incentive to signal to specialists when they suspect their client is informed, in order to avoid subsequent sanctions from the specialist and to reduce overall costs for their clients.

far away from the information event as possible.[61] Park, Jang and Loeb (1995) provide a simple model of how insiders time their trades with respect to forthcoming earnings announcements. Their model predicts that insider trading decreases substantially as the earnings day approaches to the point where immediately before the announcement insiders trade less than they 'normally' would. Their analysis of reported (i.e. legal) insider trades supports the predictions of their hypothesis. Ke, Huddart and Petroni (2003) provide contributing evidence for this conclusion. They examine reported insider trading activity before earnings announcements, in which reported earnings decrease compared to the corresponding quarter of the previous year. Such events, which the authors term a 'break', are shown to involve significant abnormal negative price reactions on the announcement day. The authors find an absence of insider selling activity in the two quarters prior to a break. However, there is evidence of significant selling activity between seven to three quarters prior to the break. This is consistent with detection minimisation behaviour on the part of insiders and like Park, Jang and Loeb (1995) suggests that the probability of detection is lower the further away an insider trades from the event. Both of these papers examine SEC lodged trades by insiders prior to earnings announcements. To the extent that this behaviour extends to covert trades committed before earnings and merger announcements, trading further away from the announcement should decrease the probability of detection.

3. *Proximity to the non-public information* – the degrees of separation between the trader and any individual who has access to non-public information might determine the volume they trade. To successfully prosecute an individual for illegal

[61] An alternative explanation, unrelated to the probability of sanction but with the same expected outcome, is that insiders will trade larger amounts as early as possible to maximise expected profit before the information is impounded into the price by other informed traders.

insider trading, the regulator must establish possession of material non-public information. If it is easier to establish possession of information for employees of the company in question than those that are separated from that information, then direct insiders will trade less, if at all, because their probability of sanction is higher.

4. Normal trading volume of security – if the volume traded by the insider is significant relative to the usual volume traded in the security then the regulator may be more likely to investigate those particular trades. If this is the case, then the insider will trade fewer shares in illiquid securities.

4.3. Data and sample selection

To construct the variables necessary to test the predictions of the model, the following data for each insider trade are required: the position taken by the insider in the relevant security, the day of the insider's trade, general trading data for the security, the penalty levied against the insider and features of the case or insider's employment to determine how proximate the insider is to the information. This section describes the sources and collection methodology of these data.

Insider trading data are drawn from litigation reports made available on the SEC website (http://www.sec.gov/litigation/litreleases.shtml) when the SEC formally brings an action against a defendant. This source is similar to the one used by Meulbroek (1992), but the sample period is more recent than that covered in her paper and is not supplemented by non-public information. Data collection involves examining all litigation reports[62] available on the website between the creation of the SEC website, 28 September, 1995, and 31 December, 2007. On the website, the litigation reports are ordered according to the date on which the litigation report is released, rather than the actual date of the defendants' crimes. There can be considerable difference between these two dates. The delay between the commission of the crime and subsequent regulatory action reflects the time needed to detect the transgression, establish the case and finally initiate civil proceedings. It is at this stage when the website would first make mention of the defendant and the alleged transgression. After this step, more time is required as the matter is seen through the relevant court to determine if the defendant is indeed liable and if so, the penalty to be imposed upon the defendant. Each of these additional determinations might warrant a separate litigation report. Care is taken to follow through all cases to determine the eventual verdict and penalty. All cases for which the defendant is deemed not liable are removed from the sample.

Due to the significant time lags involved in this process, the dates for which litigation reports are available do not correspond to the dates on which illegal insiders performed their trades. For example, the first insider trading case covered by these litigation reports concerns a trade made in 1988. A natural question arises as to whether the sample period is determined according to the date of the defendants' crimes or the date of its first public release by the regulator on the SEC website. The former is chosen because, it is considered more useful to have results which reflect the totality of insider trading activity that *occurred* during a particular period, rather than the totality of insider trading activity that was *reported by the regulator* during a

[62] The litigation reports presented on the website concern all types of securities fraud, however this essay concerns insider trading cases only. For expositional convenience the phrase 'litigation reports' implies only litigation reports concerning illegal insider trading.

particular period. As such, this essay concerns all illegal insider transactions that were made between 1 January, 1996 and 31 December, 2004.[63]

These dates are chosen to ensure that over the course of the sample period, there is maximum access to the population of detected insider trading activity that occurred during that period. Outside of this range there is less certainty with respect to this criterion. For example the electronic data available on the SEC website provides information for only one case (within the relevant sample of mergers and earnings announcements in common stock) in 1988. Meulbroek (1992) shows that there is clearly more than one case of insider trading that occurred in 1988, and therefore, if the sample begins in 1988, the data available from the SEC website captures only a very small percentage of the insider trading activity that occurred in that year. Therefore, the start of the sample period corresponds with the first full year in which the SEC began publishing litigation reports on its website, 1996. The sample period ends in 2004 because beyond this date, one cannot be certain of the outcome of many of the civil proceedings because a significant majority are not resolved before 31 December, 2007.

To further focus the scope of this study, only trades in common stock are investigated because the model outlined in Section 4.2 is relevant for describing the volume traded by an insider in a given type of security (e.g. common stock, options, futures, contracts for difference), but not how they allocate across multiple types of

[63] Using the alternative sample period criterion of all litigation reports *released* between 28 September, 1995 and 31 December, 2007 only increases the sample size by 20 – as such, the results remain relatively unchanged under the alternate sample period criterion.

securities.[64] Since common stock trades have by far the greatest representation in the litigation reports available on the SEC website, this security type is chosen for analysis. This essay focuses exclusively on trades before merger and earnings announcements since these are common yet significant events in financial markets. Furthermore, as recommended by Chakravaty and McConnell (1999), part of the methodology involves matching insider trades to non-insider trades to determine the extent of the difference in behaviour between insiders and the uninformed. One aspect of the matching criteria involves matching on information type and often it is not possible to match trades associated with (relatively) rare or idiosyncratic information events.

The litigation reports are non-standardised documents and provide varying levels of detail about the insiders' trades. The name of the defendant, the volume traded, the price of the transaction, the date of trade, the date the insider's information became public, the security being traded and the penalty levelled against the insider are collected from the litigation reports if available. Additional information is sourced from *Lexis Nexis* database which provides case judgements. These judgements are primarily used to track down the penalty imposed upon the defendant.

Using this information, trade packages are constructed by aggregating all volume traded by an individual before a given news announcement in a given security. Aggregation of insider volume occurs because the model outlined in Section 4.2 is a one period model and describes the total volume traded by an insider before a given announcement, and not how the insider chooses to break up orders across time before

[64] Cases involving solely options or derivatives trading are not examined. Cases where the insider(s) traded both options and common stock are included but only the common stock trades are analysed.

the announcement. Therefore trade 'packages' rather than individual trades are the unit of observation in this study.

While it is possible for individuals to trade in more than one listed company or for several different individuals to trade shares in the same company, each observation in the sample represents a unique insider-company combination.[65] For each trade package, the closing and opening prices surrounding the first trading day in the package and the date of the news announcement are collected. Total daily traded volume in the security in the 30 days preceding the first trade in the package is also collected. All price and volume data is sourced from Bloomberg. Finally, the annual report corresponding to the financial year of the insider's trade is consulted to determine which exchange the stock was listed on at the time of the illegal trading activity.

The litigation reports are not standardised and therefore, many observations are lost due to incomplete case data. Table 4.1 describes the proportion of observations that are included in the sample compared to the population of all trade packages over the sample period. The sample consists of 296 trade packages out of a possible 441 (earnings and merger announcements for publicly listed companies only), representing 67.12% of the population. As a point of comparison, Meulbroek (1992) who uses publicly available litigation reports and confidential case files to build her sample, is only able to analyse data that captures 69% of defendants charged with

[65] In one case an individual traded the same security before two different news announcements pertaining to the same company. This was defined as two separate trade packages and so technically each observation in the sample represents a unique insider-company-news announcement combination.

insider trading between the years 1980 to 1989.[66] While this unit of observation – 'defendants' – is not the same as the unit analysed in this study – 'trade packages' – it nevertheless highlights the fact that significant data loss occurs when attempting to extract information from non-standardised litigation reports.

Table 4.1
Trade packages: January 1996 to December 2004

This table reports the total population of trade packages in all litigation reports filed between January 1996 and December 2007. The population of trade packages consists of all trades in common stock before merger and earnings announcements. The year corresponds to the year in which the insider trade occurred (not the year of prosecution). This table also reports the number of trade packages remaining in the sample once all filters are applied.

Year	Trade packages in population	Trade packages in sample	Percent in sample
1996	33	23	69.70%
1997	53	32	60.38%
1998	57	31	54.39%
1999	65	47	72.31%
2000	98	67	68.37%
2001	38	25	65.79%
2002	28	19	67.86%
2003	47	40	85.11%
2004	22	12	54.55%
Total	441	296	67.12%

Table 4.2 depicts the sample selection criteria. There are 441 observations available over the sample period. Sixty nine observations are lost because the litigation reports do not provide the number of shares traded by the insider. A further 67 observations are removed from the sample because the litigation reports do not mention the penalty imposed upon the illegal insider. Finally nine observations are lost because the date on which the insider executed the trade is unavailable. The final sample is 296 packages which represents the trading of 256 defendants across 156 stocks, prosecuted in 158 cases (see Table 4.3). Two hundred and forty eight observations involve prior knowledge of mergers or tender offers, while 48 observations relate to earnings announcements.

[66] The sample selection criteria are similar to Meulbroek's (1992) except that her analysis does not require data on the penalty levelled against the insider.

Table 4.2
Sample selection criteria

This table shows how the final sample of 296 insider trading packages is determined from an initial pool of 441 available observations. All data is sourced from SEC litigation reports available from the SEC website.

Filter	Observations Lost	Observations Available
All insider trade packages	0	441
No data on volume traded by insider	69	372
No data on penalty	67	305
No data on date of trade	9	296
Total Available trade packages		296
Percentage of total		67.12%

Table 4.3
Distribution of sample across years

This table reports the distribution of the sample across years, by trade packages, defendants, stocks and cases. The value in the "All years" field does not necessarily equal the sum of the individual years because several defendants / stocks / cases are present in the sample in more than one year.

Year	Trade Packages	Defendants	Stocks	Cases
1996	23	23	13	17
1997	32	20	22	16
1998	31	29	17	19
1999	47	42	26	29
2000	67	59	31	31
2001	25	24	13	15
2002	19	19	12	10
2003	40	37	16	21
2004	12	12	10	11
All years	296	256	156	158

Descriptive statistics for the sample are presented in Table 4.4. Table 4.4 documents significant skewness to the right in almost all the variables. The median amount of stock traded by insiders is 4625 shares per package with a value of approximately $75,000. This amount of stock is within the range designated by Barclay and Warner (1993) as 'medium sized' trades (500 – 9,900), the amount most likely to be used by informed traders to 'stealth trade'.[67] The volume traded by insiders represents 4.54%

[67] Barclay and Warner (1993) analyse individual trades rather than trade packages as is the case in this study. The median individual trade size of the sample is 2000, which also fits within the 'medium sized' category of Barclay and Warner.

(median) of the average daily trading volume in the security over the previous 30 days, indicating that insiders have a reasonably significant presence in the market during their trading window. Insiders trade around seven days before the announcement and use between one to two transactions to implement their strategy, suggesting that the behaviour of the median insider is consistent with a one period allocation decision.

Table 4.4 also presents the imputed profit or loss avoided by the insiders. This value is calculated by first determining the absolute price change between the closing price the day before the first trade in the package and the last trade on the day of the news announcement.[68] This is then multiplied by the number of shares in the package to calculate the imputed profit or loss avoided. The median profit reaped by insiders per security they traded is $26,860.

The median penalty is $67,511 and the median penalty per dollar of (imputed) profit is 2.00. In civil cases the penalty assessment is the sum of all monies that the defendant is forced to pay. This usually involves full disgorgement of profits, some civil penalty and interest assessments. If a defendant is given a criminal sanction beyond a civil penalty, this is added to the total penalty levelled against the individual. In a handful of instances, defendants who have been tipped are not required to pay any penalty. Instead, the tipper is ordered to pay the full disgorgement and civil penalties of the tippee. When this happens, the penalty of the tippee is truncated to $1

[68] Where the last trade on the day prior to the first trade of the package is not available, the price documented in the litigation report is used, if available.

to ensure in the empirical analysis definability of the natural log of the variable.[69] In litigation reports sanctions are often reported *per individual*. When determining the penalty *per trade package*, penalty assessments for individuals are scaled by the profit made per trade package for the individual in question. For example, if a defendant makes a profit of $10,000 in one trade package and $40,000 in another trade package, the penalty for that individual is split across those packages using a ratio of 1:4. Legislation restricts civil penalties to three times the profit made, implying an upper limit of this variable to four times (assuming full disgorgement). However, it is possible for the penalty per dollar profit ratio to exceed four times. This can occur if insiders are ordered to pay the disgorgement of tippees as well as their own penalties. The ratio can also exceed theoretical statutory limits if there is a significant period between the trade and the imposition of sanction, leading to very large interest assessments. Finally, the penalty per profit ratio can exceed four if significant criminal sanctions are imposed.

[69] To test the sensitivity of the results to this truncation all observations where the defendant is not required to pay a penalty are excluded. The results are very similar to those reported in the body of the text.

Table 4.4
Descriptive statistics of illegal insider trading

This table provides mean, median, maximum and minimum values for the sample of trade packages across several variables. *Volume* represents the amount of stock traded by the insider per package. *Volume / Liquidity* represents the total insider volume divided by the average daily market volume in the 30 days prior to the day in which the insider traded. *Dollar Value* is equal to the volume of the trade package multiplied by the closing price on the day before the first trade in the package. *Price Change* is the absolute percentage price change between the closing price on the day of the announcement and the day before the first trade in the package (net of market). *Days* represents the volume weighted average number of calendar days before the information announcement that the insider executed the trades. *Number of trades* is the number of trades per trade package executed by the insider. *Imputed Profit (Loss Avoided)* is the dollar value of profit made or losses avoided by the insider. This value is calculated by first determining the absolute price change between the closing price the day before the first trade in the package and the last trade on the day of the news announcement. This is then multiplied by the number of shares in the package to calculate the imputed profit or loss avoided. *Penalty* is equal to the dollar value of the penalty imposed by the SEC. The penalty is the total sum of disgorgement, civil penalties, criminal sanctions and interest and is on a per trade package basis. The penalty is also scaled by the profit of the insider and reported below.

	Mean	Median	Maximum	Minimum
Volume	24454	4625	1400000	50
Volume / Liquidity	34.49%	4.54%	1224.63%	0.02%
Dollar Value	$531,597	$74,969	$29,844,030	$995
Absolute Price Change (dollar value)	$10.18	$6.78	$64.50	$0.02
Absolute Price Change (%)	48.11%	40.27%	297.62%	0.00%
Days	18.33	7.00	254.00	0.00
Number of trades	1.52	1.00	12.00	1.00
Imputed Profit (Loss Avoided)	$215,696	$26,860	$15,050,000	$30
Penalty	$341,068	$67,511	$7,819,509	$0.00
Penalty (scaled by imputed profit)	11.96	2.09	897.00	0.00

4.4. Empirical results

To test the hypotheses outlined in Section 4.2 several different specifications of a log linear model of insider volume is estimated. The dependent variable is regressed against a suite of determinants designed to proxy for the theoretical determinants mentioned previously. A log-linear model is estimated because Table 4.4 indicates that many of the variables exhibit significant skewness. The dependent variable, *ln*(*volume)* is the natural log of total volume transacted by the insider in the trade package standardised by the average daily traded volume in the security over the previous thirty days. As is apparent from the specification of the dependent variable, the analysis does not explicitly consider the effect that ‘normal’ liquidity of the security has on insider volume by incorporating it on the right hand side of the equation. Rather insider volume is scaled by extant liquidity. This produces a more appropriate measure of the dependent variable in a cross-sectional regression where traded volumes can differ substantially simply due to variations in liquidity. Furthermore, scaling insider volume by some measure of broader liquidity is common in papers on insider trading.[71]

The variable *ln(price change)* is the natural log of the absolute dollar return between the last trade on the day before the first trade in the package and the last trade on the day of the information announcement. When the information announcement occurs after the market close, the opening price on the next day is used to calculate the price change. This variable captures the expected return of the stock plus the incremental return associated with the news announcement, $\mu + \Delta$, in Equation 4.4. The variable, *ln(penalty)* is equal to the natural log of the penalty per trade package (described earlier) scaled by volume of the trade package and represents c, in Equation 4.4. The variable, *ln(std. dev.)* is the natural log of the standard deviation of daily closing price returns (in dollars) in the thirty days prior to the first trade of the package. This variable captures the variability of the asset returns, σ^2, in Equation 4.4. It is apparent that the specification of these three variables implies that the return of the asset, r, is defined using dollar returns, rather than rates of return.[72]

Several variables are used to proxy for the detection function, *P(s). Specialist* is a dummy variable which equals one if the insider traded on the NYSE or AMEX and

[71] See for example Seyhun, (1992 p. 168); Cornell and Sirri, (1992, p.1045); Chakravaty and McConnel, (1997, p26); Fishe and Robe (2005, p479).
[72] The analysis contained in Section 4.4 is repeated using rates of returns. The signs of the coefficients and the significance of the variables remain the same under either specification.

zero otherwise (NASDAQ). The variable *ln*(*days)* is equal to the natural log of one plus the volume weighted average number of calendar days before the information announcement that the insider executed the trades.[73] *Direct insider* captures the proximity of the illegal trader to the inside information. It equals one if the individual is an employee, legal advisor or consultant to the company about to make the information announcement or in the case of a merger an employee, consultant or legal advisor of the target or acquiring firm. It is equal to zero otherwise.

