Three Essays on Informed Trading

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Statement of Originality

This is to certify that to the best of my knowledge, the content of this thesis is my own work. This thesis has not been submitted for any other degree or purpose.

This further certifies that the intellectual content of this thesis is my own work, and that any assistance and sources used have been acknowledged.

Signature of Candidate

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Abstract

This thesis consists of three essays examining the behavior of informed traders in financial markets and how they affect asset pricing. It examines informed traders' role in shaping securities prices in three ways. It examines whether on a macro and micro basis insider traders move prices to a different degree than non-insiders. In addition, it uses econometric methods to determine what exchange generates permanent price trends in UK shares. Lastly, it looks at another side effect of fragmentation – how a 'best execution' mandate and related market structure changes affect transactions costs in liquid UK, French, and German shares.

These studies expand on current literature in various ways – extant insider trading literature has either primarily focused on daily price movement and volume or had consisted of case studies, the conclusions of which may be idiosyncratic and therefore unrepresentative of typical insider behavior. The new phenomenon of multilateral trading facilities (also known as electronic communications networks) and the proliferation of algorithmic or computer-mediated trading had not been examined in price discovery papers, due to their relative novelty. In addition, despite a bevy of literature offering informed insight into the impact of the European Union's Markets in Financial Instruments Directive (MiFID), there has been a dearth of empirical studies assessing its impact on European securities markets. Chapters 2 and 3 examine MiFID and computerized trading from two different perspectives: that of which trades lead to permanent prices, and that of transactions costs.

The conclusions drawn in this thesis will be of interest to regulators, market operators, and traders, as they offer insight into the impact of market structure and how it impacts informed traders who participate in them.

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Chapter One:

Introduction

'The difficulty lies not so much in developing new ideas as in escaping from old ones.' - John Maynard Keynes

Informed trading is critical to the determination of asset prices. According to Efficient Market Theory (Fama, 1969, 1998), asset prices respond to new information by informed traders' activity and thereby find appropriate prices in securities markets. By their participation in the market, informed traders will seek to capitalize on private holdings on information, and short of brief disturbances such as order imbalances, prices will adjust to the arrival of new information. Informed traders are distinguished from the bulk of traders (liquidity traders) by their holdings of private information, derived either from superior analysis as to an asset's fundamental prospects or from so-called 'insider' information – material non-public information obtained from within the company.

Theoretical work on informed traders ranges from the hypothesis that informed traders will execute trades multiple times in order to extract maximum rent from their private information (Kyle, 1985) to empirical findings that informed traders will use multiple execution channels in order to mask their presence in the market (Menkveld, 2008). Other theories of informed trading speculate that uninformed market participants will widen the bid-ask spread (increase transactions costs) to compensate them for the potential of adverse selection (Glosten and Milgrom, 1985). Research questions arise from how the impact of informed traders affects price formation, both

in terms of trade-to-trade price movement as well as what trades lead to permanent prices and what trades produce only transitory shocks.

This thesis examines both types of informed traders: Chapter 3 investigates the daily and intraday effects of insider trades – those trades whose information comes from the company in which the insider trades. Chapter 4 examines the locus of price discovery – on which exchange do informed traders both quote and execute their trades- while Chapter 5 studies transactions costs at various exchanges in Europe, a metric highly influenced by the presence (or absence) of informed traders.

1. **Introduction to Chapter 3 – Insider Trading in Transaction Time: Impacts and Profits**

A type of market abuse performed by informed traders is insider trading, in which a corporate insider or another party in possession of proprietary non-public information trades upon it. In most countries, insider trading is a violation of the law, but economists have also contended that it increases price efficiency by impounding fundamental information into asset prices.

Chapter 3 investigates the impact of insider trading on share prices and volumes, both on a daily basis as well as on an intraday basis. Chapter 3 seeks to determine whether the impact of insiders on both a daily and an intraday basis is statistically significant both in terms of price movements as well as the lot sizes insiders transact. By employing a database created from US Securities and Exchange Commission prosecutions of insider trades, Chapter 3 segments insider trades from non-insider trades in the same 30 minute interval (to control for market-wide factors) and investigates insider trades' impact on price and volume. Chapter 3's sample also allows for analysis by different market structure, as both specialist (New York Stock

Exchange and American Stock Exchange) and dealer (NASDAQ) market structures are examined. Using the Lee and Ready (1992) algorithm, trades are classified as either buyer-initiated or seller-initiated, and insider trades are compared with trades with similar classifications.

Glosten and Milgrom (1985) note that price reactions are more pronounced in a specialist market structure, under which the specialist is counterparty to all trades in a security, as opposed to a dealer market structure. This is due to the relative anonymity of an informed trader active in a dealer marketplace. Garfinkel and Nimelandram (2003) show that counterparties' price reaction to a potential adverse selection situation extends to legal corporate insiders trading in their firm's securities. Easley and O'Hara (1987) theorize that uninformed traders may also refrain from trading when they perceive the presence of an informed trader, leading to diminished volume. Admati and Pfleiderer (1988) examines the importance of the spread in the case of informed traders and conclude that although the specialist will, on average, suffer losses to informed traders, he will benefit from liquidity traders paying for immediate execution.

There is also a welfare dimension to the examination of insider trading, as insider trading increases the cost of capital and alters the capital rationing function of the markets (Bhattarchaya and Daouk, 2002). Therefore, determining whether insider trades have different impacts than non-insider trades is key to assessing how insider trading affects market participants both in terms of price movements as well as volume. This thesis examines the two in tandem, as larger trades are more liable to have a larger price impact due to their greater demand for liquidity.

Chapter 3 uses ordinary least squares regressions as well as point estimates to determine the statistical significance (or lack thereof) of insider trading activity on

both a daily and intraday basis. In addition, subsets of the sample are examined in order to assess whether findings in prior literature may be influenced by sample composition. These subsets include insider trading by category of information traded upon (e.g. merger announcement, positive earnings report) and insider trading by market structure of the exchange traded on (the specialist system of NYSE and AMEX and the dealer system of NASDAQ).

Chapter 3 finds that at the intraday level, insider trades are statistically significantly different from non-insider trades in the same 30 minute period in both trade-to-trade price impact and in volume (lot size traded). This effect is most pronounced on the specialist exchanges of NYSE and AMEX, as NASDAQ insider lot sizes are not statistically significantly different from NASDAQ non-insiders. This result confirms the anonymity hypothesis of Glosten and Milgrom (1985), and shows that specialist markets react differently in the presence of an insider than dealer markets, where the insider can remain anonymous.

2. **Introduction to Chapter 4 – Price Discovery in Liquid British Stocks After the Advent of MiFID and Chi-X**

The drive to integrate previously segmented equities markets in Europe led the European Commission to promulgate the Markets in Financial Instruments Directive (MiFID). MiFID both allowed for pan-European trading of nationally-listed shares as well as catalysed the growth of new trading platforms such as Chi-X by requiring 'best execution' in equities. The launch of Chi-X spurred fragmentation in the European equities market, and can be viewed in conjunction with MiFID, the directive that enabled it. MiFID's intent was to create a pan-European securities market through two key mechanisms. First, the passport rule allows for a firm regulated by any EU national entity to operate throughout the European Union.

Second, the abolition of the concentration rule eliminated the mandatory shipping of trades to national exchanges (which was not in place in UK or German shares prior to MiFID) (Davies, 2008). With the increased competition due to lower barriers to entry, order flow fragmentation increased. In addition, Chi-X also targeted traders who were more focused on swift trade execution and highly sensitive to marginal fee rates.

Chapter 4 uses price discovery econometrics to determine whether the origin of price formation has migrated from the London Stock Exchange to Chi-X in light of regulatory changes at the European level. By examining the source of permanent trends (caused by impounding of fundamental information into asset prices) as opposed to that of transitory shocks (caused by order imbalances), price discovery econometrics can pinpoint the prevalence of informed traders within each channel.

Securities often trade in multiple markets and across multiple execution channels within markets. Through the no-arbitrage principle, it is reasonable to believe that trading follows error correction processes towards full-information and efficient security prices. As information is impounded into each market's price, the question arises as to which market is contributing more to this on-going price discovery. The observable price can be conceived as a common factor that impounds information plus a transitory shock. Two security prices that adhere to this common stochastic trend are expected to be co-integrated. From microstructure theory (Grossman, 1976), it is expected that informed traders, those traders aware of the true path of future prices based on information, are the source of this information impounding, as they are the sole market participants with information.

Two methodologies are used in conjunction to determine the locus of price discovery. Hasbrouck (1995) proposes a vector autoregressive model that decomposes price

volatility into the variance of innovations in the common factor. Hasbrouck's Information Share (IS) represents each market's contribution to the innovations in the common factor. This contrasts with Gonzalo and Granger's (1995) Common Factor Share (CFS) approach, which is a proportion of the common factor innovations that is driven by adjustment of the price series from each of the exchanges. Yan and Zivot (2010) confirm that both methodologies need to be used in conjunction, due to ambiguity in interpreting Hasbrouck Information Share estimates, in that the Information Share can be high either when a channel is impounding permanent information or when its competitors actively chase its stochastic shocks. Meanwhile, the Common Factor Share for an exchange will be high only if its prices avoid chasing transitory shocks relative to the competing markets. Therefore, using both measures helps to avoid an equivocal interpretation of Information Share, and at the same time allows one to interpret whether the trades on one channel are informative, or simply reflect another channel's pursuit of transitory shocks.

Chapter 4 examines how the launch of Chi-X, a Multilateral Trading Facility (MTF) targeting technological traders highly sensitive to costs and low latency, affected price discovery patterns. Prior assumptions would lead one to believe that, *ceteris paribus*, price discovery should take place on each exchange at a level proportionate to its order flow. However, the low latency nature of Chi-X may attract informed traders sensitive to speed of execution. Monthly values for Hasbrouck Information Share and Gonzalo Granger Common Factor Shares are calculated and analysed to assess how developments in the pan-European equities markets affect the source of price discovery.

Chapter 4 finds that although the introduction of MiFID had no effect on price discovery flows between the London Stock Exchange and Chi-X, a subsequent event,

Chi-X's central counterparty fee cut, led to the migration of the majority of price discovery from the London Stock Exchange to Chi-X. In addition, different price discovery patterns occur for shares with single primary listings in the UK and those with dual primary listings in the UK and in Asia. Importantly, Chapter 4 shows that MiFID introduced price cointegration when sampling price tuples every 1 second, causing prices on the London Stock Exchange to respond to prices on Chi-X, Deutsche Borse – Xetra, and the foreign exchange component to ensure that no arbitrage existed between all channels. This can be interpreted as the creation of a single pan-European securities market in equities.

3. Introduction to Chapter 5 – Liquidity and Fragmentation after MiFID on European Exchanges

Chapter 5 investigates MiFID's effects on transactions costs on pan-European equities markets. Prior to MiFID, concentration rules in some European countries mandated that securities be traded on a national exchange. More importantly, MiFID imposed a requirement that parties handling trades seek 'best execution' on behalf of their customers. Best execution is most often defined in terms of achieving the minimum (maximum) price when buying (selling) a share.

Central to the advent of MiFID was competition between a number of trading venues. As MiFID imposed a regime that required traders to obtain the best price for an order, order flow fragmentation occurred due to competition for best execution as well as a number of other preferences traders possess – from fastest execution to institutional arrangements for block trading. Prior theory offers two predictions as to what fragmentation will do to transactions costs. Hamilton (1979) hypothesizes that off-NYSE trading will spur greater competition and thus better spreads, but that it may

also increase volatility – if exchanges in fact enjoy economies of scale in transacting shares. However, Madhavan (1995) theorizes that fragmentation will drive volatility, reduce liquidity, and may lead to inefficient prices, stemming from the belief that a large exchange enjoys economies of scale in trading an asset. The debate distils into whether the effects of increased competition outweigh diminished economies of scale. Pagano (1989) suggests that if trading costs are homogenous between two markets, trading will cluster on one of them. He also notes that traders will participate on an exchange with idiosyncratic attributes conducive to their activity (e.g. block traders will trade either over the counter or on a market that facilitates large transactions, whilst liquidity traders will interact on a different market).

The literature in fragmentation suggests that there is a trade-off between the effects of stronger competition, as reflected in tighter spreads, and increased price volatility that results from the thinning of liquidity as traders migrate to satellite exchanges. In addition, market participants may split their orders between venues in order to opportunistically capitalize on different fee schedules and improved execution costs for desired order sizes.

Chapter 5 uses Bayesian Information Criteria (BIC) methodology to determine the most relevant variables to examine, and then uses Maximum Likelihood Estimation (MLE) methods to further examine relationships between transactions costs and a number of independent variables to investigate the launch of Chi-X, advent of MiFID, and a central counterparty fee cut on Chi-X to determine whether any of these three events have altered transactions costs in the UK, France, and Germany. It uses the full set of liquid stocks listed on the London Stock Exchange, Paris Euronext, and Deutsche Borse – Xetra to examine whether costs of a list of major European shares on each of these exchanges or collectively have been changed by fragmentation, the

abolition of France's concentration rule, volume traded, short-term price volatility, or interactions between these variables. Chapter 5 measures transactions costs in relative effective spread, as a 'round-trip' trading cost of a share.

Chapter 5 finds that increased fragmentation from the national exchanges to Chi-X after MiFID leads to decreased transactions costs in the form of lower relative effective spreads. However, incremental implicit pre- and post-trade costs in the form of a reduced central counterparty fee on Chi-X have a greater negative influence on transactions costs than MiFID's introduction of a 'best execution' obligation.

In summary, this thesis seeks to make a contribution to the literature on regulation and informed trading, utilizing the opportunity of a unique dataset in understanding the characteristics of insider trades in Chapter 3. A series of natural experiments created by regulatory restructures in Chapter 4 and 5 provides detailed insights as to how regulatory and market design affects the nexus between informed trading and transactions costs.

Chapter Two:

Literature Review

1. Introduction

This thesis examines the impact of informed trading on securities markets in several principal ways. Grossman (1976) defines informed traders as those traders who know 'the true underlying probability distribution that generates a future price, and they take a position in the market based on this information'. Informed traders generate price paths by trading upon their knowledge of this information, and through the interactions of informed traders with the market, prices reflect all available information. Therefore, informed traders stimulate asset markets by impounding information. This thesis examines the actions of informed traders in several fora: first, by examining the intraday impact of illegal insider traders, a subset of informed traders. Illegal insider traders possess private information on the future valuation of a company they either work for or owe a fiduciary duty towards – the Securities Exchange Act of 1934 defines insider information as 'material', thus providing a test that implies that those prosecuted for trading upon it use non-trivial information, and 'non-public', that is, not disseminated to the general investing populace. The second and third chapters of the thesis examine how fragmentation affects both the development of prices and transactions costs. Through fragmentation, the splitting of the order flow between multiple exchanges, informed traders can engage in strategic behaviour and mask their participation in the market, thus extracting maximum economic rent from their information. The competition inherent in fragmentation may allow informed traders to capitalize upon their information at a lesser price, although existing literature offers differential evidence on this topic, as economies of scale may be diminished. As price discovery methodology allows for the determination of where

informed traders trade, in that it separates permanent price trends from stochastic price shocks (often caused by order imbalances, as opposed to the impounding of information into market prices), research in this field can determine if market structure innovations attract informed traders.

2. Insider Trading

According to microstructure theory, informed trades, which are trades made on the basis of private information or analysis thereof, should cause traders to react to offset the costs of predation. This predation can be conceptualized as the difference between the trading price of the asset and the 'true' price of the asset that only the informed trader knows. Glosten and Milgrom (1985) model price setting in a specialist market. They theorize that with the adverse selection problem facing the specialist, the specialist will ensure a positive bid-ask spread, even when he is not seeking a profit, to provide a margin to compensate for unidentified insider activity due to information asymmetry. This problem may not confront the dealer, as he is anonymous and cannot detect any abnormal behaviour by floor brokers. Glosten and Milgrom (1985) see the specialist as requiring a higher price for liquidity when there is a chance that insiders or informed traders are present in the market who can take advantage of the specialist. As the specialist has a duty to ensure liquidity in the share, he is the monopolist provider of liquidity in the exchange, and thus, any sort of predation in the market is likely to take place at his expense. Easley and O'Hara's (1987) theory compounds the specialist's dilemma, in that if liquidity traders do not trade due to the perceived presence of an informed trader, the specialist incurs a greater loss as he must provide liquidity to the informed trader as opposed to mediating between uninformed traders and informed traders.

Benveniste, Marcus, and Wilhelm (BMW) (1992) suggest that the influence of a specialist-based exchange can compensate for the presence of an informed trader with price changes, notably by increasing the spread whenever the specialist perceives an informed trader is active in the market. This model demonstrates that as a result of repeated interaction between brokers and specialists on the floor, specialists will be able to spot informed trading, as the broker has a disincentive to deceive the specialist, as the specialist has the ability to sanction those who behave counter to his interests through mechanisms like failing to improve quoted prices. Through the repeated interaction of traders and specialists, the specialist will be able to detect when anomalous behaviour exists in the market and consequentially increase his spread or fail to improve prices. As opposed to the specialist's means of detecting informed traders, the dealer is only able to infer the presence of informed traders through order imbalances. Fishe and Robe (2002) empirically test Benveniste Marcus and Wilhelm (1992) using a natural experiment around traders in possession of a stock-picking column prior to publication. Their results show that spreads after the insider trades increased and depth shrinks, especially for NYSE-listed and AMEX-listed shares. Interestingly, they find no change in spreads on NASDAQ, which is consistent with the anonymity inherent in a dealer market. As Chakravarty, Harris, and Wood (2009) show, information occurs first in changes in depth levels; dealers may be adjusting their risk exposure due to the perception of an insider in the market. Easley and O'Hara (1987) and Admati and Pfleiderer (1988) examine the importance of the spread in the case of informed traders and conclude that although the specialist will, on average, suffer losses to informed traders, he will benefit from liquidity traders who are willing or are forced to pay a spread for immediate execution.

Garfinkel and Nimelandran (2003) test the impact of market structure on transactions costs using a set of legal corporate insider trades falling within Barclay and Warner's (1993) definition of 'medium-sized trades' (500-9999 shares). They posit and find that due to the anonymity of a dealer market such as NASDAQ versus a specialist system such as NYSE and AMEX, spreads and price impact costs on NASDAQ, the dealer market, will be lower, as dealers cannot detect the presence of an insider in the market.

Kyle (1985) theorizes that insider traders will trade over a prolonged period to extract maximum value from their private information. Therefore, one should expect insiders to trade repeatedly and in such a way that does not cause their information to be exposed, which would erode their competitive advantage. Therefore, in a Kyle (1985) universe, insiders may use limit orders to avoid detection and trade over a period of several days in order to extract the maximum rent from their monopoly information.

Meulbroek (1992) is the first empirical research paper on the daily impact of insider trading on share prices. She compiles private SEC files detailing insider trading prosecutions with publicly available data and news reports to profile and examine insider trading behaviour in cases prosecuted from 1980 to 1989. She tests for insider activity (proxied by abnormal returns on the day(s) of insider trading) using a market model with an estimation period of 150 days, controlling for news announcements and examining the return on the day of the public disclosure of the news upon which the insider traded. She uses the Centre for Research in Securities Prices (CRSP) value-weighted index of all shares traded as the basis for the market model. Meulbroek (1992) also uses a lagged market model to test for abnormal volume on the days insiders are active in the market, controlling again for news. As a robustness test,

she examines abnormal volume net of insider volume to determine whether the differential increase in volume is directly attributable to the insider.

She finds that price movements on insider trading days are almost half (47%) of the size of price movements on days when the news is publicly disclosed. She discovers an average run-up of 3.06% on the day of insider trading, and a cumulative abnormal return of 6.85% on insider trading days. This provides good support for the assumption that the information is leaking into the market and is impounded into prices. As Meulbroek's sample consists primarily (80%) of insiders trading upon news of imminent mergers, her results reflect price movement around mergers, and are not driven by earnings or other announcements. Meulbroek attributes the run-up to information leakage from insider traders. She finds a higher price impact for insiders trading on news of impending mergers (2.55% abnormal return and 6.01% CAR) versus that of insiders trading on earnings announcement news, which is consistent with the findings of Jarrell and Poulson (1989), who find a 40% run-up prior to merger announcements that they credit to rumours and arbitrageurs. Some of Meulbroek's results may be driven by her sample, which is composed of mostly specialist stocks (70%) and mergers (79%), which may exaggerate the impact of an insider trade. Meulbroek finds that insiders provide the marginal volume distinguishing insider trading days from non-insider days, and thus insiders are not driving additional participation in the market. She further notes that since insider trading drives abnormal volume, insider trading leads to abnormal returns, but asks whether insider trading is detected by trade aspects or by abnormal volume, and discovers that both have a marginal effect on abnormal returns.

Cornell and Sirri (1992) and Chakravarty and McConnell (CM) (1997, 1999) examine a serial insider trader or ring – in Cornell and Sirri's case, a group of insiders trading

in advance of a merger announcement, and in Chakravarty and McConnell's case, arbitrageur Ivan Boesky's insider trading in Carnation shares. Cornell and Sirri determine that insider trading's effect in this acquisition was complex – while price was affected and volume increased. Contrary to Meulbroek's findings, Campbell-Taggart's liquidity improved. This is unexpected in that an aggressive insider ring would lead specialists to protect themselves through changes in the spread (Glosten and Milgrom, 1985), and thus, liquidity would be expected to decrease. Cornell and Sirri (1992) attribute these seemingly contradictory results to the presence of noise traders, who are defined as falsely informed traders[1]. Falsely informed traders can be defined as those traders who believe they are trading on superior information and analysis, but in fact do not have any advantage over other traders. Cornell and Sirri cite technical traders ('chartists') as a classic example of falsely informed traders. They argue that the specialist's problem dissipates when he can match falsely informed traders and informed traders, as he is not subject to inventory effects, as the informed traders are counterparties to the falsely informed traders' trades. This coincides with Admati and Pfleiderer's (1988) conclusion that informed traders increase activity when liquidity traders are present in the market.[2] Therefore, Glosten and Milgrom's (1985) finding may not hold because insiders, not the specialist prey upon falsely informed traders. Cornell and Sirri's case study is distinct from other studies in that the insider ring purchases a substantial proportion of traded shares. In their study, insider purchases constitute 29% of the total volume and represent a significant increase in volume. Cornell and Sirri attribute all the effects in their study to the presence of insiders and falsely informed traders, because the target company,

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[1] Noise traders are differentiated from liquidity traders in that noise traders believe they are trading on 'special' information. See DeLong, Shleifer, Summers, and Waldmann (1990).
[2] In Cornell and Sirri's case, 10 trades out of 78 (12.8%) were executed via limit orders.

Campbell Taggart, did not exhibit any confounding behaviour, such as news stories speculating on its potential as a merger target that could be driving abnormal volume. Through tracking short interest (unchanged), volume, and the share price of Anheuser-Busch (the acquirer), Cornell and Sirri conclude that the only informed traders present are the insider traders.

Chakravarty and McConnell (1997) find a weak link between insider trading and subsequent stock prices, showing a lagged correlation between Boesky's purchases in the market and subsequent prices with the strongest significance displayed in the link between Boesky's purchases and the stock price two hours later but also showing a link between Boesky's buying and contemporaneous price increases. However, price increases immediately after Boesky's purchases may just be a liquidity effect, as any large trader aggressively buying in the market will push up the price and is thus not an effect *per se* of insider trading. Boesky's trading, as in Cornell and Sirri (1992), did not affect spreads. Also, although Boesky contributed to the increased volume on days he traded, he was responsible for only half of it, with the other half potentially coming from falsely informed traders or momentum traders. By using time stamped trades and segmenting their sample into Barclay and Warner's (1993) categories, Chakravarty and McConnell (1997) discover that the Boesky trades correlated with price movements are the 'large' trades. They further conclude that since insider trading may be beneficial, as it assists in price discovery, and if spreads do not change as in this case, there is no adverse selection component. However, Chakravarty and McConnell (1997) were unable to discern as to whether Ivan Boesky's trading spurred the price run-up, or whether he chose to trade on days after observing such an increase in prices.

Chakravarty and McConnell (1999) reprise the 1997 study, but with an important inclusion of trade direction through the use of the Lee and Ready (1993) algorithm. They find that Ivan Boesky's trades (buys) in Carnation did not have a different impact than other buy trades, and thus, conclude that a large component of price impact in that case was due to overall trade imbalance as opposed to the presence of an informed trader in the market. They also estimate Meulbroek (1992) and Cornell and Sirri's (1992) regressions on the Ivan Boesky data, and discover that when adjusting their methodologies for trade direction, insider trading is statistically no different from a trade in the similar direction. They verify with the Boesky data Meulbroek's (1992) contention that higher returns exist on insider trading days than on days with no insider trading or public news announcements. Chakravarty and McConnell (1999) notably state that their critical assumption is that all non-Boesky trades are uninformed.

Fishe and Robe (2004) discuss the impact of insider trading in advance of a news column. This can be differentiated from the other cases inasmuch as the insiders' trading pattern is relatively regular – to wit, they trade the day prior to public disclosure of the information. Fishe and Robe (2004) use spreads and depth in the limit order book as key metrics to measure the impact of illegal insider trading, ascertaining that when an insider is present in the market, depth shrinks in both dealer and specialist markets, but spreads increase only under specialists[3]. These results substantiate Glosten and Milgrom's (1985) model. They find that volume increases substantially only after the insiders are present in the market, and attribute this to the presence of falsely informed traders. The insiders are only responsible for a marginal increase in volume (9.2%), which seems to suggest that either the information on

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[3] Fishe and Robe (2004) find that only ask depth changes significantly. As their data is comprised solely of purchases of shares, this may be a natural conclusion.

which the insiders trade leaks or liquidity or falsely informed traders are goaded into the market after observing a spike in price and volume. Fishe and Robe (2004) use a control group of equities in which information was available to the insiders but they did not trade, and find that normal price, volume, and spread patterns prevail.

In summary, Cornell and Sirri (1992), Meulbroek (1992), and Chakravarty and McConnell (1997, 1999) all identify a significant price and volume impact on the day of the insider trading, but do not have sufficiently granular data to identify whether the increased volume and price are spurred by insider trades. In addition, each of these studies use aggregated data (for Cornell and Sirri and Meulbroek, daily data, for Chakravarty and McConnell, hourly data), leaving unanswered the question as to how insider trades immediately impact prices and volumes. Furthermore, all the studies with the exception of Meulbroek (1992) are comprised solely of insiders purchasing shares – which may provide an unrepresentative sample of data with which to make blanket conclusions as to the effect of insider trading. Meulbroek's (1992) sample is driven by speculation on merger announcements, which she shows to have a higher abnormal return than the impact of other information disclosed into the marketplace.

These inconsistent explanations merit further study, as Chakravarty and McConnell (1999) wrote, is whether results from a small population (with one insider trader or a small ring) are valid amongst a larger sample, or if the results are driven by idiosyncratic attributes of the trades (e.g. a trader accounting for a large proportion of trading volume).

3. Fragmentation

3.1 Regulation and Market Integration

The United States Securities and Exchange Commission (SEC) promulgated Regulation NMS with the intent of protecting retail investors and promoting robust competition between markets, while ensuring markets remained integrated on a security level. Reg NMS's intent is encapsulated in the idea that '[v]igorous competition among markets promotes more efficient and innovative trading services, while integrated competition among orders promotes more efficient pricing of individual stocks for all types of orders, large and small' (Reg NMS, 2007). As United States securities law has historically focused on protecting the retail investor from potential predation on the part of the more sophisticated institutional investors, Reg NMS also includes a battery of provisions to ensure the protection of retail investors. Foremost among these is the Order Protection Rule, which mandates that an order be 'shipped', or sent, to whatever exchange (known in Reg NMS as 'market centers') offers the best price, defined in terms of the highest price for a sell order and lowest price for a buy order. This principle is commonly known as 'best execution' in obtaining the optimal terms for an order. As is apparent in MiFID, best execution can take different forms, including speed of trade and likelihood of execution, as well as price.

Concurrent with the drafting of Regulation NMS, the European Union launched the Markets in Financial Instruments Directive (MiFID), a successor to the Investment Services Directive (ISD), MiFID meant to develop a pan-European securities market and, like Reg NMS, ensure the protection of retail investors in European financial markets. While MiFID was drafted by the European Commission, as per European Union subsidiarity, it was the responsibility of individual European Union nation financial market regulators to enforce it and draft national regulations to that end.

Like Reg NMS, MiFID aimed to obtain the International Organisation of Securities Commissions' (IOSCO) twin goals of efficiency and fairness, and to a similar end, sought to encourage innovation and competition between markets and market participants within. Another similarity between Reg NMS and MiFID is that to comply with MiFID, market participants needed to invest in technological systems in order to ensure that they met best execution obligations. With these routing and trading systems, transparency arguably increased, as a trader could view and access order books in not only all of the established European exchanges, but on the new Multilateral Trading Facilities (MTFs), most notably Chi-X. MTFs differ from the established exchanges in their highly electronic nature and lean operating budgets. They also offer trading terms that may appeal more to technological traders - an increasing breed of market participants. The economic effect of MiFID was a transformation of the marketplace for security services from a monopoly, or highly concentrated oligopoly (in the case of states without concentration rules), to active competition to provide trading services across Europe.

Reg NMS differs from MiFID in several fundamental ways. Whereas MiFID institutes transparency and requires firms to report on best execution policies, Reg NMS's order protection rule mandates that brokers prevent execution of orders without regards for improved quotes on other exchanges. In short, Reg NMS categorizes best execution through the lens of price. However, as noted by many academics, this rule does not apply to certain types of trades. By contrast, MiFID defines best execution in terms of price, speed, size, likelihood of execution, and a number of other variables (European Commission, 2007). Reg NMS also places the affirmative burden on exchanges and other trading venues to ship an order to a preferential quote whereas MiFID only applies to brokers. Therefore, MiFID's

structure encourages, but does not ensure, best execution in trading, due to the nebulous definition of best execution in MiFID. Furthermore, critics of MiFID have asserted that MiFID's obligation to publish a best execution policy and statistics indicating the extent of a broker's compliance is ineffective, as European securities regulators have not threatened sanctions on any firm in breach of its best execution duty. However, critics of MiFID have stated that competition may come at the price of 'a transparent and effective price formation process' (Lannoo, 2007). Blume (2007) argues that Reg NMS's uniform/one-size-fits-all framework harms investors with heterogeneous preferences, and advocates for a MiFID-like regulatory framework to maximize choice among market participants.

 The literature on fragmentation suggests that there is a trade-off between the effects of stronger competition, as reflected in tighter spreads, and increased price volatility that results from the thinning of liquidity as traders migrate to satellite exchanges. One can view this as the diminution of monopoly rents as the marketplace shifts to imperfect competition. In addition, market participants may split their orders between venues in order to opportunistically capitalize on different fee schedules and improved execution costs for desired order sizes. A cream-skimming effect may also take place with additional small size venues entering into the market.

3.2 Fragmentation

MiFID's intent was to create a pan-European securities market through two key mechanisms. First, the passport rule allows for a firm regulated by any EU national entity to operate throughout the European Union. Second, the abolition of the concentration rule eliminates the mandatory shipping of trades to national exchanges (which was not in place in UK or German shares prior to MiFID) (Davies, 2008). With the increased competition due to lower barriers to entry, order flow

fragmentation increased. MiFID can be compared and contrasted with the United States' Reg NMS. Whilst both had the intent of ensuring best execution (Lannoo, 2007), MiFID's goal of harmonizing securities market rules created different standards for the achievement of best execution than those in Reg NMS. The ultimate enforceability of the best execution requirement, however, is at issue in MiFID where market participants are at liberty to define their own meaning for best execution as long as that meaning is well known to their clients. However, increased pre- and post-trade transparency requirements have bolstered competition as a vehicle to facilitate best execution. In addition, it can be argued that the national exchanges enjoyed a quasi-monopoly privilege in Europe pre-MiFID, whereas that was not the case prior to Reg NMS.

Petrella (2009) details the fragmentation in major index components that occurred after the advent of MiFID. Chi-X's market share of FTSE 100 equities moved from 2% in November 2007 to 7% in May 2008 to 12% in November 2008. Over the same period, LSE incurred a gradual decline in its market share, as it slipped from 70% in November 2007 to 58% in May 2008 to 59% in November 2008. Petrella (2009) notes that fragmentation can be attributed to the establishment of new MTFs offering different pricing schemes, and that are often owned in part by major brokers and dealers.

Hamilton (1979) hypothesizes that off-NYSE trading will spur greater competition and thus better spreads, but that it may also increase volatility if exchanges in fact enjoy economies of scale in transacting shares. Empirically, Hamilton finds that both effects exist, but that the competition effect outweighs the volatility effect attributable to fragmentation. Mendelson (1987) presents a theoretical framework in which he compares monopolists against a fragmented market, and shows that price variability

increases for individuals but that the overall amount traded decreases. In addition,

overall price volatility decreases, as fragmentation/competition effects dominate the

removals of economies of scale. Pagano (1989) suggests that if trading costs are

homogenous between two markets, trading will cluster on one of them. He also notes

that traders will participate on an exchange with idiosyncratic attributes conducive to

their activity (e.g. block traders will trade either over the counter or on a market that

facilitates large transactions, whilst liquidity traders will interact on a different

market). Pagano (1989) submits that search can be beneficial for large traders'

liquidity needs, despite having some cost. Chowdry and Nanda (1991) focus on the

information transmission dynamic, theorizing that competition between market

makers will speed-up information impounding into prices, and that liquidity traders

will split their orders between markets. In a finding of significance to this thesis, they

find that one market will become the information-dominant exchange for trading in a

security.

Madhavan (1995) theorizes that fragmentation will drive volatility, reduce liquidity,

and potentially lead to inefficient prices. Batallio (1997) finds decreased spreads in

NYSE-listed shares in which Madoff Securities competed. However, it is worth

noting that Madoff only executed share volumes at or beneath 5000 shares, so he may

have engaged in cream-skimming. As a result, fragmentation may lead to this sort of

predatory behaviour. Fong, Madhavan, and Swan (2001) provide empirical evidence

corroborating Pagano's (1989) theory that differential liquidity needs affect a trader's

cost of whether to trade on-market or in an alternative venue, such as an upstairs

market or ECN. Bennett and Wei (2006) empirically examined Madhavan's findings

and document how fragmentation in NYSE-listed shares affects liquidity and

volatility through a natural experiment in which NASDAQ firms switch to the NYSE,

discovering that NYSE firms have lower bid-ask spreads attributable to the reduced fragmentation. Lannoo (2007) contends that this was the intent of MiFID's regulatory predecessor, the EU's Investment Services Directive, which allowed for the concentration of trading at a national exchange. In this vein, MiFID's encouragement of competition and the resultant fragmentation may simultaneously increase liquidity and spreads, but at the detriment of the price discovery process.

Lee (1993) focuses on execution quality in US satellite exchanges, and discovers that in the presence of paid order flow, the payment amount tends to capitalize itself into the spread. To wit, non-NYSE trades have larger execution costs than NYSE trades by roughly the amount of the order flow payment. Lee also discovered that satellite exchanges had better execution costs in medium size trades while the NYSE dominated in large trades, while NASDAQ performed worse than both NYSE and satellite exchanges. In a caveat, Lee noted that he focused only on execution costs, and other attributes of execution may reflect better on the NASDAQ.

Economides (1996) documents potential network externalities in the context of financial markets. While markets must have a minimal level of liquidity to execute transactions, as O'Hara and Ye (2009) note, fragmentation has no detrimental effect. To the extent that fragmentation leads to an increase in liquidity, welfare increases for all participants. In the context of price discovery, this would imply that overall price discovery would not be harmed by fragmentation, and that migration to a new exchange offering will be determined by factors other than liquidity.

Huang and Stoll (1996) attribute the larger spread on NASDAQ shares as compared to a matched sample of NYSE shares to both order preferencing agreements and a lower degree of competition from ECNs in NASDAQ listed shares, which diminish

competitive effects. Another factor to which they attribute higher spreads on NASDAQ to is the lack of a specialist with knowledge of complete order flow; therefore, each market-maker must protect himself from predation by informed traders. While this is theoretically possible, Huang and Stoll (1996) do not find evidence corroborating this. The two largest factors affecting the spread are NASDAQ's existing interdealer market[4], and internalizing and preferencing arrangements that reduce the incentive to compete, as that order flow is hypothecated to certain dealers.

A number of recent studies have examined the effect of fragmentation and market integration on measures of liquidity. Liquidity can be posited to affect price discovery as informed traders need sufficient liquidity on which to execute their trades, and thus impound information into prices. In the absence of sufficient liquidity, information fundamentals may not drive prices, but rather order imbalances caused by a patchy limit order book. Moulton and Wei (2009) find that during overlapping ADR trading hours for European cross-listed securities spreads decrease while quoted depth increases. This is attributed to either competition for order flow between the European exchanges and NYSE or the influx of additional liquidity into the market during overlapping hours. Menkveld (2008) provides evidence of order-splitting behaviour in extending Chowdry and Nanda's (1991) model to a sample of British and Dutch shares with ADRs. O'Hara and Ye (2009) examine how the growth of non-exchange trading venues affects market execution costs. They find that fragmentation occurs most frequently on small NASDAQ shares and least frequently on large NYSE shares. They conclude that fragmentation lowers transactions costs and increases transaction speed, which further verifies the competition hypothesis.

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[4] This system is similar to SETS's hybrid system – see Gresse and Gajewski (2007).

The literature in fragmentation suggests that there is a trade-off between the effects of stronger competition, as reflected in tighter spreads, and increased price volatility that results from the thinning of liquidity as traders migrate to satellite exchanges. In addition, market participants may split their orders between venues in order to opportunistically capitalize on both different fee schedules and improved execution costs for desired order sizes. A cream-skimming effect may also take place with the entrance of additional small size venues into the market. Recent literature, such as Jain and Johnson (2009) proposes a 'network effect' with the influx of many additional liquidity providers due to technological changes in the marketplace facilitating trading.

3.3 MTFs, Algorithmic Trading and Fragmentation

Barclay, Hendershott, and McCormick (2003) demonstrate how lower latency in ECNs can lead to more informed trading, and therefore, greater adverse selection costs. In addition, they show that ECNs provide the majority of price discovery compared to traditional exchanges. Hendershott and Moulton (2009) find that lower latency leads to the greater incorporation of information into prices. They also outline how latency can lead to greater competition for liquidity providers, and attribute an increase in effective spreads to the price of immediate execution. Boehmer and Boehmer (2003) investigate the new listing of three exchange traded funds (ETFs) on NYSE and find that a significant amount (10%) of order flow migrates to NYSE, and that in two out of the three shares, NYSE impounds the most information relative to order flow. NYSE's over performance in proportion to its overflow can be attributed to the influx of informed order flow. Boehmer and Boehmer (2003) note that NASDAQ's quotes come from the Island ECN, which provides further support to the theory that a large proportion of informed participation occurs on ECNs, although,

some informed traders may have moved to NYSE with the introduction of competition. The implications of this is that price discovery is expected to follow the order flow of the informed traders, as per Grossman (1976), informed traders are the market participants aware of the future expected value of the asset, so in trading, they will impound permanent valuation fundamentals.

Smith (2008) outlines the growth of non-exchange trading in the United States and speculates that MTFs will develop differentially to appeal to various sorts of traders. This coincides with existing literature[5] positing that traders have heterogeneous preferences and endowments. Smith (2008) highlights Markit BOAT's emergence as an alternative trade reporting facility (where trades that take place on another venue or over-the-counter can be reported to comply with regulation) and Chi-X's advantage due to a speedier order book and a direct clearing system. Chistella et al (2007) describes Chi-X's market model as comparable to Xetra and Euronext. Chi-X's share of the order flow for the largest FTSE 100 components is under 1%, as compared to its 3-5% share of major Dutch and German equities.

Hendershott and Riordan (2009) examine the information shares of algorithmic trades and non-algorithmic trades on Deutsche Borse's Xetra Platform in the thirty shares comprising Germany's main index, the DAX. They use a set of algorithmic trades on Xetra provided to them by Deutsche Borse. Using quotes, they find that algorithmic trading has an information share of 51%. Importantly, they find that algorithmic trading is sensitive to the price of liquidity, demanding liquidity when it is inexpensive, and supplying it when liquidity's cost increases. They do not find that algorithms raise price volatility.

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[5] Kyle (1985) and Foster and Vishwanathan (1990) are examples of this literature.

Gresse and Gajewski (2007) compare execution costs on Euronext Paris's NSC trading system with the London Stock Exchange's SETS. Drawing on prior literature showing that an electronic order driven market has lower trading costs than a quote-driven market, they conduct an event study following the introduction of the LSE's SETS system. The key difference between the two trading systems is that NSC (Paris) routes all systems to a central limit order book whilst LSE's hybrid system includes SETS's central limit order book with other trading mechanisms that are not displayed. The centralisation of Paris's limit order book is an artefact of certain EU member states' 'concentration rule' that stymied the development of ECNs outside of the United Kingdom (UK) by mandating that all trades in a nationally-listed share be sent to that country's national stock exchange. By way of example, prior to MiFID, BP, a UK-listed share, could be traded on the London Stock Exchange, Deutsche Borse's Xetra, and ECNs in the European Union (EU), while Total, a Paris-listed share, could only be traded on Euronext Paris. A result is that dealers are on standby to bilaterally offer non-displayed quotes outside the order book on London, while all quotes in Paris must be visible on the order book. Gresse and Gajewski (2007) find that prices are more volatile on SETS and that spreads are higher there which is in part driven by the marginally larger size of trades on SETS. Using Huang and Stoll's (1997) spread decomposition[6], they show that SETS has roughly half the proportion of the spread falling under both adverse selection and inventory holding that NSC has, which is in accord with most of the literature on adverse selection that shows that adverse selection is lower on venues with less pre-trade transparency. Gresse and Gajewski (2007) thus display that market structure affects local price volatility and can induce trading migration. Therefore, to the extent that market structure changes attract

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[6] Huang and Stoll split the spread into 'inventory holding and adverse selection' and order-processing components.

increased informed order flow, fragmentation will alter price discovery patterns as well as drive changes in transactions costs.

