Empirical Analysis of Microstructural Dynamics Across Cross-listed Stocks on the London and Moscow Exchanges

Slawa Roschkow

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In memory of my mother

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Declaration of Copyright

Abstract

This thesis investigates the average and conditional price discovery relationship between the Moscow equity markets and London market for eight Russian cross-listed securities in six overlapping and continuous trading hours. The price discovery analysis is based on a range of sampling frequencies of quote and trades data derived from MICEX, RTS and LSE limit order books and the investigation is divided into two sub areas: the home market and the cross-border market. The analysis was carried out with respect to data type, price discovery contribution methodology, a cross-section of individual securities, chosen sampling, trading time, volatility and trading volume conditions. Overall, there is evidence from the analysis that MICEX is the major price discovery market for the eight cross-listed most liquid Russian securities, while RTS and LSE are satellite markets and have a supportive role. The findings of the conditional price discovery relationship suggest that volatility is positively correlated with the higher price discovery contribution of the higher volume trading market. In addition, the time at which trading takes place in overlapping trading hours has been shown to be associated with different price discovery proportions in the London and Moscow markets. Mid day trading has the lowest Moscow price discovery contribution. The daily price discovery relationship may not be affected by relative trading size, given that the findings for trading size effect were inconclusive. The overall findings can be attributed to the fact that MICEX is a more active trading market than RTS and LSE.

List of Abbreviations

ADF	Augmented Dickey-Fuller
ADR	American Depository Receipt
CET	Central European Time
CBR	Central Bank of Russia
CME	Chicago Mercantile Exchange
DAX	Deutsches Aktien Index
DJIA	Dow Jones Industrial Average
DR	Depository Receipt
DTB	Deutsche Termin Boerse
ECM	Error-Correction Model
ECN	Electronic Crossing Network
EMH	Efficient Market Hypothesis
ETF	Index Tracking Fund
FOK	Fill-Or-Kill
FX	Foreign Exchange
GDR	Global Depository Receipt
GG	Gonzalo and Granger (1995) common factor weight
GOC	Good-Until-Canceled
HF	High-Frequency
HIS	Hasbrouck (1995) Information Share
IBM	International Business Machines
IOB	International Order Book
LIFFE	London International Financial Futures and Options Exchange
LOB	Limit Order Book
LSE	London Stock Exchange
LR	Likelihood Ratio
MDH	Mixture of Distributions Hypothesis
MICEX	Moscow Interbank Currency Exchange

min	minute(s)
MLE	Maximum Likelihood Estimation
NASDAQ	National Association of Securities Dealers Automated Quotations
NYSE	New York Stock Exchange
OTC	Over-The-Counter
OLS	Ordinary Least Squares
PT	Permanent-Transitory
RQ	Realised Quarticity
RTS	Russian Trading System
RUB	Russian Ruble
RV	Realised Variance/Volatility
s	second(s)
SAS	Statistical Analysis System
SEHK	Hong Kong Stock Exchange
SETS	Stock Exchange Electronic Trading Service
SQL	Structured Query Language
SIC	Schwarz Information Criterion
SSE	Santiago Stock Exchange
S&P	Standard and Poor
TAQ	Trades And Quotes
TORQ	Transactions-Orders-Quotes
TSX	Toronto Stock Exchange
UHF	Ultra-High-Frequency
UK	United Kingdom
US	United States
USD	United States Dollar
VAR	Vector Auto-Regressive
VECM	Vector Error-Correction Model
XETRA	Exchange Electronic Trading

List of Cross-listed Securities

EESR	RAO United Energy Systems
GAZP	Gazprom
GMNK	Norilsk Nickel
LKOH	Lukoil
RTKM	Rostelecom
SIBN	Sibneft
SNGS	Sergutneftgas
TATN	Tatneft

Trading Volume Regimes

HH	Moscow High trading-London High trading volume
HL	Moscow High trading-London Low trading volume
LH	Moscow Low trading-London High trading volume
LL	Moscow Low trading-London Low trading volume

Volatility Regimes

Hi	Moscow High volatility
MedHi	Moscow Medium-High volatility
MedLo	Moscow Medium-Low volatility
Lo	Moscow Low volatility

Chapter One: Introduction

Chapter 1: Introduction

1.1 *Background to this Thesis*

While financial markets are extremely competitive by nature, the competition between two major stock exchanges on the Moscow market has come to an end as a result of the merger. Prior to the merger announcement, formerly known MICEX and RTS stock exchanges competed for order flow. Generally, competition across stock exchanges expresses itself through each market's order flow volume, e.g. equity securities, which are cross-listed across these exchanges. The competition for order flow across multiple markets reflects the informational contribution of each market, which can be measured by the concept of contribution to price discovery. One of the measurements of the informational contribution of a market is Hasbrouck (1995) information share. The information share of a market is an estimate of the proportion of information from the total order flow that the market has captured. As a consequence, markets which compete for order flow discover an unobservable equilibrium price of cross-listed security. The equilibrium price is, in essence, the result of order flow competition across the stock exchanges' trading process, a reflection of the reactions of market participants to the flow of information.