The regression results are presented in Table 4.5. Model 1 denotes the most parsimonious representation of the theoretical model – containing only those variables which are readily observable – the price change, penalty and variance determinants. The results of Models 2, 3 and 4 depict how the model changes as an extra determinant, from those designed to proxy for the detection function, is added to this base specification. Models 5, 6, 7 represent the basic specification plus two additional determinants, while Model 8 represents the full specification. As indicated by the respective F-statistics, the variables are jointly significant at the 1% level across all specifications. The models describe between 23.45% (Model 1) to 28.89% (Model 8) of the variation in the dependent variable. As for individual coefficients the results are generally consistent regardless of the specification.

73 $Days = \sum_{i=1}^{n} \frac{d_i * v_i}{V_n}$ where *n* is the number of trades in the package, d_i is the number of calendar days before the information announcement that the insider performed trade *i*, v_i is the volume for trade *i*, and V_n is the total volume traded in the package.

Table 4.5
Regression results

Coefficient estimates and corresponding test statistics for several regression specifications. The regressions contain the following variables: the dependent variable, *ln*(*volume)* is equal to the natural log of the total volume traded by an individual before a given news announcement standardised by the average daily traded volume in the preceding 30 days; *ln(price change)* is the natural log of the return between the last price on the day preceding the first trade in a package and the last price on the day of the news announcement; *ln*(*penalty)* is equal to the natural log of the penalty levelled against the insider for that particular trade, divided by trade size; *ln(std. dev.)* is the natural log of the standard deviation of closing prices in the 30 days preceding the first trade by the insider; *Specialist* is a dummy variable equal to one if the stock is traded on the NYSE or AMEX and zero otherwise; *ln(days)* is the natural log of the volume weighted number of days before the information announcement that the insider traded the shares; and *insider* is a variable equal to one if the individual is an employee, legal advisor or consultant to the company and zero otherwise.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	-3.83 (-11.10)*	-3.39 (-9.54)*	-4.36 (-11.28)*	-3.61 (-9.83)*	-3.89 (-9.68)*	-3.24 (-8.69)*	-4.14 (-10.45)*	-3.74 (-9.18)*
ln(price change)	0.46 (3.71)*	0.49 (3.98)*	0.46 (3.69)*	0.43 (3.45)*	0.48 (3.95)*	0.46 (3.76)*	0.42 (3.36)*	0.45 (3.65)*
ln(penalty)	-0.33 (-4.34)*	-0.36 (-4.74)*	-0.35 (-4.66)*	-0.33 (-4.36)*	-0.37 (-5.00)*	-0.36 (-4.73)*	-0.36 (-4.74)*	-0.37 (-5.03)*
ln(std. dev.)	-1.08 (-6.91)*	-1.01 (-6.55)*	-1.04 (-6.69)*	-1.06 (-6.83)*	-0.97 (-6.38)*	-1.00 (-6.50)*	-1.01 (-6.55)*	-0.96 (-6.28)*
Specialist		-0.91 (-3.87)*			-0.85 (-3.61)*	-0.88 (-3.69)*		-0.79 (-3.34)*
ln(days)			0.28 (2.90)*		0.28 (2.56)**		0.32 (3.26)*	0.28 (3.28)*
Direct Insider				-0.42 (-1.73)		-0.32 (-1.33)	-0.56 (-2.28)**	-0.45 (-1.84)
n	296	296	296	296	296	296	296	296
F-Stat	31.12*	28.20*	26.03*	24.24*	24.30*	22.97*	22.17*	20.98*
Adjusted R^2	23.45%	26.94%	25.34%	23.96%	28.31%	27.13%	26.40%	28.89%

* Denotes significance at the 0.01 level
** Denotes significance at the 0.05 level

The following discussion will refer to the results from all models but with a focus primarily on the results from the fully specified model (Model 8). Consistent with Hypothesis 4.1, the coefficient on the price change variable is positive across all models, ranging from 0.42 (Model 7) to 0.49 (Model 2). The value of the coefficient in the full model (Model 8), 0.45, indicates that for every 1% increase in dollar return, insiders will trade 0.45% more shares relative to the average daily volume in the security. Therefore, in total dollar terms and holding all other things equal, a 1% increase in the dollar return increases the payoff to the insider by 1.45%, because the insider also enlarges their trading position. This is consistent with models of informed and insider trading, where individuals trade larger volumes when there are greater rents to be made (e.g. Seyhun, 1992, Easley and O'Hara, 1987). As indicated by the respective t-statistics, this variable is significantly different from zero at the 1% level across all specifications.

The coefficient on the natural log of penalty is negative and significant at the 1% level across all models. The parameter coefficient is robust to the exact model specification ranging from -0.33 to -0.37, suggesting that the volume traded by insiders is sensitive to the magnitude of the penalty. The results from Model 8 indicate that for every 1% increase in penalty per share traded volume decreases by 0.37%. The finding of penalty effect is supported empirically by Garfinkel (1997) who examines the effect of increased sanctions under the *Insider Trading and Securities Fraud Enforcement Act (1988)* (ITSFEA) on insider trading before earnings announcements. In the post-ITSFEA environment, the paper documents significantly less (legal) insider trading before announcements as well as larger price movements after the date of the earnings announcement. Both of these findings are consistent with the notion that insiders respond to the possibility of harsher sanctions by reducing their traded volume.

Consistent with Hypothesis 4.3, it appears that insiders respond to variability in asset returns by reducing their traded volume. The coefficient on the natural log of return standard deviation is a significantly negative 0.96. This is an interesting finding, given that one might not expect insiders, with certainty of information, to consider the variability of asset returns. This result suggests that insiders may not have completely precise information, or at the very least, do not believe they have perfect information.

This might occur, for example, when an insider is aware a takeover is about to occur, but does not know the exact offer price. This result is consistent with Markowitz (1957) mean-variance optimisation behaviour, with the obvious difference that insiders, because they tend to have inside information in only a very small number of securities (typically one), are concerned with the total variability of the assets they trade rather than beta variability.

The variables used to proxy for the detection function indicate that insiders respond to the probability of detection by reducing their traded volume. The coefficient on *specialist,* -0.79 (Model 8)*,* is negative and significant at the 1% level indicating that insiders are more likely to trade greater volumes in a multiple dealer environment than with a specialist on the NYSE or AMEX. This is consistent with previous studies that show NYSE specialists are more easily able to detect informed trading and adjust their quotes or spreads accordingly (Fishe and Robe, 2004; Garfinkel and Nimalendran, 2003). Insiders appear to have their volume constrained when trading with specialists compared to other market structures.

The coefficient on *ln(days)* (0.28 – Model 8) is significantly positive at the 1% level, indicating that insiders trade less as the announcement day approaches, consistent with detection minimization behaviour and the model proposed by Park, Jang and Loeb, (1995). Finally, as indicated by the coefficient on *direct insider*, direct insiders of companies – employees, legal advisors and consultants – trade 45% less volume than those tipped off by direct insiders. This coefficient is slightly outside the 5% significance level (*p-value* is 0.066). Nevertheless, the sign on the coefficient is consistent with the hypothesis that those closer to the information will trade less (assuming they choose to trade at all) because it is easier for the regulator to establish a connection between the insider and the information.

Overall the results are consistent with the model and associated hypotheses outlined in Section 4.2. Consistent with Becker (1968), the magnitude of crime is positively related to the expected gains, and negatively related to the expected penalty. Interestingly, illegal insider traders also appear to be sensitive to the variability of asset returns, consistent with risk-return optimisation behaviour.

4.5. Additional tests

4.5.1. Sample selection bias

The sample used in this study consists of illegal insiders who were caught and successfully prosecuted by the SEC. However, the model described in Section 4.2 and the conclusions drawn in this essay concern all individuals who trade on non-public information, not just those who are caught. Since some proportion of illegal insider trading goes undetected it is possible that the results provided in Section 4.4 are biased because the behaviour of detected insider traders may be systematically different to the behaviour of non-detected insider traders.

It is worthwhile considering what this bias might be. It is reasonable to expect that non-detected insider traders, because of the fact they remain undetected, might exhibit behaviour that is more furtive than their detected counterparts. For example, for a given level of expected return, the non-detected sample of insiders might be less aggressive in their trading – i.e. they trade less relative to the detected group. Seeing as the sample consists only of detected transgressors, this might create a bias towards finding a significant relationship between expected returns and the position taken by the insider.

What about the other determinants outlined in the model? In terms of the expected penalty components – the magnitude of the penalty and the probability of detection - any bias of this nature probably works against finding significance. This is because, for a given level of expected penalty, less aggressive trading implies greater sensitivity to this determinant in the direction predicted by the hypothesis. Therefore, the coefficients on levied penalty and the variables that proxy for the detection functions, presented in Section 4.4, would likely be greater in magnitude with a non-detected sample. A similar argument can be made for the other determinant – asset return variability. Therefore, if sample selection bias exists it might change the magnitude, but not the overall conclusions for the penalty, detection and asset variability components. However, as stated previously, it might affect the conclusions drawn from the interpretation of the coefficient on *ln(price change)*.

To empirically test for the affects of any bias, this essay broadly draws upon the same rationale that Meulbroek (1992) uses to account for sample selection bias in her study. Meulbroek's (1992) study concludes that insider trading moves stock prices. This conclusion is reached because the author documents a correlation between insider trading days and abnormal returns. A selection bias exists because a part of the detection methodology used by the SEC is to examine days of abnormal price movements. Meulbroek (1992) overcomes this potential bias by dividing up her sample based on the method used to detect the illegality, noting that some forms of detection do not necessarily involve abnormal price movements as part of the detection criteria. Essentially her methodology involves identifying those observations in her sample that most closely resemble the non-detected sample of traders. Thus, she is able to divide her sample of insider trades into two groups - those likely to exhibit a bias in the same direction as her findings and those that are least likely to exhibit a bias.[74] A comparison between the two groups provides an indication of the extent of sample selection bias, if any.

Meulbroek (1992) recognises that there are numerous ways for an individual to be detected and prosecuted by the SEC. She uses confidential and unique referral data sourced from the SEC to ascertain how an individual is detected. Similar data are not available for the sample used in this study. Fortunately, an insight into the primary detection methodology can be found in Harris (2003). He states that large price and volume movements before an information announcement trigger suspicion (Harris, 2003, p588). After this the investigators compare lists of traders in that security with those that could know the information (Harris, 2003, p589). His description of the typical investigation procedure implies three potential criteria for detection – trading with concurrent abnormal price movements, trading with concurrent abnormal volume movements and trading with *apparent* access to the sensitive information.

Of course, not all insiders are detected in this fashion. Some are incidentally detected outside of this methodology. Using this fact, the sample is split into two groups based on the potential for bias, as per Meulbroek (1992). For each trade package in the sample, analysis is conducted to determine if one of the trades in that package corresponds to a day with abnormal price movements or abnormal volume. Following

[74] For more detail see Meulbroek (1992, p1679).

Meulbroek 'abnormal' refers to any value that is more than three standard deviations away from the mean, where mean and standard deviation benchmarks are calculated during the 150 days before the first trade by the insider in that security. Furthermore, all individuals classified as direct insiders are considered to satisfy the criteria of apparent access to non-public information. Extreme conservatism is used when assessing a trade package as having a low potential for sample selection bias. Therefore, any trade package that satisfies at least one of the three criteria is considered 'detected under normal SEC and exchange procedures' and has a high potential for sample selection bias.

Of the 296 trade packages, 185 are considered to be detected via the method described in Harris (2003). The remaining 111 observations are considered to have a low potential for sample selection bias. The log-linear regression is re-estimated for each sub-sample. However since the dummy variable, *direct insider*, is used to partition the sample it cannot be used in the regression. This is unproblematic since the variable had marginal significance in the first instance. The results of the regression are presented in Table 4.6.

The results indicate that there are only modest differences between the two sub-samples. In terms of sign, all coefficients are the same and in the direction predicted by the model. Sample selection bias, however, might affect the magnitude of the response to the determinants. Previous discussion of potential sample selection bias issues highlights *ln(price change)* as the variable that could be most affected by sample selection bias. In terms of magnitude, the coefficient value on *ln(price change)* is considerably larger for the low sample selection bias sample. This is actually contrary to *ex ante* expectations of how sample selection bias should affect the estimates. Interestingly, the low sample selection bias group appears to be about 2.5 times more sensitive to price changes, *ceteris paribus*.

Table 4.6
Sample selection bias

This table reports the coefficient estimates and t-statistics (in brackets) for the following regression:

$$\ln(volume) = \alpha + \beta_1 \ln(price\ change) + \beta_2 \ln(penalty) + \beta_3 \ln(std.\ dev.) + \beta_4 specialist + \beta_5 \ln(days_i) + \beta_7 specialist_i + \varepsilon$$

The first column presents the results from the regression using a sub-sample of trade packages deemed to have a high potential for sample selection bias. These observations are concurrent with abnormal volume or abnormal price movements of the security on the day, or are traded by an individual who is an employee, legal or financial consultant to the firm (*direct insider* = 1). The second column presents the results from the regression from the remaining observations which are deemed to have a low potential for sample selection bias.

	High potential for sample selection bias (n=185)	Low potential for sample selection bias (n=111)
Intercept	-3.84 (-7.70)*	-3.93 (-5.70)*
ln(price change)	0.35 (2.44)*	0.81 (3.48)*
ln(penalty)	-0.31 (-3.07)*	-0.46 (-3.68)*
ln(std. dev.)	-0.91 (-4.77)*	-1.11 (-4.11)*
Specialist	-0.70 (-2.39)*	-1.31 (-2.96)*
ln(days)	0.27 (2.39)*	0.08 (0.42)
F-Stat	11.09*	13.58*
Adjusted R^2	21.51%	36.38%

* Denotes significance at the 0.01 level
** Denotes significance at the 0.05 level

A Chow test is performed to formally test the overall differences in the coefficient values between the two models. The resultant test statistic is 0.87 (degrees of freedom 6, 284) which does not allow rejection of the null hypothesis that the coefficient values between the models are equal (*p-value* is 0.52). This is reassuring since it appears the conclusions with respect to how illegal insiders respond to key drivers of the model are not materially affected by sample selection bias.

4.5.2. Comparison to 'normal' trades

The results of Section 4.4 are not completely conclusive insofar as they may just reflect normal trading behaviour of which insider trading behaviour is a subset. For example, the results show that insiders trade less when engaging with specialists. It is unclear whether this is a general phenomenon of all trading or unique to illegal insiders. Essentially, the initial results are not able to distinguish between insider and normal trading behaviour, and therefore any implications drawn from these results may not be useful.[75]

To overcome this problem the analysis in Section 4.4 is repeated using a sample of matched trades which are not committed by illegal insiders. After pooling both insider trades (the treatment sample) and non-insider trades (the control sample), a regression is estimated that allows identification of the effect of the variables on insider volume *beyond what would otherwise occur with regular trades*.

For each announcement, a suitable control announcement is found which most closely resembles the features of the treatment announcement. Following Huang and Stoll (1996), Cao, Choe and Hatheway (1997) and Cao, Chen and Griffin (2005), matching is based on three primary criteria – price, volume and market capitalisation. An additional criterion is imposed that announcements of the same information type are matched to each other (i.e. treatment merger announcements are matched against a pool of other merger announcements) and also that the control announcement is made within one year of the treatment announcement. A list of merger and earnings announcements, sourced from Thomson DataStream, forms the pool of potential

[75] One of the first papers to incorporate non-insider trades into their analysis of insider trading behaviour is Park, Jang and Loeb (1995), p600. This issue is also raised by Chakravaty and McConnell (1999).

control announcements. For each unique announcement in the treatment sample, *i*, the following score is constructed for each potential control announcement, *j*:

$$score_{i,j} = \left(\frac{price_i - price_j}{\frac{price_i + price_j}{2}} \right)^2 + \left(\frac{volume_i - volume_j}{\frac{volume_i + volume_j}{2}} \right)^2 + \left(\frac{size_i - size_j}{\frac{size_i + size_j}{2}} \right)^2 \qquad (4.5)$$

where price, volume and size represent the daily averages of price, traded volume and market capitalisation over the period t = -200 to t = -100 (t = 0 is the announcement date). This benchmark period is consistent with Cao, Chen and Griffin (2005). The announcement which has the minimum score is chosen as the control announcement.

Once a suitable announcement is found, the entire stream of trades *x* days prior to the announcement are sourced from the Securities Research Centre for the Asia Pacific (SIRCA), where *x* corresponds to the closest integer value for the *days* variable of the particular package. A trade is drawn at random to match the insider's trades, with each trade in the sampling window having an equal probability of selection. For each matched trade, the dependent variable and the covariates ln(*price change)*, *ln(std. dev.)*, *ln(days)* and *specialist* are constructed in the same manner as for the treatment sample. The variables *ln(penalty)* and *direct insider* can be constructed for the control sample though their utility in regression analysis is questionable given that all observations in the control sample have the same value for these variables.