4. Price Discovery

4.1 Price Discovery Across Channels

Securities often trade in multiple markets and across multiple execution channels within markets. From the no-arbitrage principle, it is reasonable to believe that trading follows error correction processes towards full-information and efficient security prices. As information is impounded into each market's price, the question arises as to which market is contributing more to this on-going price discovery. The observable price can be conceived as a common factor that impounds information plus a transitory shock. Two security prices that adhere to this common stochastic trend are expected to be cointegrated. From microstructure theory (Grossman, 1976), it is expected that informed traders - those traders aware of the true path of future prices based on information - are the source of this information impounding, as they are the sole market participants with information.

Two alternative econometric approaches seek to provide an answer to the question of contributions to price discovery. Hasbrouck (1995) proposes a vector autoregressive model that decomposes price volatility into the variance of innovations in the common factor. Hasbrouck's Information Share (IS) represents each market's contribution to the innovations in the common factor. This contrasts with Gonzalo and Granger's (1995) Common Factor Share (CFS) approach, which is a proportion of the common factor innovations that is driven by adjustment of the price series from each of the exchanges. De Jong (2002), Lehmann (2002), and Baillie et al (2002), have surmised that a combination of the two may be informative. Yan and Zivot (2010) argue that CFS is needed to more effectively interpret the IS. The IS for an exchange

can be large either because an exchange's trades impound permanent information, or because its competitors' trades are chasing transitory shocks. Meanwhile, the CFS for an exchange will be high only if its prices avoid chasing transitory shocks relative to the competing markets. Therefore, using both measures helps to avoid an equivocal interpretation of Information Share, and at the same time, permits a determination of whether the trades on one channel are informative, or simply reflect another channel's pursuit of transitory shocks.

Roughly four generations of price discovery technology have existed since Engle and Granger (1987) launched their study of cointegration/error correction systems. The first is exemplified by Harris, McInish, Shoesmith, and Wood (1995), when they specify a vector error correction model (VECM) to determine whether prices in IBM, a NYSE listed security, were solely formed from NYSE price changes, or whether there was an error correction dynamic between trade-based price adjustments in New York and those on the Chicago and Pacific Exchanges. At the time, all markets employed a specialist system, and although New York had ten times the trades of Midwest (and 3.5 times the trades of Pacific), Harris et al were able to match roughly 80 observations per day for analysis. After performing a Johansen (1991) test for cointegration, discovered that the Midwest and Pacific exchanges contribute meaningfully to the price discovery process. IBM prices on NYSE error correct to permanent innovations on the Midwest and Pacific exchanges as well as the Midwest and Pacific exchanges reacting to movements in the NYSE price.

Hasbrouck (1995) investigates the price formulation process in Dow shares by determining how much of the variability in a share's quote-based returns can be attributed to trading in all tape-reported execution channels in Dow shares. Hasbrouck notes that his sample includes alternative trading systems, but not overseas trades.

Both Harris et al (1995) and Hasbrouck (1995) seek to determine the dynamics of price adjustment, namely which price reacts to adjustments on another exchange. Hasbrouck proceeds to note the sensitivity of his analysis to reporting mechanisms such as auto-quotes, delayed posting of quotes, and to 'stale' behaviour in infrequently updated quotes and trades. In addition, due to the econometric specifications of Hasbrouck's (1995) model, simultaneous correlation between quote updates on the primary exchange and on the satellite exchanges will result in a large range of estimates when the order of the series is reversed in the Cholesky factorization procedure.

Harris et al (2002) pioneer a third generation of price discovery technology, adapting Gonzalo and Granger (1995)'s common factor share approach to financial markets. This extends their previous 1995 work, providing a snapshot in time across the Dow components to see if common factor weights are dynamic. Harris et al (2002) note that the Gonzalo-Granger measure is robust to cross-equation correlations, and characterise it as a representation of the permanent price trend caused by the incorporation of information into asset prices.

Yan and Zivot (2010) and Harris, McInish, and Wood (2010) reconcile the Hasbrouck and Gonzalo-Granger approaches for determining price discovery by showing that although Hasbrouck's IS approach measures informativeness, it also reflects the chasing of transitory shocks. An IS can be high either because a channel is impounding permanent information, or because its rivals are chasing transitory shocks. In contrast, the Gonzalo-Granger approach will produce a high CFS only if competing execution channels are chasing transitory shocks. Therefore, use of the two measures in conjunction will be required to determine which channel is impounding new information and which is chasing transitory shocks.

Kim et al (2000) investigate price discovery in American Depository Receipts (ADRs) and their underlying securities, using VAR and Impulse response functions, finding that although the domestic price is the leading indicator in price adjustment (roughly 65% of the innovations), exchange rates (roughly 15%) and the ADR market (roughly 10%) play some role in the dynamics of price adjustment between the ADR and the underlying asset.

4.2 Price Discovery Across Borders

The international finance literature demonstrates the sensitivity of modelling of the exchange rate. Ding et al (1999) are the first in this literature with an examination of Sime Darby Berhad, one of Malaysia's largest corporations, which trades on both the Kuala Lumpur Stock Exchange and the Singapore Stock Exchange. Given the relative stability of the ringgit-Singapore dollar exchange rate, they convert all prices at several times in the day into a common currency. They note that the rate is sufficiently stable that practitioners do not convert prices on a real time basis. Ding et al (1999) discover that a significant amount of price discovery (from 26-32%) occurs in the foreign (Singapore) market, a price discovery share larger than its proportion of trading volume. The estimation of a VECM shows that although foreign prices strongly error correct to Malaysian prices, Malaysian prices' error correction to Singaporean price adjustments is relatively weak.

Grammig, Melvin, and Schlag (2005) study the rate of price discovery in German shares and their ADRs and find that an overwhelming (80-90%) amount of the information is impounded in German markets. They also display the importance of modelling the exchange rate process as a separate vector of prices, as opposed to converting to a common currency. Grammig et al (2005) draw the conclusion that a firm's foreign earnings can affect the price discovery processes. For example, they

find that the New York Stock Exchange influenced price discovery more in DaimlerChrysler, a firm with significant earnings on both sides of the Atlantic, than in Deutsche Telekom or SAP, the German software company.

5. Transactions Costs

5.1 Transactions Costs – Theory and Empirics

Demsetz (1968) was the first to investigate transactions and conceptualized the bid-ask spread as a way of incorporating 'immediacy' into the study of transactions costs. This is the first illustration of a concept of liquidity in the literature, and Demsetz illustrates it either as the direct cost of immediacy or as a profit margin on inventory. Demsetz enumerates five factors that will lead to the narrowing of the spread: competition from others to become the specialist, competing markets, order aggressiveness, trades directly between counterparties, and other specialists. Benston and Hagerman (1974) provide a framework where the spread is affected by the cost of holding inventory, matching orders, 'trading with insiders', and competition. Therefore, they expand Demsetz's framework by incorporating what have come to be known as 'order-processing costs' and adverse selection. Grossman and Miller (1988) model liquidity as the supply and demand for 'immediacy' as negotiated between market makers and liquidity demanders. Market makers recapture the costs of inventory deviating from optimal levels and the costs of their presence in the market through the bid-ask spread. Copeland and Galai (1983) pioneer the modelling of the bid-ask spread as the dealer's situation between trading with liquidity traders and informed traders. As the dealer profits from trading with liquidity traders and loses from trading with anonymous traders, the spread is set as a way to mediate that interaction. Glosten and Milgrom (1985) model price setting in a specialist market. They theorize that with the adverse selection problem facing the specialist, the specialist will ensure a positive bid-ask spread, even when he is not seeking a profit,

to provide a margin to compensate for unidentified insider activity due to information asymmetry. This problem may not confront the dealer, as he is anonymous and cannot detect any abnormal behaviour by floor brokers. Even in the presence of multiple market makers, the factor of interest that will allow the market maker to detect abnormal behaviour is the concentration of order flow, and her ability to compare the entire order flow with historical patterns. Easley and O'Hara (1987) and Admati and Pfleiderer (1988)[7] examine the importance of the spread in the case of informed traders and conclude that although the specialist will, on average, suffer losses to informed traders, he will benefit from liquidity traders who are willing or are forced to pay a spread for immediate execution. McInish and Wood (1992) note the presence of an intraday pattern in bid-ask spreads in the NYSE market. Examining all these models of transactions leads one to conclude that a number of factors set liquidity's price, but ultimately liquidity's price works as a supply and demand interaction. Another variable this thesis considers is pre- and post- trading fees, costs levied by an exchange for access to it and for certainty and insurance of transactions. While the bid-ask spread can be conceived as an explicit and fluctuating cost, trade-related fees are often fixed costs (platform access fees), or a fixed amount per trade.

Therefore, the spread can be conceived both as a price and insurance for the inventory holder to protect against the possibility of predation by an informed counterparty. Glosten and Harris (1988) are the first to estimate these ratios, and are unable to verify that the adverse-selection components of the spreads of a series of NYSE-stocks in 1981-1983 were positive, and find that the primary determinant of spread size is trade size. This size effect can be seen as a cost of liquidity for large trades that need to walk the book in order to fully execute. However, this is a key driver in the

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[7] Foster and Vishwanathan (1990, 1993) model how an informed trader's decision and timing of trading is reliant on the timing of disclosure of public information.

innovation of 'upstairs' platforms where institutional traders can exchange large blocks of shares. In this vein, Huang and Stoll (1997) and Lin, Sanger, and Booth (1995) derive models that identify two components constituting the spread: order-processing costs, which can be conceived as economic rents to trading service providers, and adverse selection costs, which can be conceived as the insurance premium captured in the spread to compensate the liquidity provider from the possibility of trading with an informed counterparty. The two papers diverge in that Lin, Sanger, and Booth (1995) study the impact of the size of the trade on the adverse selection component of the spread[8]. Literature diverges on whether inventory risk (the risk of the market maker maintaining a level of inventory different from his preferred level) is a prime component of the spread. Grossman and Miller (1988) theorize it may be. Two empirical studies offer different evidence: while Hasbrouck (1988) finds mixed evidence to conclude whether inventory risk is a significant component in the spread, Bollen, Smith, and Whaley (2004) note that in a sample of NASDAQ stocks in 1996 through 2001, that 29% to 44% of the spread is attributable to inventory costs, a larger proportion than the adverse selection component various papers determine as the driver of the size of the spread.

Sidhu, Smith, Whaley, and Willis (2007) document that the implementation of Regulation FD in the US, ostensibly in order to 'level the playing field' with regards to corporate disclosure of material information, led the adverse selection component of the spread to increase 36%. They hypothesize that this may be due to slowing the dissemination of corporate information into the market, leading to 'longer lived' information that is more useful to insiders, as opposed to the opposite scenario wherein multiple insiders simultaneously transact, leading to information to be nearly

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[8] Lin et al (1995) find a monotonic increase in the adverse selection component with the size of trades.

instantaneously incorporated in prices. Sidhu et al (2007) may be discovering that informed traders after Regulation FD behave similarly to Kyle (1985) inside traders, seeking to extract monopoly rent from their unique information. Chung and Chuwonganant (2010) examine the implementation of Reg NMS in the United States. Reg NMS, by prohibiting exchanges 'trading through' superior quotes, attempts to integrate satellite exchanges, ECNs, and traditional exchanges into a single market for liquidity. This is driven by the fragmentation debate, and especially the discussion on preferencing agreements, leading retail investors to be disadvantaged when active in the marketplace. Reg NMS explicitly mandates, through its Order Protection Rule, price priority in terms of execution, in that a dealer must 'ship' an order to the exchange at which she can receive the best price for the volume desired. Interestingly, Chung and Chuwonganant (2010) find that the effect of Reg NMS on NYSE and NASDAQ-listed stocks to not be statistically different, but find that spread increases and depth decreases. They attribute this to dealers interested in alternative dimensions of market quality, namely execution speed and execution probability. Following from the fragmentation theoretical literature, it is not improbable that Reg NMS catalysed additional fragmentation, leading market participants to enjoy lesser economies of scale. One could also conceive this as an additional fragmenting of the order book, which leads to higher execution costs as Gresse and Gajewski (2007) find. Gresse (2010) finds that post-MiFID fragmentation increased spreads on local exchanges, although traders able to access multiple exchanges benefited from MiFID-spurred fragmentation by lower overall spreads. She also finds that depth decreases, but that may be an artefact of smaller trade sizes as traders seek to minimize overall trading costs by utilizing multiple venues as well as internalisation (matching systems within banks and other brokers).

Bessembinder (2003) analyses execution costs in NYSE stocks both on NYSE and on competing exchanges and determines that off-NYSE trades are executed when off-NYSE liquidity providers offer competitive quotes for large trades, and that competitive quotes serve as a means by which non-NYSE liquidity providers indicate their willingness to trade. He states that non-NYSE exchanges use quotes as a means to attract order flow when they wish to trade. While the NYSE is always at one side of the NBBO (national best bid-offer, which is the consolidated tape's tightest bid and ask spread), off-NYSE exchanges tend to match or offer a smaller (greater) bid (ask) on the alternate side of the spread. When non-NYSE liquidity providers offer competitive quotes, execution costs are not significantly statistically different from NYSE.

Grossman (1992) models an interaction between an upstairs and downstairs share market. He concludes that both the cost of search and differential needs of market participants (examples may include price and liquidity) will cause the development of an upstairs market to supplement traditional markets. The additional liquidity provided comes with the drawbacks that upstairs traders are likely to be more informed about both overall order flow (in that while they can observe the downstairs market, upstairs markets may be opaque to downstairs participants), and a potential risk of trading with informed counterparties. In this nature, Grossman's model mirrors empirical findings by Barclay, Hendershott, and Jones (2003).

Choi, Salandro, and Shastri (1988), examining options, cite two basic schools of thought on the determination of bid-ask spreads – in the Demsetz (1968) and Ho and Stoll (1981) framework, as a dealer cannot hold the market portfolio and diversify away the idiosyncratic risk, the inventory risk, the risk that constitutes a dealer's holdings in a particular security deviating from the optimal level, is a key determinant

of the bid-ask spread. In the Copeland and Galai (1983) and Easley and O'Hara (1987) models, the specialist contends with the presence of informed traders in the market, to whom it is expected that he will make a loss. Therefore, the bid-ask spread theoretically maximizes the net gains from liquidity traders' presence in the market and the specialist's losses from trading with informed traders. Choi et al (1988) modify the Roll (1984) model to adjust for serial correlations in returns and find it is a proper estimator for options markets.

Van Ness, Van Ness, and Warr (2001) empirically test five models of adverse selection using volatility, volume, and corporate finance variables, and find a degree of variation among them in measuring adverse selection. As they state that adverse selection proxies ought to measure the amount of asymmetric information in the market, they assert that these proxies may be capturing other trading costs, especially as three of the models generate a significant amount of theoretically impossible values (negative components of adverse selection). In addition, they are confused by the lack of correlation between the adverse selection models with corporate finance variables, such as analyst forecast error, that may also represent the presence of asymmetric information in the marketplace.

Zhao and Chung (2007) study the SEC's introduction of Rule 605, a regulatory action which requires exchanges to disclose execution quality in equities. Rule 605 was implemented in two phases, where it first applied only to nationally listed equities, but later was widened to include all listed equities. The goal of the rule is to allow public investors to compare execution costs across exchanges, and it mandates the display of effective spreads, execution speed, and fill rates. In a finding related to the competition literature, Zhao and Chung (2007) discover that spreads decreased by

roughly 20% in NYSE-listed and AMEX-listed stocks after Rule 605, with a slightly

greater decrease in the spreads of NASDAQ-listed stocks.

Chung, McInish, Wood, and Wyhowski (1995) suggest that market makers can assess

the risk of adverse selection by examining a share's coverage by analysts in the

banking industry, as industry coverage is a useful proxy for publicly available

information held, and that the greater the number of analysts, the greater the extent of

asymmetric information in the shares. Chung et al (1995) use industry profit forecasts

to further determine that, *ceteris paribus*, a greater number of analysts follow stocks

with larger spreads.

5.2 Alternative Trading Systems and Trading Costs

The transformation of the equity markets may affect both characteristics of spread and

trade size. A number of recent studies[9] show that the average size of a NYSE order

has fallen three times in the past five years. In addition, the proliferation of

algorithmic/high-frequency traders has led to an increased sensitivity to pre and post-

trade costs. With these changes in the attributes of orders, conclusions in previous

studies may not hold for traders seeking decreased latency, anonymity through order-

splitting, and other competitive advantages offered by electronic communications

networks (ECNs).

Hendershott, Jones, and Menkveld (2010) show that the introduction of algorithmic

trading on the NYSE in 2003 increased liquidity and significantly decreased the

adverse selection component of the spread. Riordan and Storkenmaier (2009) show

that a decrease in latency from 50 milliseconds to 10 milliseconds on Deutsche

Borse's Xetra platform led to a dramatic decline in the adverse selection component

of the spread. This must be distinguished from Barclay, Hendershott, and

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[9] Grant (2010) cites a number of empirical studies on average order sizes.

McCormick's (2003) conclusion that ECNs offer a more suitable platform for informed traders due to anonymity and lower latency. Hendershott and Moulton (2009) demonstrate that NYSE's introduction of a hybrid trading system (where orders can either seek automatic execution or specialist prices - the automated system is likely to lead to speedier executions, but specialists may be able to provide improved prices) leads to increased spreads, and they attribute that to an increase in the 'cost of immediacy', as time-sensitive traders offer more. Hendershott and Moulton (2009) find that an increase in adverse selection drives the spread increase. Therefore, while algorithms increase liquidity and decrease adverse selection, they tend to migrate to ECNs, despite the higher likelihood of finding an informed counterparty. One must weigh this against the possibility, as suggested in price discovery literature, that algorithmic traders may be informed. Barclay et al (2003) find that small trades (below 1,000 shares) have a lower effective spread on exchanges with market makers than on ECNs, concluding that market makers perceive a greater adverse selection issue on the anonymous ECNs.

Fragmentation between ECNs and exchanges can influence transaction prices. Hendershott and Jones (2005) show that when the Island ECN ceased to display its limit order book, trading costs of its competitors declined, while Island trading costs increased. However, the overall trading costs of the instrument increased. They attribute this effect to the migration of Island liquidity providers to its competitors and conclude that the additional liquidity on non-Island ECNs generates more liquidity in a feedback effect. In addition, they posit that competing exchanges or ECNs may lead to liquidity suppliers being more responsive to liquidity demanders due to competitive

pressures. Gresse (2010) finds that the introduction of Multilateral Trading Facilities[10] (MTF) reduces spreads by the amount of competition between the traditional exchange and the MTF. She proceeds to describe MiFID as a 'catalyst' for the growth of MTFs, so the effect of MiFID may not be fully separable from MTFs' introduction. She draws attention to a market-structure debate over fragmentation – although prior literature (Bennett and Wei 2006, Gresse and Gajewski 2007) finds that a centralized order book has lower transactions costs, the fragmentation literature argues that this may be more than offset by competitive pressures leading dealers to vie for order flow on the basis of price.

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[10] MTF is a legal definition in the EU's MiFID directive, comparable to the US definition of ECN.

Chapter Three:

Insider Trading in Transaction Time: Impacts and Profits

1. Introduction

The market turmoil following the Global Financial Crisis has reignited focus on the extent to which illegal behaviour may be occurring in markets. This behaviour can constitute a violation of fiduciary duty on behalf of the broker or represent a form of manipulation of the securities markets that results in a misleading price of the asset. The United States' equity market regulator, the Securities and Exchange Commission (SEC), statutorily possesses the lead regulatory role in detecting and prosecuting forms of market abuse. Recently, the SEC has come under heavy scrutiny regarding the effectiveness of its fulfilment of its mandate, which originated from the public policy necessity for markets to be perceived as efficient and fair. The most noted form of market abuse – which includes fraud, market manipulation, and bucket shops – is insider trading. Insider trading[11] increases the cost of capital and distorts the capital rationing function of the markets (Bhattarchaya and Daouk, 2002). Insider trading occurs when a party privy to information that will affect an asset's price trades before public disclosure of that information. Insider trading violates a fiduciary duty that the insider has to the owners of a company's securities. It also contravenes the International Organization for Securities Organizations' (IOSCO) guidance for regulators to ensure a 'fair' and 'efficient' market.

This chapter tests the impact of insider trading on market performance and price distortion. It examines whether changes can be measured that capture the presence of

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[11] A brief overview of US legislation and legal opinions on insider trading is found in Appendix 1 of this chapter.

an insider in the market, and how the market responds to the insider's activity. The data is analysed on macro (daily) and micro (intraday) levels. This chapter uses a series of time-stamped trades prosecuted by the SEC to generate data files for both daily trading and intraday trading intervals. This data provides a natural experiment to examine the effects of insider behaviour as the prosecution provides an *ex post* identification of insider trading within the larger pool of liquidity trades. In all the cases, the defendants traded on the basis of inside information, contravening US federal law. The defendants either are 'insiders' - corporate officers who received private information in the course of their duties, or those who had been informed by corporate officers but do not have a duty to the corporation. The latter are known as tippees, as they received 'tips' from insiders. The sample is composed of shares from NASDAQ, AMEX, the New York Stock Exchange, and over the counter (OTC) markets, which allows for an examination of insider behaviour within different market structures. Daily analysis is initially performed to examine whether conclusions drawn in previous literature are idiosyncratic to samples. The analysis is then extended to intraday data to permit examination of trader behaviours both by insiders and uninformed traders as the trades occur. Existing literature contends that in the presence of an insider, market participants will increase the spread to compensate for adverse selection, and this may lead to increased price movement on a trade-by-trade level as market orders absorb this increased cost[12].

The key findings of this chapter is that at the micro level, insider trades are significantly different from surrounding trades in both trade to trade price impact and trade lot volume, when compared with trades executed in the same thirty minute interval by other traders. The size and volume effect is most pronounced on the two

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[12] Glosten and Milgrom (1985), Kyle (1985), and Benveniste, Marcus, and Wilhelm (1992) theorize on the specialist's reaction to the presence of an insider in the market.

specialist exchanges of the American Stock Exchange (AMEX) and the New York

Stock Exchange (NYSE). Trade to trade price movements are statistically significant

at the 1% level for the panel of NYSE and AMEX shares. This result offers support

for the anonymity hypothesis advocated by Glosten and Milgrom (1985) and others.

In respect to NASDAQ, price effects are due only to insider trades that are of similar

lot size with surrounding trades on NASDAQ. These findings would suggest that

price formation responses to insider activity may differ across various market

structures.

The chapter is organized as follows: section 2 presents how this chapter follows with

the existing threads of discussion in insider trading and market microstructure, while

section 3 discusses the chapter's data and design. Results are discussed in section 4

with the conclusion in section 5. An appendix sets out the history of United States

insider trading laws and their historical application by the SEC.

2. Models and Hypotheses

This chapter expands the existing literature on insider trading by examining a varied

sample in transaction time to provide a general assessment about the impact of insider

trades – previous studies have aggregated data into intervals of either 15 minutes or an

hour[13]. A first pass analysis is based on daily data in concert with prior studies, such

as Cornell and Sirri (1992), Meulbroek (1992), and Chakravarty and McConnell

(1997,1999). Then an intraday analysis examines how market participants conduct

themselves trade-by-trade when an insider is in the market.

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[13] Fishe and Robe (2002) use 15 minute intervals, while Chakravarty and McConnell (1997, 1999) use hourly data.

The regression estimated examines the daily impact of insider trading while controlling for other events[14]. It is posited that the regression will identify whether returns are noticeably higher on days insiders are trading than on days when they are not (while controlling for interim news announcements):

$$R_{it} = \alpha + \beta_1 Index_t + \beta_2 Announcement_{it} + \beta_3 Insider_{it} + \Sigma\beta_4 News_{it} + \varepsilon_{it} \qquad \textbf{(3.1)}$$

where $\textbf{\textit{R}}_{it}$ is the daily return on a security,

$\textbf{\textit{Index}}_t$ is the daily return on the Frank Russell 3000, a value-weighted market index,

$\textbf{\textit{Announcement}}_{it}$ is an indicator variable equal to 1 on the day of the public disclosure of the information upon which the insider traded,

$\textbf{\textit{Insider}}_{it}$ is an indicator variable equal to 1 on days the insider transacts,

and $\textbf{\textit{News}}_{it}$ comprises a series of indicator variables equal to 1 on days of confounding news announcements over the estimation period. As the insider occasionally trades mere hours in advance of the public release of information, *Insider* and *Announcement* can be (and are frequently) on the same day. *News* is subjectively defined in the insider trading literature (no paper gives strict criteria for what constitutes a confounding news announcement as opposed to an immaterial news announcement). However, due to the prevalence of almost daily news, analysis, and analyst recommendations on major corporations, an arbitrary filter must be set to estimate this regression. For the purposes of this chapter, any day with a news announcement and a return of 4% will constitute a day with a news dummy.

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[14] Regressions 3.1 and 3.2 are adapted from Meulbroek (1992).

A second model is used to capture abnormal volume effects that may occur around insiders:

$$ln(vol_{it}) = \alpha + \beta_1 ln(vol_{mt}) + \beta_2 ln(vol_{it-1}) + \beta_3 ln(vol_{it-2}) + \beta_4 Monday_{it} + \beta_5 Tuesday_{it} +$$
$$\beta_6 Wednesday_{it} + \beta_7 Thursday_{it} + \beta_8 Announcement_{it} + \beta_9 Insider_{it} + \beta_{10} NetInsider_{it} +$$
$$\Sigma\beta_{11} News_{it} + \varepsilon_{it} \qquad\qquad (3.2)$$

where $ln(vol_{it})$ is the natural logarithm of the daily volume of shares traded in a security,

$ln(vol_{mt})$ is the natural logarithm of the daily market volume for the exchange on which the share is listed,

$ln(vol_{it-1})$ is the natural logarithm of the total shares traded lagged one day,

$ln(vol_{it-2})$ is the natural logarithm of the total shares traded lagged two days,

$Monday_{it}$ through $Thursday_{it}$ are indicator variables equal to one on the relevant day of the week,

$Announcement_{it}$ is an indicator variable equal to one on the public disclosure of the information on which the insider traded,

$Insider_{it}$ equals one on the day the insider traded,

$NetInsider_{it}$ is the daily volume traded in the security minus the volume the insider traded,

and $News_{it}$ is the collection of individual news variables, each equal to one on the day of a confounding public news announcement in the traded company.

The use of Meulbroek's (1992) equations is because hers is the only cross-sectional study of insider trading behaviour to date. Other studies, such as Cornell and Sirri (1992), Chakravarty and McConnell (1997, 1999), and Fishe and Robe (2004) are case studies of individual firms. Meulbroek's empirical tests use data that she associated with identified insider trades by employing Securities and Exchange Commission private files merged with daily trading prices and volumes. She found that there is a statistically significant abnormal return on days of insider trading and a statistically significant abnormal volume on days of insider trading. She also tested to see if the abnormal volume on days of insider trading was solely attributable to the presence of the insider in the market, and found that it was. This diverges from Cornell and Sirri (1992), who find that 'falsely informed traders', traders who think they are trading on information but are misled, flock into the market on days of insider trading. An example of falsely informed traders could be trend followers or technical analysts.

Meulbroek's sample was heavily skewed by insider trading in advance of mergers, which constituted 79% of her sample. She asserts that insider trading is responsible for this abnormal return in advance of mergers. However, Jarrell and Poulson (1989) document that on average there is a nearly 40% run-up in share prices prior to merger announcements. As it is unlikely that insiders trade before every merger, it is possible that Meulbroek's (1992) sample is upwardly biased and may not accurately represent a cross-section of marketplace events or the actual impact of insider trading on price patterns. Whether this run-up is due to insiders or standard market activity prior to merger announcements is debatable. Shleifer and Vishny (2003) also document activity prior to mergers and the concurrent phenomenon of price run-ups prior to the announcements and culminations of mergers. However, further tests are needed, as a

price run-up is a common factor in merger target firm trading, and may be attributable to risk arbitrageurs, who could be considered informed traders, instead of insider traders trading on the illegitimate leakage of corporate information.

The present sample is more heterogeneous with a plurality of merger-related information (45%), as well as miscellaneous bad news, 21.57% of the sample. Table 1 documents the information announcements traded upon in the present sample. The majority of insider trading episodes examined in this chapter take place in NASDAQ-listed shares(68.6%). This differs from previous studies, such as Meulbroek (1992) and Cornell and Sirri (1992), which focus on NYSE-listed shares. This chapter's sample characteristic allows for the analysis of the impact of market style on insider trading.

Table 1: Information On Which Insiders Trade

Table 1 displays the nature of the information on which insiders traded.

Type	Total	Percent
Merger	23	45.10%
Negative Earnings	5	9.80%
Positive Earnings	6	11.76%
Miscellaneous good news	6	11.76%
Miscellaneous bad news	11	21.57%
Total	51	

Theory argues that insider trading on the NYSE is fundamentally different from the NASDAQ due to market structure issues[15]. A focus on NASDAQ-listed shares versus those of the NYSE leads to greater diffusion of information, as the specialist is not counterparty to all trades and is therefore not privy to all order flow information. Per academic literature, this lack of order flow concentration leads to a greater difficulty on behalf of market participants to detect anomalous behaviour, as on NASDAQ, an insider can split his orders between many dealers and market makers. However, in this chapter analysis is performed both on the entire sample as well as the NYSE/AMEX (specialist market) sample and NASDAQ to elucidate whether there is a differential effect. In summary, firstly, the data is examined to see if existing findings (Meulbroek, 1992, Cornell and Sirri, 1992, Chakravarty and McConnell,

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[15] For example, Glosten and Milgrom (1985) contend that the presence of a specialist will lead to higher spreads, as the specialist uses the spread to protect against adverse selection.

1997, 1999) are idiosyncratic to their data or can be found in out-of-sample tests. Secondly, the effects of exchanges' market design are analysed to determine if insider trading affects asset prices differently in different market types.

This section's hypotheses are thematically structured. Because existing theoretical literature describes the expected reaction to the presence of an insider in the market without specifying differential behaviour whether the insider transactions within a day or over a longer time horizon, hypotheses are constructed for both daily and intraday data using the same theoretical justifications. Kyle (1985) discovers identical activity whether the insider is trading on an intertemporal or a continuous basis.

Therefore, *ceteris paribus*, it is hypothesized that:

$H_{1.1}0$: Daily returns will be no different on days when insiders trade than on other days.

$H_{1.1}A$: Daily returns will be statistically greater on days when insiders trade than on other days.

$H_{1.2}0$: Volume net of insider trading will be no different on days when insiders trade than on other days.

$H_{1.2}A$: Volume net of insider trading will be different on days when insiders trade than on other days.

Hypothesis 1.1 suggests a positive direction as Glosten and Milgrom (1985) notes that the presence of an insider will lead the specialist to compensate for her adverse selection problem by increasing the spread. Consequently, prices, when adjusting for signs (multiplying returns by -1 for a sell) should be expected to have higher returns. Hypothesis 1.2 is one-directional as volume cannot be lower than zero.

Easley and O'Hara (1987) model behaviour of markets in the presence of an informed trader, and suggest that uninformed, or liquidity, traders refrain from trading when they perceive informed traders to be present in the market. Therefore, according to their model, when insiders trade, volume will be lesser than normal. However, Cornell and Sirri (1992) suggest that in the presence of insider traders, 'falsely informed traders' flood the market perceiving a change in valuation fundamentals. Chakravarty and McConnell (1997, 1999) find in a case study of Ivan Boesky's trades in Carnation that Boesky was only responsible for half of the increased volume. Cornell and Sirri (1992) document that insiders use a statistically significant amount of limit orders, which may account for lesser returns. Admati and Pfleiderer (1988) theorize that execution certainty is most important to insiders, so they will use market orders, which may lead to increased daily returns. Kyle (1985) models an inside trader seeking to extract maximum rent from his information, and posits that insiders will trade over a prolonged period. He further notes that this behaviour and the use of limit orders will help the insider trader avoid detection by authorities, as limit orders have a lesser price impact than market orders. Meulbroek (1992) finds no increase in abnormal volume net of insider trading activity in her sample, and Fishe and Robe (2004) document only a marginal increase in volume (9.2%) on days insiders trade. Meulbroek (1992) finds that days on which insiders trade account possess abnormal returns relative to days when insiders are not present in the market (while accounting for confounds such as news announcements). Therefore, the first hypothesis expects that abnormal volume will be statistically significant on days the insiders trade, as the 'falsely informed traders' described by Cornell and Sirri (1992) enter the market. As there is no theoretical agreement as to how insider trades should be different from non-insider trades (on one hand, the insider may seek to trade stealthily to avoid

detection, but the insider may also need to immediately execute his trade), the hypotheses do not suggest a direction, as depending upon the results, different economic outcomes are implied.

H$_{2.1}$0: Insider trades are statistically different from surrounding trades in the same 30 minute interval in terms of price movements.

H$_{2.1}$A: Insider trades are not statistically different from surrounding trades in the same 30 minute interval in terms of price movements.

H$_{2.2}$0: Insider trades on specialist (NYSE/AMEX) exchanges will not be statistically different from surrounding trades in the same 30 minute interval in terms of trade-to-trade price movements.

H$_{2.2}$A: Insider trades on specialist (NYSE/AMEX) exchanges will be statistically different from surrounding trades in the same 30 minute interval in terms of trade-to-trade price movements.

H$_{2.3}$0: Insider trades on dealer (NASDAQ) exchanges will be statistically different from surrounding trades in the same 30 minute interval in terms of trade-to-trade price movements.

H$_{2.3}$A: Insider trades on dealer (NASDAQ) exchanges will not be statistically different from surrounding trades in the same 30 minute interval in terms of trade-to-trade price movements.

Glosten and Milgrom (1985) model price setting in a specialist market and theorize that when the specialist perceives an adverse selection problem, usually driven by information asymmetry, she will increase the bid-ask spread to compensate for the presence of any undetected insiders. Therefore, liquidity is more costly under such

terms. The specialist is able to do this as all trades on the exchange flow through her, so she has a total awareness of order flow. Glosten and Milgrom (1985) note that this issue is not present in a dealer market, as order flow is fragmented through numerous counterparties and therefore detection of unusual behaviour is difficult. Benveniste, Marcus, and Wilhelm (1992) find that through repeated interaction between specialists and traders, the specialist will be able to detect informed trading, as the specialist's counterparty has no incentive, and may even be sanctioned (such as by the specialist's failure to update quotes), by the specialist if she detects that the trader is behaving in a way contrary to her interests. Therefore, on a specialist exchange, the specialist will increase the spread when she suspects insiders are present in the market to compensate for her adverse selection problem. Fishe and Robe (2004) only document that the dealer can infer that unusual behaviour is occurring through order imbalances, and conduct a natural experiment using traders illegally trading upon an advance copy of a stock-picking column. They find that spreads after the insider trades increased and depth decreased on NYSE and AMEX (specialist) markets, but do not change on NASDAQ. Chakravarty, Harris, and Wood (2009) determine that information first appears in depths, so liquidity providers may be adjusting their positions by increasing or decreasing the volume available at the best bid-offer due to the perception of an insider active in the market. Garfinkel and Nimelandran (2003) use a sample of legal corporate insider traders to find that spreads and price impacts on NASDAQ, due to its anonymity as a dealer market, are lower than that of NYSE, as there is no specialist to detect an informed trader's presence. Chakravarty and McConnnell (1997) find only a size effect correlation in price movements around insider trades that arbitrageur Ivan Boesky made – only when Boesky made a 'large' trade (as per the categories of Barclay and Warner, 1993), did prices move. Therefore,

they cannot conclude that the price movements were due to the presence of an insider because they could also be due to any parties execution of large trades. Therefore, hypothesis two holds that the insider will be stealthy in the NASDAQ market, as no party is able to deduce his presence, and thus, insider trade-to-trade price movements will not differ from surrounding trades. However, on NYSE/AMEX, the specialist is expected to detect the presence of the insider and increase her spread to compensate for the adverse selection problem. Therefore, insider trade-to-trade price movements are expected to be statistically different from surrounding trades on NYSE-AMEX. As this chapter's sample is primarily composed of NASDAQ trades, the aggregate trade-to-trade price movement is expected to be statistically insignificant, so no difference between insider trades and non-insider trades is expected. As abnormal volume can only be positive, these hypotheses are directional.

$H_{3.1}0$: Insider trades are not statistically different from surrounding trades in the same 30 minute interval in terms of shares traded.

$H_{3.1}A$: Insider trades are statistically different from surrounding trades in the same 30 minute interval in terms of shares traded.

$H_{3.2}0$: Trades on specialist (NYSE/AMEX) exchanges will not be statistically different from surrounding trades in terms of lot sizes.

$H_{3.2}A$: Trades on specialist (NYSE/AMEX) exchanges will be statistically different from surrounding trades in the same 30 minute interval in terms of lot sizes.

$H_{3.3}0$: Trades on dealer (NASDAQ) exchanges will be statistically different from surrounding trades in the same 30 minute interval in terms of lot sizes.

H$_{3.3}$A: Trades on dealer (NASDAQ) exchanges will not be statistically different from surrounding trades in the same 30 minute interval in terms of lot sizes.

H$_{3.4}$0: Insider trades will not be statistically different from surrounding trades of the same initiation in the same 30 minute interval in terms of trade-to-trade return.

H$_{3.4}$A: Insider trades will be statistically different from surrounding trades of the same initiation in the same 30 minute interval in terms of trade-to-trade return.

The academic literature modelling price determination in specialist and dealer markets focuses on the ability of parties to detect the presence of an informed trader and either protect against predation or mimic the patterns of an informed trader. Although Cornell and Sirri (1992) note that there will be an influx of falsely informed traders, there has been little analysis in terms of the size of trades of the insider versus that of a non-insider. Glosten and Milgrom (1985) and Benveniste, Marcus, and Wilhelm (1992) provide evidence that a specialist is able to detect the presence of an informed trader in the market as opposed to the anonymity of a dealer market. As a result, parties may behave differently when they can detect the presence of an insider as opposed to when they cannot. Kyle (1985) models insider trading as a number of repeated interactions with the markets in order to maximize rent and ensure avoidance of detection. An observer might expect the insider to trade strategically to ensure he is not caught. However, this is grounded in the assumption that the insider acts strategically. As this chapter's data set consists of cases that the SEC successfully prosecuted for insider trading, insiders may not be behaving in a rational manner.

H$_4$0: Insider trades will not be statistically different from surrounding trades of the same initiation in terms of lot volume.

H$_4$A: Insider trades will be statistically different from surrounding trades of the same initiation in terms of lot volume.

Admati and Pfleiderer (1988) and Kyle (1985) posit that informed traders will use market orders to ensure maximum likelihood of execution. Therefore, as informed traders are sensitive to both time and execution failure, insider traders, as a subset of informed traders, will use market orders. Resultingly, they will walk the limit order book. Glosten and Milgrom (1987) and Garfinkel and Nimelandram (2003) theorize and show that informed trading on specialist markets has a stronger effect than that on dealer markets. Hypothesis 4 of this chapter examines buyer-initiated trades by insiders with buyer-initiated trades by non-insiders, and seller-initiated trades by insiders with seller-initiated trades by non-insiders. One should expect informed (insider) trading to be more noticeable than other trades on specialist markets, even compared to trades initiated by the same party.

It is worth noting that there is a detection bias inherent in the sample, because it consists of insider trades that the SEC successfully prosecuted. Thus, results may not be fully representative of all insider trades that occur.

3. Data and Method
3.1 Data

This study utilizes a sample of insider trading in common stocks assembled from the Securities and Exchange Commission's (SEC) litigation releases[16] from 1 November 1998 to 1 November 2007. This is a set of all legal complaints filed by the SEC when in cases against defendants accused of market abuse. For the cases in which the SEC

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[16] Found at http://www.sec.gov/litigation/litreleases.shtml.

accuses the defendant of insider trading, information extracted includes: defendant (such as name, whether he is a tippee or insider, date of prosecution), security name, volume traded, price traded, profit accumulated, date of trade, time-stamp of the trade, and date of the public disclosure of the news on which the insider trades. However, the SEC's legal complaints are occasionally incomplete, and do not always include each descriptor. These files contain solely trades identified by the SEC as performed by illegal insiders. After filtering to exclude incomplete, potentially corrupt, or confounding data, the sample consists of a set of 4,031 separate transactions, each defined as a single trade in a security. As this study solely focuses on equities, the chapter further omits cases that concern only futures or options, and do not include option trades in cases when the insider transacts in both equities and options reducing the sample to 3,055 trades. A further filter excludes all trades where the SEC does not provide a time-stamp for the insider transaction narrowing the sample to 430 trades. All newly listed shares which lack a 150-day period of daily returns have also been removed from the sample, as there is not enough data to sufficiently estimate regression 3.1 and 3.2. Finally, this chapter excludes those episodes for which there is no intraday data obtainable from the Securities Industry Research Centre of the Asia-Pacific (SIRCA)'s Reuters DataScope Tick History (RDTH[17]). This leaves a final sample of 51 episodes. An episode is defined as a single defendant transacting in a single security, no matter how many times the defendant trades in that security. There are 101 different thirty-minute intervals within which insiders transact. Daily data (including opening price, closing price, and volume) was sourced from the *Bloomberg Professional* service, with gaps (for merger targets now delisted) supplemented with *Thomson Reuters Datastream*. In addition, *Thomson Reuters Datastream* provided

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[17] RDTH is now renamed as TRTH, Thomson Reuters Tick History.

daily values for the Frank Russell 3000 index, used to compute regression 3.1.

Exchange volume was obtained from the NYSE and NASDAQ fact books[18]. Intraday

trade and quote data was acquired from the Securities Industry Research Centre of the

Asia-Pacific's *(*SIRCA) TAQTIC (now TRTH) service using *Reuters* data.