Historically, the Moscow equity market was made up of MICEX and RTS exchanges, which competed for and facilitated the trading of Russian cross-listed securities. It could be argued that the completion for the order flow of the most liquid cross-listed equity was lost by RTS to MICEX, since despite its earlier start, RTS equity trading volume migrated slowly to MICEX over the course of a decade. RTS has, nevertheless, managed to reposition itself, despite its loss of the leading liquidity providing position on the Moscow market. It accomplished this firstly by changing the security denomination from the USD to the RUB currency of the order driven market in 2010. By doing so, RTS became similar to MICEX - a national currency based market. Secondly, RTS has established itself as a leading derivatives market place by attracting more foreign institutional investors, gaining an advantage over MICEX in this segment of the market.

The securities of major Russian companies are cross-listed locally in Moscow and abroad, for instance in London and Frankfurt, in the form of depository receipts (DRs). Despite the showdown of the domestic Moscow competition for cross-listed securities, the battle for supremacy in order flow continues. Besides over-the-counter (OTC) trading, trading on cross-border venues is the third serious competitor. The largest cross-border competition representative is the London Stock Exchange, which has been facilitating trades for eight major cross-listed "blue chip" stocks in the form of American Depositary Receipts/Shares (ADR/ADS) since before 2006.

The pricing behaviours of the stocks traded across domestic and foreign markets are not necessarily identical, and the objective of this research project is to investigate the dynamics of the spreads by examining the locally traded stock and their foreign traded ADRs over a four month period. The most intriguing aspect of the undertaking is the analysis of the price discovery relationships and their further analysis based on high-frequency intra-day data reconstructed from the limit order books. This thesis aims to provide insight into the process of information transmission and the micro-dynamic behaviour of cross-listed securities across the competing markets.

1.2 *Motivation for the Research*

There are many publications in the field of cross-listing microstructure which examine price discovery on the domestic as well as on international markets. According to the findings of Eun and Sabherwal (2003), Grammig et al. (2005) and Phylaktis and Korczak (2007), and other research, there is evidence that the order flow intensive market may occupy the price discovery dominant position. However, there is still disagreement about conclusions based on the vast range of data and chosen sampling frequencies. Although there is strong evidence that market liquidity affects the price discovery contribution, the literature hardly touches on the subject of emerging markets, especially the Russian cross-listed equity market. The evidence in the cross-listed equity price discovery literature is insufficient to validate the established thesis that the more liquid market dominates the price discovery process in the case of the Russian cross-listed equity market.

The issue of where price discovery occurs for internationally traded securities does not seem to have been studied in any detail. It remains unclear if, as questioned by Grammig and Peter (2008), trading abroad, in the presence of microstructure effects, follows the home market or the home market follows trading abroad. A choice of higher sampling frequency may adversely affect the foreign market contribution to price discovery due to increased interaction of microstructure effects. Furthermore, clarification is required as to price adjustability in both markets. Does the law of one price or the assumption of no arbitrage opportunities require both markets to adjust simultaneously to new information, or is the adjustment completely asymmetrical, occurring in only one market?

In order to conclude that prices are mainly discovered in the home market, especially on the Russian emerging market, further research in the field of cross-listing and price discovery is required. It is necessary to prove that the lack of liquidity of the foreign market does not significantly affect the home price discovery relationship. For instance, according to Baruch et al. (2005), there is evidence that liquidity in the form of order flow is a strong determinant of where the price is discovered. However, it may also be true that if liquidity in a peripheral or satellite market rises, the price discovery relationship may change over time e.g. Harris et al. (2002a). It may also lose significance or become inconclusive, and the causality direction may become bi-directional. Assuming that prices are discovered in the underlying home emerging market by the means of higher liquidity, this would prove that the initial assumption made is correct. However, research using a larger, deeper and more diverse sample size is needed to confirm this hypothesis.