Consistent with the matching criteria, there is little difference in either the market capitalisation or trading activity between the treatment and control samples. The average market capitalisation of the firms in the treatment sample is $3.44 billion while for the control sample it is $3.51 billion. The average traded volume for the treatment sample is 426,300 shares while for the control sample it is 432,000 shares. The average score is 0.07 indicating that the cumulative difference over the three matching criteria is small. Overall, the control sample is a reasonable match to the treatment sample.

As a first test to determine the overall difference between the control and treatment samples the following restricted regression is estimated:

$$\begin{aligned} \ln(volume) = \alpha + \beta_1 \ln(price\ change) + \beta_2 \ln(std.\ dev.) + \beta_3 specialist \\ + \beta_4 \ln(days) + \varepsilon \end{aligned} \tag{4.6}$$

for the entire sample and for each sample of control and treatment samples. This regression omits the variables *ln(penalty)* and *direct insider*, since these variables exhibit zero variability (and therefore, perfect multicollinearity) for the control sample. The results of the regressions are presented in Table 4.7.

For the treatment sample, the results are broadly similar to those reported in Table 4.5. The value of the information and the number of days till the announcement date both have a positive effect on traded volume. Greater variability of asset returns and trading with a specialist have a negative effect on traded volume. In contrast, the results of the treatment sample indicate that greater changes in price of the asset have a negative correlation with traded volume, while the standard deviation of returns has a positive correlation with traded volume. The coefficient on *specialist* is negative but not significant at the 5% level. Only the coefficient on *ln(days)* exhibits the same sign and significance as in the treatment sample. A Chow test is estimated to ascertain whether the regression coefficients of the control sample exhibit overall similarity to the treatment sample. The F-statistic is 54.27, which rejects the null hypothesis of overall similarity between the samples at the 1% level. This provides evidence that the relationship between volume and the determinants is materially different between the control and treatment samples and lends greater support to the initial findings.

Table 4.7
Comparison of insider trades to non-insider trades

This table presents the results of the following regression:

$$\ln(volume) = \alpha + \beta_1 \ln(price\ change) + \beta_2 \ln(std.\,dev.) + \beta_3 specialist + \beta_4 \ln(days) + \varepsilon$$

The first column presents the results of the regression using the primary sample of 296 trade packages. The second column presents the results of the regression using a sample of trades matched to the primary sample. The matching procedure involves finding information announcements with similar price, volume and market capitalisation characteristics for the stock.

Variable	Treatment	Control
Intercept	-4.63	-5.95
	(-11.60)*	(-22.67)*
ln(price change)	0.27	-0.31
	(2.23)**	(-4.22)*
ln(std. dev.)	-1.17	0.48
	(-7.52)*	(5.06)*
Specialist	-0.62	-0.38
	(-2.52)**	(-1.70)
ln(days)	0.20	0.39
	(2.03)**	(4.26)*
Sum of squared residuals	1211.61	976.34
F-Stat	21.17*	14.40*
Adj. R^2	21.48%	15.51%

* Denotes significance at the 0.01 level
** Denotes significance at the 0.05 level

As a second test the following cross-sectional regression is estimated on the combined sample of treatment and control observations:

$$\begin{aligned}\ln(volume) = \alpha &+ \beta_1 \ln(price\ change) + \beta_2 \ln(std.\,dev.) + \beta_3 specialist_i \\ &+ \beta_4 \ln(days_i) + \beta_5 * D + \beta_6 \ln(price\ change)*D \\ &+ \beta_7 specialist_i*D + \beta_8 \ln(days_i)*D + \varepsilon\end{aligned} \tag{4.7}$$

where D is a dummy variable which equals 1 if the trade is part of the treatment sample and zero otherwise. Effectively these coefficients identify the incremental effect that a covariate has on volume if the trade is an illegal insider trade. The results are presented in column one of Table 4.8.

Table 4.8
Comparison of insider trades to non-insider trades II

This table reports the results of several regressions. The first regression specification is:

$$\ln(volume) = \alpha + \beta_1 \ln(price\ change) + \beta_2 \ln(std.dev.) + \beta_3 specialist_i$$
$$+ \beta_4 \ln(days_i) + \beta_5 D + \beta_6 \ln(price\ change)*D + \beta_7 specialist_i*D$$
$$+ \beta_8 \ln(days_i)*D + \beta_9 \ln(penalty)*D + \beta_{10} direct\ insider*D + \varepsilon$$

which is estimated on a sample representing 296 insider trading packages and a control sample of trades matched on announcement type, market capitalisation of security, traded volume and price.

Variable	**All**	**Matched pairs involving only one trade by insider**
Intercept	-5.95 (-21.48)*	-5.85 (-18.97)*
ln(price_change)	-0.31 (-4.00)*	-0.36 (-3.94)*
ln(std. dev.)	0.48 (4.79)*	0.47 (4.08)*
Specialist	-0.38 (-1.61)	-0.36 (-1.29)
ln(days)	0.39 (4.03)*	0.35 (3.14)*
D	1.32 (2.80)*	1.19 (2.30)**
*ln(price_change) * D*	0.57 (4.18)*	0.55 (3.60)*
*ln(std. dev)*D*	-1.64 (-9.22)*	-1.67 (-8.18)*
*Specialist * D*	-0.24 (-0.73)	-0.44 (-1.15)
*ln(days) * D*	-0.19 (-1.38)	-0.18 (-1.18)
n	592	436
F-statistic	32.56*	30.24*
Adj. R^2	37.06%	34.62%

* Denotes significance at the 0.01 level
** Denotes significance at the 0.05 level

There are several important findings. Firstly, the results reinforce the initial conclusions with respect to the price change variable. The coefficient on *ln(price change) * D* is positive, 0.57, and significant at the 1% level which indicates that insiders respond to greater expected returns by increasing their traded volume. This outcome stems from the fact that randomly selected trades exhibit a significant negative relationship between trade size and absolute price change following the announcement. This is to be expected given that there is likely to be a positive relationship between absolute price change and share price and, in the course of normal trading, there is a negative relationship between share price and trade size.

The second important finding is that the coefficient on *ln(std. dev.)* * *D* is negative and significant, consistent with the initial findings of Section 4.4. Perhaps the most surprising aspect of this result is that the control trades do not exhibit a negative relationship between asset variability and volume. This finding is somewhat at odds with standard portfolio theory, though it is important to note that the proxy for asset return variability (standard deviation) contains both the idiosyncratic and systematic components of risk, whereas portfolio theory only describes the relationship between systematic risk and overall position in a security. Importantly, in the period just before a significant stock specific information announcement, like a merger, it is reasonable to expect that the standard deviation of asset returns will primarily describe idiosyncratic rather than systematic risk. Therefore, the relationship between standard deviation and volume is uncertain *ex ante* and a finding of a positive correlation between the variables is not completely antithetical to portfolio theory.

Thirdly, the results indicate that the two variables which proxy for the detection function, *specialist* and *ln(days)*, are not incrementally significant for insider trades beyond what would be expected of normal trades. The coefficient on the *specialist* * *D* variable is however, in the expected direction and the total effect of trading by insiders in a specialist market (-0.38 + -0.24) is significant. Surprisingly, the coefficient on *ln(days)*D* is insignificantly different from zero, which suggests that the strong positive relationship between trade size and days to announcement documented in Section 4.4 is consistent with all types of trading, not just that of illegal insiders. While, few studies, if any, examine the relationship between trade size and days to announcement,[76] a large body of literature documents significant price increases before mergers and earnings announcements (e.g. Keown and Pinkerton, 1981; Dennis and McConnell, 1986; Jarrell and Poulsen, 1989; Morse, 1981). The slight positive relationship between trade size and days to announcement, therefore, might be explained by a general negative relationship between trade size and share price, and an increase in share price prior to the announcement. The net effect is that the significance of the initial finding is totally removed given that randomly selected trades also exhibit a similar positive relationship between the size of trades and days to announcement.

Fourthly, it appears that illegal insiders trade far larger quantities than non-insider traders, even when controlling for the additional determinants. The coefficient on the dummy variable is 1.32 and significant at conventional levels. This result, however, might be driven by the fact that the dependent variable for the treatment sample might represent multiple trades in a security[77], whereas the randomly selected trades of the control sample represent only one trade in a security. More broadly speaking, this feature might affect the preceding results since the dependent variable is biased

[76] However, many studies examine the changes in total volume prior to merger announcements and typically find significant increases in volume as the announcement day approaches (e.g. Jarrell and Poulsen, 1989; Pound and Zeckhauser, 1990; Schwert, 1996; Jayaraman, Frye and Sabherwal, 2001; Cao, Chen and Griffin; 2005).
[77] However, 219 observations, or approximately 74% of the treatment sample involve only one trade and 262 observations or 89% of the sample involve one or two trades.

upwards for the treatment sample. To further ensure the robustness of the results, the analysis is re-run with a sample that only includes those insider trading packages involving one trade in the security. There are 219 such observations in the treatment sample. The results are presented in column two of Table 4.8. The results of this analysis are not materially different from that discussed previously.

The results of this section indicate that the determinants of non-insider volume are not the same in an overall sense to the determinants of insider volume. This is evidenced by a Chow test which strongly rejects the hypothesis that the coefficients of Equation 4.6 are the same for the treatment and control samples. However, in a combined regression the results indicate that the variables which proxy for the detection function do not influence the volume traded by insiders any more than they would influence the volume traded by non-insiders.

4.6. Conclusion

This study is the first empirical research of illegal insider trading to examine the determinants of the volume traded by individuals who choose to commit this crime. Building upon the initial insights of Becker (1968) a model is developed which predicts that the volume traded by an insider is positively related to the value of their information and negatively related to the expected penalty. Furthermore, the model predicts that the volume traded by insiders is negatively related to the idiosyncratic risk of the asset for which they have non-public information.

The predictions of the model are tested on a sample of illegal insider trading cases drawn from the SEC website. Results indicate that there is a positive relation between subsequent price change in a security and the volume traded by insiders. The results also indicate that there is a negative relationship between imposed sanction and volume. This suggests that insiders trade off the costs and benefits associated with utilising their illegal information. Illegal insider traders are also sensitive to variability in asset returns and trade less as the value of their stock specific information becomes less precise. This is an interesting result since it suggests that, despite expectations, insiders do not possess information (or perceive that they possess information) that is completely certain.

The analysis also indicates that insiders trade less as the announcement day approaches and if they have a close connection through employment to the firm undertaking the information announcement. These initial results provide evidence that insiders tend to trade less as the announcement day approaches and also when they trade in specialist markets but the results of a final robustness test suggest that this phenomenon is typical of all trades in securities before an information announcement, not just for insider traders. As such, future research in this area might consider what determinants appropriately proxy for the probability of detection of illegal insider trading.

4.A. Appendix

Proposition 1. Assume $r \mid z = 1 \sim N(\mu + \Delta, \sigma^2)$ and $U(rz) = -\exp(-\lambda rz); \lambda > 0$, $P(s) = P(0)\exp(sv)$ and c is the fixed detection cost expressed as a return.

Then the optimal traded volume, s, is given by

$$s = \frac{(\mu + \Delta - P(0)c)}{\lambda\left(\sigma^2 + \frac{2P(0)cv}{\lambda}\right)}.$$

Proof ;

$$V(s) = \quad -\exp(-\lambda s(\mu + \Delta - c) + \frac{\lambda^2}{2}s^2\sigma^2)P(0)\exp(sv)$$

$$-\exp(-\lambda(\mu + \Delta) + \frac{\lambda^2}{2}s^2\sigma^2)(1 - P(0)\exp(sv))$$

$$V(s) = \quad -\exp(\frac{\lambda^2}{2}s^2\sigma^2 - \lambda s(\mu + \Delta))$$

$$(\exp(c\lambda s)P(0)\exp(sv)) + (1 - P(0))\exp(sv)$$

maximising this with respect to *s* is equivalent to minimising –V(s) or $\ln(-V(s))$ or maximising $-\ln(-V(s))$ so

$$-\ln(-V(s)) = \lambda s(\mu + \Delta) - \frac{\lambda^2}{2}(s^2\sigma^2)$$

$$-\ln(\exp((c\lambda + v)sP(0) + (1 - P(0))\exp(sv))$$

This is clearly non-linear in *s* but we can approximate the last term by Taylor's series first on exp(x) and then on $\ln(1 + x)$:

$$\ln((1-P(0))(1+sv+½s^2v^2)$$

$$+P(0)(1+(c\lambda+v)s+½(c\lambda+v)^2s^2))$$

$$=\ln(1+P(0)(c\lambda s)+½\mathrm{P}(0)(c^2\lambda^2+2\lambda cv)s^2).$$

Using

$$\ln(1+x)\approx x-\frac{x^2}{2}$$

$$\approx P(0)c\lambda s+½\mathrm{P}(0)(c^2\lambda^2+2\lambda cv)s^2$$

$$-½\mathrm{P}(0)c^2\lambda^2s^2$$

$$=P(0)sc\lambda+P(0)\lambda cvs^2.$$

It is possible to show:

$$-\frac{1}{\lambda}\ln(-V(s))=s(\mu+\Delta)-\frac{\lambda}{2}s^2\sigma^2$$

$$-P(0)cs=P(0)cvs^2$$

$$=s\lambda(\mu+\Delta-P(0)c)-\frac{\lambda^2}{2}s^2(\sigma^2+\frac{2P(0)cv}{\lambda})$$

This leads to:

$$s=\frac{(\mu+\Delta-P(0)c)}{\lambda\left(\sigma^2+\frac{2P(0)cv}{\lambda}\right)}$$

QED.

Chapter 5: Does Broker Anonymity Hide Informed Traders?

5.1. Introduction

The literature reviewed in Section 2.3.4 reveals that while the issue of broker anonymity in electronic markets has received considerable attention, the predominant research focus is limited to the effects of anonymity on market quality. Broker anonymity, however, may also affect the market beyond altering liquidity. The purpose of this essay is to examine how broker anonymity influences the transmission of information in securities markets. This study examines the change that occurred on the ASX on 28 November, 2005 when pre- and post-trade broker identifiers were removed from trading screens of the ASX. As noted previously, this study investigates the ability of informed traders to remain undetected in the lead up to takeover announcements and is the first study of broker anonymity to examine periods of large information asymmetry. This study provides three pieces of evidence that informed traders remain less detected after the switch to broker anonymity – a result which has important policy implications for market regulators deciding whether or not to reveal broker identifiers around trade.

The rest of this chapter is organised as follows: Section 5.2 presents the theory concerning the detection of informed trading and related hypotheses. Section 5.3 provides institutional detail on the market structure of the ASX and the exact changes to broker identification that occurred on 28 November, 2005. Section 5.3 also describes the data used in this study. In Section 5.4 the results of the analysis are presented. Section 5.5 includes additional tests, while Section 5.6 presents the conclusions of the study.

5.2. Hypothesis development

In this section, three hypotheses are outlined which allow for the determination of whether informed traders are more hidden after the removal of broker identifiers. These three hypotheses relate to the three metrics of informed trading discussed in Sections 2.3.1, 2.3.2 and 2.3.3. The first hypothesis relates to permanent price impact, and how an investigation of this metric at the broker level reveals the extent to which the identifier is used to distinguish informed and uninformed traders. The second hypothesis relates to the bid-ask spread and how this measure reflects informed trading in an electronic market where all traders can provide liquidity. Thirdly, the price impact of order imbalances and its connection with informed trading is discussed.

5.2.1. Dispersion in broker level permanent price impact

The price impact of a trade can be divided into two components: transitory and permanent (Kraus and Stoll, 1972). The transitory component measures the price impact associated with temporary liquidity constraints at the time of the trade. In contrast, the permanent component measures the longer lasting price impact of the trade. For this dissertation, the metric of interest is the permanent component of price impact because it can be used to ascertain the market's assessment of the information content of that order. Since broker identifiers are attached to all orders in the transparent regime, but not in the anonymous regime, a comparison of permanent price impact across regimes provides some insight into the information content of the identifiers, if any.

Consider two brokers, one which is perceived by the market to execute trades from informed traders, broker *I* and another broker *U*, which executes trades from uninformed investors. In terms of real world examples, broker *I* could fit the description of an institutional broker and broker *U* could be a discount internet broker catering mainly for retail investors. All other things being equal, the trades executed by broker *I* will have greater permanent price impact than those of broker *U*. Now consider the case where the market cannot identify the broker behind each trade and thus cannot use the incremental signalling value it provides. In this case, all other things being equal, the trades of broker *I* and broker *U* should have the same perceived information content and thus the same permanent price impact. Therefore, in the transparent regime, *assuming the broker identifiers have some informational value*, the dispersion in the average permanent price impact across brokers should be higher than in the anonymous regime. On the other hand, if the broker identifiers have no value then the dispersion should be similar across the regimes. By definition, if broker identifiers have informational value then the absence of these identifiers means that informed traders are more hidden after the change to anonymity. Therefore, an investigation of the dispersion in permanent price impact furthers the overall aim of this study – namely, whether the removal of broker identifiers hides informed traders.