The insider trade lots are identified using the SEC's reported volume and price for

transactions – while the SEC notes the time, average price, and aggregate volume of

transactions, it does not go so far as to identify the individual transactions. These are

matched against trades with the same price and volume stamp. Meulbroek (1992)

notes that the SEC opts not to disclose the full details of insider transactions to better

mask their detection methodologies, so this method may have its limitations. The Lee

and Ready (1992) algorithm is used to determine the party initiating the trades, both

for the insider trade as well as for the entire sample of transactions in the same 30

minute interval as the insider trade.

While individual regressions are estimated in the case of each insider trading episode,

parameter estimates are averaged (after multiplying trading on negative information

by -1, as this test estimates the magnitude of returns) and t-statistics are constructed[19].

One drawback of this methodology is that a smoothing effect takes place. Keim

(1983) suggests a number of benefits that can accrue from averaging coefficients,

including adjustments for size effects and seasonal returns. As a significant portion of

the sample examined consists of stocks listed on AMEX and lower-cap NASDAQ

stocks, averaging corrects for any biases introduced by low-frequency trading.

Insider trades are examined in transaction time – allowing for the examination of the

differential impact of insider trades to non-insider trades in the market. By comparing

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[18] The factbooks are found on the exchanges' respective websites.
[19] Meulbroek (1992) uses this methodology.

the impact of insider trades to non-insider trades only in the same 30 minute trading interval, market characteristics and time of day effects are minimized. After segmenting the 30 minute trading interval into insider trades and non-insider trades, trade to trade price changes are calculated as the natural logarithm of the last trade divided by its predecessor.

The final sample is slanted towards both NASDAQ shares (69%) and to news announcements involving mergers (45%). In addition, the sample has a bias towards 'good news', that is, news that is expected to bolster a company's share price[20]. The NASDAQ bias in the sample composition may lead to more 'anonymous' insider trades, due to market structure[21].

An insider trading ring in 2005 constitutes half of the sample. This ring (henceforth referred to as the LHV ring) was comprised of several Estonian financial market professionals who intercepted news releases prior to their public disclosure. Therefore, robustness tests are performed to ensure that the 2005 ring does not bias the results obtained for analysis. An additional cross-sectional regression is performed to examine the interaction of the ring with variables of interest. As none of the interaction variables is statistically significant, it is concluded that the ring does not affect the daily results[22]. The LHV ring traded on a variety of types of information (earnings, product announcements, mergers), and intraday analysis is not performed,

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[20] This information encompasses merger offers, improvement on earnings forecast, and development of new products and contracts. In addition, as Meulbroek (1992) does, short sales' abnormal return is multiplied by -1 to standardize returns.

[21] Due to the competitive market maker system in NASDAQ, an oligopoly exists between a diffuse number of dealers, some of whom may be acting as quasi market-makers. Competitive effects between dealers/market makers and the diffusion of order flow and information is likely to cause NASDAQ market makers to react less dramatically than the specialist on NYSE/AMEX. Insiders may also split orders between various market makers.

[22] Regression results are displayed in Appendix 2, showing that none of the LHV ring's interactions are statistically significant.

because it is assumed that intraday analysis is not distorted by LHV trades due to the varied composition of LHV announcements.

Separate analysis is not performed on direct insiders and tippees, the latter defined as those who received the insider information on which they traded from another party. As the nature of the information on which insiders and tippees traded is not different, results are not expected to be divergent, as the economic impact of the arrival of both types of information to the market is the same.

3.2 Descriptive Statistics

Table 2 displays the characteristics of the sample of examined insider trades, showing how many insider trades occurred in each year and how many securities in the sample were traded.

Table 2: Frequency of Insider Trading and Prosecution

Table 2 sets out characteristics of the sample of insider trades examined in this chapter. Column 1 is the year of the trade, columns 2 and 3 are the number of trades and the percentage of the total sample of trades. The last two columns are the number of securities trades and their percentage of total securities. The trading ring of 2005 can be clearly seen in the trade spike[23].

1	2	3	4	5
Year	Number of securities traded	Percentage of total securities traded	Number of trades	Percentage of total trades
1998	1	1.96%	1	0.40%
1999	3	5.88%	30	12.10%
2000	6	11.76%	38	15.32%
2001	4	7.84%	8	3.23%
2002	3	5.88%	4	1.61%
2003	2	3.92%	11	4.44%
2004	4	7.84%	6	2.42%
2005	22	43.14%	124	50.00%
2006	6	11.76%	23	9.27%
2007	2	3.92%	3	1.21%
Total:	53		248	

Table 3 sets out the financial returns to trading by the insider, the number of securities traded, the average profit per security, and the profits of tippees and insiders. Profit gained is distinguished from loss avoided in that profit is defined as the acquisition or short sale of shares in which the insider did not have a prior position, and loss avoided is defined as an insider liquidating his existing position in shares due to

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[23] Column 2 sums to 53, although 51 unique securities were traded, as two shares had multiple insider-trading episodes.

foreknowledge of negative news[24]. In the case when an insider liquidates his holdings and then sells shares short due to negative information, such behaviour can be categorised as both averting loss (on existing holdings in a firm) and gaining a profit (in further shorts after holdings sold). In general, losses averted were larger than profit gained due to the nature of the cases – while the minimum profit gained was $340, the minimum loss averted was $35,088.08. The high standard deviation reflects variation in the sample, as several insiders traded into the millions. Where the SEC did not decompose profits of an insider trading ring individually, it is treated as one episode. While the mean number of securities traded is 1.67, the median insider trades 1 security, primarily due to the fact that most insiders are privy only to material non-public information on the nature of their own company. The most prolific insider traded in 14 securities. Insiders generated more financial gain than tippees, but that is driven by two outliers in the sample driven by parties with a multi-million dollar position in the securities gaining profit or liquidating positions.

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[24] Some transactions include both an avoidance of a loss on shares (selling existing shares in a company with a pending negative news announcement) and a profit (short selling more shares on the same announcement). Table 3 pools those proceeds separately for purpose of analysis.

Table 3: Insiders' Returns per Episode

Table 3 shows descriptive statistics for the sample examined in this chapter. As some insider rings involve multiple trades in a single security, the 60 events examined occur in 51 securities, and N represents the number of incidents in each category. Profit gained encompasses both buy-and-hold as well as shorting strategies for capitalizing on insider information, while loss avoided represents an insider who sold existing shares to avoid a decrease in price. Therefore, some episodes include multiple trades which are both avoidance of loss and a gain of profit. Number of Securities Traded represents how many securities were traded by an insider. Average profit per security represents the average profit gained or loss avoided by an insider in a single security. Trades are categorized as insider profit if they were executed by a corporate insider privy to confidential information, or as tippee profit if they were executed by someone who was informed by another inside the corporation.

	Mean	Median	Standard Deviation	Minimum	Maximum	N
Total Profit Gained	$178,951	$59,380	$369,446	$340	$2,425,000	53
Total Loss Avoided	$528,140	$122,086	$765,274	$35,088	$1,938,465	7
No. of Securities Traded	1.67	1.00	2.33	1.00	14.00	51
Average Profit/Security	$278,020	$86,612	$553,313	$16,683	$2,425,000	
Tippee profit	$100,401	$58,066	$96,395	$1,969	$259,525	22
Insider profit	$269,082	$72,594	$522,243	$340	$2,425,000	38

Table 4 presents the incidence of insider trading days relative to news announcements and the public disclosure of the information traded upon. In this case again, several cases involving insider trading 'rings' (constituting a group of defendants who shared privileged information) lead to a median number of days on which insiders trade as 1.8 days per episode, although the median number of trading days is one. Similarly, insiders trade on average nine days before the announcement, although this is skewed by some corporate insiders trading as far as 117 days in advance. Insiders who trade repeatedly in the same episode tend not to trade on subsequent days – instead, they split their trades three to nine days apart in most cases. One cannot discern as to whether this is a masking strategy on the part of the insider or whether he needs to raise further capital to effect purchases. On average, there are five news days per insider case, but due to the lack of objective definition of news days in the insider trading literature, it is hard to compare this result with prior literature.

Table 4: Incidence of Insider Trading and News Announcements

Table 4 details the frequency of trading around news announcements. Panel A displays how many days on which the insider traded of the 150 days prior to the public announcement of the information, and how many news days existed in those 150. Panel B shows the timing on insider trades, both how many days prior to the public announcement of the news the insider traded on, and in the case of multiple trades, the number of days between insider trades. Minimum and Maximum represent the minimum and maximum values for each category.

	Panel A: Number of Days		Panel B: Timing of Trade	
	Insider Trading Days	News Days	Number of Days before Public Announcement	Number of Days between Trades
Mean	1.80	5.45	9.16	7.14
Standard Error	0.26	0.44	2.35	1.20
Median	1.00	5.00	1.00	3.00
Minimum	1	1	88	1
Maximum	10	17	0	71

4. Results

4.1 Daily Analysis and Results

This chapter initially tests hypothesis 1.1 that returns on days insiders trade are not statistically different from those on which the insiders do not trade, when accounting for news days. Table 5 illustrates that returns on the days insiders trade are significant at the 1% level, with a t-statistic of 3.3, and thus, hypothesis 1.1 can be rejected, because returns on days insiders trade are significantly different than on other days. However, whether this is attributable to the insider or to 'falsely informed traders' who enter the market perceiving the presence of an informed trader is at issue, and will be evaluated in the intraday analysis. One must examine whether volume is different on the days that insiders trade to discern whether abnormal returns are due to insiders or to a higher trading volume on those days. When looking at types of information on which insiders traded, returns on negative earnings is the only statistically significant subset, with a t-statistic of 1.89, indicating significance at the 10% level, as insiders sell shares on the expectation of a decline in share value upon the public announcement of the information. Due to the lack of significance for certain subsets of news on announcement days such as positive earnings, the statistical significance of returns on negative earnings appears to be an artefact of the data. Interestingly enough, the days on which insiders trade on takeover announcements is not statistically significant. This is potentially due to insiders trading sufficiently in advance of mergers that there is no media speculation, or due to the fact that any subsequent price run-up due to information leakage is in fact triggered by their trades. As this study finds that merger announcements lead to the most statistically significant returns (at the 5% level), it is surprising that insiders trading on merger information do not move the price, and may indicate that they are

trading in a stealthy manner to minimise market impact. Other forms of news announcements did not produce a statistically significant result in terms of returns.

This chapter proceeds to test hypothesis 1.2 - that volume net of insider trading is not statistically different on days when insiders trade than on other days using regression 2.2. Volume net of insider trading is defined as the natural logarithm of the difference between daily volume and the number of shares in which the insider transacted, and is represented by *NetInsider*.

Table 5 – Daily Returns on Insider Trading

Table 5 shows parameter estimates for $R_{it}=\alpha + \beta_1 Index_t + \beta_2 Announcement_{it} + \beta_3 Insider_{it} + \Sigma\beta_4 News_{it} + \varepsilon_{it}$. News coefficients are not reported. Negative events were multiplied by -1 to assess directional impacts of insider trading. The dataset was winsorized for outliers at the 5% level. Averages for the entire sample as well as segments based upon the news traded on are displayed. T-Statistics are in brackets. The values reported are averages for individual regressions pooled on type of announcement.

	All	Takeover Related	Negative Earnings	Positive Earnings	Miscellaneous good news	Miscellaneous bad news
Intercept	0.01	0.01	0	0.01	0	0.01
	(1.08)	(0.61)	(-0.02)	(0.35)	(-0.86)	(0.44)
Index	0.89	1	0.17	0.95	0.01	0.92
	(1.24)	(0.69)	(1.04)	(0.39)	(0.13)	(0.5)
Announcement	0.13	0.14	0.11	0.13	0.06	0.13
	(5.46)***	(2.90)**	(1.86)*	(1.68)	(1.92)*	(2.19)*
Insider	0.04	0.04	0.03	0.04	0.03	0.04
	(3.30)***	(1.77)	(1.89)*	(1.03)	(1.66)	(1.33)
Adjusted R-Squared	0.33	0.33	0.33	0.33	0.33	0.33

***, **, and * represent significance at the 1%, 5%, and 10% levels respectively.

This chapter finds highly statistically significant volume and volume net of insider trading on days when insiders are present in the market, as volume on days insiders trade has a t-statistic of 4.59, indicating significance on a 1% level, while volume net of insider trading has a t-statistic of 3.57, indicating significance on a 1% level. Table 6 displays the results of the test. Therefore, hypothesis 1.2 - that volume net of insider trading is not statistically significantly different on days when insiders trade than on other days - is rejected. As expected, volume is statistically significant on the day of the announcement of the news on which the insider traded. Volume on the day on which the insider traded is statistically significant for all sub-categories of insider information except for negative earnings. The lack of statistical significance in that subcategory may be driven by its composition involving a number of cases where the insider traded the day before the announcement.

Volume net of insider trading could be interpreted as Cornell and Sirri (1992)'s falsely informed traders entrance into the market upon the perception of an order imbalance instigated by the insider, and interpreting that as a change in the fundamental value of the firm. These results contrast with previous studies in that Meulbroek (1992) shows significance in every scenario except for abnormal volume, when neither insiders are trading nor news is released, and uses that to argue that insiders are the marginal traders directly accountable for abnormal volume on days of insider trading. However, in the current sample, as abnormal volume net of insider volume is significant at the 1% level, clearly the insider is not the sole party demanding additional liquidity on days on insider trading days. This may reflect greater trend following or an increased sophistication in financial participants' perception of incremental volume, creating a herding effect. Interestingly, abnormal return is not significant in the current sample, whilst it is in Meulbroek's. This may be

accountable to the difference in market structure, as a majority of this chapter's sample is comprised of NASDAQ (dealer) shares, while Meulbroek's sample is driven by specialist market shares. This is in line with Glosten and Milgrom (1987); Benveniste, Marcus, and Wilhelm (1992); and Garfinkel and Nimelandran (2003), who argue that the specialist uses the spread as a means to protect against predation from informed traders. The results straddle the discoveries of Meulbroek (1992) and Cornell and Sirri (1992) because although insider activity is responsible for a large proportion of the marginal volume on insider trading days (30%), there remains an additional 8% of trading activity above that on days lacking insider trading or news that is unexplained. These may be the 'falsely informed traders' attracted to the market by the prospect of high returns and the perception of momentum in the market. Alternatively, these could be other informed traders trading on their judgment as to the nature of forthcoming news in the target company.

Table 6: Volume Changes around Insider Trading

Table 6 shows parameter estimates of $ln(vol_{it}) = \alpha + \beta_1 ln(vol_{mt}) + \beta_2 ln(vol_{it-1}) + \beta_3 ln(vol_{it-2}) + \beta_4 Monday_{it} + \beta_5 Tuesday_{it} + \beta_6 Wednesday_{it} + \beta_7 Thursday_{it} + \beta_8 Announcement_{it} + \beta_9 Insider_{it} + \beta_{10} NetInsider_{it} + \Sigma\beta_{11} News_{it} + \varepsilon_{it}$. *Lag1* and *Lag2* represent $ln(vol_{it-1})$ and $ln(vol_{it-2})$ respectively. The dataset was winsorized for outliers at the 5% level. Averages for the entire sample as well as segments based upon the news traded on are displayed. T-statistics are in brackets. The values reported are averages for individual regressions pooled on type of announcement.

	All	Takeover Related	Negative Earnings	Positive Earnings	Miscellaneous good news	Miscellaneous bad news
Intercept	1.01	-9.38	5.34	-2.05	2.47	16.10
	(0.19)	(-1.24)	(0.95)	(-0.46)	(0.41)	(0.75)
Exchange volume	0.53	0.38	0.59	1.02	0.66	0.32
	(3.87)***	(1.52)	(7.32)***	(9.38)***	(3.90)***	(0.65)
Lag1	0.07	0.28	0.00	-0.09	0.00	-0.10
	(0.62)	(1.46)	(0.01)	(-1.28)	(0.02)	(-0.26)
Lag2	-0.03	0.32	-0.23	0.00	-0.19	-0.37
	(-0.38)	(1.72)	(-1.94)*	(0.00)	(-1.19)	(-1.64)
Monday	-0.04	-0.12	-0.07	0.04	-0.02	0.03
	(-1.51)	(-1.75)	(-2.0)*	(1.21)	(-0.63)	(0.60)

Tuesday	0.01	-0.01	-0.07	0.03	-0.01	0.10
	(0.21)	(-0.24)	(-2.24)*	(0.68)	(-0.23)	(0.76)
Wednesday	-0.04	-0.05	-0.10	0.03	-0.03	-0.05
	(-1.62)	(-0.81)	(-1.44)	(0.68)	(-0.80)	(-0.88)
Thursday	-0.02	-0.02	-0.09	0.02	-0.02	-0.01
	(-0.81)	(-0.33)	(-2.19)*	(0.49)	(-0.47)	(-0.23)
Announcement	1.94	3.22	1.24	0.69	1.35	1.59
	(9.33)***	(7.55)***	(2.90)**	(4.15)***	(4.93)***	(4.95)***
Insider	0.66	0.72	0.43	0.64	0.46	0.93
	(4.59)***	(2.40)*	(1.74)	(6.60)***	(1.89)*	(2.23)**
NetInsider	0.47	0.26	0.34	0.63	0.38	0.88
	(3.57)***	(1.17)	(1.25)	(6.76)***	(1.44)	(2.13)*
Adjusted R-Squared	0.24	0.26	0.17	0.28	0.21	0.26

***, **, and * indicate significance at the 1%, 5%, and 10% levels.

4.2 Intraday Analysis

Having investigated the daily impact of insider trading, this chapter progresses to examine the intraday impact of insider trades. As per the data section, trades are identified from intraday trade and quote files by time stamps as cited in the SEC's complaint. Trade to trade returns are computed, and then t-tests are performed to measure the difference of insider trade lot sizes and trade to trade returns from their non-insider peers in the same 30-minute interval. T-tests are also used to determine statistical significance of means of insider trades lot sizes and returns. The Lee and Ready (1993) algorithm is used to determine whether a trade was buyer-initiated or seller-initiated. The mean and median trade values for the pooled sample of insider trades, as well as the mean and medians for NYSE insider trade lot sizes, fit into Barclay and Warner's (1993) definition of 'medium sized trades', trades in lot sizes between 500 and 1,000 shares. As Barclay and Warner found that category to be instrumental to price formation, the insider trades are thus 'stealth trades', those trades that move prices but are not immediately noticeable. The results of the test of hypothesis 2.1- that insider trades are not statistically different from surrounding trades in terms from price movement - are displayed in table 7.

Table 7: Intraday Returns to Insiders and Non-insiders

Table 7 presents trade-to-trade returns on both insider trades and non-insider trades in the same 30-minute interval measured as point estimates. It presents the average returns for insiders and non-insiders, their difference, and a t-statistic from a Wilcoxon rank sum test. Table 7 also presents the average price at which the insider traded as a percent of the price at the opening point of the 30-minute interval. Trade-to-trade returns are calculated as the log differential of prices.

Panel A: Trade-to-Trade Returns to Insiders

	Average Trade to Trade Return for Insider	Average Trade to Trade Return for Non-insiders	Difference	T-stat
Mean	0.002	0.000	0.002	3.42***
Median	0.000	0.000	0.000	
Standard Error	0.000	0.000	0.000	

Panel B: Trade to Trade Returns (Percentage of Opening Price)

	Average Trade to Trade Return for Insider as %age of opening price	Average Trade to Trade Return for Non-Insiders as a %age of opening price	Difference	T-stat
Mean (percent)	100.10%	100.07%	0.03%	2.04**
Median (percent)	100.00%	100.01%	0.00%	
Standard Error	0.19%	0.21%	-0.02%	

** and *** indicate significance at the 5% and 1% levels respectively.

With a t-statistic of 3.42, hypothesis 2.1 is rejected, as 3.42 is statistically significant at the 1% level. In terms of percentage of the average daily volume, a t-statistic of of 2.06 is still significant at the 5% level, implying that insider trades are statistically significantly different from surrounding trades in terms of trade-to-trade price movement. Despite the statistical significance of returns, there is no economic sign in this outcome, given the very marginal trade-to-trade price changes, as the average insider trade-to-trade return is 0, when rounding to 2 decimal points. Results for hypothesis 3.1 are in table 8, to discern whether insider trades are statistically different from surrounding trades in the same 30-minute interval in terms of both lot sizes traded as well as trade to trade price movements. Aggressive insiders would be expected to utilize market orders to ensure maximum likelihood of execution, therefore, between theory that a specialist reacts by increasing the spread in the presence of an informed trader and the nature of a market order to 'walk the book' to execute, Table 8 displays median and mean values for trade lots for insider and non-insider transactions[25] within the 30-minute interval in which the insider transacts.

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[25] These are not order sizes, but trade lot sizes; an order can be executed in several sequential (or non-sequential, in the case of limit orders) trades.

Table 8 : Intraday Trading Volume

Table 8 provides aggregate statistics for insider trades and non-insider trades that occurred in the same 30-minute interval. It catalogues both the absolute number of lot sizes for insider trades and those not executed by insiders. It also displays the difference between the statistics as well as a Wilcoxon t-test to indicate difference.

Panel A : Trade Size (Shares)

Trade Size (Shares)	Average Trade Size by Insider	Average Trade Size by Non-Insiders	Difference	T-Statistic
Mean	1030.76	657.45	373.30	1.71*
Median	411.20	348.36	62.84	
Standard Error	273.85	165.42	108.43	

Panel B :Trade Size (% of Average Daily Volume)

	Average Trade Size by Insider	Average Trade Size by Non-Insiders	Difference	T-Statistic
Mean as % of Average Daily Volume	0.115	0.073	0.042	1.71*
Median as % of Average Daily Volume	0.046	0.039	0.007	
Standard Error as % of Average Daily Volume	0.030	0.019	0.011	

* indicates significance at a 10% level.

The difference in the median size of trade lots is not significant at the 10% level. However, the difference in the mean lot is significant at the 5% level. This indicates that while most trades are not noticeably different from surrounding trades, insiders occasionally transact in disproportionately large lots. Therefore, hypothesis 3.1 is rejected, as insider trades are statistically significantly larger than surrounding trades, on average. One could attribute this to naive or foolish insiders skewing the result, although the average insider trades in a more sophisticated manner. However, as a proportion of average daily volume (calculated over the 30 days prior to the insider trade), insiders' mean transactions represent one-tenth of 1%, so although insiders may occasionally transact in large lots, they by no means represent a large amount of the daily turnover, and thus, it is unlikely that any order imbalance that may spur the influx of falsely informed traders seeking to capitalise on what they perceive as a change in valuation fundamentals is unlikely. Combining this finding with the discovery that 8% of abnormal volume net of inside volume on insider days is unexplained may be consistent with Cornell and Sirri's (1992) hypothesis that falsely informed traders enter the market when inside traders are present. This is also consistent with Fishe and Robe's (2002) finding that there is a marginal increase in volume on days that insiders are present – 9.2% in their case, 8% in the case of this chapter. This behaviour may also be due to daily trend followers and momentum traders entering the market when perceiving that there is increased activity.

Hypotheses 2.2 and 2.3 test the nature of trade-to-trade returns on both NYSE/AMEX and NASDAQ relative to peer trades in the same 30-minute interval to discern whether insiders spur price changes in an abnormal fashion or if they are indistinguishable from liquidity traders. Glosten and Milgrom (1987) and Benveniste, Marcus, and Wilhelm (1992) infer that a specialist will increase the spread in the

presence of an informed trader, and therefore, one would expect specialist-based exchanges such as the NYSE and AMEX to have a higher price change than a dealer exchange such as NASDAQ, as the specialist is able to detect the presence of the informed trader and will thus raise the spread.

An overall look at intraday returns in Table 9 displays that the returns to insider trades are highly significant only in the case of NYSE, with a t-statistic of 2.85, leading to significance at a 1% level. Therefore, hypothesis 2.2 is not rejected - that insider trades on NYSE are statistically significantly different from surrounding trades in terms of trade to trade price movements. Hypothesis 2.3 is also not rejected - that NASDAQ insider trades are not statistically significantly different from surrounding trades in terms of price-to-price movement. As lot sizes are statistically insignificantly different from surrounding trades under all market structure regimes, hypothesis 3.1 and 3.2 are not rejected.

Table 9 : Intraday Volume and Returns by Market Structure

Table 9 presents trade sizes and trade-to-trade returns segmented by the type of exchange on which they trade. Specialist exchanges (NYSE and AMEX) are examined separately from dealer exchanges. It presents the average returns for insiders and non-insiders, as well as their difference and a t-statistic from a Wilcoxon rank sum test. Table 9 also examines trade lot sizes by market structure, displaying descriptive statistics and the result of a Wilcoxon rank sum test for the difference in lot size. Trade-to-trade returns are calculated as the log differential of prices.

Panel A: Trade Sizes by Market Structure

Trade Size (Shares) - NASDAQ	Average Trade Size/Insider	Average Trade Size/Non-Insider	Difference	T-Statistic
Mean	947.36	425.38	521.98	0.34
Median	363.64	348.85	14.78	
Standard Error	225.55	92.04	133.51	
Mean as % of Average Daily Volume	0.089	0.039	0.05	
Median as % of Average Daily Volume	0.034	0.033	0.001	

Trade Size (Shares) - NYSE & AMEX	Average Trade Size/Insider	Average Trade Size/Non-Insider	Difference	T-Statistic
Mean	1143.66	1069.53	74.14	1.52
Median	500.00	329.76	170.24	
Standard Error	327.39	278.99	48.40	
Mean as % of Average Daily Volume	0.191	0.179	0.012	
Median as % of Average Daily Volume	0.084	0.055	0.029	

Panel B: Trade-to-Trade Returns by Market Structure

Returns (NASDAQ)	Average T2T Return/Insider	Average T2T Return/ Non-insider	Difference	T-Statistic
Mean	0.002	0.000	0.002	1.62
Median	0.000	0.000	0.000	
Standard Error	0.000	0.000	0.000	

Returns (NYSE & AMEX)	Average T2T Return/Insider	Average T2T Return Non-insider	Difference	T-Statistic
Mean	0.001	0.000	0.001	2.85***
Median	0.000	0.000	0.000	
Standard Error	0.000	0.000	0.000	

*** indicates significance at a 1% level.

Two possible explanations can be drawn from for the significance of trade-to-trade price movements on NYSE/AMEX – in models of informed trading, the specialist raises the cost of liquidity when he believes an informed trader may be present in the market – in this circumstance, the insider is accepting the additional cost of liquidity (in terms of higher spreads) and is therefore causing a larger price impact. As mentioned, this holds with Glosten and Milgrom (1985), Benveniste, Marcus, and Wilhelm (1992) and Garfinkel and Nimelandran (2003). However, this could be an artefact of trade size, although the lack of significance for the difference between NYSE insider trades and non-insider trades argues against that, as NASDAQ trade lot sizes resemble surrounding trades, yielding a t-statistic of 0.34. Therefore, the specialist may be adjusting his spread based on the size of the trade alone, as opposed to any other characteristics which may allow him to determine that it may be an informed trade. On the other hand, the lack of significance of NYSE/AMEX insider trades to non-insider trades argues against that phenomenon. Due to the relative anonymity on NASDAQ, the insider does not generate statistically significant abnormal returns relative to non-insider trades when he opts to trade. However, specialist system (NYSE + AMEX) insider traders have a return significant at the 1% level, which either indicates aggression or willingness to move through several levels of the order book to purchase the quantity desired and pay the requisite liquidity premium, or indicates that the specialist is adjusting the spread to compensate for the perception of an insider in the market. An exogenous factor that cannot be tested for is the relative use of limit versus market orders. Cornell and Sirri's (1992) case study shows that in their sample, 10 out of 78 (12.8%) of orders are limit orders. As limit orders will presumably have a lesser price impact than market orders, it is possible that differential use of orders on both exchanges impacts trade-to-trade price returns.

This chapter proceeds to test hypotheses 3.4 and 4, whether the insider trades differ from other parties with similar trade initiators (that is, comparing insider buyer-initated trades with non-insider buyer-initated trades, and insider seller-initated trades with non-insider seller-initated trades). The Lee and Ready (1992) algorithm is used to determine the party initiating trades – this analysis is performed in case the insider traders, potentially using market orders, are compared against limit orders. The algorithm uses three methods to classify trades as either buyer-initiated or seller-initiated. If a trade takes place above the midpoint of the bid-ask spread, it is classified as buyer-initiated (likewise, if the trade takes place below the midpoint, it is seller-initiated). If a trade takes place at the midpoint, it is either buyer (seller) initiated depending upon whether it is higher (or lower) than the previous transaction price. Similarly, if the trade both equals the midpoint price as well as the previous transaction price, it is classified as buyer (seller) initiated depending on whether it is greater (or lesser) than the last different trading price. One can conceive a buyer-initiated insider trades as a market order and seller-initiated trades as limit orders. Hypotheses 3.4 and 4 compare buyer-initiated trades by insiders with uninformed buyer-initiated trades and seller-initiated trades by insiders with uninformed sell-initiated trades, to determine whether insider trades are singular in this respect. Table 10 shows t-tests of insider trades against non-insider trades paired with the same initiating party. Of the sample of trades, 49 are buyer-initiated by an insider, 11 are seller-initiated by an insider (limit orders), 31 are buyer-initiated, but not-initiated by an insider, and 10 are seller-initiated, but not initiated by an insider.

Table 10 - Buyer/Seller Initiated Trade Characteristics

Table 10 displays insider trades compared with non-insider trades of the same initiation within the same 30-minute interval. The Lee and Ready (1992) algorithm is used to determine whether trades are buyer-initiated or seller-initiated. Initiated by Insider details the characteristics of the insider trades which the algorithm determines are buyer-initiated in the case of insiders buying, and seller-initiated in the case of insider selling. These can be conceived as market orders. The returns and volume under Not Initiated by Insider are insider trades that are either seller-initiated buys or buyer-initiated sells, which can be conceived as limit orders. Non-insider displays returns to non-insider trades in the same 30-minute interval.

	Initiated by Insider				Not Initiated By Insider				
Returns	Buying	T-stat	Selling	T-stat	Buying	T-stat	Selling	T-stat	Non-insider
Mean	0.002	3.33**	-0.001	-1.05	0.002	1.83	0.00	0.41	0.000
Median	0.000		0.000		0.000		0.00		0.000
Standard Error	0.000		0.001		0.001		0.00		0.000
Difference Between Opening Price and Trading Price (in percent)	Buying	T-stat	Selling	T-stat	Buying	T-stat	Selling	T-stat	Non-insider
Mean	0.32%	1.59	-1.23%	-0.96	0.04%	0.17	0.14%	0.51	0.07%

	Buying	T-stat	Selling	T-stat	Buying	T-stat	Selling	T-stat	Non-insider
Median	0.04%	0.20	0.00%		-0.08%	-0.30	-0.01%	-0.04	0.01%
Standard Error	0.20%		1.29%		0.27%		0.28%		0.21%

Intraday Volume

Trade Size (Shares)	Buying	T-stat	Selling	T-stat	Buying	T-stat	Selling	T-stat	Non-insider
Mean	985.68	5.14***	2614.26	1.17	635.75	3.53***	734.31	1.54	657.45
Median	500.00	2.60***	434.38	0.19	341.94	1.90	231.45	0.49	348.36
Standard Error	191.59		2238.94		180.10		475.49		165.42
Trade Size (% of Average Daily Volume)	Buying	T-stat	Selling	T-stat	Buying	T-stat	Selling	T-stat	Non-insider
Mean as % of Average Daily Volume	0.21%	5.14***	0.37%	1.17	0.04%	3.53***	0.12%	1.54	0.0733
Median as % of Average Daily Volume	0.11%	2.60***	0.06%	0.19	0.02%	1.9	0.04%	0.49	0.0389
Standard Error as % of Average Daily Volume	0.04%		0.31%		0.01%		0.08%		0.0185
N	49		11		31		10		

*** indicates significance at a 1% level.

Out of these categories, the only significant one is trade size for buyer-initiated insider trades and seller-initiated insider trades, with respective t-stats of 5.14 and 3.53, significant at the 1% level. Therefore, hypothesis 3.4 and 4 can be rejected, as insider trades are distinct from trades with the same initiating party. This would imply that the insiders move prices disproportionately, to a degree that that non-insider aggressive buy and sell orders do not move prices. One can conclude that aggressive insiders trading in significant volume will stand out from the crowd sufficiently to be potentially detected, but other insiders may not strongly affect price changes, as seen in Chakravarty and McConnell (1997, 1999).

For the entire sample, mean returns to insider trades are positive and significant at the 1% level (see Table 7). Table 10 segments the sample and finds that this return is driven by buyer-initiated insider 'buy' trades, and that buyer-initiated insider 'sell' trades and seller-initiated insider trades are not statistically significant in terms of trade-to-trade price movement. This may be linked to buyer-initiated insider 'buy' trades executing in larger lot sides than comparative non-insider trades (significant at the 1% level, with a t-statistic of 5.14). However, seller-initiated insider 'buy' trades also execute in a statistically significantly larger size than comparable trades (significant at the 1% level, with a t-statistic of 3.53), but do not move prices in a statistically significant sense. It is also worth noting that the median buyer-initiated 'buy' trade is significant at the 1% level, with a t-statistic of 2.60.

Intraday analysis is used to assess whether insiders have a differential impact from non-insider trades sharing their characteristics, and assists, as it both controls for market conditions and allows one to see the immediate impact of insider entrance into the market. While Chakravarty and McConnell (1997,1999) found that Ivan Boesky's insider trades had a relationship with volume two hours after he traded, that finding could be idiosyncratic. Using a sample of 53 trades allows for robust examination as to the intraday impact of insiders' activity in markets, as it controls for time of day effects and any economic activity that may

take place throughout the day in the market. In addition, intraday analysis allows one to test

whether Glosten and Milgram's (1985) theoretical findings of specialists compensating for

the adverse selection problem posed by insider activity in the markets is found in empirical

results. As this chapter has shown very pronounced activity (both in terms of volume as well

as trade-to-trade price returns) around the presence of an insider, one can see this as empirical

support for Glosten and Milgram (1985).

The data is admittedly an imperfect set, due to the inherent selection bias in examining only the trades in which the insider is detected. There is furthermore an inherent evidentiary bias because the aspects of insider trading that the SEC detects must meet a certain threshold for successful prosecution – examples of suspicious behaviour in which the insider was not ultimately prosecuted, such as consent decrees, are unavailable.

An additional note is that those insiders who were financial markets professionals (broadly defined as brokers, lawyers, and bankers) performed transactions that were not as noticeable in daily and intraday behaviour as individuals less familiar with financial markets. This may be due to financial markets professionals' awareness of surveillance and insider trading regulation, so they may trade more strategically to attempt to avoid detection.

5. **Conclusions**

This chapter discovers that on average, insider trades do possess attributes that differentiate them from surrounding trades, but a great deal of those attributes depend on the trade characteristics – aggressive market orders will draw scrutiny due to their price impact, whereas limit orders are less noticeable. Insiders trade lot sizes that are also larger than other market participants at the time, thereby potentially drawing attention from regulators and surveillance departments.

The results confirm the anonymity hypothesis of Glosten and Milgram (1985) and Garfinkel and Nimelandran (2003), displaying the strong impact of the specialist in regulating fluid market performance. However, insider trading on NASDAQ is significant, yet not to the degree that it is on specialist markets, due to the ability of the specialist to protect herself against uncontrolled loss to the insider. An investigation of this impact using foreign markets with similar structures would be of interest. The results further imply that order type matters,

but without a database of illegal insider trades sorted by order time, one cannot confirm this

hypothesis. In addition, characteristics of the insider, such as profession, may affect their

trading practices.

Appendix 1: A Historical Overview of US Insider Trading Legislation

The Securities Act of 1933 and its companion, the Securities Exchange Act of 1934, inaugurated enforcement of market abuse in the United States. Originally crafted to focus on bucket shops and stock promoter rings, the Act was modified by Rule 10-b5 to respond to market practices the SEC judged as prejudicial. Rule 10-b5 (1942) targeted fraudulent practices by insiders. Most of the cases the SEC has litigated on insider trading have resulted from Rule 10-b5's authority. However, subsequent judicial holdings by courts have expanded this prohibition from insiders to anyone in possession of 'material non-public information'. Materiality of the information is most commonly defined as information that would influence any potential purchase or sale of securities, while non-public information is that which is unavailable to the general public[26]. Courts have established a rather subjective and encompassing view of materiality, and most of the discussion has hinged upon the obligation of defendants to either refrain from trading or to disclose the information to the public, as determined in *SEC v Texas Gulf Sulphur Corp* (1968).

Legal thought on insider trading rests on two key principles: the misappropriation principle and unjust enrichment. The former treats information as a form of property, and accordingly, an insider using information as the pretext for trading is 'stealing' that information from his employer, to whom he owes a duty. Courts affirmed this principle in *United States v O'Hagan* (1997), a case in which an attorney advising a company in the pursuit of a takeover bought shares in the target. Despite O'Hagan's assertion that he was not engaged by the target, and therefore did not owe it a duty, the Supreme Court found that he had misappropriated the information from his client by using it for a purpose that it was not

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[26] Regulation FD has subsequently changed this by prohibiting the selective release of non-public information to individuals such as securities analysts and institutions.

intended. This overturned the precedent set by *United States v. Chiarella* (1980), where a prospectus printer's possession of material non-public information was not held to be criminal[27]. The misappropriation doctrine also brings tippees under the cover of the law, as they are in receipt of improperly acquired 'property'. Meanwhile, unjust enrichment doctrine holds that if one gains assets through no effort of his own, he should repay those assets to the rightful owner. Insider trading can be viewed as unjust enrichment because the insider's benefit at the cost of the counterparty to his trade, who is oblivious of the impact of this information on the securities' future value. Unjust enrichment is used as a legal basis for requiring disgorgement of any gain on insider trading.

The SEC's enforcement of insider trading allows for bounties to be paid to informants from civil penalties assessed to guilty insider traders up to 10% of the penalty. This form of detection is supplemented by referrals from both exchange operators and the Financial Industry Regulatory Association (FINRA). As the successor of the National Association of Securities Dealers, FINRA has authority under the Securities Exchange Act to function as a self-regulatory organization supervising all firms and individuals engaged in business with the public. As part of that function, FINRA monitors securities markets for suspicious behaviour, which it reports to the SEC for further investigation that may lead to prosecution.

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[27] The Supreme Court did not entertain the misappropriation theory, because it had not been put forth by prosecutors. See 'Insider Trading and the Duty Analysis', a speech by SEC Commissioner James Treadway http://www.sechistorical.org/collection/papers/1980/1983_0602_TreadwayChiarella.pdf

Appendix 2: Robustness Test for 2005 and LHV Results

Appendix 2 examines whether the composition of the sample biases the results found in regression 3.1. Regression 3.1 is estimated twice, with an additional dummy variable for cases occurring in 2005, and then with a dummy variable representing those cases in which the LHV ring transacted in. Parameter estimates for each of the coefficients are presented.

Panel A: 2005

	Intercept	Index	News1	News2	Announcement	Insider	Not2005	R-Squared
Parameter Estimate	-0.0004	1.1211	0.0140	0.0264	0.1418	-0.0171	0.0206	0.0004
Standard Error	0.0121	1.0325	0.1059	0.1108	0.1060	0.0847	0.0166	
p-value	(0.9765)	(0.2776)	(0.8951)	(0.8115)	(0.1809)	(0.8400)	(0.2147)	

Panel B: LHV Ring

	Intercept	Index	News1	News2	Announcement	Insider	Not2005	R-Squared
Parameter Estimate	0.0001	1.1522	0.0173	0.0289	0.1407	-0.0187	0.0226	0.0004
Standard Error	0.0114	1.0324	0.1059	0.1107	0.1060	0.0847	0.0166	
p-value	(0.9958)	(0.2644)	(0.8700)	(0.7942)	(0.1843)	(0.8251)	(0.1739)	

Chapter Four:

Price Discovery in Liquid British Stocks after the Advent of MiFID and Chi-X[28]

1. Introduction

In 2007, the European Commission instituted the Markets in Financial Instruments Directive (MiFID), a public policy measure intended to establish a pan-European market for shares. Introducing a 'passport' function for clearing and settlement plus a best execution mandate, MiFID proved to be a catalyst for the growth of new multilateral trading facilities (MTFs). MTFs are designed to serve a fast-growing breed of technological traders who rely heavily on computer algorithms and other techniques demanding low latency. As MTFs proliferated in 2007-2008, European order flow fragmented on those national exchanges previously subject to a concentration rule. When fragmentation occurred in response to Reg NMS in the US, price discovery migrated away from the central exchange. In contrast, the introduction of MiFID had no such comparable effects on the price discovery process in London, as the majority of price discovery remained on the London Stock Exchange. Instead, seven months later, after a clearing and settlement fee schedule change by Chi-X, the bulk of price discovery moved to Chi-X. This is due to the migration of informed trades attributable to the transfer of high frequency traders to Chi-X from the London Stock Exchange.