1.3 *Objectives of the Thesis*

The primary objective of the thesis is to investigate the price discovery relationship of three major stock markets MICEX, RTS and LSE, for eight Russian cross-listed securities in six overlapping and continuous trading hours. The data samples of all investigations are to be derived from the three underlying limit order books (LOBs), and the price discovery investigation are to be based on a range of sampling frequencies, different data types, samples and methodologies.

The first objective of the thesis is to reconstruct the MICEX, RTS and LSE IOB limit order books (LOBs) for the eight most liquid Russian cross-listed securities, and in order to minimise inaccuracies in the LOB reconstruction and data sampling, the processing is performed systematically via a SQL program. All the markets under consideration are order-driven, and are traded on the double sided auction principle; however each of the limit order books requires a distinct approach because of the differences in the data field nomenclature and peculiarities of the trading rules. The ultimate goal is to create chronologically synchronised time series samples based on each data type, and sampling frequency for each security of the chosen markets.

The second objective is to investigate the price discovery relationship on the domestic Moscow stock market between the RTS and MICEX exchanges, which have facilitated trading for the eight most liquid stocks. The analysis is to be based on an examination and comparison of the results for both data set types: order quotes and transaction prices. The inferences will be based on a range of sampling frequencies, and the analysis will focus on the performance between the two major and established price discovery contribution methodologies in the context of a range of different sampling frequencies. Cointegration between the underlying time series is expected. Lead-lag causality relationship is a point of interest as well as cointegration relationship restriction testing.

The third objective is to examine the cross-border price discovery relationship between Moscow and the LSE market. This differs from the second objective in that the sample now includes a cross-border trading competitor and the analysis can be performed in a trivariate fashion with existing state of the art methodologies. Here, the presence of market microstructure effects will be taken into account. The analysis seeks to optimize the choice of a sampling frequency, which, given the presence of microstructure effects, is crucial to the accuracy of the findings, and bases its inferences on this optimised choice, in contrast to an arbitrary chosen range of frequencies in the previous objective. The choice of an inopportune sampling frequency may lead to misleading results, and therefore the goal is to choose a sampling frequency which minimises the distortion induced by the effects of the microstructure noise, without, at the same time, being adversely affected by the contemporaneous correlation. Moreover, the results of cointegration restriction test of the MICEX-LSE can then be compared to the results of MICEX-RTS.

The fourth objective is to analyse the MICEX-LSE price discovery relationship in detail, by conditioning the original data set from the previous objectives. The investigated price discovery relationship is conditional because it is no longer based on an aggregated average of a common sample. The price discovery analysis is based on the standard multi-market methodology, however on prior conditioned samples upon the chosen factor. A sample can be conditioned by a factor by permuting the variables in a specific order. This is achieved by ordering the main sample by the chosen factor e.g. trading hour and then dividing the main sample into sub samples, which contain only the values of the temporal factor e.g. the first half an hour of each trading day. The permutation can be organised according to temporal factors such as the trading time and trading days, as well as the main trading variables such as volatility and trading volume.

Overall, the following key questions have been addressed in this thesis:

- Is there an unobservable equilibrium price as a result of the order flow competition from multiple (fragmented) market trading?
- Which of the markets leads/lags by discovering the equilibrium efficient price?
- What is the relative contribution of the individual market to the common efficient price?
- How sensitive are the results to the type of data, methodology and sampling frequencies?
- How stable is the price discovery when conditioned upon daytime, weekday and information conditions such as trading volume and volatility?

The thesis aims to contribute to the understanding of the information dynamics of cross-listed securities from the microstructure, emerging-developed market perspective. The thesis is to consist of three empirical chapters; Chapter 7 analyses the price discovery on the fragmented national Moscow equity market, while Chapter 8 examines the combination of the national markets and the international ADR counterparts on the London Stock Exchange. Chapter 9 seeks to investigate the effect of factors such as time, trading size and intraday volatility on cross-border pricing, based on the conditioned data set from Chapter 8.

1.4 *Contribution to the Literature*

This thesis aims to add value to the existing price discovery, cross-listing and LOB reconstruction literature in following ways: firstly, by addressing the price discovery issue in the context of the fragmented equity market in Moscow (Chapter 7); secondly, by investigating the cross-border price discovery relationship between the Moscow and LSE markets (Chapter 8); thirdly by analysing the MICEX and LSE price discovery relationship conditionally (Chapter 9). The main aim of the research is to contribute new insights to informational transmission and dissemination between the London and Moscow cross-listed equity markets. The uncovered evidence is based on the analysis of high frequency data derived from the three limit order books.