Hypothesis$_{5.1}$: *In the lead up to takeover announcements the dispersion in permanent price impact across brokers is narrower after the switch to anonymity.*[78]

5.2.2. Bid-ask spread

It is well established that the bid-ask spread incorporates the risk associated with trading with an informed trader (Bagehot, 1971). Therefore, the magnitude of the bid-ask spread should be an increasing function of the probability of informed trading in the market (Copeland and Galai, 1983; Glosten and Milgrom, 1985; Easley and O'Hara, 1987). However, this relationship breaks down when liquidity providers and dealers incorrectly assess the probability of informed trading or at the extreme, fail to discern the presence of informed traders whatsoever. For example, Fishe and Robe (2004) show that NASDAQ dealers did not widen bid-ask spreads in the presence of trading by those who had foreknowledge of the influential *Business Week* stock analysis column, 'Inside Wall Street'. Therefore, assuming informed traders are active in a market, one can examine bid-ask spreads to determine the extent to which other market participants have detected informed traders. Indeed, Garfinkel and Nimalendram (2003) use bid-ask spreads as a means to determine the extent to which traders are recognised as informed on the NYSE compared to the NASDAQ.

The above reasoning applies when informed traders act as liquidity demanders in a market. However, the model outlined in Foucault, Moinas and Thiessen (2007) shows that in electronic order driven markets, the bid-ask spread is still a useful indicator of uninformed liquidity suppliers' beliefs concerning the presence of informed liquidity suppliers. Whether informed traders demand or supply liquidity, it is hypothesised

[78] Note this hypothesis does not require identification of which broker identifiers are associated with informed traders and which ones are not.

that, if informed traders are able to conceal their informed status as a result of broker anonymity, then other liquidity suppliers should factor in a lower adverse selection cost component into the spread and hence bid-ask spreads should fall.

Hypothesis$_{5..2}$: *The bid-ask spread of target firms in the lead up to the takeover announcement is lower in the anonymous broker regime.*

5.2.3. Order imbalance and returns

The third metric used to determine the extent to which informed traders are detected is the relationship between order imbalances and returns. Order imbalance is a measure of excess buyer over seller initiated trading in a given period. Easley, Kiefer, O'Hara and Paperman (1996) formalise the intuition that this measure can be used to ascertain the extent of informed trading in markets. Cao, Chen and Griffin (2005) show that contemporaneous and lagged order imbalances are positively related to stock returns prior to takeover announcements, providing empirical evidence that order imbalances are a manifestation of information transmission in markets.

Before outlining the hypothesis, it is important to note the inferential differences between order imbalances in a specialist or dealer market compared to a completely order driven market. At the most basic level, order imbalances are equivalent in either market structure – order imbalances measure the difference between liquidity demanded by buyers over liquidity demanded by sellers of securities. The primary difference between the markets is that in order driven markets public traders, rather than dealers, provide the liquidity. As such, there is an argument to suggest that the term order imbalance, in the context of order driven markets, is a misnomer and therefore uninformative, since ‘for every buyer there is also a seller’. This view is not adopted in this study, but it is important to note the difference in interpretation of order imbalances in an order driven market *vis-à-vis* specialist or dealer markets.

In an order driven market, order imbalance represents the magnitude of excess buy *market* orders over sell *market* orders. This metric is not completely uncorrelated with the extent of informed trading in the market, since it can be argued that informed traders are more likely to use market orders, rather than limit orders, to rapidly utilise their information before others trade on the same information (Conroy and Winkler, 1981; Glosten, 1994; Harris, 2003). This might be particularly the case in the period leading up to takeover announcements where it is likely that a larger group of individuals (employees of the target, the bidder and the corporate and legal advisors for both parties) possess the price sensitive information, compared to announcements for a single company (such as earnings announcements for example). If market orders are in general correlated with informed trading during the periods analysed in this study, and broker anonymity impairs the discovery of informed traders then this can manifest itself in two ways within the order imbalance-return relationship. Firstly, for a given return, if uninformed traders cannot discern which trades are informed then they are less likely to trade in the same direction as informed traders, reducing the level of order imbalance. Alternatively, for a given order imbalance, trades by informed individuals should incur a smaller permanent price impact if anonymity means that the market does not correctly interpret the information content of their trades. In either case, the correlation between order imbalance and returns should be weaker when informed traders are hidden due to broker anonymity.

Hypothesis$_{5.3}$: *In the lead up to a takeover announcement, the relationship between order imbalances and returns for target firms is weaker in the anonymous broker regime.*

5.3. Institutional detail and data

The ASX operates a centralised electronic limit order book similar to other prominent exchanges in Europe (e.g. Euronext) and Asia (e.g. Tokyo Stock Exchange, Hong Kong Stock Exchange and Korea Stock Exchange). The market opens with a call auction and thereafter all trading is conducted via a continuous order driven auction, until the close of the day when another call auction is used to set the closing price. During normal trading, brokers submit orders with size and price conditions which are matched with an order(s) on the opposite side of the book, if possible, otherwise they remain in the limit order book. Orders with the most competitive price are executed first and where prices are the same, orders that were submitted first have precedence. Prior to 28 November, 2005 brokers were able to see broker identifiers of other limit orders as well as the broker counter parties to a trade after a transaction occurred. Since the change to an anonymous regime, all pre-trade identifiers have been removed. In terms of post-trade information, participants can obtain, for a fee, an aggregated summary of each broker's transactions after the close of trading. The summary provides the total volume per broker per security traded on that day. Complete trade by trade broker counterparty information, formerly reported immediately after the trade, is now only available three trading days after the initial transaction. The purpose of this study is to investigate how this change in the disclosure of pre- and post-trade broker identifiers allows informed traders to conceal themselves from other market participants. This research investigates the ability of the market to detect informed trading in the forty days prior to takeover announcements announced two years either side of the transparency shift on 28 November, 2005.

A list of merger and takeover announcements is obtained from Thomson DataStream and supplemented by another list obtained from Bloomberg. To ensure the cleanliness of the pre-announcement period, where a firm has been the subject of multiple takeover offers, only the first announcement in the list is considered.

The intraday trade and quote data used in this study is obtained from two sources: the Securities Institute Research Centre of Asia-Pacific (SIRCA) and the internal database of the ASX. Both data sets include the price, size and time of every trade for each firm in the sample. Trades that occur during the opening and closing call auctions are excluded from the sample. The SIRCA data set provides best quotes that prevailed immediately before each trade (required for the calculation of trade direction), while the ASX data provides the broker counterparties to each trade. The SIRCA data set covers a period that allows analysis of all takeover announcements made two years either side of the transparency change – 28 November, 2003 to 28 November, 2007.[79] This dataset is used to test Hypothesis 5.2 and Hypothesis 5.3. The data set sourced internally from the ASX covers only one year either side of the change, 28 November, 2004 to 28 November, 2006. This data set is merged with the SIRCA data set and is used to test Hypothesis 5.1.

If a trade is executed at the prevailing ask price (or greater if the order walks up the book) then the trade is classified as buyer-initiated. Seller-initiated trades are

[79] The actual data set sourced from SIRCA spans a period slightly longer than four years, since the analysis also requires 150 days of trading data prior to the announcement in order to calculate various benchmarks for volume and returns.

classified in a similar way. Unlike studies conducted in U.S. markets, trade classification via an algorithm, such as Lee and Ready (1991), is unnecessary since the structure of the ASX requires that trades are executed against existing standing limit orders. Therefore, there is less ambiguity with respect to whether a trade is buyer- or seller-initiated, with all trades classified accurately.

The primary period of analysis for this study is the 40 days prior to the takeover announcement not including the day of the takeover announcement (hereafter, the 'pre-announcement period'). However, intraday trading data up to 150 days prior to the announcement is also required to determine benchmark metrics for the calculation of abnormal volume and returns. The benchmark period in this analysis is from days *t=-50* to *t=-150*, where *t=0* is the day of the announcement. A target firm is purged from the sample if it does not have at least 20 days of trading during the pre-announcement period or at least 50 days of trading during the benchmark period. Ten firms whose pre-announcement period spans both the transparent and anonymous regimes are excluded from the main analysis. These firms are kept aside for an additional robustness test to ascertain whether the observed results are caused by the switch to anonymity or by broader market trends. After all filters are applied, this leaves a total of 258 takeover targets over the period 28 November, 2003 to 28 November, 2007. Of this final sample 95 were announced in the transparent broker regime and 163 announcements occurred in the anonymous broker regime. For the restricted ASX sample used to test Hypothesis 5.1, there are 178 takeover targets, 68 in the transparent regime and 110 in the anonymous regime.

Table 5.1
Summary statistics

This table reports summary statistics of the takeover targets in the sample. *Market capitalisation* is the average daily market capitalisation of the firm during the 'benchmark period' (days t = -150 to t = -50 where the announcement date is t = 0). *Daily trading volume* is the average daily number of shares traded in the firm's stock during the 'pre-announcement' period (days t = -40 to t = -1). *Trade Size* is the average size of each trade during the pre-announcement period. Daily volatility is the average daily value of $(High - Low)/(High + Low) \div 2$ for each firm. *Pre-announcement return* is the simple return over the pre-announcement period. *Post-announcement return* is the return from days t = 0 to t = 2.

Panel A: All takeovers (n=258)	Mean	Median	Max	Min	Std Dev
Market capitalisation (pre-runup, $millions)	736.65	112.85	15893.96	2.12	1780.48
Daily trading volume ('000s shares)	2610.10	968.04	34799.58	2.79	47840.80
Trade size ('000s shares)	13.31	6.96	180.94	0.14	21.11
Daily volatility (%)	3.31	3.00	12.68	0.61	1.73
Pre-announcement return (%)	6.61	4.68	121.30	-80.52	20.63
Post-announcement return (%)	9.10	4.77	79.37	-14.99	14.00
Panel B: Transparent Regime (n=95)	Mean	Median	Max	Min	Std Dev
Market capitalisation (pre-runup, $millions)	686.44	140.81	7408.82	6.52	1373.95
Daily trading volume ('000s shares)	2465.07	1157.61	29926.35	2.79	4279.17
Trade size	13.90	8.42	117.35	0.63	19.41
Daily volatility	2.98	2.70	12.68	0.80	1.71
Pre-announcement return (%)	7.26	3.12	121.30	-80.52	21.44
Post-announcement return (%)	8.11	2.56	79.37	-14.68	14.22
Panel C: Anonymous Regime (n=163)	Mean	Median	Max	Min	Std Dev
Market capitalisation (pre-runup, $millions)	765.92	106.80	15893.96	2.12	1982.78
Daily trading volume ('000s shares)	2694.62	806.54	34799.58	4.32	5067.10
Trade size	12.96	6.10	180.94	0.14	22.09
Daily volatility	3.51	3.26	9.14	0.61	1.72
Pre-announcement return (%)	6.23	5.54	89.33	-50.49	20.20
Post-announcement return (%)	9.96	6.34	54.19	-14.99	13.56

Summary statistics of the target firms for the entire sample are presented in Table 5.1. The statistics indicate that the nature of the takeover firms is not materially different between the two sample periods. The mean value for market capitalisation of the firms (calculated by taking the average daily market capitalisation in the benchmark period) is reasonably similar between the regimes, taking the value of $686.44 million in the transparent environment compared to $765.92 million in the anonymous environment. This is important since firm size is correlated with a number of important metrics such as the level of informed trading (Hasbrouck, 1991), the bid-ask spread (Roll, 1984) and the magnitude of the stock price to volume relationship (Breen, Hodrick and Korajczyk, 2002). This makes it less likely that results are driven by differences in the characteristics of the firms across the two regimes. The daily pre-announcement traded volume during both periods is similar, with a mean value of 2,465,070 shares in the transparent regime compared to 2,694,620 shares in the anonymous regime. Again, this is a reassuring statistic since overall trading activity is a known determinant of bid-ask spreads (Demsetz, 1968; McInish and Wood, 1992) and price impact (Breen, Hodrick and Korajczyk, 2002). Other potential indicators of informed trading such as trade size and volatility are also similar between the two trading environments. In the transparent (anonymous) period the mean trade size is 13,900 (12,960) shares and the average daily volatility is 2.98% (3.51%).

There is a difference in the ratio of pre-announcement and post-announcement stock abnormal return before and after the structural change. The ratio between mean pre- to post-announcement abnormal returns is higher when broker identifiers are visible (0.89) compared to when they are anonymous (0.63). This result provides the first indication that informed traders are generally more hidden after the switch to an anonymous regime since less of the overall abnormal stock return occurs before the announcement is made. This issue is examined with greater rigour in the following section by examining bid-ask spreads, the order imbalance to return relationship and the dispersion in permanent price impact using univariate and multivariate analyses.

5.4. Empirical results

5.4.1. Dispersion in permanent price impact across brokers

This section documents the dispersion in broker level permanent price impact and compares this metric between the two regimes. For each buyer-initiated market order in the sample[80], indicated by the subscript *i*, the permanent price impact is calculated as:

$$Permant\ Price\ Impact\ (or\ PPI_i\ ) = \frac{P_{i,t=+5} - P_{i,t=-5}}{P_{i,t=-5}} \tag{5.1}$$

where $P_{i,t}$ represents the midpoint of the bid-ask spread at time *t*, which denotes the trade relative to the trade of interest $P_{i,t=0}$.[81] Since an important determinant of price impact is the size of the trade, trades are divided into four relative trade size groups. This is accomplished by first calculating each stock's median trade size during the pre-announcement period and then comparing each trade to the median value:

$$Relative\ Trade\ Size = \frac{Trade\ Size}{Median\ Trade\ Size} \tag{5.2}$$

Trade size groups are defined as follows: *Group 1* contains all trades where *Relative Trade Size (RTS)* < 1; *Group 2* contains all trades where 1 ≤ *RTS* < 2; *Group 3* contains all trades where 2 ≤ *RTS* < 5 and Group 4 contains all trades where *RTS* ≥ 5.[82] The variable of interest is the average permanent price impact per broker, *b*, per trade size group, *g* subdivided by the two market structure regimes, denoted by the Bernoulli variable *d* (*d*=0 for the transparent broker regime):

---

[80] Only buyer-initiated orders are considered to restrict the sample to trades which can be motivated by information. An assumption is made that seller initiated trades prior to a takeover announcements are not informed trades.

[81] For robustness, alternative specifications are considered, where the permanent price impact is calculated from *t=-10* to *t=+10*, from *t=-1* to *t=-5* and from *t=open* to *t=close*. The conclusions drawn from the results of these alternate specifications are not different. Thus only the results from *t=-5* to *t=+5* are presented.

[82] These values are chosen to approximately represent the following percentile groups: Group 1 – 0 to 50th percentile; Group 2 – 50th to 75th percentile; Group 3 – 75th to 90th percentile; Group 4 – 90th to 100th percentile. Other cut-off values are considered with similar results.

$$\frac{\sum_{i=1}^{N(i_{b,g,d})} PPI_{i,b,g,d}}{N(i_{b,g,d})} = \overline{PPI}_{b,g,d} \tag{5.3}$$

where $N(i_{b,g,d})$ equals the number of market-order buys initiated by broker *b*, falling into trade size group *g*, in market structure regime *d*. The dispersion characteristics of this value are compared between different transparency regimes. Two measures of dispersion are used. The first measure is the standard deviation (or its square, the variance) of average permanent price impact across brokers. Differences between the regimes are tested using the traditional F-test for equal variances.

The second measure of dispersion, developed by Fligner and Killeen (1976), is a non-parametric measure which utilises the ranks of the absolute deviates from the median, $\left|\overline{PPI}_{b,g} - Median(\overline{PPI}_{b,g})\right|$. Once ranked, the variables are transformed into scores according to $s_{b,g} = \left[\Phi^{-1}\left(\frac{N(b_g)+1+r_{b,g}}{2(N(b_g)+1)}\right)\right]^2$, where Φ is the function for the standard normal distribution, $N(b_g)$ is the number of brokers which executed trades of size *g* and $r_{b,g}$ is the rank of broker *b*'s absolute deviate from the median for size group *g*. The Fligner-Killeen (1976) test statistic (*FK*) is calculated by summing these scores across the transparent regime, $FK_g = \sum_{b=1}^{N(b_{g,d=0})} s_{b,g}$. Following Donnelly and Kramer

(1999), the z-approximation of the *FK* statistic is calculated.[83] The Fligner-Killeen test is preferred to the traditional F-test for equal variances, since the F-test is very sensitive to non-normality (McGrath and Yeh, 2005). Furthermore, the Fligner-Killeen test accounts for differences in scale of the underlying comparison variables. Finally, Donnelly and Kramer (1999) show that the Fligner-Killeen (1976) is superior to a number of other tests for equal dispersion in terms of maintaining an appropriate balance between Type I and Type II error rates. Nevertheless, the traditional F-test is included for completeness.

Table 5.2
Dispersion in permanent price impact across brokers

This table reports the standard deviation of permanent price impact across brokers according to the size of the trade. The trade size groups are defined as such: *Group 1* contains all trades where *Relative Trade Size (RTS)* < 1; *Group 2* contains all trades where 1 ≤ *RTS* < 2; *Group 3* contains all trades where 2 ≤ *RTS* < 5 and Group 4 contains all trades where *RTS* ≥ 5 where *RTS* is defined as the size of the trade divided by the median trade size in the pre-announcement period. The table reports the F-statistic for the test of equal variances and the z-approximation to the Fligner-Killeen statistic for equal dispersion. Both tests are unidirectional tests against a null hypothesis of equal dispersion between the regimes.