In preparation for MiFID, Chi-X, an exchange developed from the private institutional network Instinet Europe, launched seven months prior to the implementation of MiFID. Chi-X aimed to capitalise on investors' abilities to trade on non-national exchanges after the

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[28] A version of this chapter focusing on the empirical methodology of Harris, McInish, and Wood (2009) is currently a working paper with Frederick DeB. Harris and Michael J. Aitken. A copy of this paper is in Appendix 1 of this chapter.

abolition of the concentration rule. Furthermore, MiFID's regulatory obligation to make traders find 'best execution' stimulated competition in the provision of liquidity, and thus in the order flow fragmentation across exchanges (European Commission, 2004). MiFID's changes to European public policy provided a business case for Chi-X, as prior to that, trading was either on the national exchange (London Stock Exchange) or on upstairs institutional platforms. In addition to capitalizing on the potential opportunities offered by new cross-border trading within Europe, Chi-X focused on capturing market share by offering trading services better suited to a growing number of technological and computerized traders focused on both low latency (thus, a higher speed of transaction with the concurrent lower probability of failure to execute or being front-run by a competitor) and the related reduction in execution and transactions costs resulting from the entrance of a competitor into the trading services market. With the public interest necessity offering a higher standard of protection to retail investors as opposed to institutional investors, Chi-X had lower operative costs due to lower compliance burdens. Additionally, Chi-X perceived an opportunity to compete with existing exchanges through not only transactions costs, but also 'implicit' trading costs such as clearing and settlement costs. Chi-X targeted market participants like High Frequency Traders, whose business models tend to involve accumulating very small inefficiencies in market pricing and frequently trading on them to produce a significant aggregate profit. As High Frequency Traders must pay trading costs in terms of both explicit execution costs and implicit trading fees, they are highly sensitive to these marginal costs. This chapter investigates how Chi-X's entry into the market, catalysed by MiFID, as well as how the concurrent emergence of this style of traders, altered the formation of prices among European exchanges.

MiFID was officially implemented throughout the European Union by national authorities on 1 November 2007. Prior to that date, the concentration rule in many European countries mandated exchange-located trading. Although there was no concentration rule in the UK, the Netherlands, or Germany, fragmentation prior to MiFID in these three markets was minimal[29]. The diminution of existing monopoly power took two forms – increased competition via competitive liquidity provision on other existing European exchanges (for example, German insurers made a market in UK equities on Deutsche Borse – Xetra) and the launch of new MTFs aiming both to capitalise on a new breed of increasingly technological traders and national parties wishing to trade European equities outside their countries of origin. By abolishing the concentration rule and creating a regulatory requirement, a gap emerged in the market for a low cost competitor to the London Stock Exchange. Meanwhile, MiFID created a gap in the market for competitive liquidity provision. Chi-X, with its low latency and competitive fee structure, was poised to take advantage of changes in the marketplace to compete with established exchanges.

A recent study commissioned by the World Federation of Exchanges, the umbrella body for securities exchanges, offers insight into how fragmentation spurred by MiFID affected securities markets. Gresse (2010) finds that spreads have narrowed after the introduction of MiFID, although depth has decreased, and that traders with access to both the local exchange and the MTF have benefited from a reduction in costs, an advantage not shared by traders with only access to the local exchange. This empirical finding substantiates Hamilton's (1979) thesis that fragmentation may increase costs, thus diminishing liquidity by limiting the economies of scale that result from a single liquidity provider.

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[29] Oriol (2008) and Riordan, Storkenmaier, and Wagener (2010) provide studies of fragmentation before and after MiFID.

Industry publications report Chi-X has over 90% algorithmic order flow, as opposed to 40% on Deutsche Borse –Xetra, and lower levels for the London Stock Exchange. Gresse (2010) finds that Chi-X quickly assumed 10% of the order-flow in FTSE 100 stocks, and finds that FTSE stocks are the only European index components that have increased short-term price volatility, another empirical finding suggested by the fragmentation literature. Therefore, as the theoretical effects of order flow fragmentation appear to have taken hold in London, London is the ideal venue with which to examine the effects of fragmentation on price discovery.

Recent research similar to this chapter is Hendershott and Riordan (2009), who examine algorithmic trading and Hasbrouck (1995) Information Shares in price discovery on Deutsche Borse – Xetra, an exchange which has unique identifiers for algorithmic trades due to German tax treatment of algorithmic trades. This chapter expands upon Hendershott and Riordan (2009) by examining a different market, the UK, and using Gonzalo Granger (1995) Common Factor Shares to supplement the interpretation of price discovery channels through Information Shares. While Hendershott and Riordan (2009) partition their sample into algorithmic trades on Deutsche Borse – Xetra and non-algorithmic trades on the same exchange, this chapter examines several exchanges as execution channels. These exchanges/MTFs have differing fee schedules, and this chapter also examines the difference in price formation patterns between trades and quotes. The contribution of this chapter is how fragmentation spurred by regulatory changes in Europe has affected the formation of prices - a key welfare function of exchanges in ensuring that capital markets are efficient, as per the International Organisation of Securities Commissions (IOSCO) guidance to regulators and exchange operators.

MiFID allows for shares traded on a regulated market within the European Union to be listed on any other European Union regulated exchange. In this respect, MiFID's arrangements differ from the extant literature on Dual Listed Companies (DLCs), because DLCs are firms with two different classes of share with ultimate claims on the same corporate entity, but with different claims on that firm's cash flows, whether due to corporate history or for purposes of tax arbitrage (Froot and Dabora, 1999). Under MiFID, a share listed in the UK, such as Vodafone, may be traded on any other European exchange. As a result, the no-arbitrage principle is expected to be held under MiFID while not for DLCs, as DLCs are heterogeneous, while the shares traded under MiFID are identical.

This chapter initially examines the interaction in prices between the London Stock Exchange, its chief domestic competitor, Chi-X, and the other leading European exchange, Deutsche Borse – Xetra, while using fluctuations in the British pound/Euro exchange rate. Prices are anticipated to error correct between London and Frankfurt to the foreign exchange rate, as well as changes in fundamental news and stochastic shocks created by order imbalances on each of the three exchanges. This chapter proceeds to examine price discovery between the London Stock Exchange and Chi-X, the two venues primarily competing for UK order flow. As fragmentation has lowered execution costs for traders able to access multiple markets, has it led the price discovery process to migrate from the London Stock Exchange, the 'home' exchange for FTSE 100 shares, to competitor exchanges such as Chi-X and Deutsche Borse – Xetra?

2. Hypotheses and Theory

Markets are presumed to have one efficient price, and only brief random disturbances will cause security prices to fluctuate from the true price. Therefore, when new information

arrives in the market, prices will adjust to reflect it. The methodology of price discovery in this chapter examines a homogenous asset in several different markets, and therefore the price of the asset should not deviate from its true price, because otherwise a lack of price efficiency in markets would exist. In addition, as the prices of a homogenous asset should reflect similar fundamentals regardless of the market in which it is traded, this informational linkage should cause the two series of prices to be cointegrated[30].

As mentioned, MiFID permits market participants to trade securities already regulated by other EU securities market authorities on any other EU exchange. As a result, securities traded on alternate exchanges under MiFID are identical and thus fungible. Therefore, no-arbitrage equilibrium is expected to hold.

In order to evaluate the dynamics of price adjustment, the model of Engle and Granger (1987) is used. To implement price discovery methodology, the following constructs are assumed to exist in the data: It is assumed that security prices are generated by a random walk process $P_t = P_{t-1} + w_t$, where P_t is the unobservable implicit efficient price, P_{t-1} is the unobservable implicit efficient price in the period prior to observation, and w_t is the permanent innovation in valuation fundamentals. When the identical security is traded in multiple exchanges, these prices are expected to be cointegrated at order one C(1,1) across exchanges and will error correct to changes between the prices in home P_h and foreign P_f exchanges or in competing P_i, P_j execution channels. Observed prices can be written as $P_{ht} = P_{ht-1} + w_t + \varepsilon_{ht}$ and therefore $P_{ht} = \Sigma w_t + \varepsilon_{ht}$,where ε_{ht} is any one of the various liquidity shocks (e.g., order imbalances due to sector rotations, redemptions, portfolio rebalancing, etc.). These liquidity shocks are short-

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[30] Fama (1998) reviews the development of the theories on market efficiency. From the perspective of sceptics in efficient markets theory, Shleifer (2000) and Shleifer and Vishny (1997) discuss market efficiency.

term in nature and reflect transitory deviations in price, as opposed to permanent changes in valuation fundamentals.

By the Engle-Granger Representation Theorem (1987), any such C(1,1) series has adjustment dynamics described by the Vector Error Correction Model always being specified to include an error correction term z_{t-1}:

$$\Delta P_{ht} = \alpha_h + \Sigma\, \beta_{ht\text{-}s}\Delta P_{ht\text{-}s} + \Sigma\, \beta_{ft\text{-}s}\Delta P_{ft\text{-}s} + z_h(P_{ht\text{-}1} - P_{ft\text{-}1}) + \Delta\varepsilon_{ht} \qquad (4.1)$$

$$\Delta P_{ft} = \alpha_f + \Sigma\, \beta_{ht\text{-}s}\Delta P_{ht\text{-}s} + \Sigma\, \beta_{ft\text{-}s}\Delta P_{ft\text{-}s} + z_f(P_{ht\text{-}1} - P_{ft\text{-}1}) + \Delta\varepsilon_{ft} \qquad (4.2)$$

In equation 4.1, the terms are as follows:

$\beta_{ht\text{-}s}\Delta P_{ht\text{-}s}$ represents price innovations on channel h in share t,

$\beta_{ft\text{-}s}\Delta P_{ft\text{-}s}$ represents price innovations on channel f in share t,

$z_h(P_{ht\text{-}1} - P_{ft\text{-}1})$ represents the correction of prices on channel h to the lagged difference of prices of channel h in share t with the lagged prices of channel f in share t,

z_h on its own represents channel h's contribution to price adjustments in share t,

$(P_{ht\text{-}1} - P_{ft\text{-}1})$ is a cointegrating vector that represents the size of the arbitrage opportunity available,

and $\Delta\varepsilon_{ht}$ is a white noise residual term that can represent liquidity shocks, such as short term order imbalances.

Equation 4.2 and the coefficients of the resulting VECMs (4.3 - 4.6) are defined in the same way as 4.1, with differing subscripts representing different channels. z_h and z_f are the parameters estimated by Information Shares (Hasbrouck, 1995) and Common Factor Shares

(Harris et al, 1995), and represent the share of price discovery attributable to channels h and f respectively.

As security prices traded in two currencies are examined, the dynamic of the pound/euro exchange rate provides another factor to be considered, because the exchange rate process itself is a random walk process, with its own transitory shocks due to order imbalances caused by intraday supply and demand of currencies, as well as with innovations in valuation fundamentals such as trade flows and changes in interest rates. As a result, the model tested including a foreign exchange channel is:

$$\Delta P_{LSEt} = \alpha_{LSE} + \Sigma \beta_{LSEt\text{-}s} \Delta P_{LSEt\text{-}s} + \Sigma \beta_{DEt\text{-}s} \Delta P_{DEt\text{-}s} + \Sigma \beta_{CHI\text{-}Xt\text{-}s} \Delta P_{Chi\text{-}Xt\text{-}s}$$

$$+ \Sigma \beta_{FXt\text{-}s} \Delta FX_{t\text{-}s} + z_{LSE}(P_{LSEt\text{-}1} - P_{DEt\text{-}1} - P_{Chi\text{-}Xt\text{-}1} - FX_{t\text{-}1}) + u_t \qquad (4.3)$$

$$\Delta P_{Chi\text{-}Xt} = \alpha_{Chi\text{-}X} + \Sigma \beta_{LSEt\text{-}s} \Delta P_{LSEt\text{-}s} + \Sigma \beta_{DEt\text{-}s} \Delta P_{DEt\text{-}s} + \Sigma \beta_{Chi\text{-}Xt\text{-}s} \Delta P_{Chi\text{-}Xt\text{-}s}$$

$$+ \Sigma \beta_{FXt\text{-}s} \Delta FX_{t\text{-}s} + z_{Chi\text{-}X}(P_{LSEt\text{-}1} - P_{DEt\text{-}1} - P_{Chi\text{-}Xt\text{-}1} - FX_{t\text{-}1}) + n_t \qquad (4.4)$$

$$\Delta P_{DEt} = \alpha_{DE} + \Sigma \beta_{LSEt\text{-}s} \Delta P_{LSEt\text{-}s} + \Sigma \beta_{DEt\text{-}s} \Delta P_{DEt\text{-}s} + \Sigma \beta_{Chi\text{-}Xt\text{-}s} \Delta P_{Chi\text{-}Xt\text{-}s} +$$

$$\Sigma \beta_{FXt\text{-}s} \Delta FX_{t\text{-}s} + z_{DE}(P_{LSEt\text{-}1} - P_{DEt\text{-}1} - P_{Chi\text{-}Xt\text{-}1} - FX_{t\text{-}1}) + v_t \qquad (4.5)$$

$$\Delta FX_t = \alpha_{FX} + \Sigma \beta_{LSEt\text{-}s} \Delta P_{LSEt\text{-}s} + \Sigma \beta_{DEt\text{-}s} \Delta P_{DEt\text{-}s} + \Sigma \beta_{Chi\text{-}Xt\text{-}s} \Delta P_{Chi\text{-}Xt\text{-}s}$$

$$+ \Sigma \beta_{FXt\text{-}s} \Delta FX_{t\text{-}s} + z_{FX}(P_{LSEt\text{-}1} - P_{DEt\text{-}1} - P_{Chi\text{-}Xt\text{-}1} - FX_{t\text{-}1}) + z_t \qquad (4.6)$$

where ΔP_{LSEt} , $\Delta P_{Chi\text{-}Xt}$, ΔP_{DEt} , ΔFX_t represent price changes on the London Stock Exchange, Chi-X, Deutsche Borse – Xetra, and in the foreign exchange market, respectively.

When examining price dynamics of a homogenous asset, cointegration is required, because it shows that the time series examined has common stochastic trends. If the series lacks a

common trend, it can be inferred that it is not responding in a similar fashion to the arrival of information into the marketplace. In keeping with the existing literature, two metrics are used in the examination of price discovery. Each of these methods estimates the coefficients of the respective channels proposed in equations 4.1 through 4.6, thereby estimating each channel's contribution to the permanent price trend. Hasbrouck (1995) proposes a vector autoregressive model that decomposes price volatility into the variance of innovations in the common factor. This model, known as Information Share (IS), represents each market's contribution to the innovations in the common factor. Hasbrouck's Information Share contrasts with Gonzalo and Granger's (1995) Common Factor Share (CFS) approach, which is a proportion of the common factor innovations that is driven by adjustment of the price series from each of the exchanges.

Both methodologies are used as in Harris, McInish, and Wood (2009), in addition to Yan and Zivot (2010), who show that CFS is needed to interpret an ambiguous IS. IS can be large if a channel (in this case, an exchange) is impounding permanent information, or if its competitors are chasing transitory shocks. Meanwhile, a CFS of a channel (exchange) will only be large if it avoids chasing transitory shocks. Therefore, use of CFS in conjunction with IS allows the determination which channel is the source of information impounding.

To study fragmentation's effects on price discovery within this sample, the following events are examined: the impact of the launch of Chi-X, the implementation of MiFID, and the central counterparty fee cut on Chi-X. In light of Hamilton (1978) and Madhavan (1995), fragmentation may have competitive effects or reductions in economies of scale that drive order flow. As Harris, McInish, and Wood (2009) find, the advent of a regulatory change (Reg NMS), combined with the launch of a new exchange focused on technological traders,

caused price discovery to migrate to the new exchange, NYSE ARCA. These events are paralleled in the launch of Chi-X and MiFID, analogous to the SEC's Reg NMS. Analysing the launch of Chi-X separately from the implementation of MiFID allows for an experiment to test whether the presence of an alternate trading venue without regulatory directives affects transactions costs, or whether MiFID catalysed competition in European equities markets. The examination of the effect of Chi-X's central counterparty fee cut shows the implications of changes in market access costs (implicit costs, in that they are not set by market participants, but by infrastructure providers).

From this basis, several hypotheses regarding cointegration and relative shares of price discovery are tested:

$H_1$0: Deutsche Borse – Xetra will not contribute in a statistically significant manner to the process of price discovery in liquid UK shares.

H_1A: Deutsche Borse – Xetra will have a statistically significant impact on price discovery in liquid UK shares.

Hypothesis 1 tests the marginal effect of fragmentation on price discovery by looking at whether any non-UK exchange contributes to price discovery in British shares. Prior to the advent of MiFID, the Frankfurt Stock Exchange and its electronic component Deutsche Borse – Xetra represented the largest forum for trading UK shares outside of the London Stock Exchange.[31] This is due to the pre-eminence of the German economy and German fund managers within Europe. While Deutsche Borse – Xetra trades a small fraction of the turnover in respective shares in London, it is expected that any fundamental knowledge

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[31] World Federation of Exchanges Factbook (2007).

derived by German-based fund managers would find its way into UK shares traded on German platforms, not London. Ding, Harris, Lau, and McInish (1999) examine a similar scenario in the case of Sime Darby Berhad, a Malaysian company traded on both the Kuala Lumpur Stock Exchange and the Singapore Stock Exchange. They find that Sime Darby Berhad's price fundamentals are discovered in Singapore by an amount greater than Singapore's proportion of Sime Darby Berhad's order flow. As there is no evidence to support that Singapore's order flow has a higher proportion of informed traders than Malaysia's, this is an unexpected finding.

The Hasbrouck (1995) and Harris (1995) methodologies test what proportion of permanent innovations in price fundamentals (as to be distinguished from transitory price shocks, caused by intraday order imbalance) comes from each exchange. Therefore, this is a directional test, as values below zero cannot be obtained.

$H_2 0$: The launch of MiFID will not change the absence of cointegration in the price series of UK liquid shares between Deutsche Borse – Xetra, London Stock Exchange, and Chi-X.

$H_2 A$: The advent of MiFID will introduce cointegration in the price series of UK liquid shares between Deutsche Borse – Xetra, London Stock Exchange, and Chi-X.

Prior to the advent of MiFID, cointegration did not exist in many homogenous assets between the British exchanges (London Stock Exchange and Chi-X) and Deutsche Borse – Xetra. The absence of this phenomenon means that there is no co-movement between the two time series, implying that the two series are unlikely to be informationally linked. The failure to cointegrate can be seen as a situation where fundamental information is not finding its way

into share prices on both exchanges. As, under MiFID homogenous shares are examined, their long-term values will be determined by fundamental information, and thus, a share of Vodafone in London and a share of Vodafone in Frankfurt should respond equally to changes in information. Therefore, it would be unusual if the same asset in two different markets were not responding in the same way to innovations in fundamental information.

Since MiFID, in integrating European securities markets, mandated market participants to seek 'best execution' when routing client orders, making market participants heavily invested in systems that would allow them to find the best prices (among other factors) upon which to execute client (and their own) orders. This obligation, together with the abolition of the concentration rule, implies that previously segmented or imperfectly integrated securities markets may become integrated (European Commission, 2004). Integration can be interpreted as a signal that MiFID has contributed towards a single European securities market, as evidenced by the introduction of cointegration between prices of the same asset traded on different European exchanges. If homogenous assets lack cointegration, then they are not responding in a similar way to the arrival of new information in the market, and one can infer that the market is not integrated. Therefore, if cointegration exists in the same asset listed on European securities markets after the implementation of MiFID, it can be interpreted as leading to an integrated pan-European securities market.

Gresse (2010) shows that spreads are diminished (and depth affected) with the introduction of fragmentation and the consequent competition between exchanges and liquidity providers caused by MiFID. Hence, price discovery patterns should fluctuate around the advent of MiFID, as price sensitive market participants respond to the changes in transactions costs and select between the multiple exchanges for the minimal transactions price. Prior to MiFID, UK

market participants only had the ability to obtain a minimal amount of liquidity on other exchanges. Hamilton (1979) theorizes that the fragmentation of equity trading will induce short-term volatility into price patterns in the home market. Madhavan (1995) suggests that fragmentation additionally reduces liquidity and may lead to inefficient prices. Mendelson (1987) dissents, claiming that the competition effect will outweigh diseconomies of scale and lead to lower price volatility. Despite differing conclusions regarding the effect of fragmentation, both Mendelson (1987) and Madhavan (1995) propose a disturbance from the status quo. Accordingly, price discovery patterns should be changed with an increasing amount of fragmentation. Even if a unitary amount of price impounding as a proportion of order flow were assumed, the fluctuation of order flow percentage should change price discovery. Therefore, the introduction of competitive venues for liquidity ought to change the proportion of price discovery performed on each of the venues, even in the absence of competitive pressures through exchange fee (implicit) cost changes.

H_30: The advent of MiFID will not affect price discovery patterns in Information Shares and Common Factor Shares in liquid UK shares between the London Stock Exchange and Chi-X.

H_3A: The advent of MiFID will affect price discovery patterns in Information Shares and Common Factor Shares in liquid UK shares between the London Stock Exchange and Chi-X by shifting more price discovery to Chi-X, due to the directive of best execution.

MiFID, with its goal of integration securities markets, imposes an instruction that market participants seek 'best execution' in their orders. MiFID defines 'best execution' in a variety of ways, including price, time (fastest execution of the order), execution likelihood, and size

of order (in which one exchange may be offering a preferable price at the best bid-offer, but given the size of the order, the value-weighted average price can be found at a different exchange). One can expect MiFID's implementation to dissolve existing client relationships in the financial services field that may not be of optimal value to the end-user client. A contrast to this is the multi-faceted definition of best execution under MiFID, and although a treatment of an order may not obtain best execution in terms of one attribute, for example, price, the broker may argue that best execution is obtained in another dimension, for example, probability of execution of the full order.

This may be anticipated by its analogue in the United States, Reg NMS. Harris, McInish, and Wood (2009) show that the introduction of Reg NMS, which ordered best execution specifically by price and altered price discovery flows, increasing the Information Share of NYSE ARCA, a new exchange focused on attracting traders with a sensitivity for speedy execution. The interplay between ARCA traders walking the limit order book and NYSE floor traders following those stochastic shocks as indicative of future price movements led to the post-Reg NMS increase in the Common Factor Share of NASDAQ. Chi-X entered the European market with a similar strategy of attracting technological traders as NYSE ARCA. Hence a similar dynamic may take hold, with time-sensitive traders migrating to the new electronic-focused exchange. Bennett and Wei (2006) provide further theory on the role of fragmentation altering liquidity patterns. Hendershott and Moulton (2009) display how a reduction in latency on the NYSE leads to greater information impounding in stock prices, something that may be mirrored by the presence (and potentially mandated use) of Chi-X in a post-MiFID environment. Moulton and Wei (2009) show that when American Depository Receipts (ADRs) are traded contemporaneously with European underlying equities, spreads

decrease and depth increases. This is either due to additional liquidity in the market with both exchanges open, or represents competition for order flow. Menkveld (2008) extends Chowdry and Nanda's (1991) model to dual listed securities in Amsterdam and London and finds substantial evidence of order-splitting. As the literature seems to have determined that liquidity is affected by fragmentation, price discovery patterns should also change.

$H_4$0: Chi-X's central counterparty fee cut did not affect price discovery patterns in Information Shares and Common Factor Shares in liquid UK shares between the London Stock Exchange and Chi-X.

H_4A: Chi-X's central counterparty fee cut affected price discovery patterns in Information Shares and Common Factor Shares between the London Stock Exchange and Chi-X by causing price discovery to shift from the London Stock Exchange to Chi-X.

Chi-X, as previously mentioned, was designed to capture two growing segments of market participants: those looking for a pan-European platform on which to trade and those technological traders highly sensitive to speed and the marginal costs of trading inclusive of both explicit execution costs (the bid-ask spread) and implicit trading costs (platform access fees, co-location fees, and clearing and settlement fees). Demsetz (1968) models liquidity as a supply and demand interaction, and both he and Benston and Hagerman (1974) mention competition as a factor that alters the supply and demand of liquidity. Taking this into account, competition in implicit costs should galvanize fragmentation just as competition in explicit costs leads to greater fragmentation of order flow. The clients Chi-X targeted with the central counterparty (CCP) fee cut includes high frequency traders and algorithmic traders highly sensitive to implicit fee costs, as those are fixed costs they pay each time they trade.

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As high frequency and algorithmic traders have based a business model around rapid and frequent trading, they should be extremely responsive to a cut in CCP fees, and thus flock to whatever forum the 'all-in' (implicit and explicit costs inclusive) costs of trading are lowest.

3. Data and Empirical Model

Five British shares - HSBC, BP, GlaxoSmithKline, Rio Tinto, and Vodafone, were selected based on their trading liquidity on both Instinet/Chi-X and Xetra. They are also some of the most heavily weighted constituents of the FTSE 100, and consequently they can be regarded as being representative of large-cap UK shares.[32]

Synchronous monthly trade and quote files are produced from the TRTH feed for the five securities as traded on the London Stock Exchange, Deutsche Borse's Xetra System, and Chi-X. The observation period runs from April 2007, with the launch of Chi-X, to December 2008. However, due to the relative lack of activity in trades on Chi-X in the early months, analysis of trades is performed from July 2007 to December 2008. As the price discovery methodologies need roughly 150 observations, or tuples, to arrive at a stable estimate, the lack of synchronous trade-based activity during the launch of Chi-X leads to an insufficient number of tuples for April 2007 to June 2007. The analysis of quote-based activity encompasses the entire observation period. Separate quote and trade files are created per security. These files include prices on Chi-X, the London Stock Exchange, and Deutsche Borse – Xetra, as well as the pound/euro exchange rate. Due to London reporting rules, the files filter out off-book trades (dealer negotiated, manually reported, and upstairs trades), as they can be reported to the tape up to 3 minutes later than their execution. Similarly, worked

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[32] Data is from Thomson Reuters Tick History (TRTH), an academic licence of the commercial Reuters data feed service provided through SIRCA (The Securities Industry Research Centre of the Asia-Pacific).

principal agreements may not be printed at representative prevailing prices in the London

Stock Exchange, as they represent negotiated block trades.

From these constituent files, MINSPAN files in trades and quotes are assembled as per Harris

et al (1995). The MINSPAN methodology captures synchronous adjustments in price across

each 'channel' examined. In this chapter, the channels are defined as the three trading venues

and the exchange rate. MINSPAN looks both forwards and backwards in time to capture

simultaneous price changes in all the channels[33]. For example, the MINSPAN number of

trade observations for BP ranges from 791 in July 2007 to 112,073 in September 2008. For

quotes also in BP, MINSPAN ranges from 384 in April 2007 to 187,787 in September 2008.

Not all of the 5 stocks possess a similar number of observations - Rio Tinto's maximum

number of trades and quotes are 79,199 trades and 172,930 quotes in September 2008. For

preliminary investigations of Hasbrouck's (1995) Information Share price discovery metric, a

FILL FORWARD procedure is used as per Hasbrouck, which creates tuples (ordered lists of

values) of observations at 4 specified time intervals (every 1 second, every 10 seconds, every

1 minute, and every 2 minutes). FILL FORWARD uses the most recent (stale) price until a

new trade or quote arrives. One potential drawback is that due to stale prices, some

observations can be relatively misleading. MINSPAN, by focusing on synchronous

observations (See Diagram 4.1) censors stale price fill-ins that may distort the adjustment

dynamics. As a result, the common factor share analysis is performed on the MINSPAN

intervals, as well as the Information Share tests, to ensure investigation is performed on

homogenous files.

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[33] Booth et al (2002) and Kurov and Lasser (2004) discuss methodological issues in data sampling and provide a more detailed description of the MINSPAN procedure.

Figure 4.1

Figure 4.1 presents the difference in MINSPAN and FILL FORWARD sampling methodology. P_0^A and P_0^B represent observations on channel A and B respectively.

MINSPAN   **FILL FORWARD**

      CENSORED

P_0^A P_1^A P_2^A P_3^A P_4^A P_0^A P_1^A P_2^A P_3^A P_4^A

P_0^B P_0^B P_0^B P_3^B P_4^B P_0^B P_0^B P_0^B P_3^B P_4^B

                                                 STALE PRICES

Price adjustment dynamics are tested across the three exchanges to examine how fragmentation affects the methods of price discovery. Chi-X targets pan-European and technological traders, the London Stock Exchange is an established stock exchange with lesser technological traders, while Xetra sits between the two, with 40% reported algorithmic order flow, due to both institutional design features and special German tax treatment for algorithmic trades[34]. This contrast in exchange characteristics allows for the analysis on the level of stock characteristics as well, providing further opportunities to examine both exchange-level effects and stock-level effects. This cross-sectional differential provides for a natural experimental setting to test whether key exchange attributes will affect price discovery. The implementation of MiFID provides a test for how regulation impacts price discovery, given idiosyncratic exchange attributes.

Although five of the most traded FTSE 100 shares were selected for examination, they have different aspects. Glaxo SmithKline (GSK), British Petroleum (BP), and Vodafone (VOD)

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[34] http://www.automatedtrader.net/news/algorithmic-trading-news/12383/deutsche-boerse-to-cut-xetra-transaction-fees details the relative algorithmic order flow shares of Chi-X and Deutsche Borse – Xetra.

have sole primary listings in London, while the Hong Kong and Shanghai Banking

Corporation (HSBC) has a primary listing in London as well as one in Hong Kong. Rio Tinto

(RIO) has a primary listing in Sydney. As this chapter examines how the fragmentation

spurred by MiFID and the launch of Chi-X affects the patterns of price formation, only the

London listing prices of HSBC and Rio Tinto are examined.

The first analysis of the data requires identification of the presence of cointegration between

markets before the 1 November 2007 introduction of MiFID. The Johansen (1991) test is

used to test for the presence of cointegration, and its trace test is used to determine whether

cointegration is present.

4. Results
4.1 Results with Four Channels – the UK and Germany

Based on the FILL FORWARD data files, no securities are cointegrated in September 2007,

prior to the advent of MiFID. However, as of May 2008, the middle of the sample period, for

each security, all four channels are cointegrated with one cointegrating vector and two

common factors, which represent valuation fundamentals for the security as well as the

fundamental of the exchange rate (See Table 1). In addition, prior to the advent of MiFID, a

large theoretical arbitrage opportunity (tens of pence) exists between the three channels

(obtained by summing the eigenvectors).

The theoretical arbitrage opportunity between the four channels disappears with the

integration of European securities markets after MiFID, as the prices in the London Stock

Exchange, Chi-X, and Deutsche Borse - Xetra error correct to each other while including

fluctuation in foreign exchange between the UK and Germany. Table 1 shows how a 0.7

pence (BP) to 1.2 pence (Vodafone) arbitrage opportunity reduces to .04 pence (BP) and .02

pence per share (Vodafone). As the range after MiFID is less than transactions costs, no arbitrage opportunity exists. Both BP and Vodafone are representative of the results for the sample of 5 stocks, as all experience the absence of cointegration prior to MiFID with a theoretical arbitrage opportunity. After the implementation of MiFID, these characteristics disappear.

From the results in Table 1, it appears apparent that MiFID is responsible for building a unitary, cointegrated pan-European securities market. Therefore, Hypothesis 2 is rejected. However, in the next section, an examination of monthly files before and after MiFID shows that it was not MiFID, but another event, that both induced cointegration in the FILL FORWARD files and changed the price discovery dynamic. Therefore, one can fail to reject Hypothesis 1, that the cointegration of European securities of markets is unaffected by MiFID, as another event is the stimulus. However, the price discovery estimates show a steep fall in Common Factor Shares for Vodafone (from 15.2% in September 2007 to 8.4% in May 2008) and for BP (from 13.3% in September 2007 to 8.1% in May 2008) in the interim. Table 1 displays several important findings for the four channel empirical model. The shares with dual primary listings mirror this behaviour. First, Frankfurt does not have a statistically significant element in price discovery for the UK stocks. Although results for only Vodafone and BP are displayed, this fact holds for all stocks in the sample. Therefore, Hypothesis 1 is not rejected, that Deutsche Borse – Xetra does not contribute a statistically significant amount of price discovery in UK shares, with maximum values of price discovery contribution under 1%. Also, the FX rate dominates price changes, accounting for 80% of price changes that persist, while the securities exchanges are in the noticeable minority. Furthermore, with the Frankfurt Common Factor Share statistically indistinguishable from zero, it is evident that

permanent price changes do not occur on Frankfurt – rather Frankfurt responds to price changes on Chi-X, the London Stock Exchange, and in the FX rate. Therefore, after this test, further analysis was performed solely on the London-based duo of Chi-X and the London Stock Exchange, given that the European exchange with the largest share of order flow in FTSE 100 shares outside of the UK does not contribute to FTSE price innovation. The rest of this chapter focuses on the bilateral dynamics between the London Stock Exchange and Chi-X.

Table 1: Johansen Cointegration Statistics and Common Factor Shares

Panel A displays Johansen Statistics, Eigenvalues, and Common Factor Shares prior to MiFID's implementation.

Panel B displays Johansen Statistics, Eigenvalues, and Common Factor Shares after MiFID's implementation.

Table 1 presents Johansen Cointegration Statistics and each channel's share of the Common Factors exhibited in the model tested. The Common Factors display what percentage of the common factors driving the system of prices (in the case of these 4 channels, valuation fundamentals as well as innovations in the foreign exchange rate) are attributable to each channel. The sum of the four eigenvalues exhibits whether there is a structural discrepancy in the price, which may indicate a theoretical arbitrage opportunity if it is larger than transactions costs involved in executing the arbitrage. Maximum trace statistics for hypotheses testing the number of cointegrating vectors are displayed, as well as the test values (Johansen 1991), to determine whether cointegration exists. Prior to MiFID, in September 2007, the hypothesis that there are zero cointegrating vectors cannot be rejected for both BP and Vodafone, while it can be rejected afterwards.

	Panel A: September 2007			
	Common Factor Shares			
	Xetra	London	Chi-X	FX
BP	0.07%	13.30%	4.60%	81.40%
Vodafone	0.06%	15.20%	6.70%	77.50%
GlaxoSmithKline	0.70%	5.30%	0.50%	93.50%
HSBC	2.16%	5.86%	1.09%	90.88%
Rio Tinto	1.62%	6.42%	2.94%	89.01%

	Eigenvalues				Sum
BP	1.061408	0.038523	-1.429058	1.1049959	0.775869
Vodafone	1.210779	0.206172	-1.398605	1.241882	1.260227
GlaxoSmithKline	-0.01594	-0.00084	0.001026	-0.004342	- 0.021
	0.001294	0.00052	1.36E-05	0.00011	0.0019377
HSBC					
Rio Tinto	0.00021	3.14E-05	-0.04096	7.36E-05	-0.040645

		Cointegration Test Statistics	
	H_0	Max Trace Statistic	Test value at 5%
BP	R<2	0.02051	3.84
	R<1	0.05553	11.44
	R=0	1.656659	17.89
Vodafone	R<2	0.017549	3.84
	R<1	0.511542	11.44
	R=0	1.713737	17.89
GlaxoSmithKline	R<2	0.035	3.84
	R<1	0.631	11.44
	R=0	0.903	17.89
HSBC	R<2	0.0341489	3.84
	R<1	0.5662193	11.44
	R=0	1.5501929	17.89
Rio Tinto	R<2	0.0106459	3.84
	R<1	0.3456643	11.44
	R=0	0.7538649	17.89

Panel B: May 2008

	Common Factor Shares			
	Xetra	London	Chi-X	FX
BP	0.04%	8.1%	2.5%	89%
Vodafone	0.0%	8.5%	2.0%	89.2%
GlaxoSmithKline	1.0%	43.5%	1.9%	53.6%
HSBC	3.64%	49.03%	17.84%	29.49%
Rio Tinto	1.84%	42.20%	31.24%	24.72%

	Eigenvalues				Sum
BP	0.029202	-8.24412	8.2313017	0.0251025	0.041482
Vodafone	0.014098	-5.30953	5.3069377	0.0152306	0.026732
GlaxoSmithKline	0.0002714	-0.00616	0.006176	-0.000664	- 0.0004
HSBC	0.0276508	-7.75217	7.7119502	0.0341941	-0.0060297
Rio Tinto	0.0008167	0.000122	0.0000388	-4.52E-06	0.000973681

Cointegration Test Statistics

	H_0	Max Trace Statistic	Test value at 5%
BP	R<2	0.107975	3.84
	R<1	0.590451	11.44
	R=0	33.43509	17.89
Vodafone	R<2	0.052242	3.84
	R<1	0.296498	11.44
	R=0	20.20316	17.89
GlaxoSmithKline	R<2	0.083212	3.84
	R<1	0.621891	11.44
	R=0	25.32812	17.89
HSBC	R<2	0.030843	3.84
	R<1	0.362558	11.44
	R=0	24.41113	17.89
Rio Tinto	R<2	0.032688	3.84
	R<1	0.217228	11.44
	R=0	18.90962	17.89

4.2 Empirical Results: Price Discovery in the London Stock Exchange /Chi-X Order Flow

After concluding that Deutsche Borse – Xetra is not responsible for a statistically significant percentage of price discovery in UK Shares (as seen in Table 1), the remaining hypotheses are tested only on Chi-X and the London Stock Exchange, two venues with a statistically significant amount of price discovery. Since Chi-X and the London Stock Exchange both quote share prices in pence, the pound-euro foreign exchange rate is also removed from the analysis.

A number of key discoveries result from examining monthly files and computing monthly price discovery shares from April 2007 to December 2008 for quotes and July 2007 to December 2008 for trades. All the analysis is performed on MINSPAN files, as FILLFORWARD files are used solely for cointegration testing, to ensure that Common Factor Shares (CFS) and Information Shares (IS) can be used jointly for finer interpretation (Yan and Zivot, 2010).

The following model is examined:

$$\Delta P_{LSEt} = \alpha_{LSE} + \Sigma \beta_{LSEt-s}\Delta P_{LSEt-s} + \Sigma \beta_{Chi-Xt-s}\Delta P_{Chi-Xt-s} + z_{LSE}(P_{LSEt-1} - P_{Chi-Xt-1}) + \Delta \varepsilon_{LSEt}$$

$$(4.7)$$

$$\Delta P_{Chi-Xt} = \alpha_{Chi-X} + \Sigma \beta_{LSE-s}\Delta P_{LSEt-s} + \Sigma \beta_{Chi-Xt-s}\Delta P_{Chi-Xt-s} + z_{Chi-X}(P_{LSEt-1} - P_{Chi-Xt-1}) + \Delta \varepsilon_{Chi-Xt}$$
$$(4.8)$$

4.2.1 London Stock Exchange's Plunge in Trade-Based Price Discovery

The initial finding is that after April 2008, London Stock Exchange's impounding of information plunges, as London Stock Exchange trades see temporary price movements on a thin Chi-X order book as reflective of innovation and pursue those transitory price movements. As demonstrated by Figure 4.2, Panels A and B, BP trades show CFS for Chi-X

rising from a mean of 0.01 (range 0.00-0.07) prior to April 2008 to a mean of 0.63 (range 0.49-0.77) afterwards. However, as IS rose from a mean of 0.02 (range 0.00-0.07) prior to April 2008 to a mean of 0.87 (range 0.83-0.95) after April 2008, informative trades migrated to Chi-X as well. The market participants adopting a similar intuition may explain why the London Stock Exchange's shock chasing increased, as London Stock Exchange trend-followers saw the 'smart money' of the high frequency traders moving to Chi-X and saw temporary shocks as permanent trends. Glaxo has a similar pattern in both metrics, as its monthly IS before April 2008 is 0.03 (range 0-0.1), and its IS after April 2008 of 0.54 (range 0.45-0.68). CFS surges from a mean of 0.09 (range 0.02 to 0.2) to 0.62 (range 0.47 to 0.74).