The key contribution is that Chapter 7 is the first study that addresses Russian cross-listed equity market price discovery. There are similarities in central-satellite market constellation between the Russian and US cross-listed equity markets. However, the data set of this investigation is distinctively different from US market data, because the price discovery issue addressed here is in the context of an emerging market. The price discovery relationship between the Moscow markets is unique, because of their equally unique economic, political and regulatory environment. For instance, in the research sample period, the trading is facilitated in an environment of capital control restriction, while the traded securities were denominated in different currencies. Despite the apparent similarity between the Russian and the US cross-listed equity markets, there are no studies in the price discovery literature that have touched on the subject of the Russian cross-listed equity markets. Although there is research on cross-listed equity in the US markets by Hasbrouck (1995, 2002) and Harris et al. (1995, 2002), Chapter 7 is the first study that puts forward the hypothesis about the relationship between MICEX and RTS. The hypothesis is that, the MICEX market is the central market just as NYSE is the central market in the US.

Furthermore, Chapter 8 is the only study that investigates the Moscow-London cross-listed equity market relationship; it addresses price discovery in the context of the emerging home market (MICEX and RTS) versus the foreign developed market (LSE). The major difference between Chapters 7 and 8, besides the geographical, political and economic differences in trading environments is that Chapter 8 deals with equity equivalent ADR securities, not locally traded stocks. An American Depositary Receipt (ADR) or more generally (DR), is a convertible security which though cross-listed on a foreign stock exchange is representative of an equity security that has been issued by a local public firm. The ADR or DR security traded on the foreign exchange is a mean which allows investors to trade the equity of local firms on a foreign exchange, without needing to trade on the local exchanges.

The price discovery role of the domestic market in the context of a high frequency data, previously addressed only by Grammig and Peter (2008, 2010), has been questioned in the presence of an unknown degree of microstructure effects, which can be attributed to idiosyncrasy of a market microstructure: e.g. bid–ask bounce, trading rules, type of traders, minimum tick size, etc. The fact that the degree of the microstructure effects is a function of the sampling frequency has been demonstrated by Grammig and Peter (2008, 2010) and is supported by the findings in Chapter 8. The sampling frequency choice affects the trade-off between the degree of microstructure effects and the degree of data censorship. Choosing sampling frequency extremes may lead to an inference bias. Therefore a reasonable choice of sampling frequency is crucial in order to avoid misleading inferences. Presenting the findings based on the highest sampling frequency, which is where the highest degree of microstructure effects is usually found, may lead to underestimation of the role of the satellite markets. The majority of the price discovery research literature is based on one arbitrarily chosen sampling frequency, which may, in fact, be sub-optimal, or lead to misleading or inconclusive inferences. Furthermore, the optimal sampling frequency issue is a unique feature of each sample, and therefore remains an unresolved issue.

Another important contribution is that the issues of trading volume, volatility and time are examined in the context of cross-border conditional price discovery. The literature on conditional price discovery is limited to studies by, amongst others, Martens (1998), Ates and Wang (2005) and Taylor (2008). Apart from Chapter 9, Martens (1998) is the only study, which deals with cross-border conditional price discovery relationship, in terms of the conditional trading volume and volatility effect on proportions of price discovery. This study is also important in that rather than modifying a conventional parametric model, it applies a standard methodology on a factor conditioned data set. This approach differs from conventional parametric methodologies, which are modified to control for the desired factors. Chapter 9, therefore, avoids the risk of additional model misspecification caused by controlling for highly correlated variables such as trading volume and volatility. An additional benefit of the conditioning method used in this study, is that it makes the isolation and analysis of the trading volume and volatility variables possible.

The analysis of this thesis is based on a range of sampling frequencies derived from the specialty high-frequency data (HF). Limit order book reconstruction has been the key to the HF data analysis. The methodology of limit order book reconstruction, as well as the sampling of time series, still constitutes an under-researched area. Most of the studies in the price discovery literature except, for example Grammig et al. (2005), are based on one or two LOB reconstructed data sets; this study is one of the few that utilises three reconstructed LOBs. Most price discovery studies employ, or present their findings based on, a data sample arbitrarily sampled at just one or two sampling frequencies. Additionally, the issue of which data type i.e. quotes or transaction prices, are better suited to the estimation of the price discovery relationship, is not addressed directly in the literature. In the end, this price discovery study is one of the few emerging market studies in which the continuous overlapping trading time spans a daily period of six hours on the international scale and seven and half on the domestic scale.