	Transparent Regime		Anonymous Regime		Test of Differences	
	Std. deviation (bp)	No. of brokers	Std. deviation (bp)	No. of brokers	F statistic	Fligner-Killeen statistic
All	32.34	73	27.72	77	1.36	1.67**
Group 1	39.95	68	29.34	76	1.86*	1.81**
Group 2	47.37	70	23.58	75	4.02*	3.09*
Group 3	46.88	68	25.46	74	3.39*	2.75*
Group 4	40.77	51	25.01	75	2.66*	1.65**

* Denotes significance at the 0.01 level
** Denotes significance at the 0.05 level

Table 5.2 reports the results of both tests for equal dispersion. The results indicate that the standard deviation of permanent price impact across brokers experiences a

[83] $z = \frac{FK_g - E(FK_g)}{\sqrt{Var(FK_g)}}$ where $E(FK_g) = N(b_{g,d=0}) * \overline{s_g}$, $\overline{s_g}$ is the average score for trade size group *g* and $Var(FK_g) = \frac{N(b_{g,d=0}) * N(b_{g,d=1})}{(N(b_g)-1) * N(b_g)} * \sum_{b=1}^{N(b_g)} \left[s_{b,g} - \bar{s}_g \right]$.

reduction from 32.34 basis points to 27.72 basis points. This reduction is not significant at the 5% level based on the traditional F-test (*p-value* is 0.09) but exhibits significance at that level based on the Fligner-Killeen (1976) test. When stratified by trade size group, the dispersion of permanent price impact between brokers is lower after the switch to broker anonymity. The results are significant at the 1% level for all groups except *Group 1* and *Group 4* under the Fligner-Killeen (1976) test, where the test statistics are significant at the 5% level. The greater dispersion in permanent price impact across brokers in the transparent regime suggests that broker identifiers have incremental signalling value when they are visible to the market in the lead up to takeover announcements.

The incremental signalling value appears to be greatest for the intermediate trade size groups (*Groups 2 and 3*) which possess the largest test statistics under both dispersion tests. This might be expected given the information asymmetry potential of medium-sized trades. Barclay and Warner (1993) show that 'medium sized' trades rather than large trades are perceived by the market to contain the greatest information value, though of course, not all medium-sized trades are motivated by information. Indeed Chakravaty (2001) shows that it is not medium-sized trades *per se* that generate permanent price movements, but rather, medium-sized trades initiated by institutional investors that alert other participants to the presence of informed trading. Given this uncertainty for medium-sized trades, it might be possible that the broker identifiers are used to distinguish medium-sized trades which originate from institutional investors (and are therefore more likely to represent informed trading), against those which are less likely information motivated. The data do not allow for an exploration of this hypothesis, since the broker identifiers are simply alpha-numerical codes and cannot be linked (by the researcher) to institutional investors. Nevertheless, the results of this section suggest that broker identifiers possess informational value. As such, informed traders are more concealed after the change to an anonymous broker market.

5.4.2. Bid-ask spread

Table 5.3 compares the magnitude of bid-ask spreads between the two broker identification regimes. Using univariate analysis, there is mixed evidence that spreads have declined, and therefore informed traders are less detected, after the switch to anonymity. Bid-ask spreads are sampled immediately before each trade for a given security in a given day. The volume weighted average of these observations is then used as a measure of the stock's percentage bid-ask spread for that day. After pooling these daily measures across all stocks and all days, the mean and median of the daily percentage bid-ask spreads are calculated. The results are presented in Table 5.3 as well as parametric and non-parametric tests for differences between the regimes. Univariate analysis provides mixed evidence for Hypothesis 5.2. Both mean and median daily percentage spreads are lower in the post period. The mean (median) percentage bid ask spread decreases from 1.70% (1.24%) in the transparent regime to 1.67% (1.11%) in the anonymous regime. A one way t-test indicates that daily percentage bid-ask spreads are not significantly lower at the 5% level after the switch to anonymity. However, a non-parametric Wilcoxon two-sample rank sum test indicates that daily percentage bid-ask spreads are significantly lower in the anonymous period. The z-statistic approximation to the Wilcoxon statistic is 3.87 which is significant at the 1% level.

To further investigate the robustness of these univariate results, the change in the adverse selection component of the spread is also examined. This analysis is performed because the theory underpinning Hypothesis 5.2 is that liquidity suppliers are less able to detect informed trading in an anonymous regime and therefore factor in a lower adverse selection component into the bid-ask spread. Statistics examining total bid-ask spreads might therefore be capturing changes in some other aspect of the spread (inventory holding or order processing) that is unrelated to adverse selection and as such uninformative about the hypothesis. The adverse selection cost component of the bid-ask spread is calculated using the method developed in Lin, Sanger and Booth (1995) and subsequently applied to an electronic limit order market in Brockman and Chung (1999). The adverse selection component is calculated by estimating the following regression for each firm over the entire 40 day pre-announcement period:

$$\Delta Q_{t+1} = \lambda z_t + e_{t+1} \tag{5.4}$$

where Q is the natural log of the bid-ask spread midpoint, z is the natural log of the difference between the transaction price and the bid-ask spread midpoint and e is a normally distributed error term. The coefficient on z, λ, measures the adverse selection component of the bid-ask spread. Table 5.3 presents the calculated values of the adverse selection cost component, averaged across the number of firms in the respective regime, before and after the switch to broker anonymity. The results indicate that the mean (median) adverse selection component decreases from 32.09% (32.21%) to 27.26% (26.82%) in the anonymous period. The adverse selection cost component is significantly lower at conventional levels when assessed using a t-test or a Wilcoxon two sample rank sum test. The results suggest that informed traders are not as easily detected after the removal of broker identifiers since liquidity suppliers do not incorporate as large an adverse selection cost component into the bid-ask spread.

Table 5.3
Bid-ask spreads: Univariate analysis

This table reports the mean and median of the volume weighted average daily percentage bid-ask spread as well as the mean and median adverse selection cost component of the spread. This table also reports tests of the hypothesis that the value in the transparent broker identifier regime is larger than the value in the anonymous broker identifier regime (one-tailed test). The difference is tested using a parametric t-test and a non-parametric Wilcoxon test.

	Mean		Median		Tests for differences	
	Transparent	Anonymous	Transparent	Anonymous	T-test	Wilcoxon
Percentage bid-ask spreads (%)	1.71	1.67	1.24	1.11	1.09	3.87*
Adverse selection component (%)	32.09	27.26	32.21	26.82	2.65*	2.94*

* Denotes significance at the 0.01 level
** Denotes significance at the 0.05 level

Finally, to ascertain the extent to which informed traders go undetected by liquidity suppliers in the market in a multivariate setting the following pooled cross-sectional regression is estimated:

$$PBAS_{jt} = \beta_0 + \beta_1 * D_{jt} + \beta_2 * Volume_{jt} + \beta_3 Volatility_{jt} + \sum_{i=1}^{3} \gamma_i * Size_{jti} \qquad (5.5)$$

PBAS is the volume weighted daily proportional bid-ask spread for firm *j* on day *t*, where as previously, the bid-ask spread is sampled immediately before each trade. The dummy variable, *D*, takes the value 0 during the transparent regime and 1 during the anonymous regime. Volume, volatility and market capitalisation variables are also included in the regression specification as control variables (McInish and Wood, 1992). *Volume* is the firm's turnover for the day. *Volatility* is defined as the natural log of the day's price range divided by the closing price. To avoid contamination from the stock run up that occurs during the pre-announcement period, firm size is calculated by averaging the daily market capitalisation of the firm over the benchmark period. The firms are then ranked and placed into four groups based on quartile ranking. The quartile cut-off values are \$41.92 million (25th percentile), \$112.85 million (50th percentile), \$507.38 million (75th percentile) and \$15,894 million (100th percentile). In the regression, γ_i is equal to one if the firm is in size quartile *i* and zero otherwise. To correct for possible endogeneity problems, two-stage least squares regression is employed where the instrument variables are the lag of the dependant variable and the average trade size for stock *j* on day *t* (Maher, Swan and Westerholm, 2008).

Table 5.4
Bid-ask spreads: Multivariate analysis

This table reports the coefficient values and t-statistics in brackets of a two-stage least squares regression of daily median percentage bid ask spread on the following variables: *D* is a dummy variable which takes a value of one during the anonymous broker regime and zero otherwise; *Volume* is the firm's turnover for the day; *Volatility* is defined as the natural log of the day's price range divided by the closing price. *Size 2nd Q* is a dummy variable which takes the value of one if the firm falls within the second quartile of firms by market capitalisation and zero otherwise. *Size 3rd Q* and *Size 4th Q* are similarly defined. The instrument variables for this regression are the lag of the dependant variable and the average trade size for stock *j* on day *t*. The regression is estimated using daily trading data from the forty days prior to 252 takeover announcements. The regression is also estimated using various sample subsets partitioned according to proximity to the announcement date. The relevant hypothesis is whether the coefficient on the anonymity switch dummy variable is significantly less than zero, i.e. H_a: $\beta < 0$. With respect to this alternative hypothesis, all anonymity switch dummy variable coefficients reported in this table are significant at the 1% level.

	Days -40 to -1	Days -10 to -1	Days -20 to -11	Days -30 to -21	Days -40 to -31
Intercept	21.12	24.85	22.89	19.82	18.73
	(18.16)	(7.45)	(9.71)	(10.31)	(8.01)
D	-1.13	-1.29	-1.00	-0.85	-1.44
	(-9.27)	(-3.91)	(-4.42)	(-4.45)	(-5.50)
Volume	-424.56	-566.30	-498.69	-342.95	-362.29
	(-10.99)	(-4.71)	(-5.58)	(-6.41)	(-5.33)
Volatility	4.78	(5.80	5.31	4.67	3.83
	(14.60)	(6.51)	(8.12)	(8.29)	(5.50)
Size 2nd Q	-0.45	0.24	-0.45	-0.03	-1.30
	(-2.08)	(0.47)	(-1.13)	(-0.09)	(-2.28)
Size 3rd Q	-0.16	0.77	0.10	0.36	-1.39
	(-0.65)	(1.22)	(0.20)	(0.78)	(-2.25)
Size 4th Q	0.36	1.36	0.89	0.84	-1.07
	(1.23)	(1.76)	(1.52)	(1.56)	(-1.57)
n	8505	2100	2159	2110	2136
Adj. R^2	43.61%	39.98%	36.02%	40.93%	38.12%

The results of the regression are presented in Table 5.4. The table reports results based on the entire pre-announcement period and for robustness, sub-groups of observations according to proximity to the announcement date.

The results indicate that after controlling for volatility, volume and firm market capitalisation, during the pre-announcement period, bid-ask spreads are smaller in the anonymous broker regime. The coefficient on the anonymity dummy variable is negative and significant and indicates that spreads are 113 basis points per trade lower when broker identifiers are hidden (Table 5.4, column 1). This suggests that liquidity suppliers are not price protecting as aggressively and that informed traders are therefore, more concealed after a switch to broker anonymity.

An analysis of the results based on the time to the announcement date indicates that this result is robust across the pre-announcement period. The magnitude of the coefficient on the dummy variable is greatest in the period furthest away, that is 40 to 31 days, prior to the announcement (Table 5.4, column 5). The value of the coefficient is negative 144 basis points. The results of the three other sub-periods are lower in magnitude than this ranging between a reduction of 129 basis points to 85 points. This result indicates that in the anonymous market, despite the fact that there is less detection of informed trading as indicated by the negative coefficient on the dummy variable, the ability of informed traders to remain hidden is lower in the final thirty days leading up the announcement compared to the days -40 to -31. This might be because other indicators, unrelated to broker identifiers, such as rumours, volume or price run-ups reveal the presence of informed traders to the market and these indicators are more prevalent closer to the announcement date. Alternatively, it is possible to argue that there is negligible informed trading in the period -40 to -31 during the anonymous regime and the result in this period is driven not by a lack of detection, but a lack of informed trading whatsoever. To ensure the robustness of the results, the analysis is re-estimated with only a 30 day pre-announcement window. The coefficient on the broker anonymity dummy variable is negative (-1.02) and significant at the 1% level. Therefore, the conclusions remain unchanged.

5.4.3. Order imbalance and returns

This part of the analysis tests the sensitivity of daily returns to contemporaneous order imbalances. The following pooled cross-sectional regression is estimated:

$$\begin{aligned} R_{jt} &= \beta_0 + \beta_1 * D_t + \beta_2 * OI_{jt} + \beta_3 * OI_{jt} * D_t + \\ &\sum_{i=1}^{3} \gamma_i * Size_{jti} + \sum_{m=1}^{4} \phi_m * Day_m + \sum_{k=1}^{5} \lambda_k R_{it-k} + \varepsilon \end{aligned} \tag{5.6}$$

where R_{jt} and OI_{jt} represent the standardised beta-adjusted excess return[84] and standardised order imbalance respectively of firm j on day t, and D_t is a dummy variable which takes the value of one if the day falls on or after 28 November, 2005 and zero otherwise. Included within the regression are dummy variables to control for the effect that firm size and day of the week might have on excess returns. Finally the specification also includes five lags of the dependent variable to control for possible autocorrelation in excess returns. Following Cao, Chen and Griffin (2005) both excess returns and order imbalances are standardised by the mean and standard deviation of the variables over the benchmark period. Specifically, the dependent variable is the excess return standardized by the standard deviation of excess returns during the

[84] Each firms' beta is calculated by estimating the market model of returns over the benchmark period.

benchmark period. Order imbalance is calculated by first taking the difference between the number of buyer-initiated market orders and the number of seller-initiated market orders for a given day then dividing by the average volume over the benchmark period. The variable is then standardised using its mean and standard deviation during the benchmark period. The standardisation allows observations from different firms, with potentially divergent return and volume characteristics, to be more suitably combined in a pooled cross-sectional regression.

Table 5.5
Order imbalance and returns

This table reports the coefficients and t-stats, in brackets, of the variables of interest from Equation 5.5. The dependent variable is the beta-adjusted daily excess return standardised by the variable's standard deviation over the benchmark period. *D* is a dummy variable which takes a value of one during the anonymous broker regime and zero otherwise. *OIjt* is the standardised daily order imbalance or the total volume imbalance. The relevant hypothesis is whether the coefficient on the interaction variable $OI_{jt} * D$ is significantly less than zero, i.e. H_a: $\beta < 0$. With respect to this alternative hypothesis, both coefficients of $OI_{jt} * D$ reported in this table are significant at the 1% level.

Variable	Order imbalance	Volume imbalance
Intercept	0.018	-0.009
	(0.06)	(-0.03)
D	0.351	0.437
	(1.40)	(1.71)
OI_{jt}	0.244	0.327
	(28.90)	(26.98)
$OI_{jt} * D$	-0.032	-0.193
	(-2.59)	(-13.52)
n	8116	8116
Adjusted R^2	14.73%	11.43%

The results of the regression are presented in Table 5.5. The results indicate that in both regimes greater order imbalance leads to larger returns. The coefficient on OI_{jt} is positive and significant at 0.351 which indicates that when order imbalance is one standard deviation greater than its benchmark, mean excess returns are 0.351 standard deviations greater than zero. This result is consistent with the notion that excess buying conveys positive information about the firm. However, as indicated by the coefficient on the interaction variable $OI_{jt}*D$, -0.032, this relationship is significantly weaker when broker identifiers are anonymous. During the anonymous broker regime *vis-à-vis* the transparent market, similar levels of order imbalance do not lead to as large a price movement in target firms prior to the takeover announcement. This might be because, for a given return, other traders do not trade as much in the same direction as informed traders or, for a given imbalance, there is a lower permanent price impact after buying (or both). In any case, it appears that the market does not respond as strongly to trading which suggests that a takeover announcement is imminent, after the removal of broker identifiers. To test the robustness of these results the same regression is estimated using total volume imbalance, rather than order imbalance (which disregards the magnitude of the trades). The results based on volume imbalance provide corroborating evidence that the switch to an anonymous broker market impairs the ability of the market to detect informed trading.

5.5. Additional tests

One argument that can be made against any research that investigates the effects of a one-off change to market structure is that the results could be driven by broader market trends over the sample period rather than being directly related to the structural change.[85] Applied specifically to this study, this argument questions whether the results of the preceding analysis are driven by the change in broker anonymity or, alternatively, gradual changes to the various metrics being analysed. For example, it is well accepted that bid-ask spreads decrease over time, casting doubt over the results presented in Section 5.4.

[85] See Majois (2007) for a critique of natural experiments methodology.

A second criticism that can be laid against the findings in Section 5.4 is that the results indicate a reduction in informed trading, rather than impaired detection. For example, the adverse selection component of bid-ask spreads might be lower in the anonymous regime because there are less informed traders, not because the market has become less efficient at detecting informed traders. This might occur because the market information asymmetry is decreasing over time, or there is something particular about the takeovers in the anonymous regime, relative to the transparent regime, that lends itself to having less information asymmetry. One counter argument to this supposition is that the *ex ante* expectation of increased broker anonymity is *greater* information asymmetry rather than less. Indeed Rindi's (2008) model of information acquisition and transparency predicts that broker anonymity is correlated with more informed traders, since the benefits of becoming informed are larger in an anonymous market. Therefore, if any bias exists it is likely to be directed against the findings of this essay. This however, is only a theoretical objection.