Figure 4.2 Panel A - Trading price discovery in Information Share in UK primary listings
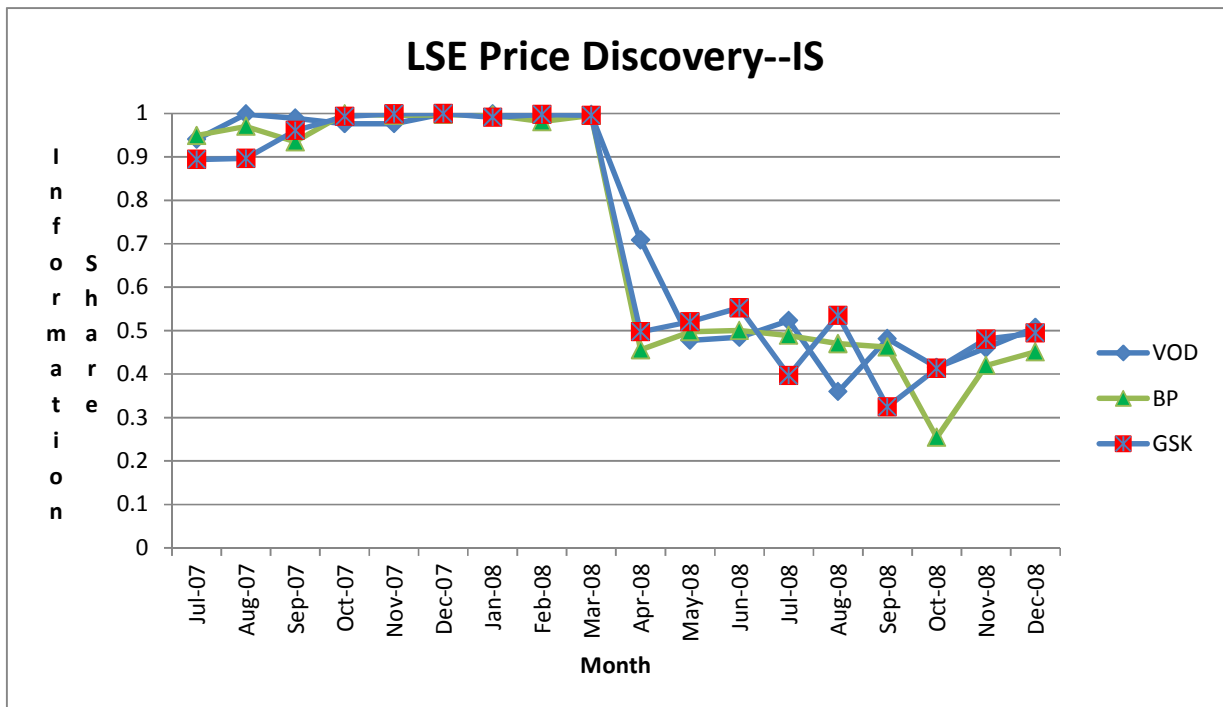
Figure 4.2 Panel B - Trading price discovery in Common Factor Share in UK primary listings
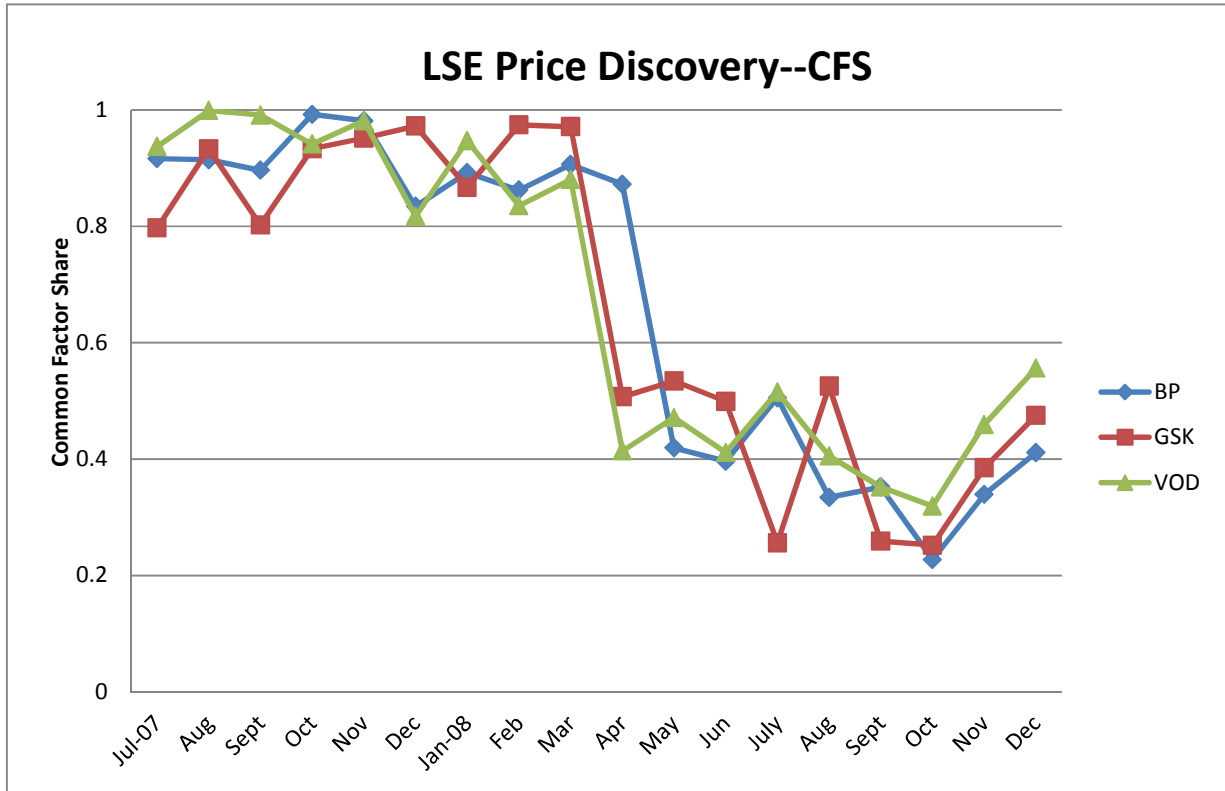
Due to the ambiguous nature of IS (it can be high either due to permanent information impounding occurring on a channel, or the opposing channels chasing relatively more stochastic shocks than it), CFS are needed for a full interpretation. As the CFS increases in conjunction with the IS, it can be concluded that the London Stock Exchange's collapse in price discovery is both due to the chasing of stochastic shocks and to less information impounding. As the chasing of transitory shocks on a competing stock exchange will only take effect with (and is largely influenced by) fragmentation, this is a direct result of the increasingly split order flow in major FTSE 100 shares.

Other shares have a similar pattern as BP and GSK. Vodafone's trades on the London Stock Exchange take a month longer to decline in their informativeness, as April 2008 Chi-X Information Share is 0.29, compared to an average of 0.5 for BP and GSK. For the entire sample, April 2008 is an inflection point, as the majority of price discovery begins to switch from the London Stock Exchange to Chi-X. With the IS of 0.29, some information is impounded in Vodafone on Chi-X in April 2008, but Chi-X's CFS spike from 0.12 to 0.59 displays the London Stock Exchange's increasing chase of Chi-X temporary price movements.

While quotes show a similar IS and CFS pattern for GSK, BP, and Vodafone after the Chi-X fee cut in April 2008, the transition is not complete, and the average falls from 0.98 in February to 0.44 (GSK) and 0.82 (BP) after Chi-X's central counterparty fee cut. However, as shown in Figure 4.3, the London Stock Exchange quickly recovers almost total primacy in quote-based informativeness, as after August, Chi-X has only 10% IS/CFS at most. This may reflect the nature of quotes as not binding obligations to trade, and thus not subject to the London Stock Exchange fee schedule, especially as regards to algorithmic players. Thus, it is

meaningless to talk about quote-based fragmentation, as decision makers see no advantage of one exchange to the other in posting quotes, and may opt to post on the exchange with the greatest order flow in order to obtain the maximal potential of execution.

Figure 4.3 Panel A Quote price discovery in Information Share in UK primary listings
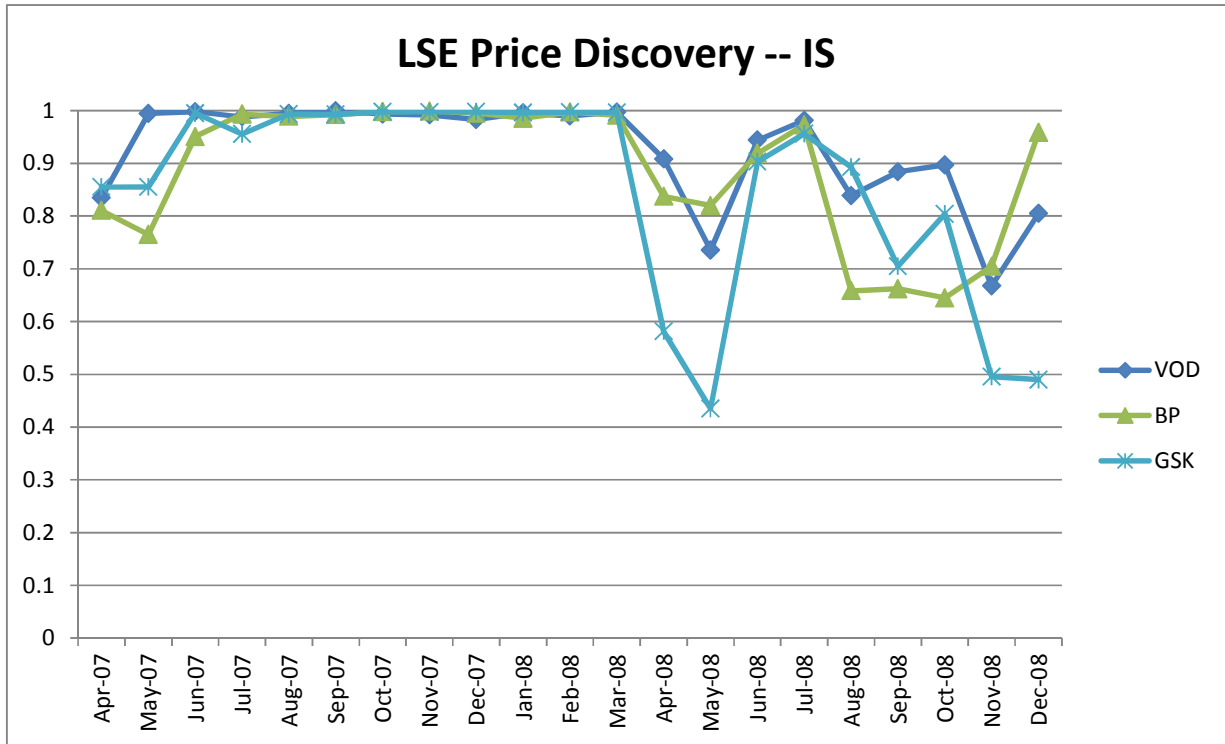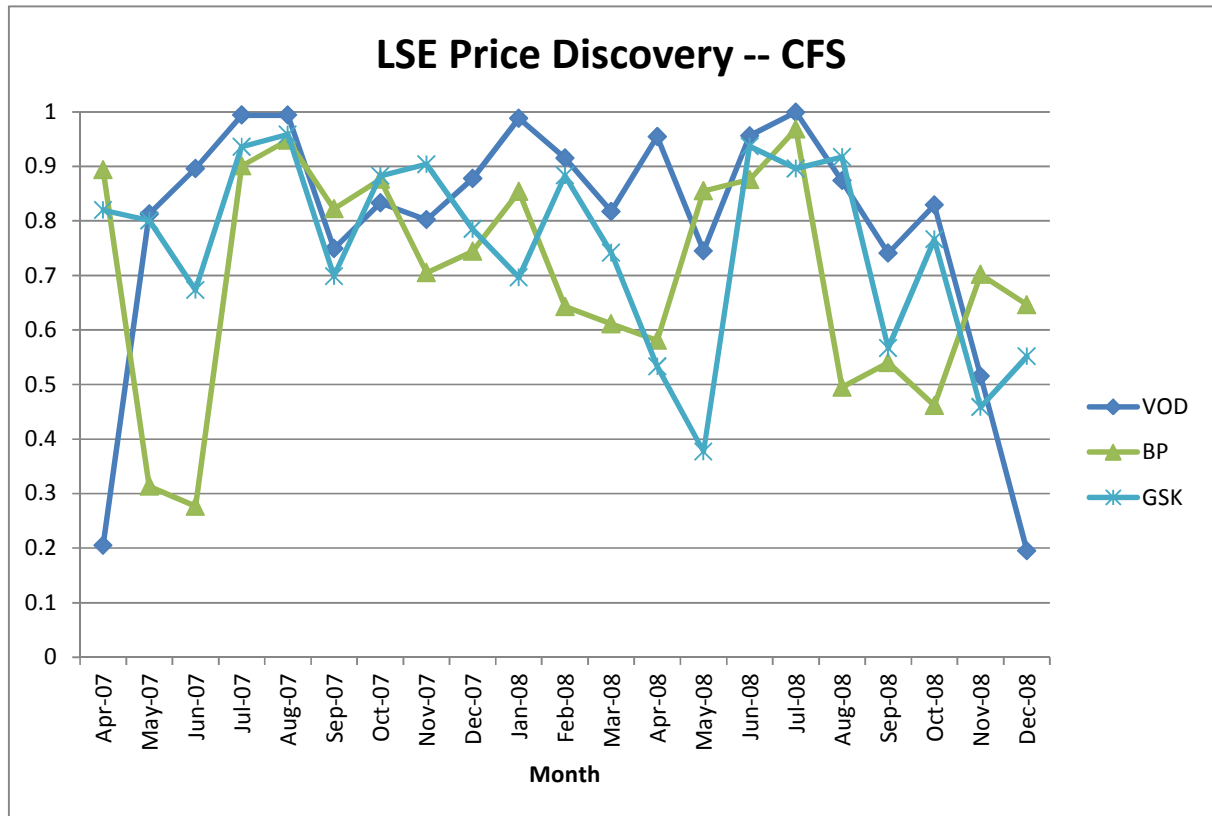
Figure 4.3 Panel B Quote price discovery in Common Factor Share in UK primary listings

This chapter formally tests the proposition that the fee schedule caused a change in trade-based price discovery using a Wilcoxon rank sum test to assess the difference in IS and CFS for the 8 months before and after March 2008, the month on which the change in fee structures occurred. Table B shows the results of the test, using July 2007 to February 2008 as the period before the fee cut, and April to November 2008 as the period after the fee cut. Z-statistics are significant at the 1% level for the UK primary listed stocks. Z-statistics are slightly less robust for dual listed stocks, notably the CFS in Rio Tinto, which is only significant at the 2.5% level. This differential may be attributable to a number of factors with regards to market participants.

Table 2: Wilcoxon test on Price Discovery around Chi-X fee schedule cut in March 2008

Table 2 presents a Wilcoxon rank-sum test on Information Shares (Hasbrouck, 1995) and Common Factor Shares (Harris et al, 1995) on BP, GlaxoSmithKline, Vodafone, HSBC, and RIO to test the statistical significance of the differences in IS and CFS before and after Chi-X's fee schedule cut. Z-statistics are used to test for whether IS and CFS prior to March 2008 are different from IS and CFS after March 2008.

London Stock Exchange Share	BP	GLAXO	VODAFONE	HSBC	RIO
Average IS Prior to Fee Cut	0.977	0.966	0.984	0.954	0.938
Average IS After Fee Cut	0.444	0.465	0.489	0.554	0.532
Z-statistic	3.31	3.31	3.31	3.31	2.68
p-value	0.00***	0.00***	0.00***	0.00***	0.01***
Average CFS Prior to Fee Cut	0.911	0.905	0.931	0.847	0.888
Average CFS After Fee Cut	0.431	0.402	0.419	0.539	0.474
Z-statistic	3.31	3.31	3.31	3.2	2.47
p-value	0.00***	0.00***	0.00***	0.00***	0.013**

** and *** indicate significance at the 2.5% level and 1% level respectively.

4.1.2 Dual Listed Stocks – a Differential Price Discovery Path

Shares with two primary listings, in this sample, HSBC and Rio Tinto, behave differently

from the shares with only a UK primary listing (Glaxo, BP, Vodafone). As Figure 4.4 shows,

in the initial months of the trade-based sample (July to September 2007), LSE's CFS is lower

than its IS by roughly 20%, which indicates that at the launch of Chi-X, London Stock

Exchange trades chased some shocks on the emerging exchange. This is not surprising, as

electronic market participants may have still been calibrating trading algorithms to exploit

transitory price differentials between the London Stock Exchange and Chi-X. The differential

can also be explained by Rio Tinto and HSBC's dual primary listings, as both shares have

primary listings in both London and Sydney (Rio Tinto) and Hong Kong (HSBC). This

would imply that order flow and fundamental pricing information for Rio Tinto and HSBC

exist in Hong Kong and Sydney as well as London, and thus, transitory shocks on Chi-X may

be seen as more reflective of fundamental innovations as opposed to order imbalances.

Figure 4.4 Panel A Quote price discovery in Information Share in foreign primary listings
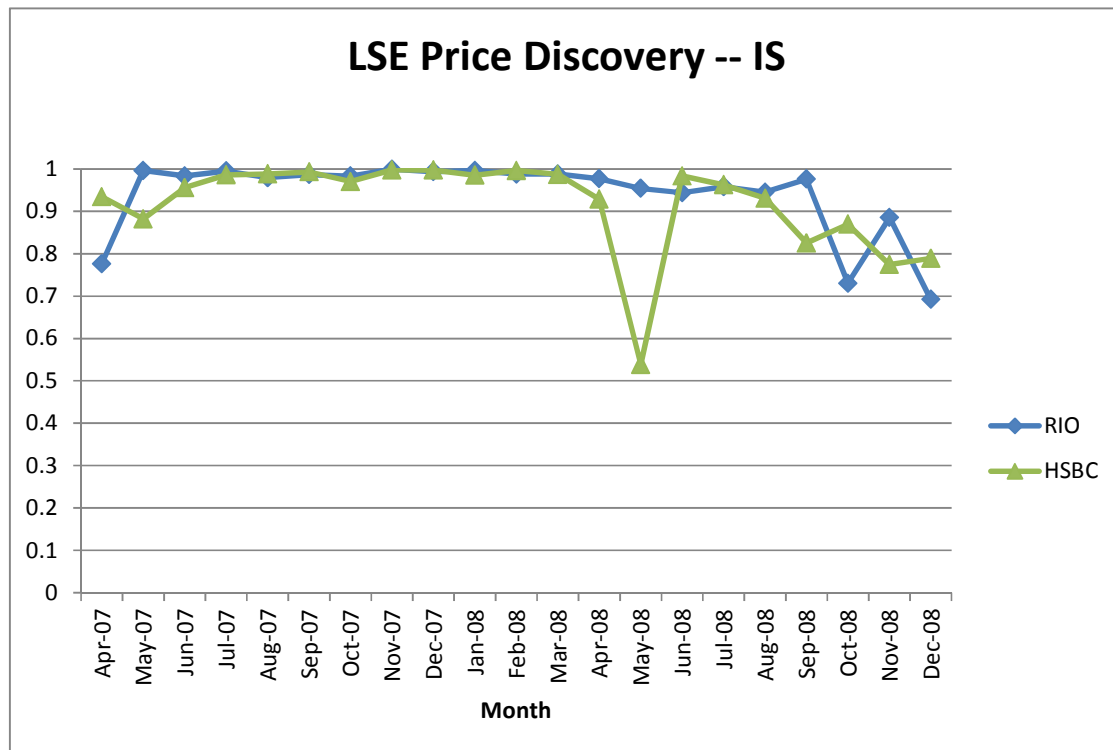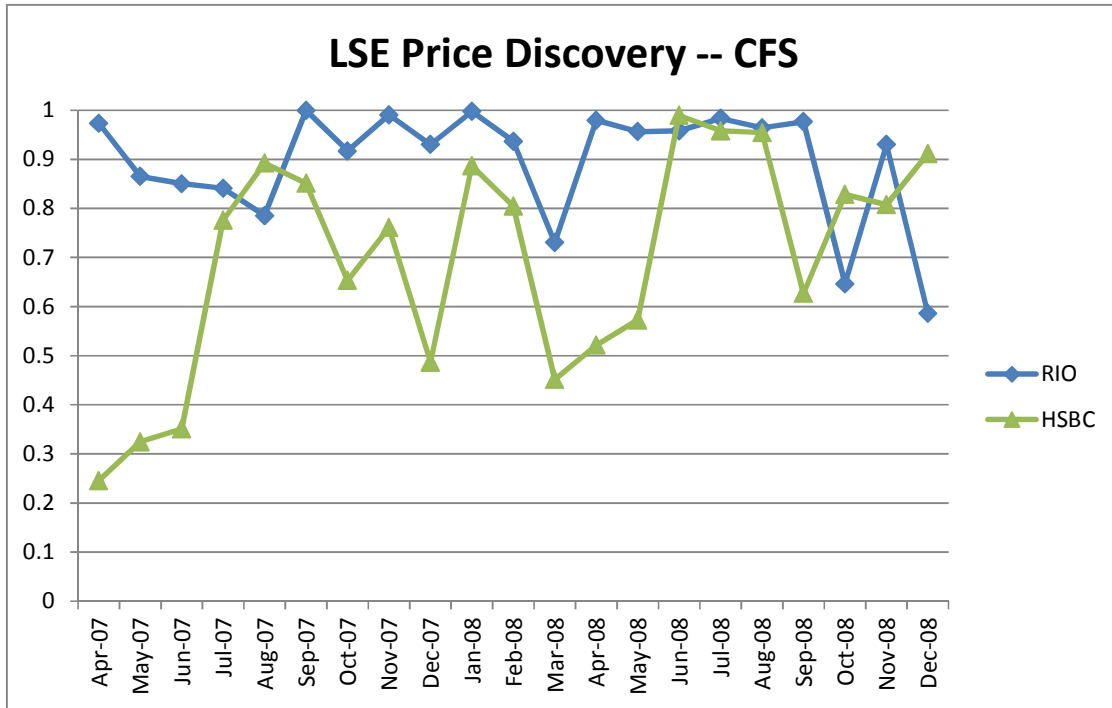

LSE Price Discovery -- IS

Figure 4.4 Panel B Quote price discovery in Common Factor Share in foreign primary listings

Trade-based IS and CFS for the London Stock Exchange on the UK primary listed shares (Vodafone, BP, and Glaxo SmithKline) exhibit parallel patterns, falling to 0.8 at the lowest point of the inception of Chi-X, and as high as 0.98 in October 2007, remaining at this level until the Chi-X central counterparty fee cut. This initial informativeness of Chi-X implies that informed traders initially used Chi-X experimentally during its advent, and then returned to the London Stock Exchange in October, remaining there until Chi-X trading costs undercut those of the London Stock Exchange.

Quote-based informativeness for dual-listed shares exhibits a different pattern than primary-listed shares as well. In the first three months of Chi-X, Rio Tinto's CFS on the London

Stock Exchange ranged from 0.23 to 0.33, far lower than its IS, which ranged from 0.89 to 0.95. From this, it can be inferred that suboptimal quotes were posted on the London Stock Exchange following patterns on Chi-X that likely reflected order imbalances but were falsely interpreted as price innovations. However, this behaviour does not exist for HSBC quotes for the April to July 2007 time range on Chi-X.

Contrastingly, the quotes for UK primary listings exhibit a high information share for the London Stock Exchange but a low common factor share. As an example, Vodafone's April to June 2007 IS on the London Stock Exchange is 0.82, while its CFS is 0.2. The low CFS combined with the high IS indicates that the London Stock Exchange is chasing a large number of stochastic shocks, but July 2007 shows the London Stock Exchange's CFS in Vodafone to rebound to 0.9, indicating that traders adapted to Chi-X behaviour, and have restrained their pursuit of transitory shocks. BP possesses an IS of 0.78 and 0.93 for May and June 2007, but low CFS scores of 0.31 and 0.29, showing that traders in BP, the largest capitalised primary listed UK share on the London Stock Exchange, tend to chase shocks on the London Stock Exchange far more than on Chi-X.

With the conclusions from sections 1 and 2, hypothesis 2 cannot be rejected, that the advent of MiFID will not affect price discovery patterns between the London Stock Exchange and Chi-X. It appears that the Chi-X central counterparty fee cut was the event that catalysed the migration of the majority of price discovery to Chi-X from the London Stock Exchange. As the central counterparty fee cut is the proximate cause of the movement of price discovery to Chi-X, Hypothesis 3 is rejected, that the Chi-X central counterparty fee cut did not affect price discovery patterns between the London Stock Exchange and Chi-X.

4.1.3 London Stock Exchange Fight Back

By September 2008, the London Stock Exchange regains its supremacy in price discovery

metrics, arguably due to the composition of traders on Chi-X, previously described as

potentially of two categories – those seeking a pan-European platform and technological

traders, including high frequency traders. By September 2008, a year after MiFID, and six

months after the dramatic change in informative trades' venues from the London Stock

Exchange to Chi-X, the London Stock Exchange regains the majority of price discovery for

HSBC, albeit only for a month. Representative of UK primary-listed shares, Vodafone and

Glaxo Smith Kline show quotes migrating back to the London Stock Exchange mere months

after Chi-X's CCP cut allows it to temporarily seize primacy in quote-based price discovery

that attracted price-sensitive clients, both high frequency traders and large institutional clients

bound by best execution principles when trading on behalf of retail investors. As CFS

decreases on Chi-X for Glaxo and Vodafone and the London Stock Exchange's share

increases, additional stochastic shock chasing on Chi-X can be observed, potentially

attributable to algorithms establishing Chi-X as their London-based venue of preference.

4.1.4 Second Inflection Point Affecting Quotes

In August to September 2008, BP and Glaxo quote informativeness is equally split between

the London Stock Exchange and Chi-X, nine months after MiFID. A potential explanation is

that the London Stock Exchange, as the main exchange for both institutional and especially

retail investors, is ripped by the turmoil in the financial markets due to the global financial

crisis. In that time range, BP and Glaxo possess IS in the 0.6 to 0.7 range, while CFS the in

0.4 to 0.7 range. As the global financial crisis led to a flight to cash, market participants

sought to convert their inventories into cash. As a result, liquidity demanders chase more

transitory shocks as time, not price, is their priority, so they ensure that their holdings will not

diminish in value any more. As a result, Vodafone's CFS for the London Stock Exchange

falls from 0.83 to 0.52 and then to 0.2, whilst IS increases from 0.65 to 0.7 to 0.95 in quotes.

This indicates that more information is finding its way into prices through quotes on the

London Stock Exchange in the last three months of the sample, October to December 2008.

4.1.5 Role of Foreign Primary Listings in Quotes

HSBC and Rio Tinto, two stocks with dual primary listings in Asia, show more quote-based

price discovery on the London Stock Exchange. An initial suggestion is that this is

attributable to Asian and Australian fund managers, who are more comfortable trading on the

more established London Stock Exchange than the insurgent Chi-X when seeking UK

exposure. Exemplifying this is that Rio Tinto's quote-based price discovery is relatively

unchanged by the Chi-X central counterparty fee cut change in April and May 2008, an

inflection point for trades and UK primary-listed share quotes. Chi-X IS in Rio is beneath

0.31 (from 0.11 to 0.31) in those months. Likewise, HSBC quotes have 0.27 share in Chi-X

on May 2008, only for the London Stock Exchange to regain its overwhelming advantage the

next months, with a June IS of 0.06, July IS of 0.02, August IS of 0.16, September IS of 0.12,

October IS of 0.1, November IS of 0.33, and December IS of 0.19. The diminution in UK

primary-listed share quote-based informativeness starting in April 2008 does not occur on the

dual listed shares HSBC and Rio Tinto, whose IS exhibit a slow decline. Meanwhile, the CFS

on the London Stock Exchange for Rio shows variability as opposed to the static IS on the

London Stock Exchange. A conclusion is that information is impounded extremely frequently

on the London Stock Exchange for Rio. HSBC's CFS fluctuates, displaying transitory shock

chasing on Chi-X.

Although the United Kingdom has historically lacked the concentration rule (prevalent in all EU countries except Germany, UK, and the Netherlands), the London Stock Exchange had the lion's share of order flow in UK securities for large-cap FTSE 100 shares. Even after the launch of MiFID and the Chi-X central counterparty fee cut, Chi-X does not exceed 20% of order flow by December 2008, and in January 2010, had only 29.9% of the FTSE 100 order flow. Among explanations for the London Stock Exchanges in order flow may include: London Stock Exchange relationship-based brokerage; a tiered fee schedule in which repeat customers received smaller fees; the ability of internalisers, OTC traders, and crossing networks to report to any exchange post-MiFID and most reported to the primary exchange, the London Stock Exchange; higher resiliency of the order book for large orders, and worked principal agreements.

Similarly to the NYSE, London Stock Exchange market participants continued to trade on the London Stock Exchange even if better prices were offered elsewhere. However, MiFID's focus on best execution combined with Chi-X's reduction in the price of trading made it unwise from a regulatory perspective, as well as uneconomical, to trade on platforms with suboptimal prices, even in the presence of established relationships.

MiFID did not affect price discovery between the London Stock Exchange and Chi-X. For five months, until April 2008, the hub of price discovery remained at the London Stock Exchange. MiFID neither produced a role for non-UK European exchanges in price discovery in FTSE shares nor affected price discovery dynamics within London between the London Stock Exchange and Chi-X. However, MiFID was successful at its aim of integrating European securities markets with regards to transactions costs and short run price volatility (Gresse 2010). As there was no concentration rule in the UK, fragmentation existed prior to

MiFID, even if only in a nugatory form – the market attribute that changed was first the launch of Chi-X, then Chi-X's central counterparty fee cut, which, for the first time, provided a cheaper trading alternative than the established London Stock Exchange. Unlike Reg NMS, MiFID does not require routing of an order to the best prices quote (this is partially due to a variety of definitions for 'best execution' under MiFID, while Reg NMS strictly defines it by price), and as order flow does not migrate, price discovery does not. If routing to optimal quotes was required, one would expect retail and algorithmic traders to move to the exchange with the best bid-offer spread and block traders move to institutional platforms.

A change in the Chi-X fee schedule on 1 March 2008[35] reduced clearing fees by 11.8% (from 17 to the minimum 15 Euro cents per share) for London Stock Exchange-listed stocks and by 32% for somewhat higher-fee Dutch, French, and German stocks. This fee reduction massively altered the order flow and the resulting price discovery process in London.

The stark effects detected on price discovery indicate that institutional market participants view the concept of best execution as inclusive of clearing fees. When spreads are roughly equivalent, order flow is highly sensitive to 2 cent clearing fee changes. Oxera (2009) surveys the cost of trading and post-trade services and draws attention to the fact that when brokers supply post-trading services to funds, the brokers take this cost out of their pre-set commission. Oxera estimates the net clearing cost as 37 to 50 euro cents per transaction (which are individual transactions – so a large order split into 5 trades will pay the clearing cost 5 times). Therefore, algorithmic traders and execution platforms will be very sensitive to changes in this flat cost per trade, and therefore may migrate to venues with marginally clearing fee schedules, because spreads on Chi-X and the London Stock Exchange are

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[35] http://www.chi-x.com/trading-notices-pdfs/TradingNotice0045.pdf displays the central counterparty fee cuts on Chi-X.

comparable. Therefore, London dealers would possess heightened sensitivity to even marginal cuts in post-trade service costs.

Three major conclusions can be drawn from analysis of monthly price discovery files. For one, a different dynamic exists between shares with dual-primary listings and shares with a sole London primary listing. For BP, Glaxo SmithKline, and Vodafone, all shares with only a London listing, the London Stock Exchange's Common Factor Share metric crumpled from 0.8 to 0.98 to 0.25 to 0.5 after Chi-X slashed its counterparty fees. Chi-X improved its order flow at the same time by offering more liquidity for trades at and inside the best-bid offer, as well as lower latency than the London Stock Exchange. These attributes attracted traders extremely sensitive to both marginal costs of trading and execution speed, and include, but are not limited to high frequency and algorithmic traders. However, dual-listed HSBC and Rio Tinto, firms with both primary listings in Asia as well as London as well as a significantly diversified and international revenue base behaved differently. Prior to MiFID, the London Stock Exchange only had a Common Factor share in Rio Tinto of 60%, versus the 90% in BP, Glaxo SmithKline, and Vodafone. Additionally, unlike the shares solely listed in the UK, the London Stock Exchange was able to fight back in terms of price discovery after Chi-X's fee cut, as opposed to the stable level to which London Stock Exchange price discovery metrics found in UK-only shares. As an example, the London Stock Exchange's Common Factor Share in HSBC moves from 0.39 in May 2008 to 0.78 in September. Potentially, this reflects HSBC trading on behalf of both Asian fund managers as well as European market participants who perceive investing in HSBC as a proxy for Chinese fundamentals.

Second, quotes do not frequently cointegrate and error correct to each other. However, trades always cointegrate. The most logical explanation for this is that quotes may not be intended as affirmative obligations to trade, but rather strategically used in order to elicit liquidity from counterparties. With low latency and high cancellation, fleeting quotes (Hasbrouck and Saar, 2009) may not represent a desire to trade, but could be a ploy. Algorithms may strategically quote, rarely in the expectation that they will cross with another order. In addition, quotes at the best-bid and offer posted in such a manner often have negligible depth, so may not realistically imply the price of trading a meaningful quantity. Chakravarty, Harris, and Wood (2009) show that information first appears in depths.

The last major finding is that London's Information Share in price discovery fell after April/May 2008 and did not recover. As Information Share may either indicate permanent information impounding or competing channels chasing stochastic shocks, one needs to use Chi-X's Common Factor Share to interpret it. As Chi-X's CFS moves in the same direction as IS, the unambiguous interpretation is that information impounding on the London Stock Exchange has fallen, allowing one to infer that high frequency informed (institutional) order flow has migrated from the London Stock Exchange to Chi-X, attracted by reduced trading costs.

Information Share in 2007 for the London Stock Exchange averages 0.95 to 0.98. After the Chi-X fee schedule cut, IS for the London Stock Exchange falls in April and May 2008 to 0.42 to 0.5, and by June collapsed to 0.12 to 0.15. Fewer bad trades that chase transitory shocks on Chi-X (measured by the CFS for the London Stock Exchange) can explain a decline in IS for LSE (Yan and Zivot, 2010 and Harris et al, 2009). However, the CFS of Chi-X throughout April to June 2008 averaged 0.48, down from 0.91 in 2007. Therefore, a

collapse of the London Stock Exchange's IS to 0.15 is not explained by the better trading patterns on Chi-X alone. Instead, information impounding must be declining on the London Stock Exchange by June 2008. These patterns or altered price discovery then stabilize at the lower level.

5. Conclusion

Economically significant price discovery in leading British stocks has moved from the London Stock Exchange to the alternative trading system Chi-X. A fee schedule change on Chi-X, not the introduction of MiFID, was the catalyst for this transition. In the absence of an order migration rule, MiFID's best execution mandate, inclusive of pre- and post-trading services, did not trigger any substantive change in price discovery. Instead, an 11% cut in clearing fees on Chi-X 7 months after MiFID went into effect attracted large informed traders from the London Stock Exchange to Chi-X. Chi-X's low latency suits algorithmic traders with information about state of the market or valuation fundamentals. The results document an accompanying reversal of the dominant price discovery role in trades involving the leading British equities from the London Stock Exchange to Chi-X.

However, as quotes are unaffected by the fee schedule for clearing and settlement, the vast majority of quote information impounding remains on LSE. Quote adjustment on the London Stock Exchange remains highly informative but the trades then execute on Chi-X. In the most liquid stocks, fragmentation between the London Stock Exchange and Chi-X has demonstrated the sensitivity of traders to clearing and settlement fee schedule changes as well as the effect on price discovery of low latency trading environments that facilitate algorithmic trading.

Appendix 1:

Price Discovery in Liquid British Shares Pre and Post MiFID: The Role of MTFs

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ABSTRACT

Analyzing LSE, Xetra, and Chi-X trades for leading British equities in an error correction framework, we find that MiFID did accomplish the intended cointegration of European equity markets that had previously been segmented. Initially, price discovery in London was largely unaffected, unlike the contemporaneous situation in the U.S. with the implementation of RegNMS. Subsequent clearing and settlement fee reductions by Chi-X, however, did fragment the order flow in London resulting in a substantial reduction in the price discovery efficiency of the London Stock Exchange trades. Quote formation remains ninety percent attributable to the LSE.

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1. Introduction

In 2007, the European Commission instituted the Markets in Financial Instruments Directive (MiFID), a public policy measure intended to establish a pan-European market for shares. Introducing a 'passport' function for clearing and settlement plus a best execution mandate, MiFID proved to be a catalyst for the growth of new multilateral trading facilities (MTFs). MTFs are designed to serve a fast-growing breed of technological traders who heavily use computer algorithms and other techniques requiring low latency. As MTFs proliferated in 2007-2008, European order flow quickly fragmented. When fragmentation occurred in response to Reg NMS in the U.S., price discovery migrated away from the central exchange. In contrast, we demonstrate that the introduction of MiFID had no such comparable effects in London; the LSE continued to dominate the price discovery process. However, seven months later, following a sharp reduction in clearing and settlement fees by Chi-X, we document a large shift of price discovery to the high frequency traders on Chi-X.

Chi-X is the successor to Instinet Europe. Instinet originated as a private electronic trading system in 1969 to facilitate institutional trading. On 16 April 2007, Instinet launched Chi-X, an MTF for non-exchange venues. Such MTFs grew quickly in market share with the increase in low latency opaque trading through algorithmic bots and the related general reduction in execution costs. Chi-X offered more competitive bid-ask spreads, though at lower depth, as well as more aggressive fee schedules for order submission and clearing. MTFs also faced lower regulatory costs due to the exclusivity of their participants (solely institutional, not retail) and the absence of the usual surveillance services. In 2008-2009, Chi-X's fee structure and latency advantage attracted to the equity markets additional algorithmic-trading participants who were highly sensitive to total transactions costs. Figure 1 shows that some of the lowest effective spreads worldwide (on Xetra and NYSE) rose slightly over this period but those on LSE, NASDAQ, and NYSE Euronext Paris all declined, the latter two below Chi-X. Echoing these MTF developments, O'Hara and Ye (2009) argue that the initial stages of fragmentation need have no detrimental effect, and to the extent that

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fragmentation leads to an increase in liquidity and lower execution costs, welfare increases for all participants. In this paper, we explore how the emergence of these new MTFs, facilitated by the advent of MiFID, has altered price discovery efficiency.

MiFID implemented two key mechanisms across the European Union on November 1, 2007. First, the passport rule allows for a brokerage firm regulated by any EU national entity to operate throughout Europe. Second, the abolition of the concentration rule eliminated the mandatory shipping of trades to national exchanges. Although the LSE had historically served as the listing and primary trading venue for British shares, there never had been a concentration rule in the UK (or Germany). Therefore, as early as 1992-93, agency brokers and crossing networks such as Instinet and ITG Posit Europe began to attract a small, but not insignificant, volume in UK stocks. With the introduction of MIFID's passport rule in late 2007, Pan-European trading and settlement by electronic crossing networks like Instinet and their successor Chi-X became full-fledged competitors in equities on the primary market. Instinet/Chi-X quickly attracted 5.6% of the order flow in Euronext Paris, 6.9% in Euronext Amsterdam, and a startling 10.1% in London. Chi-X's success in fragmenting the order flow attracted imitators Turquoise and BATS in August and October 2009, respectively[36], and by August 2010 55 MTFs were eligible to trade European equities.

Although two recent studies have offered an analysis of execution costs and fragmentation attributable to MTFs (O'Hara and Ye 2009, Gresse 2010), our paper is the first to focus on price discovery and fragmentation resulting from an MTF-–namely, Chi-X whose order flow in London is reported to be 90% algorithmic. We analyse the effect of Chi-X on price discovery in London because London is the key market in which to assess the potential trade-off between lower execution costs and the suspected informational inefficiency of fragmented markets. Long before MiFID, pressure from the LSE's SEAQ International systems induced many national exchanges across

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[36] Despite starting a little later, BATS has had more success than Turquoise in their initial quarters of European operations, reaching 5-6% share in some markets. Nevertheless, both pale by comparison to Chi-X whose market share in Euronext-listed stocks, for example, has risen to 19%. Hence, we focus attention in our empirical work on this earliest and most successful MTF.

Europe to adopt continuous trading, automated order disclosure, and electronic clearing networks. Petrella (2009) argues that the emergence of MTFs was the natural consequence of these earlier developments. Gresse (2010) finds that increased fragmentation due to MTFs like Chi-X has raised short-term price volatility in London though not elsewhere across Europe. Henderschott and Riordan (2010) find no increase in volatility from algorithmic trading in Frankfurt. Madhavan (1995) and Bennett and Wei (2006) hypothesize that fragmentation would reduce liquidity and thereby disrupt the price discovery process. Hence, London makes a perfect crucible in which to assess the effects of fragmentation on execution costs versus price discovery.

Using MINSPAN data sampling technology and price discovery metrics, we are able to capture error correction between Frankfurt, London and the Chi-X MTF adjusting for FX rate shocks. That is, we begin by modelling four channels: Xetra, LSE, Chi-X, and the foreign exchange rate £/€. This research design allows us in a first study to assess the integration of the European markets before and after MiFID. In so doing, we find that the London adjustment dynamics are integral (and Xetra is peripheral) to price discovery in the most liquid British-listed securities. Our research question becomes therefore whether Chi-X has lowered execution costs but diminished price discovery efficiency in London itself in the 21 months of competitive dynamics surrounding the implementation of MiFID. We employ the newest 4th generation price discovery techniques in this second part of the paper to reveal whether the sharply declining price discovery of LSE trading six months after MiFID is a reflection of less information impounding or more chasing of transitory order imbalance shocks as liquidity trades walk up and down a thinner LSE book. The former facilitates price discovery efficiency while the latter inhibits it.

2. Related Literature

2.1. Fragmentation

MiFID was intended to create a pan-European securities market by harmonizing securities market rules. In fact under MiFID, European market participants are at liberty to define their own

meaning for best execution as long as they formulate a best execution model reflective of price, speed, order size, etc., and as long as the meaning of that model is well known to their clients.   In contrast, Reg NMS (also introduced in the Fall of 2007) instituted an order migration duty to achieve the best price immediately executable, and fragmentation of the U.S. order flow ensued.   MiFID's avoidance of a uniform/one-size-fits-all framework may well be preferable given heterogeneous investor preferences (Blume 2007).   Nevertheless, increased pre- and post-trade transparency requirements introduced with MiFID by national regulators triggered fragmentation of the European order flow too (Lannoo 2007).

Petrella (2009) details the fragmentation in major index components. After the advent of MiFID, Chi-X's market share of FTSE 100 equities moved from 2% in November 2007 to 7% in May 2008 and 12% in November 2008. Over the same period, LSE suffered a gradual decline in its market share.   Specifically, LSE's share of the trading volume in listed securities slipped from 70% in November 2007 to 58% in May 2008 and 59% in November 2008.   Petrella connects this fragmentation to the establishment of new transaction fee schedules offered by MTFs often owned in part by major brokers and dealers.

The empirical literature in fragmentation suggests that there is a trade-off between the effects of stronger competition, as reflected in lower fees and tighter spreads, and the increased price volatility that results from the thinning of liquidity as traders migrate to satellite exchanges. Hamilton (1979) finds that both effects of fragmentation exist, but that the competition effect outweighs the volatility effect. Chowdry and Nanda (1991) focus on information transmission, theorizing that competition between market makers will speed-up information impounding into prices, and that liquidity traders will split their orders. Pagano (1989) argues that market participants may split their orders between venues in order to opportunistically capitalize on different fee schedules or price improvement for desired order sizes. A cream-skimming effect may then take place (Battalio 1997). O'Hara and Ye (2009) examine how the growth of non-exchange trading venues affects market

execution costs. They find that fragmentation occurs most frequently on small NASDAQ shares and least frequently on large NYSE shares. They conclude that fragmentation lowers transactions costs and increases transaction speed, which further verifies the competition hypothesis and augurs for further study of the price discovery effects.

2.2. MTFs and algorithmic trading

Barclay, Hendershott, and McCormick (2003) demonstrate how lower latency and anonymity in ECNs can lead to greater adverse selection costs and higher spreads on the primary market. In such settings, they show that ECNs provide the majority of price discovery compared to traditional exchanges. Hendershott and Moulton (2009) find that lower latency leads to the greater incorporation of information into prices. They also outline how latency can lead to greater competition for liquidity providers putting downward pressure on spreads, and attribute an increase in effective spreads not to adverse selection but to the price of more immediate execution. Hendershott and Riordan (2009) examine the information shares of algorithmic trading in the thirty shares comprising Germany's main index, the DAX. Using algorithmic orders from an audit trail of Deutsche Borse's Xetra Platform, they find that algorithmic trading has an information share of 51%, demanding liquidity when it is inexpensive, and supplying it when liquidity's cost increases. They do not find that algorithmic trading raises price volatility.