To address both criticisms empirically, the ten firms whose 40 day pre-announcement period straddles the change to an anonymous regime on 28 November, 2005 are examined. These firms were excluded from the original analysis. The sample period of this subset of firms is 71 trading days from 11 October, 2005 to 20 January, 2006. The rationale for analysing this sample is that these firms span the shortest possible time frame for which there is still variation in the transparency of broker identifiers, thereby minimising the effect of any gradual improvement in liquidity while still making it possible to perform the analyses conducted in Section 5.4.

In terms of the second criticism, it is expected that the level of information asymmetry within a particular event is relatively constant throughout the pre-announcement period. At the very least, the intra-event variation in information asymmetry is likely to be less than inter-event variations in information asymmetry. As such, analysing these ten firms minimises the possibility that the results are driven by changes in the level of information asymmetry.

As per the analysis in Section 5.4, the dispersion in permanent price impact across brokers is calculated for this robustness sample. Since the number of firms is much smaller than the main analysis, there are many brokers which only execute a handful of trades in these ten securities. To ensure that there is an appropriate representation of the average information content of a given broker's trades, brokers who execute less than 15 trades in these ten securities are not considered for analysis. This leaves a total of 20 active brokers in the transparent regime and 18 in the anonymous regime. When not stratified by trade size, the standard deviation of permanent price impact across brokers falls from 43.40 basis points to 19.81 basis points. This implies an F-statistic of 4.79 which is significant at the 1% level. In the Fligner-Killeen (1976) test for equal dispersion, the z-approximation to FK-statistic is 1.77 which is significant at the 5% level.[86] These results validate the findings of the initial analysis and provide evidence that the results are not driven by broader market trends or differences in the takeover targets before and after the anonymity switch.

[86] The analysis is also performed with stratification on trade size, though the statistical tests lack power due to the very small number of observations. When stratified into two trade size groups divided at *RTS = 1*, the sample size pairs for (transparent, anonymous) are (11,11) and (12,13) for the small and large trade size group respectively. Nevertheless, the standard deviation for the small group falls from 47.21 basis points to 32.91 basis points, while for the large trade size group the standard deviation falls from 32.98 to 17.89. The F-statistics implied by these values are 2.06 and 3.40 respectively, the latter of which is significant at the 5% level. The corresponding (raw) Fligner-Killeen test statistics are 11.68 and 13.78 respectively. While still in the expected direction these values are not significant at conventional levels.

To ensure the robustness of the bid-ask spread analysis Equation 5.5 is re-estimated, the results of which are presented in Table 5.6. While estimated on a small independent sample of firms, the results are reasonably similar to the main analysis. The coefficient on the anonymity change dummy variable indicates that this sample experiences an 83 basis point reduction in bid-ask spreads after a switch to broker anonymity compared to a 113 basis point reduction for the main sample. This result is significant at the 5% level, when tested against the hypothesis that the coefficient is less than zero. Given the proximity of the sub-sample sample to the anonymity switch, this indicates that the concealment effect of informed trades appears to have occurred immediately or very soon after the change. The results of this robustness test suggest that broader improvements to market quality are not driving the results of the main analysis.

Table 5.6
Additional test for bid-ask spreads

This table reports the results of regression Equation 5.5, where the regression is estimated using a sample of ten firms whose pre-announcement period includes the date of the transparency change. The relevant alternative hypothesis is whether the coefficient on the anonymity switch dummy variable is significantly less than zero, i.e. H_a: $\beta < 0$.

	Coefficient	T-stat
Intercept	11.36	5.92
D	-0.83	-2.33
Volatility	2.37	4.28
Volume	-399.72	-4.19
Size 2nd Q	-0.48	-1.00
Size 3rd Q	-0.27	-0.71
Size 4th Q	-0.78	-1.32
n	313	
Adj. R^2	34.56%	

The regression of order imbalance and returns is re-estimated using the observations of those firms whose pre-announcement period straddles the change on 28 November, 2005. The results are presented in Table 5.7. The coefficients on the variables of interest are similar to those in the main analysis. Excess returns are significantly positively related to order imbalance with a coefficient of 0.688 and also total volume imbalance which has a coefficient of 0.549. The coefficient on the interaction variable is negative at -0.135 and -0.110 for order imbalance and total volume imbalance respectively. This indicates that after the switch to anonymity the relationship between returns and imbalances is weaker, a finding which reconfirms Hypothesis 5.3. The results of this robustness test indicate that informed traders appear to be better hidden after the switch to anonymity and this finding is not driven by a secular change in the relationship between returns and imbalances over time.

Table 5.7
Additional test for order imbalance and returns

This table reports the results of the regression Equation 5.6 where the regression is estimated using a sample of ten firms whose pre-announcement period includes the date of the transparency change. Coefficient values are presented with t-values presented in brackets. The relevant hypothesis is whether the coefficient on the interaction variable $OI_{jt} * D$ is significantly less than zero, i.e. H_a: $\beta < 0$.

Variable	Order imbalance	Volume imbalance
Intercept	-1.497	0.389
	(-1.47)	(0.40)
D	2.483	0.648
	(2.04)	(0.55)
OI_{jt}	0.688	0.549
	(13.44)	(15.50)
$OI_{jt} * D$	-0.135	-0.123
	(-1.93)	(-2.38)
n	303	303
Adjusted R^2	52.17%	55.48%

5.6. Conclusion

This essay presents three pieces of evidence that show that, in the lead up to takeover announcements, informed traders are more concealed, and therefore, better off after broker identifiers were removed from the electronic trading screen at the ASX on 28 November, 2005. Firstly, the dispersion in permanent price impact of trades across brokers is significantly lower after the change. This suggests that the market used the identifiers to help distinguish informed from uninformed trades during the transparent regime. Put differently, the results suggest that broker identifiers have informational value. The fact that they have been removed indicates that informed traders are more concealed after the transparency change.

Secondly, it is shown that after the removal of broker identifiers bid-ask spreads are significantly lower in the days leading up to a takeover announcement. This suggests that liquidity suppliers are not engaging in as much price protection compared to when identifiers were revealed. Indeed, the adverse selection component of the spread falls significantly in the anonymous regime suggestive of the fact that informed traders remain less detected by the market. Finally, an analysis of the relationship between returns and order imbalances shows that while there is a positive relationship between the two variables, the relationship is weaker in the anonymous broker regime. Again, this suggests that the market is not able to detect informed traders as readily when broker identifiers are concealed.

The results have important policy implications for exchange officials of electronic markets considering whether to reveal or hide the identities of brokers surrounding trades. Evidence from prior literature indicates that the concealment of identifiers is correlated with lower bid-ask spreads. However, the results of this study indicate that bid-ask spreads remain lower, even when a significant information announcement is pending. Taken together the research suggests that the removal of broker identifiers has a mixed effect for uninformed traders. When no information event is pending uninformed traders enjoy improved liquidity. However, when information asymmetry is large, the ability of uninformed traders to detect and protect themselves from the informed is impaired. To resolve the issue as to whether broker identifiers should be revealed or not, research is required which analyses and quantifies the trade-off between these two competing factors. This is left as a possible avenue for future investigation.

Chapter 6. Conclusion

This dissertation contains three essays which investigate the interactive relationships between informed agents and other parties in investment and securities markets. The influential role of informed individuals in shaping both security specific and economy wide outcomes provides the primary motivation for exploring these relationships. Additional motivation is found in the fact that each essay also contributes to some topical yet under-developed research strand. The literature review presented in Chapter 2 outlines the literature which considers the relationships examined in this dissertation. Furthermore, the review highlights existing gaps in the literature which the essays in this dissertation seek to address.

The first essay in this dissertation examines how informed fund managers trade index futures to maintain superior returns, even when their trading decisions are determined by the liquidity demands of uninformed investors. In particular, the study examines the use of index futures by Australian managed funds, for the purposes of cash equitisation of investor flows. The study benefits significantly from access to unique survey data which indicates whether a fund uses index futures for this purpose or otherwise. This survey allows for research which is considerably more focussed than previous work on the use of derivatives by mutual fund investors (see, for example Koski and Pontiff, 1999).

The results of this study indicate that fund flows have a significant impact on the alpha and market timing performance of managers who do not trade index futures. Approximately 1.5% of all new flow is lost in trading, a value which is statistically and economically significant. Similarly, the market timing performance of these managers is negative in the presence of flow. Absent flow, the average non-user fund's alpha is not significantly different from zero and the average non-user fund's market timing ability is neutral. In contrast, managers who undertake derivative based management of new cash appear to be unaffected by investor flows. In fact, the unconditional performance of the average user fund is statistically equivalent to the performance of the average non-user fund *conditional on zero fund flow*. Put differently, funds that use derivatives are able to achieve returns as if they did not experience any investor flows at all.

These results have important implications for practitioners and investors alike. In recent years, there has been considerable controversy surrounding mutual funds' use of derivatives and market commentators have played upon perceptions that derivatives are uncertain, risky investments (Liase, 2007; 2006, Pollock, 2006). The results of this study show that when used correctly, a particular type of derivative (index futures) is a value-enhancing tool which allows informed managers to maintain their comparative advantage even when fund flows might otherwise reduce this advantage.

The essay presented in Chapter 4 investigates the relationship between a peculiar class of informed traders – illegal insider traders – and the regulatory body which prosecutes these individuals. In particular, the essay examines the determinants of an insider trader's position in a security. The primary determinants are hypothesised to be the expected return and expected penalty of the insider's trade – an insight derived from Becker's (1968) seminal work on criminal behaviour. Furthermore, the essay supposes that insiders also behave as investors and take a position negatively proportional to the variability of the asset. This study is the first empirical study of illegal insider trading to investigate the behaviour of the insider trader, rather than the market's response to insider trading (see for example, Meulbroek, 1992; Cornell and Sirri, 1992; and Fishe and Robe, 2004). Beyond academic interest, an understanding of insider trading behaviour is useful for regulators seeking to create better detection mechanisms to catch insider traders. One important contribution of this work is that it shows that insiders behave as investors would by taking smaller positions in more volatile stocks. This is an interesting result for two reasons. Firstly, one might expect insiders to take larger positions in more volatile stocks since they are able to hide amongst the volatility. The results indicate that this is not the case. Secondly, the finding suggests that insiders do not posses, or do not believe they possess, completely precise information.

Other results indicate that the volume traded by insiders is directly proportional to the value of their information. In other words, insiders trade more when there is more to be made. The position taken by an insider is also negatively related to the magnitude of the penalty. Both of these findings are consistent with predictions borne out of the economic crime literature which suggests that individuals trade off the costs and benefits of crime. The initial findings also indicate that the volume traded by insiders is influenced by several variables related to the probability of detection. Specifically, the volume traded by an insider is smaller if the trade is made in a specialist market. Trading closer to the announcement day also serves to reduce the volume traded. These results are robust to sample selection bias. Furthermore, as recommended by Chakravaty and McConnell (1999) these results are tested against normal trades rather than against a null of zero. The results show that the coefficients on a regression of randomly selected trades, matched with the insider trades, are not overall the same as the coefficients on a regression of insider trades. The magnitude of trades undertaken by insiders is affected by fundamentally different variables than the trades undertaken by non-insiders.

The final essay contained in this dissertation investigates the relationship between informed and uninformed traders in securities markets. In particular, the essay examines whether broker anonymity hinders the ability of uninformed traders and liquidity suppliers to detect informed traders in the lead up to a significant information event. This essay is the first to examine the effects of broker anonymity on information transmission in markets during periods of large information asymmetry. The study makes use of a natural experiment which occurred on the ASX on 28 November, 2005. Prior to this date broker identifiers were attached to all trades pre- and post-execution. After this date, this information was removed.

The study presents three pieces of evidence that after the change to broker anonymity informed traders are less detected by other participants. First, the dispersion in the average permanent price impact across brokers is lower after the change to broker anonymity with the standard deviation of average price impact across brokers dropping from 32.34 basis points to 27.72 basis points. The reduction in dispersion is most pronounced for trades executed by brokers that are between one to five times the median trade size for the security. Second, bid-ask spreads are significantly lower in the anonymous market setting. The magnitude of this reduction, 24 basis points, is material even after controlling for firm size, volume and volatility. Additional tests indicate that the decrease is attributable to a reduction in the adverse selection component of the spread. Third, results indicate that both before and after the switch to anonymity excessive buyer-initiated days correspond to days of greater returns. However, this relationship is significantly weaker in the post period. This suggests that the market is less able to accurately interpret the information content of order imbalances during the broker anonymity regime. Overall the results of this study suggest that informed traders remain less detected by the market and are therefore, better off after a switch to anonymity.

From a policy formation perspective the results of this study are very important for market designers. Results of previous studies suggest that broker anonymity is correlated with improved liquidity in the form of lower bid-ask spreads. This implies that broker anonymity is beneficial for liquidity motivated and other uninformed traders since their transaction costs are reduced in this environment. The essay in Chapter 5, however, shows that broker identifiers contain valuable information. As such, uninformed traders are less able to protect themselves from informed traders when this identifier is absent. Market designers need to carefully consider the implications of broker anonymity on the trading outcomes of uninformed participants in securities markets.

References

A

Admati, A. and P. Pfleiderer, 1988, 'A theory of intraday patterns: Volume and price variability', *Review of Financial Studies*, 1, 3-40.

Aitken, M.J. and A. Frino, 1996a, 'Asymmetry in stock returns following block trades on the Australian Stock Exchange: A note', *Abacus*, 32, 54-61.

Aitken, M.J. and A. Frino, 1996b, 'Execution costs associated with institutional trades on the Australian Stock Exchange', *Pacific-Basin Finance Journal*, 4, 45-58.

Alexander, G. J., G. Cici and S. Gibson, 'Does motivation matter when assessing trade performance? An analysis of mutual funds', *Review of Financial Studies*, 20, 125-150.

Anufriev, M. and V. Panchenko, 2009, 'Asset prices, traders' behavior and market behaviour', *Journal of Economic Dynamics & Control*, 33, 1073-1090.

Ausubel, L. M., 1990, 'Insider trading in a rational expectations economy', *American Economic Review*, 80, 1022-1041.

B

Bagehot, W., 1971, 'The only game in town', *Financial Analysts Journal*, March-April 1971, 12-14, 22.

Banerjee, A. and E. W. Eckard, 2001, 'Why regulate insider trading? Evidence from the first great merger wave (1897-1903)', *American Economic Review*, 91, 1229-1349

Barber, B. M., T. Odean and L. Zheng, 2005, 'Out of sight, out of mind: The effects of expenses on mutual fund flows', *Journal of Business*, 78, 2095–2120.

Barclay, M. J. and C. G. Dunbar, 1996, 'Private information and the costs of trading around quarterly earnings announcements', *Financial Analysts Journal*, November/December, 75-84.

Barclay, M. J., T. Hendershott and D. T. McCormick, 2003, 'Competition among trading venues: Information and trading on electronic communication networks', *Journal of Finance*, 58, 2637-2665.

Barclay, M. J., N. D. Pearson and M. S. Weisbach, 1998. 'Open end mutual funds and capital gains taxes'. *Journal of Financial Economics*, 49, 3–43.

Barclay, M. J. and J. B. Warner, 1993, 'Stealth trading and volatility', *Journal of Financial Economics*, 34, 281-305.

Bhargava, R., A. Bose and D. Dubofsky, 1998, 'Exploiting international stock market correlations with open-end international mutual funds', *Journal of Business Finance and Accounting*, 25, 765–773.

Becker, G. S., 1968, 'Crime and punishment: An economic approach', *Journal of Political Economy*, 76, 169-217.

Benabou, R. and G. Laroque, 1992, 'Using privileged information to manipulate markets: Insiders, gurus, and credibility, *Quarterly Journal of Economics*, 107, 921-958.

Benson, K. L., R. W. Faff and J. Nowland, 2007, 'Do derivatives have a role in the risk-shifting behavior of fund managers?', *Australian Journal of Management*, 32, 271-292.

Benveniste, L. M., A. J. Marcus and W. J. Wilhelm, 1992, 'What's special about the specialist?', *Journal of Financial Economics*, 32, 61-86

Beny, L. D., 2005, 'Do insider trading laws matter? Some preliminary comparative evidence' *American Law and Economics Review*, 7, 144-183.

Beny, L. D., 2007, 'Insider trading laws and stock markets around the world: An empirical contribution to the theoretical law and economics debate', *Journal of Corporation Law*, Winter, 237-300.

Bergstresser, D. and J. Poterba, 2002, 'Do after-tax returns affect mutual fund inflows?', *Journal of Financial Economics*, 63, 381-414.

Berk, J. B., and R. C. Green, 2004, 'Mutual fund flows and performance in rational markets', *Journal of Political Economy*, 112, 1269–1295.

Berkman, H., T. Brailsford and A. Frino, 2005, 'A note on execution costs for stock index futures: Information versus liquidity effects', *Journal of Banking & Finance*, 29, 565-577.

Bhattacharya, U. and H. Daouk, 2002, 'The world price of insider trading', *Journal of Finance*, 62, 75-108.

Bhattacharya, U, H. Daouk, B. Jorgenson and C. Kehr, 2000, 'When an event is not an event: The curious case of an emerging market', *Journal of Financial Economics*, 55, 69-101.