The closest research to our study is Riordan et al. (2010) who analyse the effects of three MTFs (Chi-X, Turquoise, and BATS) on execution costs and price discovery in London for one month May 2009. Differences between this paper or Henderschott and Riordan (2009) and our research on MTFs include 1) the use of Information Shares and Common Factor Shares in conjunction to distinguish the components of price discovery, 2) 21 months of price discovery metrics between LSE and the most successful MTF (Chi-X) with changing fee schedules, follow-on entry by BATS and Turquoise, and other competitive dynamics, and finally, 3) an analysis of the effects on price discovery in trades versus quotes that reveals a sharp distinction between them. The focal

contribution of our research is to discern whether the reduced information shares on LSE (and by analogy FSE) attributable to algorithmic trading on MTFs reflect a reduced impounding of valuation fundamentals on the national exchanges or alternatively, simply less chasing of transitory shocks on the MTFs. This distinction is pivotal to optimal market design and informed public policy.

3. Price Discovery: A Primer

Securities often trade in parallel markets and across multiple execution channels within markets. Through the no-arbitrage principle, it is reasonable to assume that trading follows error correction processes towards full-information efficient security prices. As information is impounded into each market's price, the question naturally arises as to which execution channel is contributing more to this on-going price discovery. The observable price can be conceived as a randomly-arriving information-based common factor plus an idiosyncratic transitory shock reflecting order imbalances on liquidity trades. Two security prices that impound the common factor, we expect to be co-integrated and error correct to one another.

Given cointegrated prices, two alternative econometric approaches seek to provide an answer to the question of contributions of the various execution channels to price discovery. Hasbrouck (1995) proposes an Information Share (IS) approach that decomposes the variance of innovations in the common factor into those attributable to one execution channel versus another. This contrasts with Gonzalo and Granger's (1995)'s Common Factor Share (CFS) approach, which utilizes the adjustment dynamics to estimate a long-run (permanent) impact multiplier for each price series.

Specifically, write p cointegrated series as an additively separable function of k common factor(s) $\mathbf{f}_t$ and r stationary error correction terms $\mathbf{z}_t = \boldsymbol{\alpha}' \mathbf{P}_t$ where $\boldsymbol{\alpha}'$ is an r x p matrix of the cointegrating vectors and $\mathbf{z}_t$ is I(0),

$$\mathbf{P}_t = \mathbf{A_1} \mathbf{f}_t + \mathbf{A_2} \mathbf{z}_t \tag{1.1}$$

$$= \mathbf{A_1} \boldsymbol{\gamma_\perp}' \mathbf{P}_t + \mathbf{A_2} \boldsymbol{\alpha}' \mathbf{P}_{t-1}. \tag{1.1'}$$

Let $\mathbf{P}_t$ be a p x 1 vector of cointegrated prices, $\mathbf{A_1}$ and $\mathbf{A_2}$ are loading matrices, and $\boldsymbol{\gamma}_{\perp}'$ is a k x p matrix of common factor weights on the contemporaneous prices in the k common factor vector(s) $\mathbf{f}_t$ where k = (p - r). Gonzalo and Granger (1995) show that under the above restrictions, the p x k matrix $\mathbf{A_1} = \boldsymbol{\alpha}_{\perp} (\boldsymbol{\gamma}_{\perp}' \boldsymbol{\alpha}_{\perp})^{-1}$ and the p x r matrix $\mathbf{A_2} = \boldsymbol{\gamma} (\boldsymbol{\alpha}' \boldsymbol{\gamma})^{-1}$ where by definition $\boldsymbol{\gamma}_{\perp}' \boldsymbol{\gamma} = 0$. Since the vector of common factor weights $\boldsymbol{\gamma}_{\perp}$ is orthogonal to the coefficient vector $\boldsymbol{\gamma}$ on the error correction terms in a fully-specified VECM, the $\gamma_{i,j}$ estimates in equations (1.1) provide a way to identify the permanent components $\boldsymbol{\gamma}_{\perp}' \mathbf{P}_t$. Harris, McInish and Wood (2002a) apply this GG approach to security price adjustment of Dow stocks across competing exchanges in the U.S.

De Jong (2002), Lehmann (2002) and Baillie et al (2002), recommend using both approaches, each for its own purpose. Yan and Zivot (2010) and Harris, McInish, and Wood (2009) show that CFS is needed to more effectively interpret the IS which can be large either because an exchange's trades impound permanent information, or because its competitors' trades are chasing transitory shocks. Meanwhile, the CFS for an execution channel will be large only if its prices avoid chasing transitory shocks relative to the competing channels. Therefore, using both measures serves to avoid an equivocal interpretation of the Information Share.

3.1. Four generations of price discovery research using VECMs

Price discovery methods build on Engle and Granger's (1987) seminal study of co-integration/error correction in vector error correction models (VECMs). Among the hundreds of subsequent papers using VECM techniques, one exemplifying the first generation price discovery research in Finance is Harris, McInish, Shoesmith and Wood (1995) who specify a VECM of synchronous cross-traded equity prices to determine whether price discovery in the most thickly-traded NYSE-listed security (IBM) was solely based on NYSE price changes. Instead, they show an error correction dynamic between trade-based price adjustments in New York and those on the Midwest and Pacific (later ARCA) Exchanges. Although NYSE had ten times the trades of the Midwest Stock Exchange (and 3.5 times the trades of the Pacific Stock Exchange), Harris et al. (1995)

were able to match 80 synchronous observations per day using a technique called MINSPAN analysis. Then performing a Johansen (1991) test for co-integration and estimating the adjustment dynamics in the VECM, they discovered that IBM prices on NYSE error correct to deviations from the Midwest and Pacific exchanges, albeit to a lesser extent. In short, the satellite exchanges were contributing in a meaningful way to the price discovery process, foreshadowing the later dominance of ARCA in high speed electronic trading.

After exploring variance decomposition for unrestricted VARs in Hasbrouck (1991), Hasbrouck's (1995) information share (IS) concept of variance decomposition for cointegrated price series from competing venues trading NYSE-listed stocks defined the second generation of price discovery methods. IS provides a range of estimates of the proportion of innovation variance attributable to each execution channel when the order of the series is rotated in a Cholesky factorization procedure. Most IS studies report the midpoint of this range and provide bootstrapped parametric difference tests or Wilcoxon rank sum difference tests. Easy to estimate but hard to interpret correctly, IS has been utilized in scores of subsequent studies (e.g., Huang 2002, Grammig, Melvin, and Schlag 2005, Moulton and Wei 2009, Henderschott and Riordan 2010). Contemporaneous correlation of the error terms between price updates in the various execution channels can render statistical inference about the IS midpoints indeterminate (Huang 2002). In addition, Hasbrouck's variance decomposition procedure inevitably entangles the informativeness of one channel with the chasing of transitory shocks attributable to order imbalances from liquidity trading by competing channels. Using a plausible structural errors model, Yan and Zivot (2010) show that IS can be large for either reason.

Booth, So, and Tse (1999), Ding, Harris, Lau, and McInish (1999), and Harris, McInish and Wood (2002a) introduce a third generation of price discovery methods, adapting Gonzalo and Granger (1995)'s common factor share concept to price discovery metrics for financial markets. The common factor share (CFS) is an error correction measure of whether the price dynamics of

competing execution channels chase transitory order imbalance shocks more or less than the primary channel. As such, the Gonzalo-Granger CFS concept provides an orthogonal representation of the permanent stochastic price trend caused by the incorporation of new information into asset prices. Lehmann (2002) shows that, unlike IS, CFS is robust to cross-equation correlation of the error terms in a VECM of competing execution channels. Hasbrouck (2002) criticizes CFS as limited by the linearity of the cointegrating vector and biased by divergent error variances across the competing execution channels. Harris et al. (2002b) show by simulation that this bias is small and inconsequential for statistical inference using the Gonzalo and Granger (1995) parametric tests of CFS. Figuerola-Ferretti and Gonzalo (2010) defend the linearity of arbitrage equilibrium conditions motivating the CFS metric of price discovery.

In a fourth generation of price discovery methods, Yan and Zivot (2010) reconcile the IS and CFS approaches for determining price discovery by showing that although Hasbrouck's IS approach measures informativeness, it also reflects the chasing of transitory shocks. Again, IS can be high either because a channel is impounding permanent information, or because its rivals are chasing transitory shocks. In contrast, the Gonzalo-Granger approach will produce a high CFS only if competing channels are chasing transitory shocks. Therefore, use of the two measures in conjunction is required to determine which channel is impounding new information and which is chasing transitory shocks. Harris, McInish, Wood (2009) illustrate the use of IS and CFS in conjunction to assess the effects of RegNMS on price discovery.

3.2. Price discovery across borders

The international microstructure literature demonstrates the potential sensitivity of price discovery models to exchange rate shocks. Ding, Harris, Lau, and McInish (1999) examined Sime Darby Berhad, one of Malaysia's largest corporations, which trades on both the Kuala Lumpur Stock Exchange and the Singapore Stock Exchange. Noting that the rate is sufficiently stable that practitioners do not track FX prices on a real time basis, they converted all prices to a common

currency several times a day. Ding et al. demonstrate that a significant amount of price discovery (26% to 32%) occurs in the foreign (Singapore) market, a price discovery share much larger than Singapore's proportion of trading volume.

Grammig, Melvin and Schlag (2005) argue for modelling the exchange rate as a separate stochastic process. They study price discovery in German shares and their ADRs and find that an overwhelming (80-90%) amount of the information is impounded in the German market. Nevertheless, they show that a firm's foreign earnings can affect the price discovery process. For example, they find the NYSE-based ADRs for Daimler-Chrysler (with significant earnings on both sides of the Atlantic) substantially influenced Frankfurt Stock Exchange price discovery in DCX, but not in Deutsche Telekom or SAP. Using NYSE data, Moulton and Wei (2009) find that during overlapping ADR trading hours for European cross-listed securities, spreads decrease and quoted depth increases. This is attributed either to enhanced competition for order flow when trading fragments across borders or to an influx of liquidity from arbitragers during overlapping hours.

4. Model Specification

The price discovery concept is an efficiency measure of relative market quality across arbitrage-free execution channels. Accordingly, we assume security prices in competing execution channels P_i, P_j or in home and foreign markets P_h, P_f are given by a random walk data-generating process $P_t = P_{t-1} + w_t$ where P_t is the unobservable implicit efficient price, and w_t is the permanent innovation in valuation fundamentals. Such asset prices will be co-integrated at order one $C(1,1)$ if they error correct to deviations between the prices in the competing execution channels. Observed prices can be written $P_{ht} = P_{t-1} + w_t + \varepsilon_{ht}$ and therefore $P_{hT} = \Sigma w_t + \varepsilon_{hT}$ where ε_{hT} are liquidity shocks (e.g., order imbalances due to sector rotations, redemption demand, or portfolio rebalancings).

By the Engle-Granger Representation Theorem, $C(1,1)$ series have adjustment dynamics described by a VECM made up of lagged difference equations specified to include an error correction term z_{t-1}:

$$\Delta P_{ht} = \alpha_h + \Sigma \beta_{ht-s}\Delta P_{ht-s} + \Sigma \beta_{ft-s}\Delta P_{ft-s} + z_h(P_{ht-1} - P_{ft-1}) + \Delta\varepsilon_{ht} \qquad (1.2)$$

$$\Delta P_{ft} = \alpha_f + \Sigma \beta_{ht-s}\Delta P_{ht-s} + \Sigma \beta_{ft-s}\Delta P_{ft-s} + z_f(P_{ht-1} - P_{ft-1}) + \Delta\varepsilon_{ft} \qquad (1.3)$$

If the candidate series are tested and found to be C(1,1), then at least one linear co-integrating vector such as $(1P_{ht-1} - 1P_{ft-1})$ or $(1P_{it-1} - 1P_{jt-1})$ or $(2P_{it-1} - 1P_{jt-1} - 1P_{ft-1})$ will be operative. The sum of each co-integrating vector indicates the size of the arbitrage opportunity prior to transactions costs, and the equilibrium error correction adjustment parameters z_h, z_f reveal the adjustment dynamics.

A VMA representation of these co-integrated price series displays the valuation fundamentals Σw_t as a common factor (a.k.a., a common stochastic trend), which may be partially impounded from one channel or the other:

$$\Delta P_{ht} = \beta_h \Sigma w_{t-s} + \beta_f \Sigma w_{t-s} + \Delta\varepsilon_{ht} \qquad (1.4)$$

$$\Delta P_{ft} = \beta_h \Sigma w_{t-s} + \beta_f \Sigma w_{t-s} + \Delta\varepsilon_{ft} \qquad (1.5)$$

From this VMA, Hasbrouck (1995) derived an information share (IS) metric of the price discovery in each execution channel based on variance decomposition. The greater the proportion of the variance in the permanent innovations (σ^2_w) attributable to an execution channel, the higher the IS. As long as Cov $(\Delta\varepsilon_h, \Delta\varepsilon_f) \approx 0$, the IS metric is quite precise -- i.e., the range of IS estimates from the Cholesky factorization is small. And since ε_h and ε_f are liquidity shocks, at high enough frequency this condition can be met.

Alternatively, consider Gonzalo-Granger's (1995) 3rd generation adjustment-dynamics concept of price discovery, the common factor share (CFS). The Gonzalo-Granger approach involves a permanent-transitory decomposition, in effect estimating a transitory price adjustment vector (z_h, z_f) from the VECM (1.2) and (1.3) and then calculating an orthogonal vector of proportionate factor weights in the permanent trend attributable to each channel's prices. When $\sigma^2\varepsilon_h = \sigma^2\varepsilon_f$, the CFS metric is unbiased and precise. As the variance of the order imbalance shocks in competing channels

diverges, the CFS metric displays mild bias, so CS is best applied across markets or channels with similar underlying price variance. If $\sigma^2\varepsilon_h \ll \sigma^2\varepsilon_f$ or vice versa, and yet the cross-equation correlation of $\Delta\varepsilon_h$ and $\Delta\varepsilon_f$ is near zero, the IS provides an unbiased measure of price discovery that nevertheless remains dependent on the CFS for unequivocal interpretation (see below). Both measures therefore have their uses and serve to complement each other.

To assist in refining the interpretation of IS_h, think of impounding permanent innovations w_t as "good trades" in channel h that facilitate price discovery, whereas chasing transitory shocks ε_h and ε_f constitutes "bad trades" that inhibit price discovery efficiency leading to lower IS_h because, again, IS incorporates both information impounding with "good trades" and price discovery inefficiency with "bad trades" in competing channels. These are actual terms used routinely by senior traders to describe the concepts underlying the Gonzalo-Granger decomposition. The CFS procedure can be thought about as a diagnostic technology to identify and assess the chasing of transitory shocks. And this concept has direct application in trading practices. Specifically, managers of trading desks monitor the "state of the market" in each liquid security and the more active institutional clients paying higher fees are advised when their orders would simply chase transitory shocks. Execution channels that feature this type of active monitoring of the state of the market discover price very efficiently and have higher CFS. In contrast, other execution channels with lower CFS exhibit large imbalances of liquidity trades and then follow-on trades that chase and accentuate these transitory shocks.

In the 4th generation price discovery research, Yan and Zivot (2010) show under plausible assumptions that high IS_h is equivocal in capturing both information impounding in the primary channel and "bad trades" chasing transitory shocks in competing channels,

$$IS_h = \delta_h^P \, \delta_f^T \, / \, \Delta \qquad\qquad (1.6)$$

where δ_h^P is the immediate response parameter of observable price innovations in channel h to

permanent (information) shocks (w), δ_f^T is the immediate response parameter of observable price

innovations in competing channel f to *transitory* liquidity shocks (ε_f), and Δ is the determinant ($\delta_h^P \delta$

$_f^T - \delta_h^T \delta_f^P$). Hence, IS_h can be large either because channel h impounds information shocks quickly

with high sensitivity or because channel f chases transitory liquidity shocks quickly with high

sensitivity.

On the other hand, again using Yan and Zivot's plausible assumptions about the structural

shocks, Gonzalo-Granger's (1995) price discovery concept CFS unambiguously measures the relative

incidence of bad trades chasing transitory shocks in the competing channel:

$$CFS_h = \delta_f^T / \Delta \qquad \text{and} \qquad \frac{CFS_f}{CFS_h} = \frac{\delta_f^T}{\delta_h^T}. \qquad (1.7)$$

One can therefore think of the ratio of CFSs as a ***metric of price discovery inefficiency*** in

channel f relative to channel h, and the product of the ratios of IS/CFS,

$$\frac{IS_h}{CFS_h} \frac{CFS_f}{IS_f} = \frac{\delta_h^P}{\delta_f^P} \qquad (1.8)$$

as a ***metric of permanent price impounding*** in channel h relative to channel f. As a result, IS

and CS can be used together to decipher these two dimensions of price discovery, and that is precisely

what we do in this paper.

With cointegrated exchanges across currency areas, the exchange rate may itself represent a

random walk data generating process with its own FX rate fundamentals (interest rate shocks, trade

flow shocks, commodity price cost-inflation shocks), adding another equation to the VECM system.

Writing all the price levels in the logs,

$$\Delta P_{ht} = \alpha_h + \Sigma\beta_{ht-s}\Delta P_{ht-s} + \Sigma\beta_{ft-s}\Delta P_{ft-s} + \Sigma\beta_{FXt-s}\Delta FX_{t-s} + z_h(P_{ht-1}-P_{ft-1}-FX_{t-1}) + u_t$$

(1.9)

$$\Delta P_{ft} = \alpha_f + \Sigma\beta_{ht-s}\Delta P_{ht-s} + \Sigma\beta_{ft-s}\Delta P_{ft-s} + \Sigma\beta_{FXt-s}\Delta FX_{t-s} + z_h(P_{ht-1}-P_{ft-1}-FX_{t-1}) + v_t$$

(1.10)

$$\Delta FX_t = \alpha_{FX} + \Sigma\beta_{ht-s}\Delta P_{ht-s} + \Sigma\beta_{ft-s}\Delta P_{ft-s} + \Sigma\beta_{FXt-s}\Delta FX_{t-s} + z_h(P_{ht-1}-P_{ft-1}-FX_{t-1}) + z_t.$$

(1.11)

4.1. Data

We use the Thomson-Reuters Tick History (TRTH) service from SIRCA to generate monthly trade and quote files. We selected for this study three of the most liquid British stocks GlaxoSmithKline (Glaxo), British Petroleum (BP), and Vodafone (Vodafone) plus two LSE-listed securities with foreign primary listings (HSBC in Hong Kong and Rio Tinto in Australia). These five British shares were chosen based on their more extensive trading on both Instinet/Chi-X and Xetra.

We collect 21 transaction data monthly files for these five securities as traded on the London Stock Exchange, Deutsche Borse's Xetra System, and Chi-X, screened for misprints. In addition, we create continuous OTC quote files for the pound/euro exchange rate. Our observation period starts in April 2007, around the launch of Chi-X, and ends in December 2008. However, due to the relative lack of activity in trades on Chi-X, we perform analysis of trades from July 2007 to December 2008. Our analysis of quote-based activity encompasses the entire 21 month observation period. Due to London reporting rules, we filter out off-book trades (dealer negotiated, manually reported, and upstairs trades), as they can be reported to the tape up to 3 minutes later than their execution. In addition, in London, worked principal agreements (WPAs) are printed when they are agreed to, not when the WPA-based trades are actually worked into the order flow. Therefore, WPAs are excluded as well.

From these constituent data files, we assemble 90 (18 months x 5 stocks) MINSPAN samples of trades by stock-month and another 105 (21 x 5) MINSPAN samples of quotes by stock-month. The MINSPAN procedure looks forward and backward from a focal price to identify the synchronous prices that minimize the time span between trades (or quotes) in all the competing channels (see Harris et al. 1995 and 2002). The number of MINSPAN trade observations across the LSE, Chi-X and Xetra channels for BP ranges from 791 tuples in July 2007 to 112,073 in September 2008. For quotes, MINSPAN ranges from 384 tuples in April 2007 to 187,787 in September 2008. In comparison, Rio Tinto's maximum number of trades and quotes are 79,199 trades and 172,930 quotes in September 2008.

To estimate Hasbrouck's (1995) Information Share price discovery metric, we employ not MINSPAN but a FILL FORWARD procedure, which creates tuples of continuous observations at a specified time intervals of one second. FILL FORWARD uses the most recent price in each channel (here, A and B) until a new trade or quote arrives. One potential drawback is that due to stale prices, some observations of fill-in prices can be quite misleading. Figure 2 illustrates how MINSPAN, by focusing on synchronous observations $\{(P_0^A,P_0^B), (P_3^A,P_3^B), (P_4^A,P_4^B)\}$ censors stale price fill-ins (P_1^A,P_0^B) and (P_2^A,P_0^B) that could distort the true adjustment dynamics. This explains why the Gonzalo-Granger common factor share analysis should always be performed on MINSPAN synchronous prices.[37]

4.2. Cointegration Tests

Table 1 reports our evidence that European equity markets even in the most liquid securities were highly segmented prior to MiFID but fully cointegrated afterward. Two months before final implementation of MiFID in September 2007, we find the three execution channels LSE, Chi-X, and Xetra traded BP, Vodafone, and GlaxoSmithKline without error correcting to price deviations

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[37] Other valid synchronous data collection procedures REPLACEOLDEST and REPLACEALL are investigated in Harris et. al.(1995).

between them.[38] Intraday prices between London and Frankfurt do adjust to intraday changes in the

exchange rate (and that factor itself explains 77.5% to 93.5% of the stock price adjustment in the four

channel VECM). But summing the eigenvectors for the trading price sequences in September 2007

reveals large persistent arbitrage opportunities of £0.77 and £1.24 (see Table 1, Panel A). Consistent

with this lack of no-arbitrage equilibrium, the Johansen test statistics imply a zero rank for the matrix

of cointegrating vectors. In BP the maximum eigenvalue test statistic is 1.657, in Vodafone 1.713,

and in GlaxoSmithKline 0.903 against even a 90% critical value of 15.59 (Enders, 2008, Table E).

Hence, $r = 0$ cannot be rejected meaning these markets did not error correct to erode away arbitrage

opportunities prior to MiFID.

In contrast, after the MiFID implementation, we find the three execution channels LSE, Chi-

X, and Xetra become cointegrated. For example, in December 2008 (see Table 1, Panel B), the

Johansen maximum eigenvalue test statistics for the first possible cointegrating vector ($r = 1$) and two

common factors are 33.43 for BP, 20.21 for Vodafone, and 23.88 for Glaxo relative again to 95% and

99% critical values of 17.89 and 22.99. This single cointegrating vector and the resulting implication

of two common factors is as expected in that a no-arbitrage equilibrium is being established through a

security valuation fundamental and an exchange rate fundamental, the two common factors.

Summing the first possible cointegrating vectors in May 2008 for BP and Vodafone now reveals

arbitrage opportunities thirty times smaller at 0.021 and 0.046 than in September 2007. That is, in all

three of the leading British equities cross-listed in Frankfurt, the two home market channels (LSE and

Chi-X) plus the foreign market Xetra and the FX rate between them, all error correct with zero

arbitrage opportunity to two decimal places. Therefore, MiFID appears to have accomplished the

intended coordination and coalescence of a pan-European market for equity trading.

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[38] To economize on the space required to present these extensive cointegration/error correction results,
we only report three securities in these tables, but our other securities exhibit this same result.
Subsequent reporting in graphical format displays all stocks.

Unlike RegNMS and its accompanying order migration rule in the U.S., the transition in response to MiFID was gradual. The most liquid British equities that are cross-listed in Frankfurt did not exhibit full error correction equilibrium two months after MiFID in December 2007. Table 1, Panel B shows that although arbitrage opportunities in two of the three stocks (i.e., BP and Glaxo), summing the first possible cointegrating vector, eroded away to near zero by December, none of the stocks were cointegrated this soon after the November 1 implementation of MiFID. Full error-correcting adjustment dynamics required several months (into early 2008) to develop. Some of this delay was surely infrastructure-related, but some simply reflects the absence of an order migration rule and the best execution model mandated by MiFID as opposed to the best price immediately executable mandate in RegNMS.

Our analysis of these four execution channels representing pan-European equity trading uncovered several other insights about the specification of the model. First, the FX rate shocks dominate pan-European price adjustment among these leading British stocks. Specifically, the FX rate is responsible for the great majority of the price adjustment that proves permanent in all five stocks we study. Moreover, one of the three execution channels (Xetra) has no statistically significant role in error-correction. Testing $CFS_{Frankfurt}$ for BP, Vodaphone, and Glaxo, we find London prices on LSE and Chi-X, adjusted for the contemporaneous exchange rate, do not error correct to deviations from Frankfurt prices. Specifically, using Gonzalo-Granger's (1995) χ^2 test, we find that the $CFS_{Frankfurt}$ factor weight measuring 0.07% for BP, 0.06% for Vodafone, and 0.50% for Glaxo in September 2007 both before MiFID (in Table 1, Panel A) and 1.3% for BP, 0.7% for Vodafone, and 0.6% for Glaxo after MiFID in December 2007 (see Table 1, Panel B), and 0.4%, 0.1% and 1.9% in May 2008 (see Table 1, Panel C) never proves distinguishable from zero. In contrast, the parameter estimates for CFS_{LSE} and CFS_{FX} are all statically significant at 95%, as are several of the CFS_{Chi-X} estimates. Information that leads to permanent innovations in London prices of BP, Vodaphone, and Glaxo is reflected in local price differentials only; home bias predominates. Accordingly, for our detailed analysis of month to month changes in the price discovery metrics reported below, we

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dropped Xetra altogether and therefore the FX rate from our VECM, thereby reducing the number of channels under investigation to LSE and Chi-X alone.

5. Empirical Results

5.1. Collapse of LSE price discovery in mid-2008

The first finding is that a collapse in the price discovery attributable to London Stock Exchange trades has occurred, but it was not triggered by MiFID. Figure 3, Panel A shows the LSE information share (IS_{LSE}) over 18 months for BP, Glaxo and Vodafone. IS_{LSE} was essentially unchanged throughout the six months following the implementation of MiFID from November 2007 to March 2008. Only then did IS_{LSE} decline by half, at the time of a Chi-X settlement fee cut.

On 1 March 2008, Chi-X announced a reduction by 11.8% in clearing fees (from 17 to the minimum 15 Euro cents per share) for LSE-listed stocks and by 32% for somewhat higher fee Dutch, French, and German stocks.[39] All three iconic London stocks exhibit a very similar response with a prior mean monthly IS_{LSE} of 0.97 (range 0.99 to 0.9), and an ex post mean monthly IS_{LSE} afterwards of 0.54 (range 0.45 to 0.68). We test the proposition that the fee schedule reduction caused a change in price discovery using a Wilcoxon rank sum test to assess the difference in IS and CFS for the 8 months before and after March 2008. Table 2 shows the results of the test, using July 2007 to February 2008 as the period before the fee cut, and April to November 2008 as the period after the fee cut. Z-statistics are significant at the 1% level for all five of these most heavily-traded UK listed stocks.

Remembering that the IS_{LSE} metric is equivocal, reflecting both information impounding and relative avoidance of chasing transitory shocks, common factor share results are also needed. In particular, Figure 3, Panel B shows the common factor share (CFS_{LSE}) for these same stocks declining from a mean 0.91 (range 0.99 to 0.8) prior to April 2008 to a mean 0.37 (range 0.53 to 0.23)

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[39] http://www.chi-x.com/trading-notices-pdfs/TradingNotice0045.pdf displays the CCP fee cuts on Chi-X.

afterwards. This latter finding means that trades on Chi-X chased transitory shocks less, or trades on LSE chased transitory shocks more than before the Chi-X settlement fee reduction.

One interpretation is that some informed trading switched to Chi-X to stealth trade amongst the price-sensitive liquidity traders who had migrated there, and LSE clients then chased the transitory order imbalances on Chi-X, believing them to be permanent innovations in the valuation fundamental. Only if there had been no decrease in the CFS on the LSE could we have inferred that all of the IS_{LSE} collapse in Figure 3, Panel A was attributable to a loss of information impounding on the central market. Instead, some of information share on the LSE is clearly attributable to "bad trades" that chase the transitory selling/buying pressure from increased liquidity trading in the satellite market.

A second interpretation is that reduced CFS_{LSE} after the Chi-X fee reduction simply reflects worsened order imbalances from liquidity trades walking up and down thinner books remaining on LSE once some of the price-sensitive liquidity trading migrates to Chi-X. Either interpretation of increased chasing of transitory shocks worsening price discovery efficiency on the primary market represents an undesirable consequence of the fragmentation of order flow in response to the Chi-X settlement fee cut and the subsequent migration to an algorithmic trading-dominated MTF. This suggests substantial reductions in execution costs (spreads) are needed to assure a net benefit from the more fragmented market structure.

5.2. Quote information on the LSE

Quote-based IS_{LSE} and CFS_{LSE} for UK primary-listed shares decline only temporarily after the Chi-X fee schedule cut (see Figure 4). The IS_{LSE} falls from an average of 0.98 in February 2008 to 0.63 (range 0.46 to 0.82) in April but recovers to 0.93 (range 0.91 to 0.99) by June-July. Since quotes are not affected by clearing and settlement fees, the LSE quote formation process remained highly informative and in some cases grew in importance after several months of trial experiences in setting the quotes using Chi-X.

To take a specific example illustrating the joint use of IS and CFS metrics to draw price discovery inferences, BP's quote price discovery IS_{LSE} metric from August to December 2008 (see Figure 4, Panel A) rose from 0.65 to 0.7 to 0.95 whereas BP's CFS_{LSE} metric fell from 0.9 in July 2008 to 0.7 to 0.62 in November-December (see Figure 4, Panel A). Using equations (1.6) and (1.7), this evidence is clearly interpretable as more information impounding in the quote formation process on LSE. That is, because with CFS_{LSE} declining, less chasing of transitory shocks is unambiguously taking place on Chi-X, the observed contemporaneous increase in IS_{LSE} must be attributable to more information impounding on LSE.

5.3. Dual-listed stocks

The price discovery in dual-listed stocks, which we define as those stocks with a primary listing in another country as well as the UK, exhibits a different price discovery pattern. This is not surprising given that stocks such as HSBC and Rio Tinto have substantial order flow and therefore "state of the market" information originating in Hong Kong and Sydney. Even though valuation information and analysis may be homogeneous across continents, state of the market information may well not be.

Figure 5 displays the price discovery metrics by month for dual-listed shares. The most striking difference relative to our earlier findings is the LSE dominance of quote formation throughout all but one of the 21 months. From September 2007 to September 2008, IS_{LSE} is above 94%. Only thereafter is there any decline and even then, IS_{LSE} is still 0.71 to 0.9. This maintaining of the price discovery dominance by the London exchange with all its decades of broker-dealer relationships worldwide reflects less dispersed information flows in stocks with foreign primary listings. Again, we wish to suggest that "state of the market" information in Sydney and Hong Kong may be more central to this argument than valuation information about the fundamentals of Rio Tinto and HSBC.

Also note that in the first three months of Chi-X operations in 2007, HSBC's IS_{LSE} was 0.92, 0.89, and 0.95 whereas CFS_{LSE} was much lower, only 0.23, 0.31, and 0.33. This suggests that at the

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advent of Chi-X, 'bad quote' formation in HSBC was taking place on LSE as anxious traders chased transitory (uniformed) price movements from trades that walked quickly up or down the highly illiquid Chi-X book. Once Chi-X had been in operation for a few months and began to process substantial numbers of liquidity trades, the order flow balances on Chi-X would have improved (while those on LSE would have worsened). Thereafter, the incidence of chasing transitory shocks in HSBC triggered by order flow imbalances rotated back and forth between LSE and Chi-X. This is the interpretation we place on the highly unstable seesawing of CFS_{LSE} on the right-hand-side of Figure 5, Panel B.

5.4. Clawback by LSE

Another finding in our price discovery patterns shows LSE regaining primacy in the informativeness of trading, which may be due to the composition of traders on Chi-X. Trades in HSBC show a clawback in price discovery at LSE by September 2008 approximately a year after MiFID and six months after ceding the price discovery to Chi-X. Glaxo and Vodafone quotes show a ceding of price discovery to Chi-X on their fee schedule change in April-May 2008, followed by an immediate clawback the next month by LSE which then again dominates, as transitory shock chasing on Chi-X increases. We conjecture the initially plummeting IS_{LSE} for Glaxo and Vodafone in April and May 2008 is attributable to Chi-X attracting more informed institutional participants to their platform. The subsequent decrease in CFS on Chi-X and increase of CFS on LSE for Glaxo and Vodafone is consistent with dramatically increased transitory shock chasing on Chi-X. This may be due to the emergence of intense algorithmic trading activity on Chi-X.

5.5. Discussion of Results

Even in the absence of a concentration rule in London, the LSE historically dominated the order flow volume in the most liquid British stocks, and this dominance continues. Despite its obvious success, Chi-X's share never exceeds one-fifth of the LSE's share for any of the 21 months in our sample. In part this reflects the fact that LSE prints reports of internalization, crossing network,

and OTC trades from all over Europe. But other reasons exist. First, like other market makers, LSE dealers charge known repeat-purchase customers lower pre-trade and post-trade fees.   We present stark evidence of the role these clearing and settlement fees can play in order placement strategy. Second, LSE has been able to execute size with less price impact than the ECNs. Finally, LSE developed relationship-specific execution contracts for active-monitoring brokerages. As a result, London dealers can be seen trading through with regular customer orders even though trades inside-the-quotes are going on elsewhere. In 2008, however, some of these historical advantages began to break down, and new patterns of price discovery emerged.

Although MiFID did not require order routing to best price immediately available for execution, it did greatly facilitate the MTFs whose business model, not surprisingly, is oriented towards attracting away and building anew execution cost-sensitive order flow. One would then expect liquidity traders with moderate-size orders to migrate to electronic platforms at the best bid-offer, just as block traders migrate to upstairs submarkets designed for large transactions. And if liquidity traders migrate, then informed traders would follow. This is exactly what we observe with the migration from NYSE to ARCA throughout the gradual implementation of Reg NMS over six months in 2007. Figure 6, Panel A displays the steadily declining IS_{NYSE}, essentially flat IS_{NASDAQ}, and steadily rising IS_{ARCA}. Figure 6, Panel B reveals the price discovery efficiency obtained as NASDAQ's CFS steeply rises. This finding signifies NASDAQ dealers chasing fewer transitory shocks from liquidity trades that walk up and down the ever thinner NYSE book and the thin but very resilient ARCA book.

Here our two interpretations of a rising CFS – as fewer "bad trades" that inhibit price discovery or thicker order books resulting in fewer and less severe order imbalance transitory shocks--come into complete focus. During this 2007-2008 time period in the U.S., NYSE's share of order flow volume was falling steeply but ARCA was picking that up, such that NASDAQ's volume remained essentially flat to only slightly rising. Consequently, steeply rising CFS_{NASDAQ} in Figure 6,

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Panel B unambiguously implies not thicker order books but more efficient price discovery on NASDAQ. Specifically, the more efficient price discovery is here attributable to less chasing on NASDAQ of transitory shocks appearing on NYSE and ARCA.

This same phenomenon is at work in the London data. Once NASDAQ or LSE dealers became convinced that best execution would win the uninformed business and that informed trades would then follow, there was little incentive to be whipsawed by trades that walk the books on other markets. Those order imbalances are recognized for what they are – transitory shocks to an implicit efficient price that will soon mean revert. Therefore, there is much less motivation by dealers, by trading desks actively monitoring the "state of the market" in various stocks, or by regular limit order placers themselves to place follow-on trades that accentuate the transitory shocks. The consequence is that price discovery quickly improves.

The stark effects we detect on trading price discovery patterns around the Chi-X fee schedule change indicate that institutional market participants view the concept of best execution as inclusive of clearing and settlement fees. When spreads are nearly equivalent (as between LSE and Chi-X, again see Figure 1), order flow proves highly sensitive to the two cent clearing fee change. Oxera (2009) surveys the cost of trading and post-trade services and draws attention to the fact that when brokers supply post-trading services to funds, the brokers take this cost out of their pre-set commission. Oxera estimates the net clearing cost as 37 to 50 euro cents per transaction (which are individual transactions – so a large order split into 5 trades will pay the clearing cost 5 times). Consequently, algorithmic traders and other high frequency clients will be very sensitive to changes in this uniform cost per trade, and therefore may be expected to migrate to execution platforms with marginally lower clearing fee schedules.

Our differential finding regarding the on-going dominance of the LSE in quote price discovery may be understood through several lenses. For one, price quotes today are only fleeting indications of interest. With cancellation privileges on a low-latency platform such as Chi-X, the

electronic quotes placed by algorithmic participants are not expressions of an affirmative obligation to trade. Rather, algorithmic 'quote-boxes' may be quoting strategically with no expectation of being hit by another order. That is, they may be simply 'pinging' to calibrate algorithms or to engage in 'liquidity search', a category of algorithms to elicit liquidity from other market participants.

In addition of course, only trivial depth is available at many quotes. Chakravarty, Harris, and Wood (2009) show that new information first appears in depths. Depth quotes may be a better indication of interest in trading. And public policies about information disclosure are giving more attention to depth at the quotes, appropriately in our view.

6. Conclusion

The implementation of MiFID appears to have accomplished the intended coalescence of European equity trading. In the leading British equities we find evidence post-MiFID of cointegration across European venues whose trading had previously been segmented.

Ironically, coalescence of trading information has aided fragmentation of order flow. In particular, price discovery in leading British stocks has partially moved from LSE to the MTF Chi-X. A post-trade fee schedule change on Chi-X, not the introduction of MiFID, was the catalyst for this transition. In the absence of an order migration rule, MiFID's best execution mandate did not trigger any substantive change in price discovery. Instead, a 12% cut in clearing fees on Chi-X, five months after MiFID was introduced, attracted informed and liquidity trades from LSE to Chi-X. Chi-X's low latency platform suits algorithmic traders with information about state of the market or to a lesser extent, valuation fundamentals. Our results document an accompanying reversal of the dominant price discovery role in trades involving the leading British equities from LSE to Chi-X.

As quote formation is unaffected by the fee schedule for clearing and settlement, the vast majority of quote information impounding remains on LSE. In short, quote adjustment on LSE remains highly informative but many trades then execute on Chi-X's low latency platform that facilitates algorithmic trading. Future research should jointly employ the IS and CFS price discovery metrics to explore insights about why optimal order placement migrates under some conditions of fragmentation but not others. This raises two additional questions as to what will be the effect on competitive dynamics of follow-on entry by new MTFs. And why dark pools and high frequency traders may prefer one type of market design and its accompanying price discovery over another.

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Table 1 Johansen Cointegration Test Statistics and Gonzalo-Granger Common Factor Shares
We display for a 4 channel VECM involving the London, Chi-X and Xetra exchanges as well as the
FX rate, the Johansen cointegration test statistics, the first possible cointegrating vector to go with
two anticipated common factors for the stock and exchange rate fundamentals, and finally the
Gonzalo-Granger (1995) common factor shares for three of the most thickly-traded equities on the
LSE in September 2007 (Panel A), December 2007 (Panel B), and May 2008 (Panel C). The cointe-
gration test fails in September and December 2007 at even 90% but passes at 99% beginning two
months after MiFID in early 2008 and all months thereafter (e.g., May 2008 is displayed). * represents
statistical significance for the Gonzalo-Granger common factors shares (CFS) at 5%.

Panel A: September 2007

	H₀	Max Eigenvalue	Critical values at 10/5%
		Cointegration Test Statistics	
BP	r=2	0.020	2.86/3.84
	r=1	0.056	9.52/11.44
	r=0	1.657	15.59/17.89
Vodafone	r=2	0.018	2.86/3.84
	r=1	0.512	9.52/11.44
	r=0	1.713	15.59/17.89
GlaxoSmithKline	r=2	0.035	2.86/3.84
	r=1	0.631	9.52/11.44
	r=0	0.903	15.59/17.89

	Cointegrating Vectors				Sum
BP	1.061408	0.038523	-1.429058	1.1049959	= 0.776
Vodafone	1.210779	0.206172	-1.398605	1.241882	= 1.260
GlaxoSmithKline	-0.015943	-0.00084	0.001026	-0.004342	= - 0.021

	London	Chi-X	Xetra	FX
	Common Factor Shares			
BP	13.3%*	4.6%*	0.07%	81.40%*
Vodafone	15.2%*	6.7%*	0.06%	77.5%*
GlaxoSmithKline	5.3%	0.7%	0.50%	93.5%*

Table 1, Panel B: December 2007

		Cointegration Test Statistics	
	H₀	Max Eigenvalue	Critical values at 10/5%
BP	r=2	0.046	2.86/3.84
	r=1	0.723	9.52/11.44
	r=0	0.886	15.59/17.89
Vodafone	r=2	0.072	2.86/3.84
	r=1	0.574	9.52/11.44
	r=0	0.935	15.59/17.89
GlaxoSmithKline	r=2	0.061	2.86/3.84
	r=1	0.522	9.52/11.44
	r=0	0.838	15.59/17.89

	Cointegrating Vectors				Sum
BP	0.3968182	0.1492888	-0.061727	0.0103075	= -0.005
Vodafone	1.210779	0.206172	-1.398605	1.241882	= 0.402
GlaxoSmithKline	-0.021512	-0.000745	0.0010197	-0.004466	= - 0.026

	Common Factor Shares			
	London	Chi-X	Xetra	FX
BP	6.9%*	1.1%	1.3%	90.7%*
Vodafone	28.3%*	2.2%	0.7%	68.2%*
GlaxoSmithKline	38.2%*	0.7%	0.6%	60.5%*

Table 1, Panel C: May 2008

Cointegration Test Statistics

	H_0	Max Eigenvalue	Critical value at 5/1%
BP	r=2	0.108	3.84/6.51
	r=1	0.590	11.44/15.69
	r=0	33.44	17.89/22.99
Vodafone	r=2	0.052	3.84/6.51
	r=1	0.296	11.44/15.69
	r=0	20.21	17.89/22.99
GlaxoSmithKline	r=2	0.053	3.84/6.51
	r=1	0.468	11.44/15.69
	r=0	23.88	17.89/22.99

Cointegrating Vectors

					Sum
BP	0.029202	-8.24412	8.2313017	0.0251025	= 0.0414
Vodafone	0.014098	-5.30953	5.3069377	0.0152306	= 0.0267
GlaxoSmithKline	0.0002714	-0.00616	0.006176	-0.000664	= - 0.0004

Common Factor Shares

	London	Chi-X	Xetra	FX
BP	8.1%*	2.5%	0.4%	89.0%*
Vodafone	8.6%*	2.0%	0.1%	89.3%*
GlaxoSmithKline	43.5%	1.0%	1.9%	53.6%*

Table 2 Wilcoxon test of price discovery metrics around Chi-X fee schedule cut
We perform a Wilcoxon rank sum difference test of the mean IS and CFS metrics over
an eight month before-after period for five of the most heavily-traded stocks listed on
the London Stock Exchange. The event of interest is a 12% reduction in Chi-X's
clearing and settlement fees in March 2008.