Bollen, N. P. and J. A. Busse, 2006, 'Tick size and institutional trading costs: Evidence from mutual funds,' *Journal of Financial and Quantitative Analysis*, 41, 915–937.

Bottazzi, G., G. Dosi, G. and I. Rebesco, 2005, 'Institutional architectures and behavioural ecologies in the dynamics of financial markets: A preliminary investigation', *Journal of Mathematical Economics*, 41, 197–228.

Boudoukh, J., M. P. Richardson, M. Subrahmanyam and R. F. Whitelaw, 2002, 'Stale prices and strategies for trading mutual funds', *Financial Analysts Journal*, 58. 53-71.

Breen, W. J., L.S. Hodrick and R. A. Korajczyk, 2002, 'Predicting equity liquidity', *Management Science*, 48(4), 470-483.

Bris. A., 2005, 'Do insider trading laws work?', *European Financial Management*, 11, 267-312.

Bris, A., H. Gulen, P. Kadiyala and P. R. Rau, 2007, 'Good stewards, cheap talkers or family men? The impact of mutual fund closures on fund managers, flows, fees and performance', *Review of Financial Studies*, 20, 953–982.

Brockman, P., and D. Y. Chung, 1999, 'Bid-ask spread components in an order-driven environment', *Journal of Financial Research*, 22, 227-246.

Brown, D. P. and R. H. Jennings, 1989, 'On technical analysis', *Review of Financial Studies*, 2, 527-552.

Brown, K. C., W. V. Harlow and L. T. Starks, 1996, 'Of tournaments and temptations: An analysis of managerial incentives in the mutual fund industry', *Journal of Finance,* 51, 85–110.

Brown, P., D. Walsh and A. Yuen, 1997, 'The interaction between order imbalance and stock price', *Pacific-Basin Finance Journal*, 5, 539-557.

Bushman, R. M., J. D. Piotrowski and A. J. Smith, 2005, 'Insider trading restrictions and analysts' incentives to follow firms', *Journal of Finance*, 60, 35-66.

C

Caglio, C. and K. A. Kavajecz, 2006, 'A specialist's quoted depth as a strategic choice variable: an application to spread decomposition models', *Journal of Financial Research*, 29, 367-382.

Cao, C., Z. Chen and J. M. Griffin, 2005, 'Informational content of option volume prior to takeovers', *Journal of Business*, 78, 1073-1109.

Cao, C., H. Choe and F. Hatheway, 1997, 'Does the specialist matter? Differential execution costs and inter-security subsidization on the NYSE', *Journal of Finance*, 52, 1615-1640.

Capon, N., G. J. Fitzsimons, and R. A. Prince, 1996, 'An individual level analysis of the mutual fund investment decisions', *Journal of Financial Services Research*, 10, 59–82.

Carhart, M. M., 1997, 'On persistence in mutual fund performance', *Journal of Finance*, 52, 57–82.

Carlton, D. W. and D. R. Fischel, 1983, 'The regulation of insider trading', *Stanford Law Review*, 35, 857-895.

Chakravarty, S., 2001, 'Stealth trading: Which traders' trades move stock prices?', *Journal of Financial Economics*, 61, 289-307.

Chakravaty, S. and J. J. McConnell, 1997, 'An analysis of prices, bid/ask spreads, and bid and ask depths surrounding Ivan Boesky's illegal trading in Carnation's stock', *Financial Management*, 26, 18–34.

Chakravaty, S. and J. J. McConnell, 1999, 'An analysis of prices, bid/ask spreads and bid and ask depths surrounding Ivan Boesky's illegal trading in Carnation's stock', *Journal of Financial and Quantitative Analysis*, 26, 18-34

Chalmers, J. M., R. M. Edelen and G. B. Kadlec, 1999, 'An analysis of mutual fund trading costs', working paper, University of Oregon.

Chalmers, J., R. M. Edelen and G. B. Kadlec, 2001, 'On the perils of security pricing by financial intermediaries: The wildcard option in transacting mutual-fund shares', *Journal of Finance*, 56, 2209-2236.

Chan, K. and A. Hameed, 2006, 'Stock price synchronicity and analyst coverage in emerging markets', *Journal of Financial Economics*, 80, 115–47.

Chan, L. K. C. and J. Lakonishok, 1993, 'Institutional trades and intraday stock price behavior', *Journal of Financial Economics*, 33, 173-199.

Chan, L. K. C. and J. Lakonishok, 1995, 'The behavior of stock prices around institutional trades', *Journal of Finance*, 50, 1147-1174.

Charski, M., 1999, 'Latest mutual fund game: Buy and dump', *U.S. News and World Report*, May 24, 74.

Chen, J., H. Hong, M. Hong and J. D. Kubik, 2004, 'Does fund size erode mutual fund performance? The role of liquidity and organization', *American Economic Review*, 94, 1276–1302.

Chevalier, J. and G. Ellison, 1997, 'Risk taking by mutual funds as a response to incentives', *Journal of Political Economy*, 105, 1167-1200.

Chiang, R. and P. C. Venkatesh, 1988, 'Insider holdings and perceptions of information asymmetry: A note', *Journal of Finance*, 43, 1041-1048.

Chincarini, L., 2004, 'Managing cash flow in sector portfolios: A hedging approach', *Derivatives Use, Trading & Regulation*, 10, 27-45.

Chordia, T., 1996, 'The structure of mutual fund charges', *Journal of Financial Economics*, 41, 3-39.

Chordia, T., R. Roll and A. Subrahmanyam, 2002, 'Order imbalance, liquidity and market returns', *Journal of Financial Economics*, 65, 111-130.

Chung, K. H., M. Li and T. H. McInish, 2005, 'Information-based trading, price impact of trades and trade autocorrelation', *Journal of Banking & Finance*, 29, 1645-1669.

Ciccotello, C. S., R. M. Edelen, J. T. Greene and C. W. Hodges, 2002, 'Trading at stale prices with modern techonology: Policy options for mutual funds in the internet age', *Virginia Journal of Law and Technology*, 6, 1-31.

Comerton-Forde, C., A. Frino and V. Mollica, 2005, 'The impact of limit order anonymity on liquidity: Evidence from Paris, Tokyo and Korea', *Journal of Economics and Business*, 57, 528-540.

Comerton-Forde, C. and K. M. Tang, 2009, 'Anonymity, liquidity and fragmentation', *Journal of Financial Markets*, 12, 337-367.

Conrad. J. and C. M. Niden, 1992, 'Order flow, trading costs and corporate acquisition announcements', *Financial Management*, Winter, 22-31.

Conroy, R. M. and R. L. Winkler, 1981, 'Informational differences between a limit and a market order for a market maker', *Journal of Financial and Quantitative Analysis*, 16, 703-724.

Cooper, M. J., H. Gulen and P. R. Rau, 2005, 'Changing names with style: Mutual fund name changes and their effects on fund flows', *Journal of Finance*, 60, 2825-2858.

Copeland, T. E. and D. Galai, 1983, 'Information Effects on the Bid-Ask Spread', *Journal of Finance*, 38, 1457-1469.

Cornell, B., and E. R. Sirri, 1992, 'The reaction of investors and stock prices to insider trading', *Journal of Finance*, 47, 1031-1059.

Cox, J. D., 1986, 'Insider trading and contracting: A critical response to the Chicago School, *Duke Law Journal*, 1986, 628-659.

D

Daley, L. A., J. S. Hughes and J. D. Rayburn, 1995, 'The impact of earnings announcements on the permanent price effects of block trades', *Journal of Accounting Research*, 33, 317-334.

Daniel, K., M. Grinblatt, S. Titman and R. Wermers, 1997, 'Measuring mutual fund performance with characteristic-based benchmarks', *Journal of Finance*, 52, 1035–1058.

Del Guercio, D. and P. A. Tkac, 2002, 'The determinants of the flow of funds of managed portfolios: Mutual funds vs. pension funds', *Journal of Financial and Quantitative Analysis*, 37, 523–557.

Deli, D. N. and R. Varma, 2002, 'Contracting in the investment management industry: evidence from mutual funds', *Journal of Financial Economics*, 62, 79-98.

DeMarzo, P. M., M. J. Fishman and K. M. Hagerty, 1998, 'The optimal enforcement of insider trading regulations', *Journal of Political Economy*, 106(3), 602-632.

Demsetz, H., 1968, 'The cost of transacting', *Quarterly Journal of Economics* 82, 33-53.

Demsetz, H., 1986, 'Corporate control, insider trading and rates of return', *American Economic Review*, 76, 313-316.

Dennis, D. K. and J. J. McConnell, 1986, 'Corporate mergers and security returns', *Journal of Financial Economics*, 16(2), 143-187.

Dickson, J. M., J. B. Shoven and C. Sialm, 2000, 'Tax externalities of equity mutual funds', *National Tax Journal*, 53, 607-628.

Donnelly, S. M. and A. Kramer, 1999, 'Testing for multiple species in fossil samples: An evaluation and comparison of tests for equal relative variation', *American Journal of Physical Anthropology*, 108, 507-529.

Dufour, A. and R. F. Engle, 2000, 'Time and the price impact of a trade', *Journal of Finance*, 55, 2467-2498.

DuPont, D., 2000, 'Market making, prices and quantity limits', *Review of Financial Studies*, 13, 1129-1151.

E

Easley, D., N. M. Kiefer and M. O'Hara, 1997, 'One day in the life of a very common stock', *Review of Financial Studies*, 10, 805-835.

Easley, D., N. M. Kiefer, M. O'Hara, J. B. Paperman, 1996, 'Liquidity, information and infrequently traded stocks', *Journal of Finance*, 51, 1405-1436.

Easley, D. and M. O'Hara, 1987, 'Price, trade size and information in securities markets', *Journal of Financial Economics*, 19, 69-90.

Edelen, R. M., 1999, 'Investor flows and the assessed performance of open-end mutual funds', *Journal of Financial Economics*, 53, 439-466.

Edelen, R. M. and J. B. Warner, 2001, 'Aggregate price effects of institutional trading: A study of mutual fund flows and market returns', *Journal of Financial Economics*, 59, 195-220.

F

Fama, E. F., 1970, ‘Efficient capital markets: a review of theory and empirical work’, *Journal of Finance*, 25, 383–417.

Fama, E. F. and K. R. French, 1993, ‘Common risk factors in the returns on stocks and bonds’, *Journal of Financial Economics,* 33, 3–56.

Fernandes, N. and M. A. Ferreira, 2009, ‘Insider trading laws and stock prices’, *The Review of Financial Studies*, 22, 1845-1887.

Ferson, W. E. and R. W. Schadt, 1996, ‘Measuring fund strategy and performance in changing economic conditions’, *Journal of Finance*, 51, 425-461.

Ferson, W. E. and V. A. Warther, 1996, ‘Evaluating fund performance in a dynamic market’, *Financial Analysts Journal*, 52, 20-28.

Fishe, R. P. H. and M. A. Robe, 2004, ‘The impact of illegal insider trading in dealer and specialist markets: Evidence from a natural experiment’, *Journal of Financial Economics*¸ 71, 461-488.

Fishman, M. J. and K. M. Hagerty, 1992, ‘Insider trading and the efficiency of stock prices’, *RAND Journal of Economics*, 23, 106-122.

Fleming, J., B. Ostdiek and R. E. Whaley, 1996, ‘Trading costs and the relative rates of price discovery in stock, futures, and option markets’, *Journal of Futures Markets*, 16, 353-387.

Fletcher, J., D. Forbes and A. Marshall, 2002, ‘An investigation of the impact of derivatives use on the risk and performance of UK unit trusts’, *Financial Services Review*, 11, 174-187.

Fligner. M. A. and T. J. Killeen, 1976, ‘Distribution-free two sample tests for scale’, *Journal of the American Statistical Association*, 71, 210-213.

Fong, K., D. R. Gallagher and A. Ng, 2005, ‘The use of derivatives by investment managers and implications for portfolio performance and risk’, *International Review of Finance*, 5, 1-29.

Foucault, T., S. Moinas and E. Thiessen, 2007, ‘Does anonymity matter in electronic limit order markets?’, *Review of Financial Studies*, 20(5), 1707-1747.

Franz, D. R., R. P. Rao and N. Tripathy, 1996, ‘Informed trading risk and bid-ask spread changes around open market stock repurchases in the NASDAQ market’, *Journal of Financial Research*, 18, 311-327.

Friesen, G. C. and T. R. A. Sapp, 2007, ‘Mutual fund flows and investor returns: An empirical examination of fund investor timing ability’, *Journal of Banking & Finance*, 31, 2796-2816.

Frino, A., G. Wearin and J. Fabre, 2004, ‘Do returns on synthetic portfolios constructed from stock index futures deliver capital gains, dividends and franking credits?’, *Journal of Law and Financial Management*, 3, 8-13.

Frino, A., J. Kruk and A. Lepone, 2007, ‘Transactions in futures markets: Informed or uninformed?’, *Journal of Futures Markets*, 27, 1159-1174.

G

Garfinkel, J. A., 1997, ‘New evidence on the effects of federal regulations on insider trading: The *Insider Trading and Securities Fraud Enforcement Act* (ITSFEA)’¸ *Journal of Corporate Finance*, 3, 89-111.

Garfinkel, J. A. and M. Nimalendran, 2003, ‘Market structure and trader anonymity: An analysis of insider trading’, *Journal of Financial and Quantitative Analysis*, 38, 591-610.

Gastineau, G. L., 2004, ‘Protecting fund holders from costly share trading’, *Financial Analysts Journal*, 60, 22-32.

Gemmill, G., 1996, ‘Transparency and liquidity: A study of block trades in the London Stock Exchange under different publication rules’, *Journal of Finance*, 51, 1765-1790.

Gennotee, G. and H. Leland, 1990, ‘Market liquidity, hedges and crashes’, *American Economic Review*, 80, 999-1021.

Georgakopoulos, N. L., 1993, ‘Insider trading as a transactional cost: A market microstructure justification and optimization of insider trading regulation’, *Connecticut Law Review*, 26, 1-51.

Goetzmann, W. and Z. Ivkovich and K. Rouwenhorst, 2001, ‘Day trading international mutual funds: Evidence and policy solutions’, *Journal of Financial and Quantitative Analysis*, 36, 287–309.

Goetzmann, W. N. and M. Massa, 2002, ‘Daily momentum and contrarian behavior of index fund investors’, *Journal of Financial and Quantitative Analysis*, 37, 375–389.

Goetzmann, W. N., and N. Peles, 1997, ‘Cognitive dissonance and mutual fund investors’, *Journal of Financial Research,* 20, 145–158.

Gohlke, G, 2007, ‘If I were a director of a fund investing in derivatives – Key areas of risk in which I would focus’, *Address to Mutual Fund Directors Forum on Funds’ Use of Derivatives*, New York, New York, 8 November 2007.

Gleason, K., 2007, ‘Does market maker competition affect the response to insider trading?’, *Applied Financial Economics*, 17, 691-700.

Glosten, L.R. 1994, ‘Is the electronic limit order book inevitable?’, *Journal of Finance*, 49(4), 1127-1161.

Glosten, L. R. and P. R. Milgrom, 1985, 'Bid, ask and transaction prices in a specialist market with heterogeneously informed traders', *Journal of Financial Economics*, 14, 71-100.

Greene, J. T. and C. W. Hodges, 2002, 'The dilution impact of daily fund flows on open-end mutual funds', *Journal of Financial Economics*, 65, 131-158.

Greene, J. T., C. W. Hodges and D. A. Rakowski, 2007, 'Daily mutual fund flows and redemption policies', *Journal of Banking & Finance*, 31, 3822-3842.

Grinblatt, M. and S. Titman, 1989a, 'Mutual fund performance: An analysis of quarterly portfolio holdings', *Journal of Business*, 62, 393-416.

Grinblatt, M. and S. Titman, 1989b, 'Portfolio performance evaluation: old issues and new insights', *Review of Financial Studies*, 2, 396-422.

Grinblatt, M. and S. Titman, 1992, 'Performance persistence in mutual funds', *Journal of Finance*, 47, 1977-1984.

Grinblatt, M. and S. Titman, 1993, 'Performance measurement without benchmarks: an examination of mutual fund returns', *Journal of Business*, 66, 47-68.

Grossman, S., 1976, 'On the efficiency of competitive stock markets where trades have diverse information', *Journal of Finance* 31, 573-585.

Grossman, S., and J. Stiglitz 1980 'On the impossibility of informationally efficient markets', *American Economic Review*, 70, 393–408.

Gruber, M. J., 1996, 'Another puzzle: The growth in actively managed mutual funds', *Journal of Finance*, 51, 783-810.

Grundy, B.D. and M. McNichols, 1989, 'Trade and revelation of information through prices and direct disclosure', *Review of Financial Studies*, 2, 495-526.

H

Hachmeister A. and D. Schiereck, 2006, 'The impact of post-trade anonymity on liquidity and informed trading: evidence from the introduction of the Xetra Central Counterparty (CCP)', working paper, International University.

Harris, L., 2003, *Trading and Exchanges*, New York, Oxford University Press.

Hasbrouck, J., 1991, 'Measuring the information content of stock trades'. *Journal of Finance*, 46, 179–207.

Hellwig, M., 1980, 'On the aggregation of information in competitive markets', *Journal of Economic Theory*, 22, 477-498.