	BP	GLAXO	VODAFONE	HSBC	RIO
Average IS Prior to Fee Cut	0.977688	0.966375	0.984188	0.954688	0.937625
Average IS After Fee Cut	0.443688	0.465	0.488938	0.55425	0.532188
Z-Stat	3.31	3.30	3.31	3.31	2.68
P-value	0.0009	0.0009	0.0009	0.0009	0.0074
Average CFS Prior to Fee Cut	0.9112	0.904838	0.931286	0.847194	0.887526
Average CFS After Fee Cut	0.431031	0.402336	0.418625	0.538542	0.473571
Z-Stat	3.31	3.30	3.31	3.20	2.47
P-value	0.0009	0.0009	0.0009	0.0014	0.0135

Figure 1 Lowest Effective Spreads Worldwide (2002-2009)
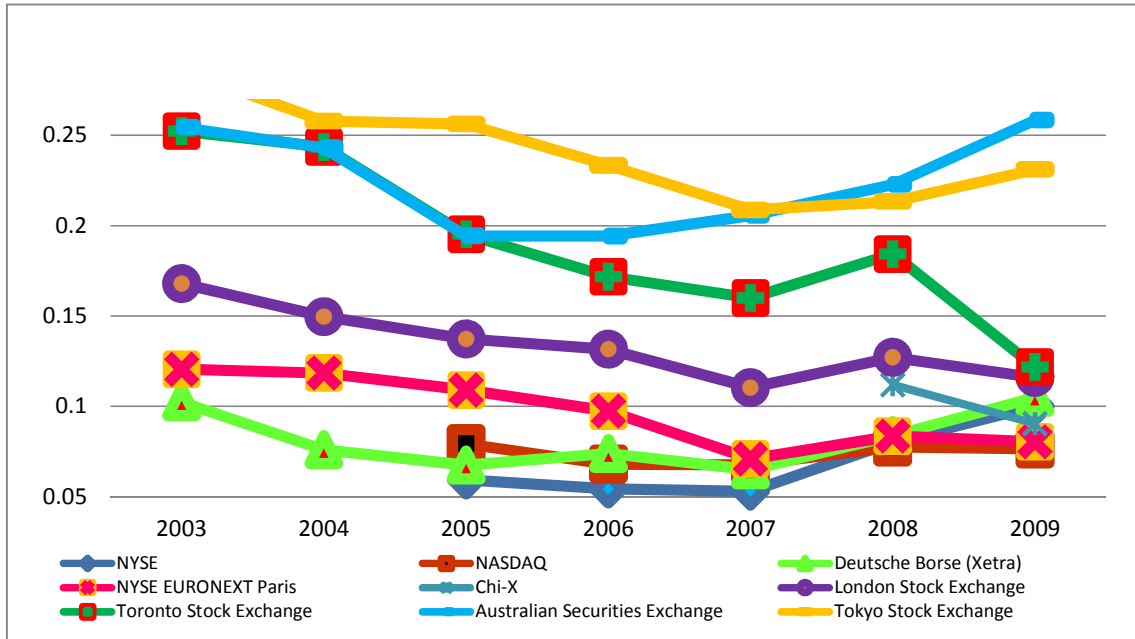
Figure 2 Two approaches to synchronous data sampling

	MINSPAN DATA			FILL FORWARD DATA

Censored

P_0^A P_1^A P_2^A P_3^A P_4^A P_0^A P_1^A P_2^A P_3^A P_4^A

P_0^B P_3^B P_4^B P_0^B P_0^B P_0^B P_3^B P_4^B

Stale Fill-ins

Figure 3, Panel A Trading price discovery in UK primary listings
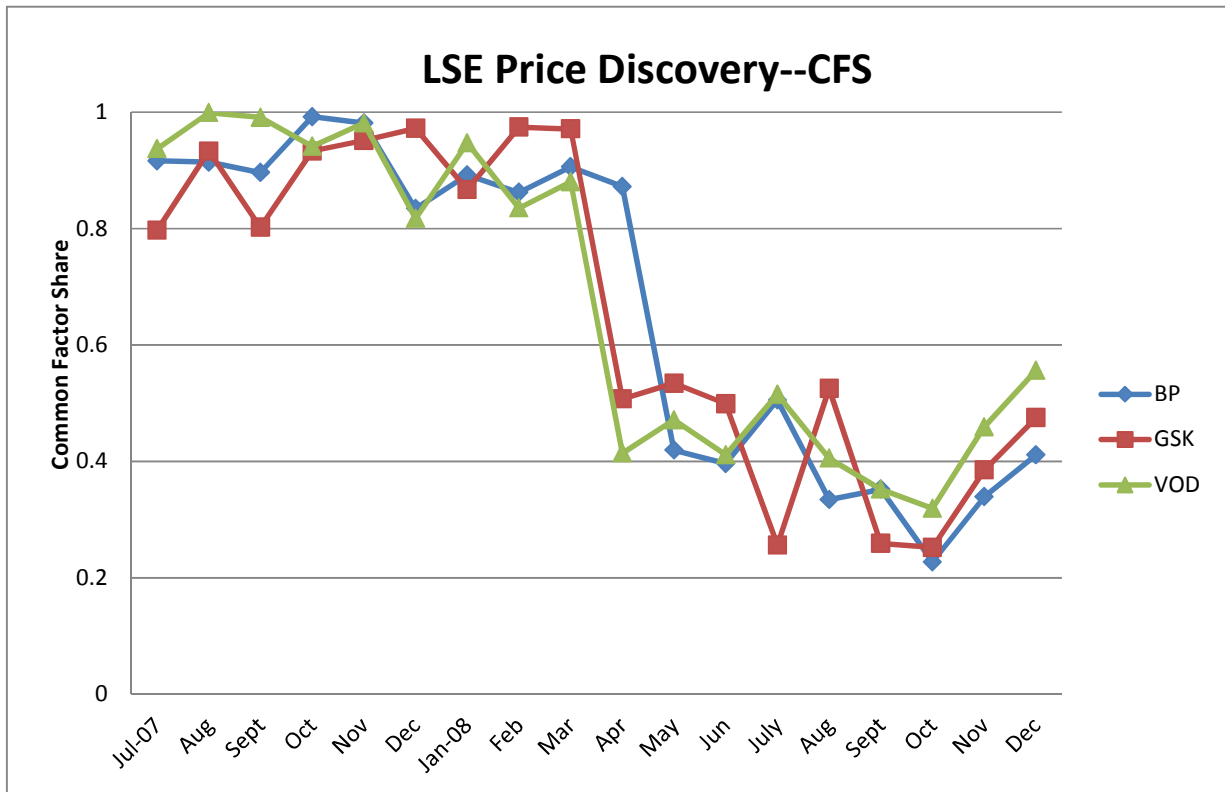
Figure 3, Panel B
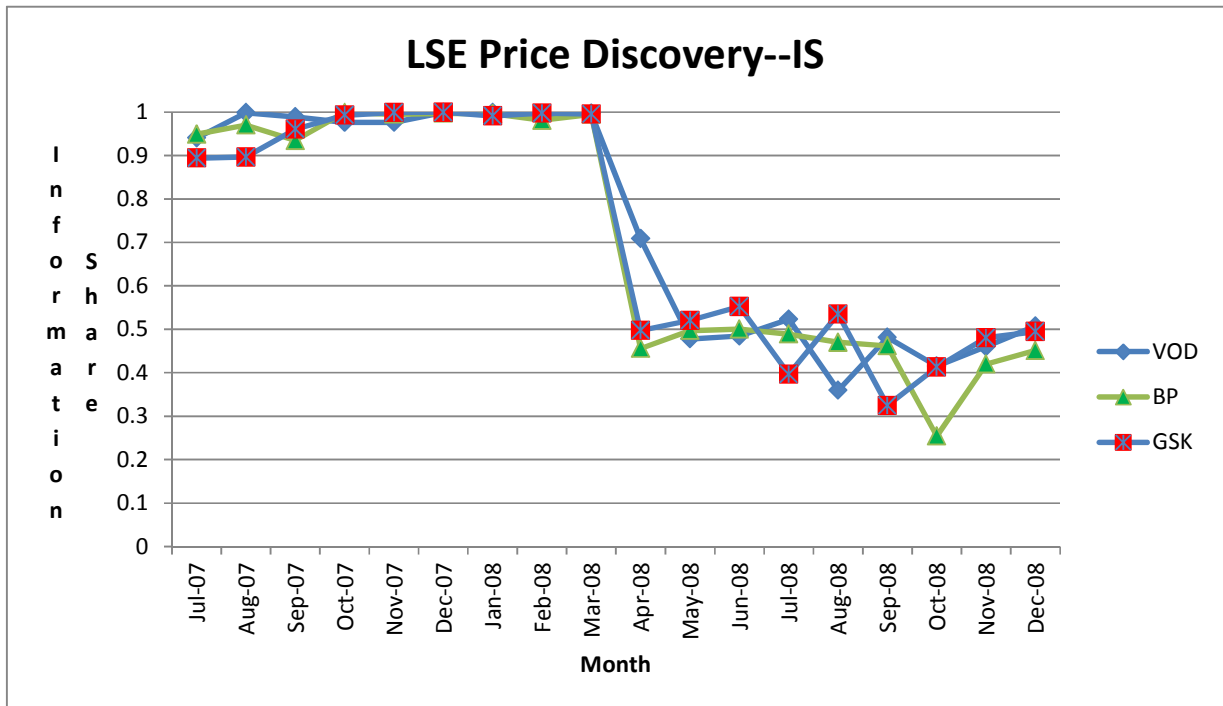
LSE Price Discovery--CFS

Figure 4, Panel A Quote price discovery in UK primary listings
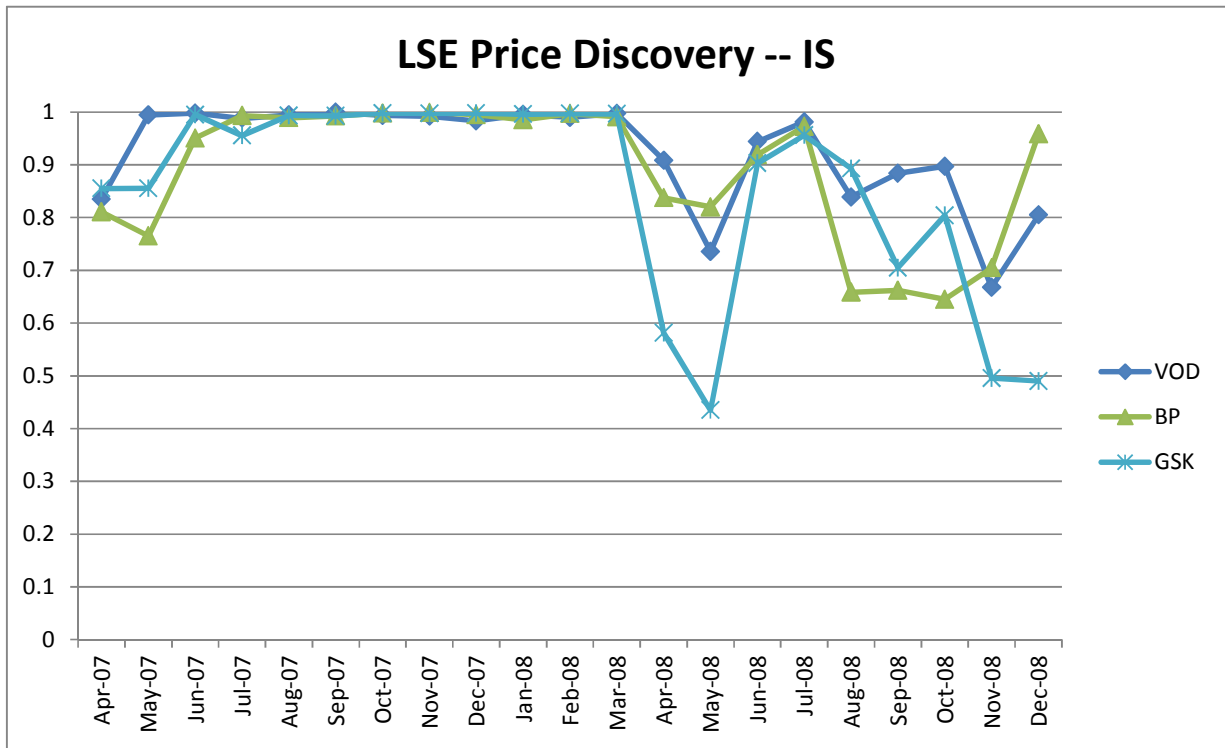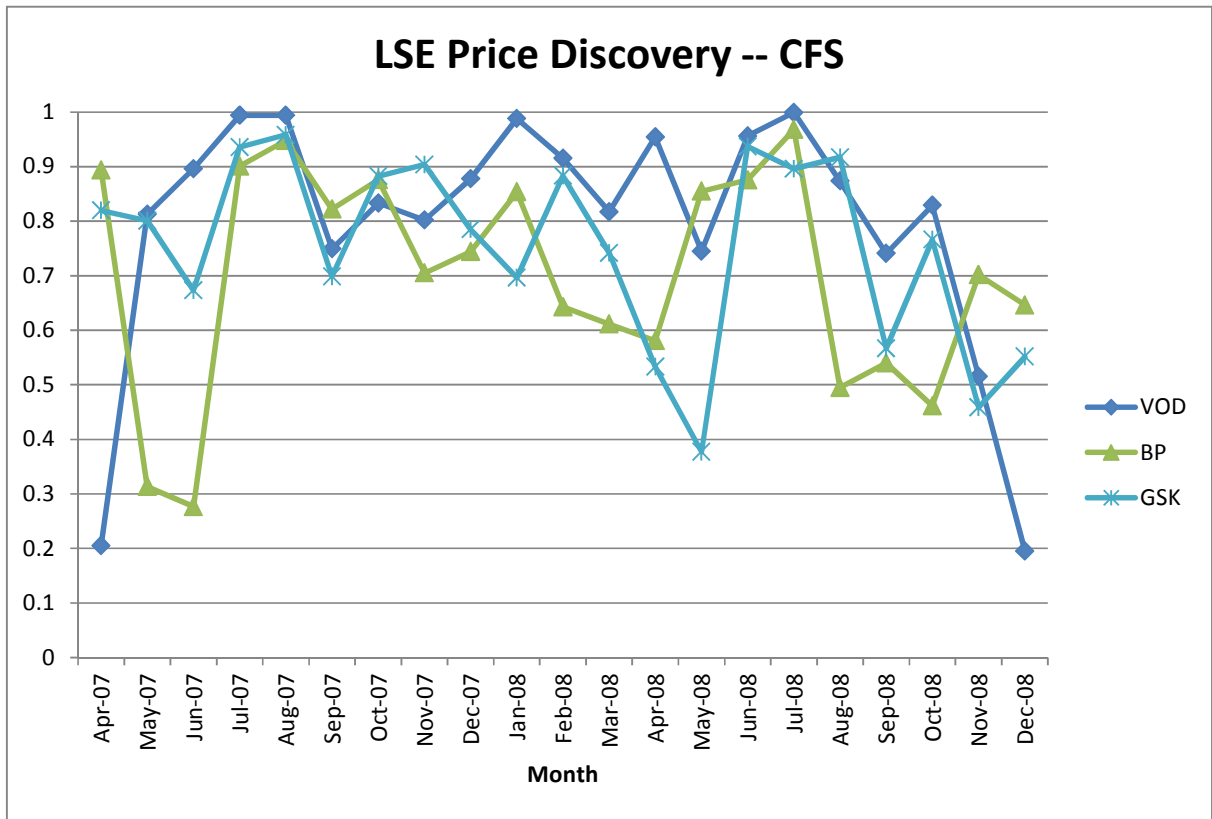
Figure 5, Quote price discovery in foreign primary listings, Panel A

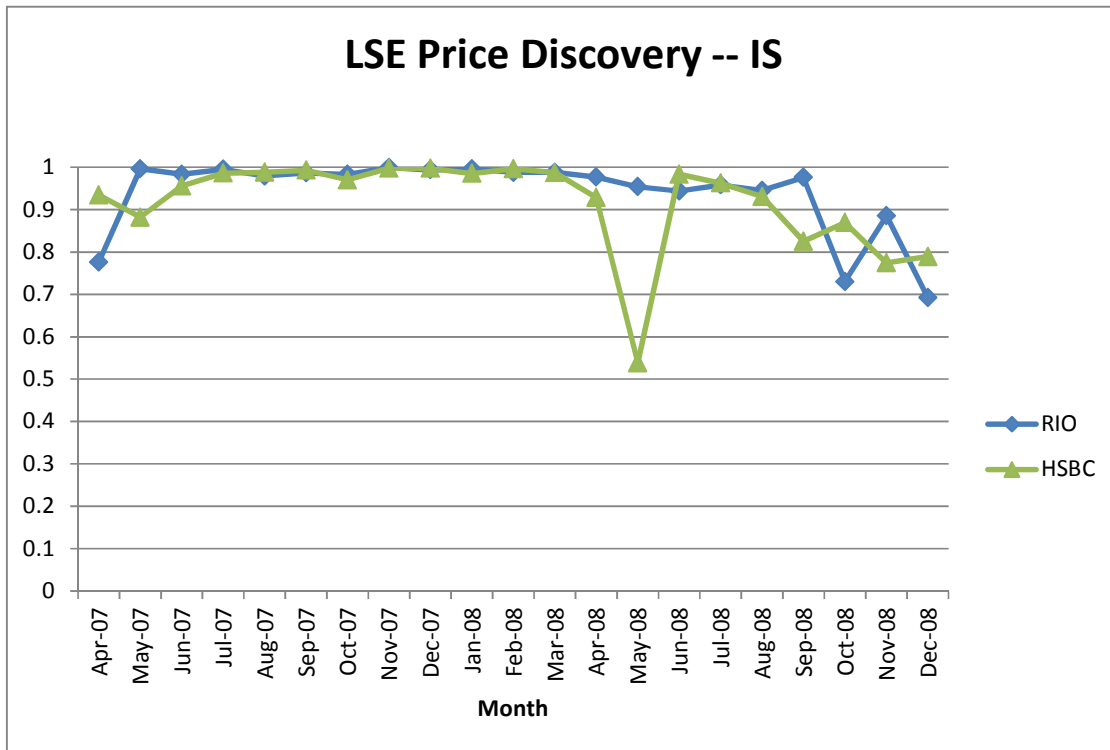LSE Price Discovery -- IS
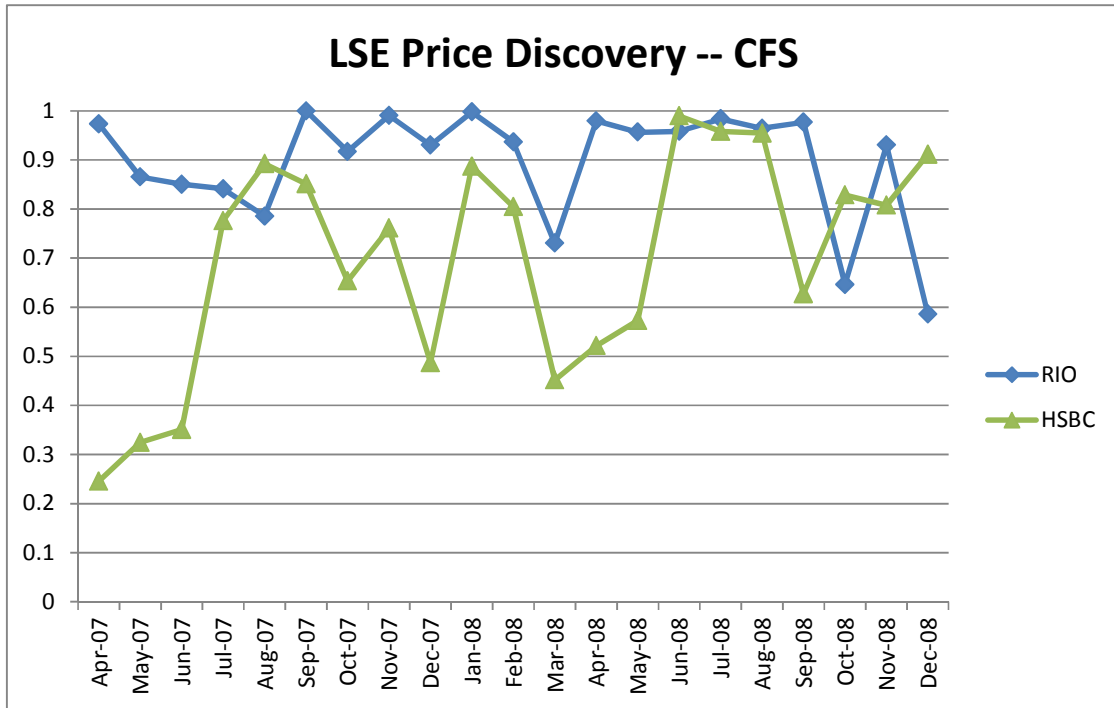
Figure 5, Panel B

LSE Price Discovery -- CFS

Figure 6, Panel A Trading price discovery in 3 execution channels, Dow 30 (2007-2008)

Mean CFS
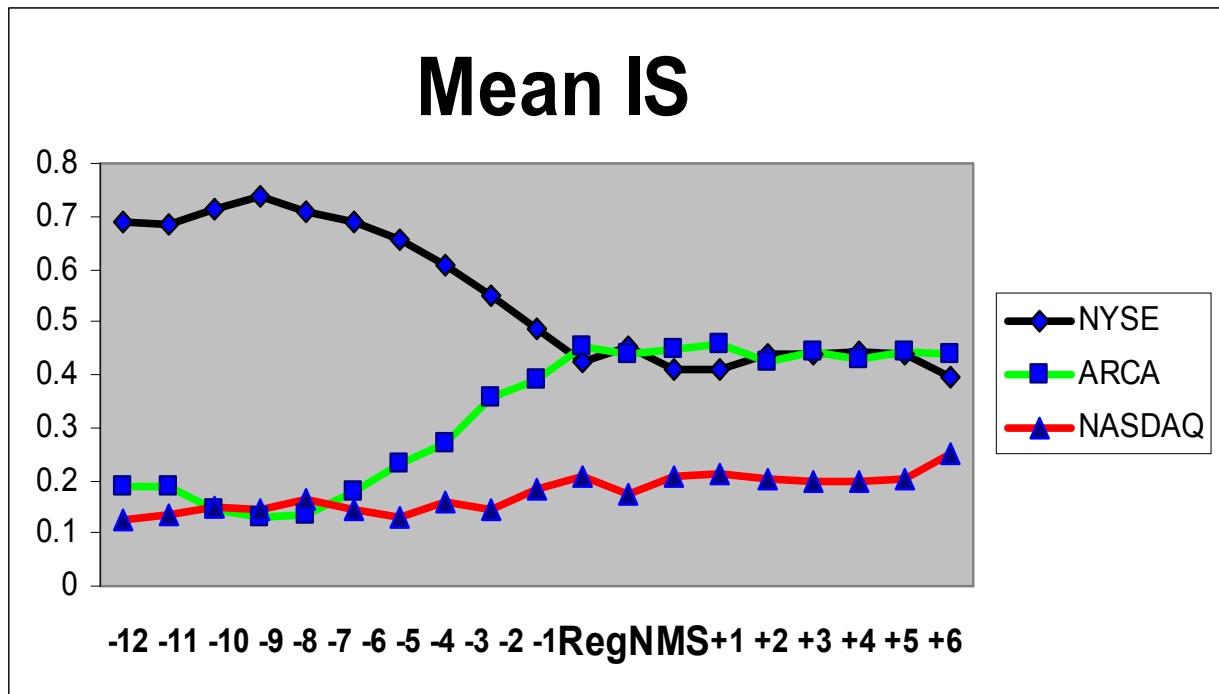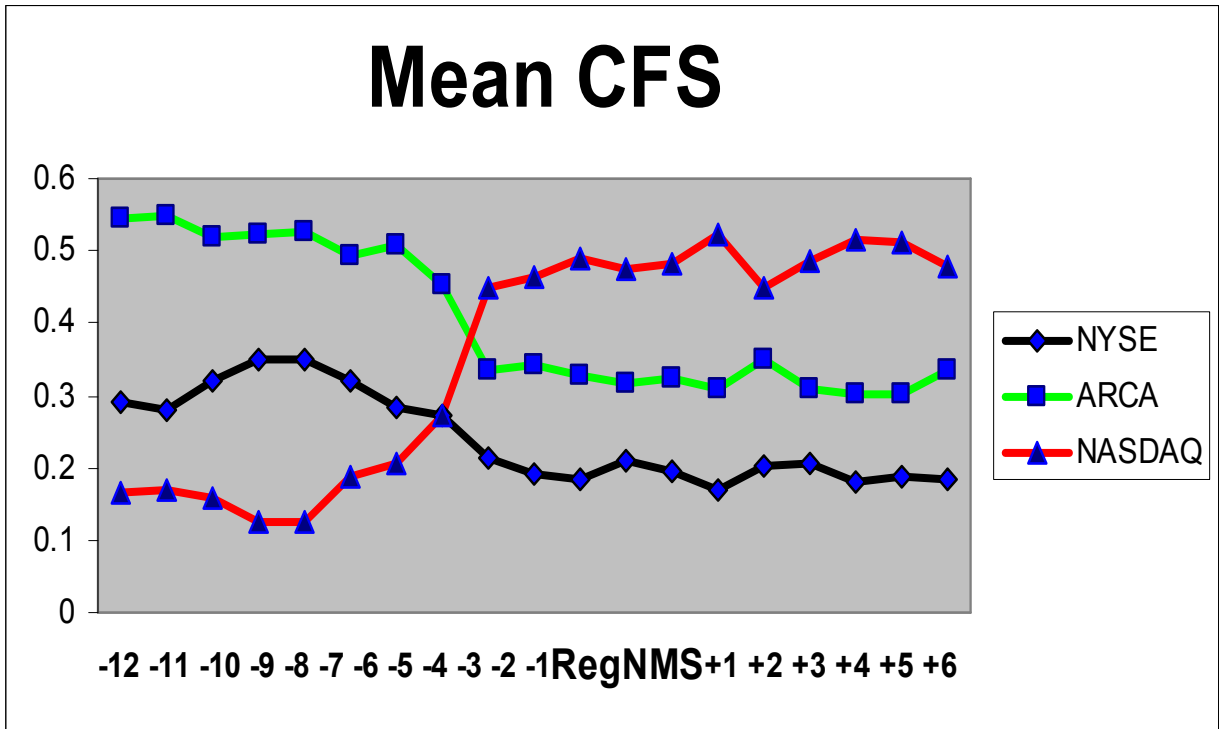
Chapter Five:

Liquidity and Fragmentation after MiFID on European Exchanges

1. Introduction

Public policy discussions often centre on improving consumer welfare. Welfare objectives in securities markets range from ensuring markets are fair and efficient to questioning how to distribute income. In the area of securities markets, the cost of transacting in shares or any asset is one of the most significant welfare questions (Demsetz, 1968) because of justice arguments that all participants in a market should be treated equitably.

MiFID aims to create a pan-European equities market by stimulating competition in liquidity provision across European exchanges. It eliminates the 'concentration rule' prevalent in many EU nations that mandated routing of orders to national exchanges (i.e. if one wished to buy a French stock, one had to purchase it on the Paris Bourse – thus giving certain national exchanges monopolies in securities). This provided for greater competition in both explicit (relative effective spreads) transactions costs and implicit transactions costs (pre- and post-trade costs such as market access fees and central counterparty fees). MiFID spurred two major changes in European securities markets: first among these is the passport rule, which allows any security supervised by a national regulatory authority to be traded at any EU exchange. National exchanges with a monopoly prior to MiFID both had to compete with other established exchanges and new Multilateral Trading Facilities (MTFs), the European analogue to ATS/ECNs in the US offering other benefits such as lower latency, which allows for quicker trading. Therefore, the competitive environment produced by MiFID provides a

natural experiment as to whether MiFID achieves one of its claimed objectives of lower transactions costs by fragmenting order flow.

With the growing transparency of transaction prices resulting from advances in the communications industry, regulatory authorities came to the opinion (Lannoo, 2007) that retail investors, a steadily growing category of market participants, may be paying sub-optimal prices due to informational asymmetry. From that possibility stems the justice argument – that institutional investors or their brokers, as more sophisticated parties privy to greater information on the securities markets, may be taking advantage of retail investors with only a casual knowledge of markets. MiFID focused on best execution. In order to reach this 'best execution'the EU followed on from the Reg NMS regulation of 'best execution' expressed through the introduction of a 'national market system' (SEC, 2004), whereby retail investors should be able to obtain the best 'execution' on their orders, defined strictly in terms of price. However, the definition of best execution under MiFID is substantially different from that in the US in that they have taken it beyond merely being an issue of price. In the European market best execution has also been defined in terms of time (speediest execution), size of trade (where one exchange may have cheaper liquidity at the best-bid and offer, but the value-weighted-average-price of the total liquidity demanded is less at a different location), and highest likelihood that the order would execute.

This chapter utilises differences in trading practices and institutional obligations on the three key exchanges (London Stock Exchange, Paris Euronext, and Deutsche Borse – Xetra) that historically have dominated order flow in nationally listed shares. Deutsche Borse – Xetra pioneered movement among established European exchanges changing to full electronic trading in the late 1990s. By the advent of MiFID in November 2007, all the exchanges

offered a capability for electronic trading. Prior to the introduction of MiFID, Paris and London were highly characterized by client relationship-based mediation, both with contracts for active monitoring of brokerages and a differential fee schedule for known repeat customers. Whilst, in Germany there was reduced taxation on algorithmic trades relative to other types of trading (Hendershott and Riordan, 2009), which led to a greater proportion of algorithmic trading on Xetra (40% of trades) than on the other established exchanges[40]. Chi-X was the successor exchange to Nomura's Instinet trading service, initially as an upstairs service for institutional clients that matched their orders with one another. This exchange allowed institutional clients to trade large volumes without paying a heavy price for liquidity as large, or 'block' trades, would 'walk the book' and have a higher transactions costs. With the launch of MiFID, Chi-X transformed into a multilateral trading facility – an open competitor with exchanges for downstairs ('lit') order flow. Chi-X sought to attract institutional participants through two means – first, it targeted highly electronic traders sensitive to lower transactions costs or faster execution by trumpeting its low latency. Furthermore, it offered equity ownership in Chi-X to those institutional participants who would execute trades on it. As a result, in 2010, Chi-X trades more European securities by volume than any other exchange, and algorithmic trading accounts for 90% of that volume[41].

To investigate the effects of MiFID, one must initially examine the functions of a market. Markets function as a forum for the transactions that determine the true value of the asset[42]. Therefore, a market characterized by high transactions costs can be portrayed as deficient in its functions of price determination in addition to providing a forum for buyers and sellers to

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[40] http://www.automatedtrader.net/news/algorithmic-trading-news/12383/deutsche-boerse-to-cut-xetra-transaction-fees.
[41] *ibid.*
[42] Fama (1998) surveys existing literature on market efficiency, starting with Fama (1969).

meet, as transactions costs can reflect a lack of liquidity supply[43]. High transactions costs can

also act as a deterrent to additional liquidity entering the market as those otherwise willing to

trade opt to not trade on cost grounds. Therefore, transactions costs, which are often

measured by relative effective spreads, (see, for example, Venkataraman 2001; Lee,

Mucklow, and Ready 1993; and Hendershott, Jones, and Menkveld 2011), are inversely

associated with liquidity, which is a cardinal measure of the robustness and resilience of a

market. High transactions costs represent a barrier to exchange and can compound existing

obstacles to trading within a market - whether they are implicit in terms of regulatory

barriers, or explicit in terms of market participants demanding a higher price for the right to

transact in an instrument, as represented by the bid-ask spread.

This chapter finds that that fragmentation arising after MiFID reduces relative effective

spreads, and therefore, increased fragmentation leads to greater liquidity. This in turn implies

that there is improved price discovery and equity in trading access across all trade types.

Infrastructure changes on rival exchanges spur increased competition and liquidity in the

form of lower spreads, possibly by the mediation of high frequency traders. Regulatory

changes also affect transactions costs in Europe, as MiFID's implicit best execution

requirement led to a reduction in spreads – its abolition of France's concentration rule

encouraged competition for liquidity provision and slashed transactions costs.

The instrument for analysis is the measure of fragmentation of a share, defined as the

proportion of a share's total volume traded on its 'home' or national exchange[44]. This chapter

finds that incremental pre- and post- trade costs explain changes (reductions) in transactions

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[43] Akerlof (1970) illustrates how information asymmetry can lead to 'frozen' markets where transactions do not occur.

[44] Fragmentation is strictly operationalised as a percentage, where the numerator is the volume of trades on the home exchange, and the denominator is the total number of shares traded.

costs far more than regulatory changes or the introduction of a competitor. It finds evidence that MiFID and the Chi-X counterparty fee cut stimulated competition in liquidity provision as measured in relative effective spreads.

The experimental design of this chapter involves the examination of three discrete events, and their impact on each of the individual stock exchanges and on the pan-European sample. Therefore, hypotheses are tested on the relevant data sets when examining the impact of a specific event on a given exchange, and on the 'pooled' sample when testing the pan-European effect of fragmentation. Each exchange has unique market design features, thus is expected to react to a technological or regulatory change in a different manner. Bayesian Information Criteria (BIC) modelling is used to determine relevant variables of testing in each of these circumstances, with the proviso that ***Fragmentation***, the key variable of interest, is tested in each regression. Some hypotheses are tested on multiple data sets to examine how market structure affects regulatory changes. As an example of how data sets are used, the hypothesis examining whether the introduction of Chi-X and the concurrent fragmentation had effected spreads is tested only on the data sets around the Chi-X launch, as this allows for the isolation of the effect of Chi-X's entrance into the pan-European equities markets and the examination of Chi-X's launch on spreads on each of the three major European exchanges. Table 1 lays out the data sets analysed in this chapter, the event they represent, and the observation period covered by the data.

Table 1 : **Events Examined in This Chapter**

Each event has a separate data set.

Stock Exchange	Event	Observation Period
London	Chi-X launch	January - July 2007
London	MiFID implementation	August 2007 - February 2008
London	Chi-X fee cut	January - July 2008
Paris	MiFID implementation	August 2007 - February 2008
Paris	Chi-X fee cut	January - July 2008
Deutsche Borse	Chi-X launch	January - July 2007
Deutsche Borse	MiFID implementation	August 2007 - February 2008
Deutsche Borse	Chi-X fee cut	January - July 2008
Pooled Sample	MiFID implementation	August 2007 - February 2008
Pooled Sample	Chi-X fee cut	January - July 2008

Section 2 of this chapter describes the model and hypotheses tested, as well as the theoretical literature substantiating the arguments put forth in both the null and alternative hypotheses. Section 3 describes the data and filters used to construct the data set. Section 4 puts forth empirical results and explanations as to what factors impact these results, and section 5 concludes the chapter.

2. Hypothesis and Model

Literature in fragmentation posits that competing forces can either increase or decrease the amount of liquidity in the market. The introduction of a competitive market for trading does not necessarily increase the total pool of liquidity, but can decrease the economies of scale enjoyed by the previous monopoly provider (Madhavan, 1995). Alternatively, competition

can lower transactions costs - another factor in liquidity, -as market participants vie for market share (Hamilton, 1979), which leads to increased liquidity. A recent empirical study of US securities markets shows that after the introduction of Reg NMS, spreads increased[45]. Therefore, it is reasonable to posit that European securities markets will not be too dissimilar in their responses to the introduction of MiFID from the US.

The questions examined can be condensed to the questions as to whether the notional existence of competition (the launch of Chi-X) is enough to drive fragmentation and reduce spreads, whether regulatory mandates alter the patterns of order flow between established exchanges and innovative newcomers (MiFID), and whether platform fees and costs are the prime determinant of order flow. If platform fees and costs do influence order flow the concurrent migration of order flow between exchanges cause changes in spreads (Chi-X central counterparty fee cut).

The launch of Chi-X, the introduction of MiFID, and the Chi-X central counterparty fee cut, provide a natural experiment to study the effects of fragmentation on transactions costs. Chi-X as opposed to institutional upstairs networks) provides the first large scale (competition to LSE for order flow, while MiFID directs market participants to achieve best execution, which is primarily seen in terms of transactions costs. The Chi-X central counterparty fee cut allows for the examination of whether implicit (pre- and post-) trading costs drive explicit transactions costs. This is because if spreads are the same after the fee cut, for the first time, Chi-X is a less expensive trading platform than LSE, Xetra, and Paris Euronext. To examine these questions, this chapter posits and then tests the following hypotheses:

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[45] Chung and Chuwonganant (2010) examine the impact of Reg NMS on relative effective spreads in US equities.

H$_1$0: Transactions costs will remain unchanged with increased fragmentation from the home exchange.

H$_1$A: Transactions costs will decrease with increased fragmentation from the home exchange.

There is varied evidence on the impact of fragmentation on transactions costs in the home exchange. Bessembinder (2003), for example, finds that increased fragmentation is associated with lower spreads. He finds that non-NYSE markets signal their intent to trade by entering the market with competitive quotes, and post quotes away from the national best bid and offer (NBBO) when they do not wish to trade. Batallio (1997) poses the cream-skimming hypothesis, which states that traders compete for certain lot sizes they find more valuable in which to trade. He documents Madoff Securities competition for order flow only in lots under 5,000 shares, and finds that when Madoff Securities opted to do execute in lots under 5,000 shares, spreads decreased. However, this behaviour was restricted to Madoff's trading preferences – spreads were unaffected except when Madoff desired to enter the market as a counterparty to liquidity seekers. Madhavan (1991) contends that additional fragmentation diminishes existing economies of scale, and Batallio (1997) provides evidence that when Madoff was not seeking to trade, Madhavan's (1991) hypothesis is correct.

Hypothesis one is tested on all data sets, to examine how differing market structures and the resultant fragmentation affect transactions costs.

H$_2$0: MiFID's best execution mandate, inducing fragmentation, will have no impact on transactions costs.

H$_2$A: MiFID's best execution mandate, inducing fragmentation, will result in significantly decreased transactions costs.

Chung and Chuwonganant (2010) find that spreads increase and depth decreases after the introduction of Reg NMS in the US. They interpret this as market participants' prioritization of their trades by metrics other than price, such as lower latency and the anonymity resulting from order splitting. Therefore, the resulting order dispersion reduces economies of scale on the original exchange, leading to a higher price of liquidity as measured by transactions costs. This evidence substantiates Madhavan's (1991) theory that increased fragmentation leads to higher transactions costs.

The implementation of MiFID required market operations to invest in substantial systems in order for them to assess where best execution is found. Additionally, MiFID increased the compliance burden on market participants, who have to report their execution results. Market operators might rationally seek to recoup these investments through higher spreads. In Grossman's (1992) model, he explicitly notes the cost of search. This cost is non-trivial, so it may be capitalized in spreads. In a vein similar to the Huang and Stoll (1996) model, the transition from a scenario in which one party (or an oligopoly) who is information-dominant in a security to a scenario in which the diffusion of that information among a plurality of players may significantly increase transactions costs. This effect may be particularly striking on Paris Euronext, where many securities have parties who are designated Liquidity Providers, whose job is to function as quasi-specialists, to ensure a consistent supply in liquidity for the share. Unlike specialists, however, they are not monopolists in the share.

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Bennett and Wei (2006) empirically test Madhavan's (1991) findings and document how fragmentation in NYSE-listed shares affects liquidity and volatility through a natural experiment in which NASDAQ firms switch to the NYSE, discovering that NYSE firms have lower bid-ask spreads that are attributable to the reduced fragmentation. Given that European securities markets operate in a similar way to US securities markets, one would expect increased fragmentation to lead to increased spreads. A factor that may influence transactions costs on Deutsche Borse – Xetra is the German government's differential treatment of algorithmic trading in terms of tax (Hendershott and Riordan 2009).

MiFID's best execution mandate may lead market participants to act as legally required in the US, and guided by MiFID, that of 'shipping orders' to the 'best' quotation by price. In this scenario, should a broker be able to obtain a better price for an asset on Chi-X than on the traditional exchanges, she will send the order to Chi-X for execution. However, it is noteworthy that neither the European Commission nor national securities regulators have taken any action against market participants for perceived failure to meet best execution requirements under MiFID.

Hypothesis two is tested on the four data sets at around the time of MiFID implementation – the data sets for London, Paris, Deustche Borse - Xetra and the 'pooled' data set including all three exchanges' shares. Because the best execution requirement in MiFID's regulatory change facilitated trading on Chi-X, MiFID's implementation is examined separately from the launch of Chi-X.

H$_3$0: The abolition of the concentration rule in France will have no impact on transactions costs, in comparison to the UK and Germany, where no concentration rule existed.

H$_3$A: The abolition of the concentration rule in France results in a significant decrease in transactions costs, in comparison to the UK and Germany, where no concentration rule existed.

One of MiFID's directives was to remove the 'concentration rule', an umbrella term used to refer to national regulatory requirements to ship orders to the established national exchange (e.g. in France, trades must go through Paris Euronext under the rule). It is clear that such a change will result in more choice to investors as to where to trade and whether on established exchanges, MTFs, or Systematic Internalisers (desks within banks matching orders). As a result, the scale of fragmentation in countries with the fragmentation rule (the EU except Germany and the Netherlands) leads to transition from a pure monopoly to competition. Under Hamilton (1979), the abolition of the concentration rule will result in competitive effects as new liquidity providers, such as Chi-X, strive to increase market share, and thus decrease transactions costs. However, if Madhavan's (1991) theory holds, additional liquidity providers across Europe will cause Paris Euronext's economies of scale to diminish, and thus, increase transactions costs.

Hypothesis three is tested on the pooled data sets. The effect of the removal of the concentration rule in French shares can be compared to Germany and English shares, two countries in which there was no concentration rule.

H$_4$0: The introduction of Chi-X will have no effect on spreads.

H$_4$A: The introduction of Chi-X will significantly reduce spreads.

The concentration rule will have a different effect than MiFID, as there are no sunk costs that market participants must recoup. Due to MiFID's best execution obligations, brokers were obligated to invest in technological solutions that would route orders to where they would execute more cheaply, because fragmentation provides a variety of venues on which trades can execute. While EU financial markets authorities do not enforce MiFID's best execution mandate strictly, they do ensure that financial markets participants publish reports stating how they achieved best execution. In the markets of Germany and the UK, where no concentration rule existed, financial markets participants can be expected to have already implemented systems that achieve best execution. However, because the abolition of the concentration rule is a side effect of MiFID, this chapter decouples the two processes by separately examining a jurisdiction (France) in which the concentration rule existed, as well as two countries (Germany and the UK) in which there was no concentration rule. Gresse and Gajewski (2007), in their study of the London Stock Exchange's SETS system, that lacked a concentration rule, find that SETS was characterized by higher stock price volatility, and hence inventory holders demand higher spreads to protect themselves against increased price risk. Conrad et al (2003) show that in the US, execution costs are reduced on Electronic Communications Networks (ECNs), the forerunners of the EU's Multilateral Trading Facilities (MTFs), of which Chi-X is the most prominent. Smith (2008) notes that traders have heterogeneous preferences, thus, some will opt for Chi-X due to lower latency (and less ability for agents to front-run principals) and greater ability for anonymity. Chistella et al (2007) mentions that Chi-X's market model and pricing structure is similar to the London

Stock Exchange and Deutsche Borse – Xetra and therefore, one may expect a differential effect from the introduction of Chi-X into the French market versus the British and Germany markets. However, one is only able to observe this effect on the margins because there is no clean observation window to examine the introduction of MiFID on the French market. Like previous hypotheses involving competition and fragmentation, existing literature presents two contradictory hypotheses. While Hamilton (1979) states that competitive effects will cause lower transactions costs, Madhavan (1991) notes that the introduction of a competitor does not necessarily increase liquidity, but cannibalises existing liquidity, leading to increased transactions costs. If *Fragmentation*'s coefficient is negative, then spreads have been reduced by Chi-X. If not, then the reduction in economies of scale caused by Chi-X's entry has increased spreads.

Hypothesis four is tested on the two data sets - those around the time of the launch of Chi-X on the London Stock Exchange and the launch of Chi-X on Deutsche Borse – Xetra.

H$_5$0: The fee cut on Chi-X, inducing fragmentation, will have no impact on spreads.

H$_5$A: The fee cut on Chi-X, inducing fragmentation, will have a significant impact on spreads.

Hendershott and Riordan (2009), find that algorithmic traders (which constitute a substantial amount of the activity on Chi-X) on Xetra engage in quasi-market-making behaviour, demanding liquidity when it is inexpensive, and offering it when liquidity's cost is expensive. Hendershott et al (2010) show that the introduction of algorithmic trading on the NYSE in 2003 decreased both spreads and the adverse selection component of the spread. However, Hendershott and Moulton (2009) show that NYSE's introduction of a hybrid system leads to

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increased spreads, as time-sensitive traders are willing to pay more for immediate execution. In addition, an increase in adverse selection under the hybrid system leads to spread increases. Notably, as many algorithmic participants execute in small blocks of shares, Barclay et al (2003) find that small trades, defined as those smaller than 1,000 shares, have a lower effective spread on exchanges with market makers than on ECNs/MTFs, and theorize that market participants see a greater adverse selection cost trading on anonymous platforms such as MTFs when compared with a known specialist or market-maker on a more established exchange. Hendershott and Jones (2005) find that overall liquidity decreased when Island, an American Electronic Communications Network, a technological antecedent to Chi-X, ceases to display its limit order book. In this vein, one may theorize that heightened activity on Chi-X will lead to more active competition on LSE, Paris Euronext, and Deutsche Borse – Xetra, and any activity that may catalyse Chi-X growth will lead to more active liquidity provision as measured in decreased transactions costs.

Chi-X cut its central counterparty clearing fees effective 1 March 2008[46], and for the first time offered less expensive implicit trading costs (pre- and post- trade costs, as opposed to transactions costs, which are explicit) than those on the established exchanges. Chi-X did not impose a uniform cut, but European CCP fee cuts were 32.1%, and UK CCP cuts were 11.8%. This reflects the different CCP fee environment in France, Germany, and the UK. Following from the Hendershott and Jones hypothesis that competition stimulated by the competitor to a domestic exchange will attract more liquidity to the market, one can assume that transactions costs in UK shares will fall upon Chi-X's entry to the UK market.

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[46] http://www.chi-x.com/trading-notices-pdfs/TradingNotice0045.pdf.

Hypothesis 5 is tested on the four data sets around the time of the Chi-X counterparty fee cut – one for London, Paris Euronext, and Deutsche Borse; and one with the pooled data set examining the Chi-X counterparty fee cut.

Testing liquidity poses some methodological challenges since existing literature does not define a specific model for liquidity. The general practice is to proxy liquidity as transactions costs[47]. It is uncertain what specific variables determine the level of liquidity, and therefore equation 5.1 posits a relationship between a number of key variables identified in the literature and transactions costs, which serve as a proxy for liquidity. This chapter operationalises transactions costs as relative effective spreads, because relative effective spreads represent the 'round trip' (buying and selling a share) trading costs. Measuring the 'round trip' cost is important, as the limit order book may have a different price for liquidity on the bid-side than on the ask-side.

This chapter presumes that trading and liquidity is a supply and demand interaction affected by several variables (See, for example, Demsetz, 1968). The model this chapter tests assumes that the associations are linear, but that it is not certain which variables are significant or in what direction (indicating differing impacts on liquidity). The estimation is made on a range of data representing order splitting (*Fragmentation*), size (*Number of Trades*), price volatility (*Standard Deviation*), and a country variable representing the presence of a concentration rule prior to MiFID (*France)*. Interaction variables are used to test the interaction between the key variable of interest, *Fragmentation*, and other variables.

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[47] Venkataraman (2004), Huang and Stoll (1996), and Bessembinder and Kaufman (1998) provide examples of execution cost studies.

The following equation is estimated using a range of data to test the hypotheses of interest:

Spread = a + β₁Fragmentation+ β₂ Number of Trades +

β₃ Standard Deviation + β₄France + β₅Fragmentation*Number of Trades +

β₆Fragmentation*Standard Deviation + β₇Fragmentation*France

+ ε.   **(5.1)**

The variables are defined as follows:

> ***Spread,*** following Venkataraman (2001), is the relative effective spread of a share
>
> measured as a percentage of the share's price. Venkataraman (2001) defines it as:
>
> ***Relative effective spread (percentage) = 200 * D_{it} * ($Price_{it}$ - Mid_{it}) /Mid_{it}.*** **(5.2)**
>
> where D_{it} is the direction of the trade (buy or sell), $Price_{it}$ is the traded price, and
>
> Mid_{it} is the prevailing bid-ask midpoint.
>
>
>
> ***Fragmentation*** is measured as the percentage of shares trading on the home exchange
>
> divided by the total number of shares trading on the home exchange and Chi-X. As
>
> volumes on other European exchanges post-MiFID are trivial, they are removed for
>
> the purpose of analysis. Therefore, a share not listed on any other exchange has a
>
> fragmentation value of 1, and a share evenly split between the home exchange and
>
> Chi-X has a value of .5. Therefore, ***Fragmentation*** represents the relative dispersion
>
> of order flow between the established exchange and Chi-X.

Number of trades is measured as the natural logarithm of the total trades in a given security. As such, it represents raw order flow in a share – the larger the number, the more activity in a share. However, this is mitigated by the price of a share – a share priced at 100 pence will likely have more transactions than a share priced at 1000 pence.

Standard deviation is measured as the 5-minute volatility of prices.

France is an indicator variable testing the effect of the concentration rule, as among the three exchanges examined (France, Germany, and the United Kingdom), only France had a concentration rule mandating orders to be shipped to the established exchange prior to MiFID. It is 1 for all stocks with primary listings on Paris Euronext and 0 for all others.

Fragmentation* Number of Trades, *Fragmentation*Standard Deviation*, and *Fragmentation*France* in equation 5.1 represent the interaction between *Fragmentation* and other variables. They test the augmented effect on *Spread* over and above *Fragmentation* and its other interacting variable.

Industry1, *Industry2*, *Industry3*, *Industry4*, *Industry5*, and *Industry6* are dummy variables for industry categories to which an individual company belongs. *Industry* dummies are Utilities, Heavy Industry, Travel and Leisure, Basic Resources, Financial Services, and Miscellaneous, respectively.

In testing the hypotheses with equation 5.1, the following outcomes are expected if the null is rejected:

The test of the first hypothesis is measured with the direction and significance of $\boldsymbol{\beta}_1$, the coefficient for fragmentation. In all tests, if $\boldsymbol{\beta}_1$ is significantly less than zero, increased fragmentation is associated with decreasing spreads, which supports Hamilton (1979). However, if the estimate of $\boldsymbol{\beta}_1$ is significantly positive, increased fragmentation is associated with an increase in spreads in line with Madhavan's (1991) contentions. This is a hypothesis tested across all data sets and all events to examine whether increased fragmentation influences spread costs, and how. As the literature discusses, depending on whether fragmentation has a positive or negative effect on relative effective spreads, different theories may explain that behaviour.

The second hypothesis is measured only on the MiFID data set, consisting of the 3 months before and after the 1 November 2007 implementation of MiFID. This hypothesis examines whether the substantial systems investment required to build efficient routing systems for best execution caused market participants to recoup this investment in the form of increased spreads. As these systems were quite expensive, the second hypothesis tests whether the fragmentation these systems were built to capitalise upon reduced costs. If $\boldsymbol{\beta}_1$, the coefficient for fragmentation, is significantly greater than zero, then the increased fragmentation is associated with rising costs. This is presumably driven by liquidity providers needing to compensate themselves for the infrastructure they created to ensure optimal execution. If $\boldsymbol{\beta}_1$ is statistically no different from zero or less than zero, it can be concluded that market participants did not demand a higher price for liquidity, and therefore recoup costs on these systems.

The test of the third hypothesis is the coefficient of β_4, the coefficient for France. This test can only be performed on the 'pooled' dataset involving all UK, French, and German shares for the time horizon around the implementation of MiFID., as the goal of this test is to determine whether the presence of a concentration rule in France had a different impact from that of Germany or the United Kingdom. If β_4 is significantly less than zero, the presence of a concentration rule has dramatically impacted the reduction in spreads on French shares in the pooled sample. Therefore, the concentration rule ensured order flow went through an oligopoly of providers on the Paris Bourse, and before MiFID's abolition of it, there was not a competitive market for liquidity. If β_4 is significantly greater than zero, the presence of a concentration rule meant that French market participants could not adroitly react to MiFID's integration of European securities markets and the concurrent competition.

The fourth hypothesis examines whether Chi-X's central counterparty fee cut affected trading costs. This test is performed on all the datasets examining the time prior to and after the introduction of Chi-X's central counterparty fee cut. As Chi-X's rationale for cutting an implicit cost would be to garner increased order flow, β_1, the coefficient of ***Fragmentation***, is examined. As a cut in the costs imposed on traders will drive fragmentation, a reduction of Chi-X's central counterparty fees is potentially of interest in that it is not an explicit (variable) cost of liquidity, but a fixed cost of trading and utilizing Chi-X's services. If β_1 is statistically significantly less than zero, the fragmentation resultant from the central counterparty fee cut reduced trading costs.

The other coefficients in equation 1 represent the following effects, and are expected to have the following signs: β_2, the coefficient for ***Number of Trades***, represents a 'size effect' and is expected to have a negative coefficient in all the hypotheses and data sets tests – the larger

the volume of trading in a share, the narrower the transactions cost. β_3, the coefficient for

Standard Deviation, examines the volatility in a share. Existing literature shows that

volatility can have two different effects – either those holding inventory seek to liquidate it

due to the risk of fluctuating prices, or they demand a larger spread to compensate for

gyrating prices. Coefficients β_5 through β_7 represent the interaction of the *Fragmentation*

variable with *Number of Trades*, *Standard Deviation*, and *France,* respectively. Given the

expectation that *Number of Trades* will have a negative coefficient at all times, the nature of

the coefficient's interaction with *Fragmentation* is dependent on whether Hamilton's (1979)

or Madhavan's (1991) theory of fragmented order flow holds. Given the differing theories in

existing literature, the same conclusion holds for the interactions between *Fragmentation* and

Standard Deviation, as well as between *Fragmentation* and *France*.

3. Data and Method

The data is constructed from Thomson Reuters Tick History (TRTH) tick data for the period

from January 2007 to September 2008[48]. Using Trade and Quote (TAQ) files, monthly data

sets are constructed, including monthly averages of certain variables for every share listed on

each of three main European exchanges: London Stock Exchange (LSE), Paris Euronext

(Paris), and Deutsche Borse – Xetra (Xetra). Further analysis past September 2008 is not

performed due to the turmoil in financial markets that would confound analysis. All the

shares traded on the three exchanges are used[49], and then shares are excised from the sample

that have primary listings elsewhere. Therefore, the data sets do not include UK shares

trading on Paris Euronext or Deutsche Borse, as the volume in UK shares on the two

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[48] The TRTH data is accessed through the Securities Industry Research Centre of the Asia Pacific's (SIRCA) platform.
[49] e.g. British Petroleum, listed on London, is BP.L, where the .L indicates London. .PA indicates Paris listing, and .DE indicates Xetra listing.

exchanges is negligible. Monthly analysis is per Sidhu, Smith, Whaley, and Willis (2008), because daily files may be overly driven by extreme events, and may hence provide unrepresentative results over the course of the time period studied. An exogenous event that may lead to high liquidity demand in the market (e.g. the default of Lehman) may bias examined values and lead to conclusions that are not related to interactions between the variables of interest. In addition, monthly data is used to produce a time series effect that can be analysed.

The data sets include variables representing liquidity (relative effective spread, realised spread, and price impact), size effects (value of shares traded in the month and number of trades in the month), price volatility (standard deviation), latency (average time between trades), and idiosyncratic variables (such as country of primary listing, industry grouping, and fragmentation percentage between Chi-X and the primary exchange upon which the shares are listed). Companies are grouped into industry according to whether they belong to one of six categories: Utilities, Heavy Industry, Travel and Leisure, Basic Resources, Financial Services, and Miscellaneous. These dummy variables were incorporated to ensure that results are robust to industry category and that industry category is not a driver of transactions costs. However, investigation of industries shows no statistical link between industrial categories and the relative effective spread, so this variable is omitted from further analysis. Furthermore, as this chapter seeks to test fragmentation's effect on prices, illiquid shares (the highest 10% of spreads) are removed. Tests on these shares show that illiquid shares bias the significance of variables around events. By way of example, spreads in illiquid shares are primarily driven by the lack of an active market for them, as opposed to fragmentation, trading country of origin, or short term volatility. Therefore, illiquid shares are not examined,

as they will not assist in the determination of whether fragmentation affects relative effective

spreads. Therefore, analysis is performed on the final clean dataset of liquid shares where the

provision of liquidity is competitive. Both a dataset including the illiquid shares traded on EU

exchanges as well as one restricted solely to liquid shares is analysed to determine whether

behaviour reflects that of the entire market, or solely liquid subsections of the market. This

segmentation allows one to determine whether behaviour is characteristic of the entire

market, or only that of liquid shares. This method of analysis allows this chapter to draw

conclusions and determine whether they are applicable to the entire market or just the liquid

section, which may reflect the behaviour of institutional traders. In addition, the exchanges

are examined both individually and collectively – although as Chi-X began to offer Paris

CAC (*Cotation Assistee en Continu*, the major index of the French market) shares only in late

September 2007, Paris is only included in 'pooled' estimates for the fee cut and MiFID[50].

Therefore, the Chi-X launch dataset's window encompasses both January to March 2007, the

three months prior to the launch of Chi-X, and May to July 2007, with April 2007 excluded

as the month of the event. The MiFID implementation dataset's window starts in August

2007, running through the end of February 2008, excluding the November implementation of

MiFID. The Chi-X central counterparty fee cut dataset starts January 2008 and ends July

2008. Further analysis on events in the European markets is not performed due to the

instability induced by the global financial crisis.

Bayesian Information Criteria (BIC) modelling is used to specify the appropriate variables

tested from equation 5.1. The model with the lowest BIC value that still includes the variable

of relevance for hypothesis testing, ***Fragmentation***, is then estimated. Bayesian inference is

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[50] The effect of Chi-X competition on Paris is excluded, as no clean event window exists, using an observation window of the three months before and after the events of interest.

used to determine which variables account for a best fit on each of the data sets over each time horizon. This procedure is used for every data set. Per Raftery (1996), Bayesian Information Criterion (BIC) modelling is useful when theory lacks a specific model and one needs a mechanism to identify which variables are relevant in testing a model. The regression is estimated on each data set using maximum likelihood estimation procedures[51], allowing for the testing of the differential impact of various events on each of the three securities exchanges individually, as well as collectively. Additionally, the models tested are not homogenous, as the Bayesian Information Criterion (BIC) filter specifies different models to test on the various data sets. For example, BIC modelling does not always indicate that the interaction variables are relevant.

Bessembinder (2003) notes the importance of averaging methods when performing intermarket studies, as measures are very sensitive to differing treatments and quote initiation measures. As a result, monthly averages are used, and the Lee and Ready (1993) algorithm identifies the party initiating the trade. Zhao and Chung (2007) and other studies[52] have settled on trade-weighted means as the unit of analysis, and their methods are followed. Stock months are used per Chung et al (2010) and Sidhu, Smith, Whaley, and Willis (2008), as daily analysis may be highly sensitive to biases with tail events occurring.

Maximum Likelihood Estimation (MLE) is a methodology that can be used when one is uncertain of the distribution of the data examined, and finds parameter estimates that would be most probable to create a distribution most likely to result in the data examined. Maximum Likelihood Estimation is statistically more robust than other estimation methodologies, and is

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[51] PROC GENMOD in SAS.
[52] Bessembinder (2003) and Chung, Van Ness, and Van Ness (2004) employ this methodology.

thus used in this experiment[53]. As it cannot be automatically assumed that transactions costs

follow a normal distribution, MLE is more appropriate than Ordinary Least Squares or

Generalized Least Squares estimation procedures.

This chapter assumes a linear association between the variables examined in the regression

5.1 and the relative effect spread, which proxies for transactions costs. In all estimates, the

relative effective spread of a share, in percentage of share price, is the dependent variable and

is represented by **Spread** in the following models. Relative effective spread represents the

round-trip (buy and sell) trading cost, and is defined as two multiplied by the natural

logarithm of the quote midpoint divided by the trading price. It is calculated as a percentage

of the traded price of the security so that securities can be compared across prices. Relative

effective spreads are the measure of analysis in many contemporaneous studies, including

Chung and Chuwonganant (2010) and Zhao and Chung (2007). These studies utilise relative

effective spreads as a 'round trip' cost of trading, so analysis includes differential liquidity on

both sides of the limit order book. As previously mentioned, relative effective spreads is a

proxy for liquidity in that it has a linear negative relationship with liquidity – the lower the

relative effective spread for an asset, the more liquid is the market for it.

4. Empirical Results and Discussion

Fragmentation affects spreads during the advent of MiFID and prior to the Chi-X fee cut. As

the coefficients for all regressions are negative, Hamilton's (1979) theory that increased

competition leads to decreased spreads holds. However, **Fragmentation**'s coefficient is only

statistically significant for LSE and Xetra (as well as the pooled sample) for the

implementation of MiFID and the Chi-X counterparty fee cut, as Table 2 displays. The

launch of Chi-X does not have a statistically significant impact on fragmentation on any

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[53] Myung (2003) describes the properties and uses of Maximum Likelihood Estimation.

exchange, and the level of fragmentation does not have a statistically significant impact on Paris Euronext at any time. In the pooled sample, consisting of shares from all three exchanges, *Fragmentation*'s coefficient is negative and statistically significant at the 1% level for the implementation of MiFID and the Chi-X counterparty fee cut, as well as the interaction between *Fragmentation* and *Number of Trades*. Differences in significance occur between the Chi-X counterparty fee cut only on LSE, because *Fragmentation* has a statistically significant effect at the 1% level on the LSE for the counterparty fee cut, while *Fragmentation*'s statistical significance for the implementation of MiFID is at the 5% level. However, the implementation of MiFID and the Chi-X counterparty fee cut are of equal statistical significance, that of the 5% level, on Deutsche Borse – Xetra. While *Fragmentation*'s coefficient is negative on Paris Euronext, it is not statistically significant. A possible explanation for the differential effect of *Fragmentation* between the London Stock Exchange and Deutsche Borse - Xetra is due to the treatment of algorithmic trades in Germany. As algorithmic trades have special tax treatment in Germany, high frequency market participants on Deutsche Borse - Xetra may not be as sensitive to marginal changes on Chi-X as those on the London Stock Exchange. Gresse's (2010) contention that the cost of liquidity under MiFID was only reduced for those who can access multiple liquidity providers seems to be borne out by the distinction in the results in Table 2 between *Fragmentation* and *Fragmentation*Number of Trades.* While *Fragmentation* has a negative coefficient, *Fragmentation*Number of Trades* has a positive coefficient. However, Table 3, displaying regression estimates, shows a number of factors impacting relative effective spreads. As one can expect, the greater the number of trades in a share, the lower the relative effective spread. Recall that a share solely traded on the London Stock Exchange, Paris Euronext, or Deutsche Borse - Xetra has a fragmentation score of 1, so a positive

coefficient means the higher the concentration of share trading, the higher the spread. The relative lack of fragmentation on Paris Euronext may drive results on Paris Euronext. As Chi-X only initially listed CAC 40 (the major French index) shares in September 2007, the order flow in Paris was not as fragmented as that in Xetra and London. Nevertheless, by the time of the fee cut, Paris's fragmentation was greater than that of that of London and Deutsche – Borse Xetra around the time of MiFID, as Table 2 displays. Due to the finding that fragmentation has a negative and statistically significant coefficient, hypothesis 1 is rejected, as transactions costs decrease with greater fragmentation in all scenarios. Furthermore, even in the case of Paris, fragmentation has a negative coefficient, albeit one that is not statistically significant.

Table 2: Parameter Estimates for Transactions Costs

The results are from the Maximum Likelihood Estimation of *Spread = a + β₁Fragmentation+ β₂ number of trades +β₃Standard Deviation +* $Spread = a + \beta_1 Fragmentation + \beta_2\ number\ of\ trades + \beta_3 Standard\ Deviation + \beta_4 Fragmentation + \beta_5 France + \beta_6 Fragmentation*Number\ of\ Trades + \beta_7\ Fragmentation*Standard\ Deviation + \beta_8\ Fragmentation*France + \varepsilon$. However, β_5 is only estimated on the pooled dataset, as only the pooled dataset allows for a comparison of French shares with British and German shares. ***Spread*** is the relative effective spread as a percentage of share price, ***number of trades*** (LNTrades) represents the natural logarithm of the number of trades in a security, ***Standard Deviation*** (stddev) represents the 5-minute volatility of share prices, and ***Fragmentation*** is the percentage of a stock's total volume transacted on the national exchange. ***France*** is an indicator dummy set to 1 if a share is listed in France. ***Fragmentation*Number of Trades*** (FragTrades), ***Fragmentation*Standard Deviation*** (FragSD), and ***Fragmentation*France*** (FragFrance) represent the interactions between these variables. P-values are in brackets underneath parameter estimates.

Exchange	Event	Intercept	LNTrades	Stddev	Fragmentation	France	FragTrades	FragSD	FragFrance
LSE	Chi-X	49.911	-4.4831	0.0143	-40.9615		3.8335	-0.0128	
		(<.0001***)	(<.0001***)	(0.2121)	(0.3438)		(0.3187)	(0.7372)	
	MiFID	40.4985	-3.1228	-0.0292	-21.4959		1.7676	0.0321	
		(<.0001***)	(<.0001***)	(0.0358**)	(0.012**)		(0.0227**)	(0.049**)	
	Fee cut	31.724	-2.5086	-0.0132	-17.5168		1.4505	0.016	
		(<.0001***)	(<.0001***)	(0.1275)	(<.0001***)		(<.0001***)	(0.1022)	
Paris	MiFID	72.1857	-5.6368	-0.964	-54.9515		4.4925	0.5283	
		(<.0001***)	(<.0001***)	(0.0073***)	(0.5041)		(0.5184)	(0.7851)	
	Fee Cut	62.7835	-4.6317	-0.7801	-54.0923		4.0568	0.6916	
		(<.0001***)	(<.0001***)	(0.0218**)	(0.3879)		(0.4452)	(0.6594)	
Xetra	Chi-X	62.4502	-5.6901	0.3172	-56.61		5.2918	-0.3164	
		(<.0001***)	(<.0001***)	(0.1988)	(0.3613)		(0.3327)	(0.4868)	

	MiFID	65.5859	-5.8901	0.2713	-58.3078		5.4085	-0.2997	
		(<.0001***)	(<.0001***)	(0.5874)	(0.0257**)		(0.0209**)	(0.7235)	
	Fee Cut	53.3868	-4.7563	0.0482	-47.8679		4.429	-0.0846	
		(<.0001***)	(<.0001***)	(0.526)	(0.043**)		(0.0346**)	(0.8522)	
Pooled	MIFID	52.606	-4.3014	-0.0224	-32.1676	-0.1487	2.7707	0.0314	0.8073
		(<.0001***)	(<.0001***)	(0.2174)	(0.0008***)	(0.8611)	(0.0012***)	(0.1415)	(0.6281)
	Fee Cut	52.2604	-4.5219	0.0158	-39.3551	1.5199	3.5809	-0.0134	-1.1883
		(<.0001***)	(<.0001***)	(0.2925)	(<.0001***)	(0.0776*)	(<.0001***)	(0.4605)	(0.4181)

*** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table 3: Descriptive Statistics of the Data Examined

This table presents average values for various data sets used. **Relative Effective Spread** represents the relative effective spread of a share, calculated as a percentage of the share's price. **Number of Trades** is the natural logarithm of the number of trades executed in a share. **Standard Deviation** is the 5-minute volatility of prices. **Fragmentation** measures the percentage of order flow between an exchange and Chi-X, where 1 indicates total order flow on the original exchange, and 0 indicates total order flow on Chi-X.

Exchange	Event	Relative Effective Spread	Number of Trades (natural logarithm)	Standard Deviation	Fragmentation
LSE	Chi-X launch	7.7067	9.2180	22.5904	0.9999
LSE	MiFID	7.5125	10.2334	31.5747	0.9916
LSE	Chi-X cut	4.7589	10.3987	33.6950	0.9319
Paris	MiFID	19.6178	9.0377	1.7163	0.9968
Paris	Chi-X cut	17.6127	9.1469	1.8075	0.9826
Xetra	Chi-X launch	12.6385	8.8940	1.6500	0.9998
Xetra	MiFID	11.6585	9.4869	1.8446	0.9916
Xetra	Chi-X cut	9.9213	9.4854	2.4859	0.9725
Pooled	MiFID	10.0578	9.8380	19.2961	0.9928
Pooled	Chi-X cut	8.8003	9.8539	20.5676	0.9524

The fee cut displays the highest statistical significance in the sample for the London Stock Exchange and the pooled sample. This would indicate that the fragmentation of the London market (a component of the pooled sample) around the time of the changes in infrastructure access costs (such as pre- and post- trading costs, including central counterparty fees) is the strongest determinant of relative effective spreads[54]. However, MiFID has a statistically significant impact on Deutsche Borse – Xetra and the London Stock Exchange both at the 5% level, and at the 1% level in the pooled sample. This finding is more startling in light of the lack of active enforcement of MiFID. Whilst the SEC actively enforced Reg NMS, MiFID's American corollary, MiFID's initial strictures only required trading firms to publish the extent to which they met best execution benchmarks. This was further complicated by the lack of a clear legal definition for best execution, as MiFID mentions 'price, costs, likelihood of execution and settlement, size, nature, or any other consideration' as factors upon which best execution is defined. However, MiFID mentions that the trading party (when brokers are trading as an agent for a customer) may ultimately define the benchmark for 'best execution'. Due to the lack of any sort of transparency in order data, one is unable to assess whether best execution has been met. Therefore, in submitting their reports for the extent to which they met their fiduciary obligation under MiFID, brokers could claim time priority in filling an order, 'size' priority (in terms of VWAP or another benchmark under which they could claim they obtained the optimum price for the size of the order), or price priority (absolute best price). Nevertheless, at least a perception that best execution was a required benchmark by national regulators led market participants to seek best execution, loosely defined in terms of price, but with time as an important factor. As a result of this competitive pressure, liquidity

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[54] The fragmentation of order flow between the London Stock Exchange and Chi-X is examined from a price discovery perspective in chapter 4.

providers offered narrower spreads to liquidity demanders, which empirical evidence

substantiates.

MiFID is found to reduce trading costs because of the fragmentation that its implementation

catalysed. On both the London Stock Exchange and Deutsche Borse - Xetra, *Fragmentation*

is statistically significant at the 5% level, and *Fragmentation* is statistically significant at the

1% level in the pooled sample. All three datasets show *Fragmentation* with negative and

statistically significant coefficients. Therefore, at least for these datasets, hypothesis two can

be rejected. However, although the Paris Euronext MiFID data set has a negative coefficient,

it is not statistically significant. It is worth noting that MiFID is the first event where

Fragmentation is statistically significant. Therefore, the launch of Chi-X does not affect

spreads at a statistically significant level. Hypothesis four is therefore not rejected, that the

introduction of Chi-X and the resultant fragmentation did not affect spreads. Therefore,

empirical results do not show any effect of fragmentation on relative effective spreads during

the launch of Chi-X in any of these three European markets. One reason for this could be the

lack of a 'critical mass' traded on Chi-X. If there is insufficient liquidity at or near the BBO

(best bid and offer), what may appear to be competition is illusory, because market

participants cannot achieve similar execution quality on Chi-X for any meaningful

transaction, and trading costs for a representative order may in fact be higher on Chi-X due to

the laddering of the limit order book. This may be explained by the pan-European nature of

MiFID and that it included a regulatory mandate to route orders to Chi-X under the best

execution requirement. Therefore trading behaviour was dictated solely at the discretion of

brokers, instead of an implicit competitive pressure essentially determined by whether

liquidity providers on Chi-X would offer comparable spreads around the launch of Chi-X, or

whether net trading costs were lower after the Chi-X central counterparty fee cut (which, ,
was differential between the three exchanges examined). While the central counterparty fee
cut was only 11% in London, it was 32% in Germany and Paris. Presumably, this reflects
different price elasticities of demand for consumers of trading services, because market
participants had an explicit legal requirement (albeit one that was not strictly enforced) to
ship trades. Another reason the advent of Chi-X may have less robust effects on a pooled
dataset is that Germany and the UK lacked a national 'concentration rule' that required any
trades in a domestically-listed security to be sent to the national exchange. This created a
monopoly on behalf of national exchanges in France, Italy, and other countries. However, in
the two nations with a history of competitive provision of trading services, the introduction of
a new competitor by itself may not dramatically alter the competitive scene for trading
services. Therefore, the existence of Chi-X as a competitor in and of itself does not catalyse
competitions, but rather, the competition and order-splitting galvanized by the
implementation of MiFID lead to competitive pressures and the reduction of transactions
costs.

In addition, costs attributable to infrastructure (pre- and post-trade) costs may create a
situation where, although relative effective spreads and other explicit costs are comparable
and competitive, the cost inclusive of infrastructure rents (like central counterparty costs)
may be uncompetitive with the traditional exchanges. Table 3 notes the average variable
values for each dataset, and it is worth noting that fragmentation is above 99% on both
Deutsche Borse - Xetra and the London Stock Exchange around the time of Chi-X's launch.
Therefore, competition between the established exchanges and Chi-X may not be sufficiently
intense to provide for any effects that may reduce transactions costs, as measured by relative

effective spreads. On one hand, Chi-X initially guaranteed liquidity in FTSE and DAX components, so a selection process is inherent in the results. However, the dominance of this result across the sample seems to indicate that there was a fair bit of competition between the traditional exchanges and Chi-X. This may reflect liquidity search on Chi-X, or a desire for some of the larger traders to split their orders between the exchanges so that their competitors could not detect their 'footprint' and free-ride off their trades. Another factor may be the lower latency of Chi-X. With the introduction of Chi-X, latency sensitive-traders migrate there. This effect would be absent in subsequent changes, as MiFID and the Chi-X central counterparty fee-cut focus more on price-sensitive traders.

With the results on the sample showing that the fee cut is the event around which *Fragmentation* has the greatest statistical significance, hypothesis five is rejected. However, although the London Stock Exchange and the pooled sample have statistical significance at the 1% level and Deutsche Borse - Xetra has statistical significance at the 5% level, Paris Euronext lacks statistical significance. *Fragmentation* possesses a negative coefficient in all regressions. This can be read in two ways: one, that market participants eagerly sought best execution inclusive of pre and post-trade costs. Two, that market participants were able to capture increased profits by migrating to venues with marginally lower implicit trading costs. Regardless of the explanation, given that lower central counterparty costs either flow to the security's owner or to the firm trading as agent for the security's ultimate owner, parties will be sensitive to lower inclusive trading costs.

A possible explanation for the divergent effect of *Fragmentation* on the two continental exchanges may be due to the market structure of Deutsche Borse - Xetra and the tax

treatment of algorithmic trading. Xetra is characterised by a higher proportion of algorithmic trading than other European exchanges, and Germany has a special tax treatment for algorithmic trades. Therefore, to remain competitive with dealers on Chi-X, presumably Xetra dealers had to slash spreads while accounting for the tax differential.

The concentration rule affected spreads, as the *France* dummy in the pooled sample is significant at the 10% level around the Chi-X counterparty fee cut. This indicates that the costs were higher due to centralisation (monopoly power of trading). After MiFID abolished that rule, French shares had a more competitive market in liquidity provision, which is reflected in this finding. Therefore, hypothesis three is rejected. An institutional characteristic of the Paris bourse is the presence of market makers known as Liquidity Providers. These participants, whose role is similar to that of a specialist – to ensure price stability and sufficient ability to potentially trade in these shares - led Parisian traders to remain on Paris Euronext, because the Chi-X order book might lack a preferred level of liquidity for trading in some shares. Liquidity Providers are quasi-specialists each backing a certain share. With this specialist system, the specialist will need to protect himself from price swings through a spread. However, once MiFID and the Chi-X fee cut spur competition, the Liquidity Provider is no longer a monopolist in certain shares, because MiFID abolishes the concentration rule - and the fee-cut may lead to competition in liquidity provision from parties other than Liquidity Providers. However, due to Liquidity Providers' substantive role in the Paris market, this may account for the finding that *Standard Deviation* is statistically significant at the 1% level for around the time of the implementation of MiFID and at the 5% level around the time of introduction of the Chi-X central counterparty fee cut. Because the coefficient is negative, the lower the volatility, the lower the transactions costs. This is consistent with existing literature modelling volatility's effect of transactions costs. While this volatility

effect is persistent on Paris Euronext, it appears on the London Stock Exchange and Deutsche Borse – Xetra only around the time of the introduction of MiFID. This may reflect a market for more competitive liquidity provision around MiFID, as European authorities seek to enforce best execution practices. However, the effect is not uniform across the London Stock Exchange and Deutsche Borse – Xetra. The London Stock Exchange has a negative and significant (at 5%) coefficient from *Standard Deviation*, but Deutsche Borse – Xetra has a positive and significant (at 5%) coefficient around the time of the implementation of MiFID. One explanation for this divergence may be the higher rate of algorithmic/high frequency traders on the established exchange in Germany due to the special tax treatment afforded to algorithmic trades.

Number of Trades, which serves as a proxy for firm size or liquidity, is continually a significant determinant downwardly affecting spreads, although this is not surprising. This may be due to two different causes. On one hand, this could be an obvious reflection of increased liquidity in the larger shares traded on exchanges. On the other hand, the magnitude of this effect seems to indicate that something else is driving it. The 'size effect' is significant at the 1% level for all data sets examined.

In all instances where *Fragmentation* is statistically significant, the interaction between *Fragmentation* and *Number of Trades* is also statistically significant. Therefore, increased *Fragmentation* in the presence of high liquidity drives lower transactions costs. Additionally, on the London Stock Exchange *circa* the implementation of MiFID, the interaction between *Fragmentation* and *Standard Deviation* is statistically significant at the 5% level. This could reflect short-term volatility induced by MiFID's best execution requirement and arbitrageurs' attempts to profit from the differences between costs on the London Stock Exchange and Chi-X.

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5. Conclusion

MiFID affected transactions costs, but not to the extent that an infrastructure change (Chi-X's fee cut) did. To that extent, MiFID must be viewed as a catalyst that facilitated the launch of MTFs such as Chi-X and stimulated competition in liquidity provision. MiFID's effect on France's concentration rule is twofold: Although country variables are not statistically significant, fragmentation increases spreads[55] in Paris. This is explained by market participants' need to recapture their investment in systems to meet the best execution mandate. The starkest results show that the augmented competition on the London Stock Exchange, stimulated by the Chi-X central counterparty fee-cut, slashed spreads. This result is still highly significant even in the presence of confounding variables.

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[55] E.g. *Fragmentation* has a negative coefficient.

Chapter Six:

Conclusion

Regulation of financial markets has focused on questions of welfare and equity since the Great Depression. Among these questions is that of the fair price of capital and the functioning of markets for all participants. A form of market abuse is insider trading – resting on the basis that the insider is capitalising on information he has misappropriated from the corporation, and is thus exploiting his trading counterparty. Central to the confidence of the public in securities markets is the belief that regulatory authorities properly monitor the markets to find and prosecute any parties participating in market abuse. These efforts raise the question of how apparent insider trading is in terms of its impact on the markets.

Chapter 3 finds that insider traders move prices more than non-insiders, but transact in marginally larger lot sizes. However, their impact on prices seems to be driven by the desire of insiders for instant execution certainty, because insiders use of buyer-initiated 'buy' orders (market orders) accounts are highly significant. This may also be driven by aggressive insiders executing significant lot sizes, and thus 'walking the limit order book', resulting in a greater price impact. In addition, the anonymity hypothesis of Glosten and Milgrom (1985) is verified, as trades on specialist exchanges move prices in a highly significant (1% confidence level) fashion, while those on dealer exchanges are not statistically significant.

The transformation of securities markets has raised two important threads of questions on informed trading – in the context of insider trading, the increasing sophistication of securities markets and communications technologies has led critics of the markets to wonder how equitable they are and whether predation of retail investors takes place by parties with better

information. In the context of informed trading, the growing move towards electronic trading and technological methods of portfolio allocation have led to new means of trading – both computer-mediated trading as well as off-exchange trading with the introduction of Multilateral Trading Facilities. The move to technology has also led to regulatory efforts to ensure retail customers obtain the best terms for their orders in terms of price. As a result, international securities markets have moved towards national (US' Reg NMS) or continental (EU's MiFID) models. These obligations have created a transformation in the securities markets.

Chapters 4 and 5 investigate two aspects of the EU's MiFID regulation. Chapter 4 finds that although MiFID enabled the launch of Chi-X, a Multilateral Trading Facility, it was not its implementation but Chi-X's infrastructure fee cut that caused the majority of informed trades in UK shares to migrate from the London Stock Exchange to Chi-X. Chapter 4 uncovers different price discovery patterns for UK shares depending on whether they have other primary listings outside of the UK, and shows that quote-based price discovery patterns are vastly different from trade-based price discovery patterns in the case of liquid UK shares on the LSE and Chi-X. Chapter 5 finds that transactions costs on the London Stock Exchange, Deutsche Borse – Xetra, and Paris Euronext are all affected by MiFID, but not to the extent that the same counterparty fee cut on Chi-X leads to a decrease in relative effective spreads. A possible interpretation of this is that there is a large number of marginal traders extremely sensitive to both latency (speed of trading) issues and marginal costs of trading, as the central counterparty fee is a fixed cost and cannot be changed by the liquidity provider, but only by exchange and other trading infrastructure providers. While MiFID's abolition of the concentration rule did not affect spreads in France, spreads increase after MiFID in France,

indicating that in the case of the French market, a reduction in economies of scale occurred on Paris Euronext. Differences in reactions to volatility (as proxied by 5 minute standard deviation of prices) between the London Stock Exchange and Deutsche Borse –Xetra may be attributable to different tax treatment for algorithmic traders in the UK and Germany.

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