Hendricks, D., J. Patel and R. Zeckhauser, 1993, 'Hot hands in mutual funds: Short-run persistence of performance, 1974-88', *Journal of Finance*, 48, 93-130.

Henriksson, R., 1984, 'Market timing and mutual fund performance: an empirical investigation', *Journal of Business*, 57, 73-96.

Henriksson, R. and R. Merton, 1981, 'On market timing and investment performance: statistical procedures for evalutation forecasting skills', *Journal of Business*, 54, 513-533.

Hiedle, H. G. and R. D. Huang, 2002, 'Information-based trading in dealer and auction markets: An analysis of exchange listings', *Journal of Financial and Quantitative Analysis*, 37, 391-424.

Holthausen, R., R. Leftwich and D. Mayers, 1987, 'The effect of large block transactions on security prices: A cross-sectional analysis', *Journal of Financial Economics*, 19, 237-268.

Holthausen, R., R. Leftwich and D. Mayers, 1990, 'Large block transactions, the speed of response, and temporary and permanent stock-price effects', *Journal of Financial Economics*, 26, 71-95.

Huang, J., K. D. Wei and H. Yan, 2007, 'Participation costs and the sensitivity of fund flows to past performance', *Journal of Finance*, 62, 1273-1311.

Huang, R. and H. Stoll, 1996, 'Dealer versus auction markets: A paired comparison of execution costs on NASDAQ and NYSE', *Journal of Financial Economics*, 41, 313-357.

Huij, J., Verbeek, M., 2007, 'Cross-sectional learning and short run persistence in mutual fund performance', *Journal of Banking & Finance*, 31, 973-997.

I

Investment Company Institute, 2008, *Investment Company Institute Fact Book 2008,* 48th Edition.

Ippolito, R. A., 1989, 'Efficiency with costly information: A study of mutual fund performance, 1965-1985', *Quarterly Journal of Economics*, 104, 1-23.

Ippolito, R. A., 1992, 'Consumer reaction to measures of poor quality: evidence from the mutual fund industry', *Journal of Law & Economics*, 35, 45-70.

J

Jacklin, C. J., A. W. Kleidon and P. Pfleiderer, 1992, 'Underestimation of portfolio insurance and the crash of October 1987', *Review of Financial Studies*, 5, 35-63.

Jagannathan, R. and R. Korajczyk, 1986, 'Assessing the market timing performance of managed portfolios, *Journal of Business*, 59, 217-235.

Jain, P. C. and J. S. Wu, 2000, 'Truth in mutual fund advertising: Evidence on future performance and fund flows', *Journal of Finance*, 55, 937–958.

Jarrell, G. A. and A. B. Poulsen, 1989, 'Stock trading before the announcement of tender offers: Insider trading or market anticipation?', *Journal of Law, Economics and Organization*, 5, 225-248.

Jayaraman, N., M. B. Frye and S. Sabherwal, 2001, 'Informed trading around merger announcements: An empirical test using transaction volume and open interest in options market', *Financial Review*, 36, 45-74.

Jennings, R., 1994, 'Intraday changes in target firms' share price and bid-ask quotes around takeover announcements', *Journal of Financial Research*, 17, 255-270.

Jensen, M., 1968, 'The performance of mutual funds in the period 1945-1964', *Journal of Finance*, 23, 389-416.

Johnson, W. T., 2004, 'Predictable investment horizons and wealth transfers among mutual fund shareholders', *Journal of Finance*, 59, 1979–2012.

Johnson, L. D. and W. W. Yu, 2004, 'An analysis of the use of derivatives by the Canadian mutual fund industry', *Journal of International Money and Finance*, 23, 947-970.

Jones, C. M. and M. L. Lipson, 1999, 'Execution costs of institutional equity orders', working paper, Columbia University.

Jones, C. M. and M. L. Lipson, 2001, 'Sixteenths: Direct evidence on institutional execution costs', *Journal of Financial Economics*, 59, 253-278.

K

Kacperczyk, M., C. Sialm, L. Zheng, 2008, 'Unobserved actions of mutual funds', *Review of Financial Studies*, 21, 2379-2416.

Kane, A., D. L. Santini and J. W. Aber, 1991, 'Lessons from the growth history of mutual funds', working paper, Boston University School of Management.

Ke, B., S. Huddart and K. Petroni, 2003, 'What insiders know about future earnings and how they use it: Evidence from insider trades', *Journal of Accounting and Economics*, 35, 315-346.

Keim, D.B. and A. Madhavan, 1995, 'The anatomy of the trading process: Empirical evidence on the behavior of institutional traders', *Journal of Financial Economics*, 25, 75-98.

Keim, D.B. and A. Madhavan, 1997, 'Transaction costs and investment style: An inter-exchange analysis of institutional equity trades', *Journal of Financial Economics*, 46, 265-292.

Kempf, A. and S. Ruenzi, 2006, 'Status quo bias and the number of alternatives: An empirical illustration from the mutual fund industry', *Journal of Behavioral Finance*, 7, 204-213.

Kempf, A. and S. Ruenzi, 2008a, ‘Family matters: Rankings within fund families and fund inflows’, *Journal of Business, Finance & Accounting*, 35, 177-199.

Kempf, A. and S. Ruenzi, 2008b, ‘Tournaments in mutual-fund families’, *Review of Financial Studies*, 21, 1013-1036.

Keown, A. and J. Pinkerton, 1981, ‘Merger announcements and insider trading activity: An empirical investigation’, *Journal of Finance*, 36, 855-869.

Khorana, A., 1996, ‘Top management turnover: An empirical investigation of mutual fund managers’, *Journal of Financial Economics,* 40, 403–427.

Kim, O. and R. E. Verrecchia, 1991, ‘Market reactions to anticipated announcements’, *Journal of Financial Economics*, 30, 273-310.

Kon, S., 1983, ‘The market timing performance of mutual fund managers’, *Journal of Business*, 56, 323-347.

Koski, J. and R. Michaely, 2000, ‘Prices, liquidity, and the information content of trades’, *Review of Financial Studies*, 13, 659-696.

Koski, J. L. and J. Pontiff, 1999, ‘How are derivatives used? Evidence from the mutual fund industry’, *Journal of Finance*, 54, 791-816.

Kraus A. and H. Stoll, 1972, ‘Price impacts of block trading on the New York Stock Exchange’, *Journal of Finance*, 27, 569–588.

Krinsky, I. and J. Lee, 1996, ‘Earnings announcements and the components of the bid-ask spread’, *Journal of Finance*, 51, 1523-1535.

Kyle, A. S., 1985, ‘Continuous auctions and insider trading’, *Econometrica*, 53, 1315-1335.

L

Lee, C. M. C., 1992, ‘Earnings news and small traders’, *Journal of Accounting and Economics*, 15, 265-302.

Lee, C. M. C., B. Mucklow and M. J. Ready, 1993, ‘Spreads, depth, and the impact of earnings information: An intraday analysis’, *Review of Financial Studies*, 346-374.

Lee, C. M. C. and M. Ready, 1991, ‘Inferring trade direction from intraday data’, *Journal of Finance*, 46, 733-746.

Lee, Y., Y. Liu, R. Roll and A. Subrahmanyam, 2004, ‘Order imbalances and market efficiency: Evidence from the Taiwan Stock Exchange’, *Journal of Financial and Quantitative Analysis*, 39, 327-341.

Lehmann, B. and D. Modest, 1987, ‘Mutual fund performance evaluation: a comparison of benchmarks and benchmark comparisons’, *Journal of Finance*, 42, 233-265.

Leland, H., 1992, ‘Insider trading: Should it be prohibited?’, *Journal of Political Economy*, 100, 859-887.

Liase, E., 2007, ‘Mutual funds add exotic fare to the mix – many are making increasing use of complex derivatives to enhance performance but the strategies carry risk’, *Wall St Journal*, 4 April 2007 edition.

Liase, E., 2006, ‘Mutual funds adopt hedge fund tactics – to bolster returns, firms seek approval to pursue short selling and other higher-risk strategies’, *The Wall St Journal*, 21 February 2006 edition.

Lin, J., G. C. Sanger and G. G. Booth, 1995, ‘Trade size and components of the bid-ask spread’, *Review of Financial Studies*, 8, 1153-1183.

Lynch, A. W. and D. K. Musto, 2003, ‘How investors interpret past fund returns’, *Journal of Finance*, 58, 2033–2058.

M

Madhavan, A. and M. Cheng, 1997, ‘In search of liquidity: Block trades in the upstairs and downstairs markets’, *Review of Financial Studies*, 10, 175-204.

Madison, T., G. Roth and A. Saporoschenko, 2004, ‘Bank mergers and insider nontrading’, *Financial Review*, 39, 203-229.

Maher, O., P. Swan and P. J. Westerholm, 2008, ‘Twilight falls on the limit order book: Endogeneity and the demise of broker identity’, working paper, University of NSW.

Majois, C., 2007, ‘Natural experiments methodology and global liquidity in financial markets’, working paper, Louvain School of Management.

Manakyan, H. and K. Liano, 1997, ‘Performance of mutual funds before and after closing to new investors,’ *Financial Services Review*, 6, 257–269.

Manne, H. G., 1966, *Insider Trading and the Stock Market*, New York, Free Press.

Manne, H. G., 2005, ‘Insider trading, Hayek, virtual markets and the dog that did not bark’, *Journal of Corporation Law*, 31, 167-185.

Manove, M., 1989, ‘The harm from insider trading and informed speculation’, *Quarterly Journal*, 104, 823-845.

Markowitz, H. M., 1952, ‘Portfolio selection’, *Journal of Finance*, 7, 77-91.

Massa, M., 2003, 'How do family strategies affect fund performance? When performance maximization is not the only game in town', *Journal of Financial Economics,* 67, 249–304.

Mayhew, S. and V. Mihov, 2004, 'How do exchange select stocks for option listing?', *Journal of Finance*, 59, 447-471.

McGrath, R. N. and A. B. Yeh, 2005, 'A quick, compact, two sample dispersion test: Count five', *The American Statistician*, 59, 47-53.

McInish, T. H. and R. A. Wood, 1992, 'An analysis of intraday patterns in bid/ask spreads for NYSE stocks', *Journal of Finance*, 47, 753-764.

Meulbroek, L. K., 1992, 'An empirical analysis of illegal insider trading', *Journal of Finance*, 47, 1661-1699.

Miller, T., and T. S. Meckel, 1999, 'Beating index funds with derivatives', *Journal of Portfolio Management*, 25, 75-88.

Morse, D., 1981, 'Price and trading volume surrounding earnings announcements: A closer examination', *Journal of Accounting Research*, 19, 374-383.

Morse, D. and N. Ushman, 1983, 'The effect of information announcements on the market microstructure', *Accounting Review*, 58, 247-258.

N

Nanda, V., M.P. Narayanan and V. A. Warther, 2000, 'Liquidity, investment ability and mutual fund structure', *Journal of Financial Economics*, 57, 417-443.

Nanda, V., Z. Wang, and L. Zheng, 2004, 'Family values and the star phenomenon', *Review of Financial Studies*, 17, 667–698.

P

Pagano, M. and A. Röell, 1996, 'Transparency and liquidity: A comparison of auction and dealer markets with informed trading', *Journal of Finance*, 51, 579-611.

Park, S., H. J. Jang and M. P. Loeb, 1995, 'Insider trading activity surrounding annual earnings announcements', *Journal of Business, Finance & Accounting*, 22, 587-614.

Pascual, R., A. Escribano, M. Tapia, 2004, 'Adverse selection costs, trading activity and price discovery in the NYSE: An empirical analysis', *Journal of Banking & Finance*, 28, 107-128.

Patel, J., R. Zeckhauser and D. Hendricks. 1991, 'The rationality struggle: Illustrations from financial markets." *American Economic Review,* 81, 232–236.

Patel, J. R. J. Zeckhauser and D. Hendricks, 1994, 'Investment flows and performance: Evidence from mutual funds, cross-border investments, and new issues', in R. Satl, R. Levitch, and R. Ramachandran (eds.), *Japan, Europe and the International Financial Markets: Analytical and Empirical Perspectives*, Cambridge University Press, New York.

Perotti, P. and B. Rindi, 2006, 'Market for information and identity disclosure in an experimental open limit order book', *Economic Notes*, 35, 97-119.

Pinnuck, M., 2003, 'An examination of the performance of the trades and stock holdings of fund managers: Further evidence', *Journal of Financial and Quantitative Analysis*, 38, 811-828.

Pinnuck, M., 2004, 'Stock preferences and derivative activities of Australian fund managers', *Accounting and Finance*, 44, 97-120.

Pollet, J. M. and M. Wilson, 'How does size affect mutual fund behavior?', *Journal of Finance*, 63, 2941-2969.

Pollock, M. A., 2006, 'Monthly mutual funds review – fundamentals: your bond fund may hold a surprise – derivatives gain big role for ability to lift returns; are they devil's spawn?', *Wall St Journal*, 6 March 2006.

Pound, J. and R. Zeckhauser, 1990, 'Clearly heard on the street: The effect of takeover rumors on stock prices', *Journal of Business*, 63, 291-309.

R

Rao, R. P., N. Tripathy and W. P. Dukes, 1991, 'Dealer bid-ask spreads and options trading on over-the-counter stocks', *Journal of Financial Research*, 14, 317-325.

Re Ivan F. Boesky Securities Litigation, 957 F.2d 65, 69 (2d Cir. 1992).

Rindi, B., 2008, 'Informed traders as liquidity providers: Anonymity, liquidity and price formation', *Review of Finance*, 12, 497-532.

Roll., R., 1984, 'A simple implicit measure of the effective bid-ask spread in an efficient market', *Journal of Finance*, 39, 1127-1139.

S

Samuelson, W. and R. Zeckhauser, 1988, 'Status quo bias in decision making', *Journal of Risk and Uncertainty,* 1, 7–60.

Schwert, G., 1996, 'Markup pricing in mergers and acquisitions', *Journal of Financial Economics*, 41, 153-192.

Securities and Exchange Commission, 2008, 'SEC announces fiscal 2008 enforcement results', Press Release: 22 October 2008.

Securities and Exchange Commission v. Guttenberg et al., 2007, C.A. No. 07 CV 1774 (S.D.N.Y.).

Seyhun, H. N., 1992, 'The effectiveness of insider trading sanctions', *Journal of Law and Economics*, 35, 149-182.

Seyhun, H. N. and M. Bradley, 1997, 'Corporate bankruptcy and insider trading', *Journal of Business*, 70, 189-216.

Shefrin, H. and M. Statman, 1985, 'The disposition to sell winners too early and ride losers too long: Theory and evidence', *Journal of Finance*, 40, 777-790.

Sirri, E. and P. Tufano, 1998, 'Costly search and mutual fund flows', *Journal of Finance*, 53, 1589-1622.

Smaby, T. R. and J. L. Fizel, 1995, 'Fund closings as a signal to investors: Investment performance of open-end mutual funds that close to new shareholders,' *Financial Services Review*, 4, 71–80.

Smith, K. V., 1978, 'Is fund growth related to fund performance?', *Journal of Portfolio Management*, Spring, 49-54.

Spritz, A. E., 1970, 'Mutual fund performance and cash inflow', *Applied Economics*, 2, 141-145.

Stigler, G. J., 1978, 'The optimum enforcement of laws', *Journal of Political Economy*, 78, 526-536.

Subrahmanyam, A., 1991, 'A theory of trading in stock index futures', *Review of Financial Studies*, 4, 17-51.

T

Taylor, J., 2003, 'Risk-taking behavior in mutual fund tournaments', *Journal of Economic Behavior & Organization*, 50, 373-383.

Treynor, J. L. and K. K. Mazuy, 1966, 'Can mutual funds outguess the market?', *Harvard Business Review*, 44, 131-136.

Tripathy, N. and R. P. Rao, 1992, 'Adverse selection, spread behavior, and over-the-counter seasoned equity offerings', *Journal of Financial Research*, 15, 39-56.

V

Verrecchia, R., 1982, 'Information acquisition in a noisy rational expectations economy', *Econometrica,* 50, 1415-1430.

W

Wang, J., 1994, 'A model of competitive stock trading volume', *Journal of Political Economy*, 102, 127-168.

Warther, V. A., 1995, 'Aggregate mutual fund flows and security returns', *Journal of Financial Economics*, 39, 209-235.

Wermers, R., 2000, 'Mutual fund performance: an empirical decomposition into stock-picking talent, style, transactions costs, and expenses', *Journal of Finance*, 55, 1655–1695.

Wilcox, R. T., 2003, 'Bargain hunting or star gazing? Investor's preference for stock mutual funds', *Journal of Business*, 76, 645-663.

Wisniewski, T. P. and M. T. Bohl, 2005, 'The information content of registered insider trading under lax law enforcement', *International Review of Law and Economics*, 25, 169-185.

Y

Yan., X., 2008, 'Liquidity, investment style, and the relation between fund size and performance', *Journal of Financial and Quantitative Analysis*, 43, 741-768.

Z

Zhao, X., 2004, 'Why are some mutual funds closed to new investors?', *Journal of Banking & Finance*, 28, 1867–1887.

Zitzewitz, E., 2003, 'Who cares about shareholders? Arbitrage-proofing mutual funds', *Journal of Law, Economics & Organization*, 19, 245-280.