1.5 *Structure of the Thesis*

The thesis consists of ten chapters. Chapters 2, 3 and 5 are supportive. Chapter 2 is a general literature review, which aims to provide an overview of the findings of the major studies in each field of the literature. It is intended to support the specific and more in- depth literature review of empirical chapters 7, 8 and 9. Chapter 3 presents the market structure of the MICEX, RTS and LSE markets, and it aims to present the overview and the idiosyncrasies of each market. Chapter 5 describes the data set employed in the thesis.

Chapters 4 and 6 are the chapters dealing with the data processing and empirical methodology. Chapter 4 seeks to illustrate the LOB reconstruction and sampling procedure in order to obtain the data samples for this study, while Chapter 6 lists the empirical methodology employed in Chapters 7, 8 and 9. Chapter 10 concludes the thesis by summarising all the major findings and discussing their implications.

Chapters 7, 8 and 9 are the main empirical chapters, and have a similar structure. They begin with an overview followed by a specific literature review and discussion. The findings are presented in the section on empirical results. The following paragraphs outline the three main chapters and summarise their main findings.

1.6 *Summary of the Main Findings*

Chapter 7 focuses on price discovery in the domestic Moscow market. It examines the price discovery process across two Moscow stock exchanges: RTS and MICEX, and provides insight into information flow and transmission between the competing domestic markets, by examining the most liquid cross-listed shares of Russian companies traded in the order driven mode. The analysis is based on transaction prices and best order quotes. The price discovery contribution is measured by two competing and complementary methods, which are based on a decomposition of price/quote time series into a permanent component associated with efficient price of the asset and a transitory component which reflects microstructure effects. The efficient price should be identical in both markets, while the transitory component may differ. The goal is to establish which market information is first impounded into the efficient price. It is hypothesised that the price discovery will occur to a larger extent in the most liquid market.

The main findings and conclusions of the chapter are, in summary: a) There is a cointegrating relationship between MICEX and RTS pricing for all cross-listed stocks. b) Both the Hasbrouck (1995) and Gonzalo and Granger (1995) measures indicate that MICEX is the central market as it plays the primary role in price discovery. c) RTS does not Granger-cause MICEX. d) The pricing on MICEX in general does not adjust to RTS pricing. e) More than 80% of innovations are impounded into the common factor by MICEX. f) The quality of the results is dependent on the type of data; the transaction based data is a less informational source for measuring the contribution of price discovery under a 120s sampling interval.

Chapter 8 investigates the cross-border price discovery between the Moscow markets and the London Stock Exchange. There is a lack of research into whether London trading follows the Moscow market or vice versa. The added value of the second chapter, besides the previously unexplored data sets, is the idea of optimising the frequency of analysis in order to minimise the microstructure effects while at the same time maintaining as much reflected information as possible. Here, the study addresses the issue caused by the effects of microstructure noise when measuring the relative importance of the Moscow and London market in the price discovery process of internationally cross listed stocks.

The analysis can be summarised as follows: a) There is at least one cointegrating relationship between MICEX, RTS and LSE pricing for all cross-listed stocks. b) The causality relationship between MICEX and RTS is unidirectional (MICEX is Granger-causing RTS); the relationship between LSE and MICEX is bi- directional. c) Restriction test results support the view that the satellite markets LSE and RTS are also contribute significantly to price discovery. d) The rejection of the theoretical cointegrating vectors between London and Moscow are indicative of the cross-border information asymmetry caused by the market frictions. e) The results do not undermine the notion that the home market MICEX makes the major contribution to price discovery. The proportion of the price discovery contributions of MICEX, RTS and LSE are in a ratio, on average, of approximately 60/20/20 respectively.

Chapter 9 analyses in detail the MICEX and LSE relationship in a conditional price discovery context, examining the time, trading volume and volatility aspects of the international price discovery. In contrast to Chapters 7 and 8, Chapter 9 relaxes the assumption of price discovery contribution as an aggregate constant. It is assumed that trading volume and intraday volatility are reflective of the information flow between the markets. The price discovery relationship between the London and Moscow markets is analysed by conditioning the data set upon factors determining information flow. The empirical analysis is based on modification of the data set from the Chapter 8.

To give a brief summary of the results: a) Relative daily trading size does not seem to affect the price discovery relationship. b) Volatility on MICEX could be positively associated with MICEX's price discovery proportions c) Trading hours are associated with different price discovery proportions between the London and Moscow markets. Price discovery on LSE seems to underperform at opening and closing times. The lowest price discovery contribution on MICEX is found at mid day overlapping trading time. d) Days of the week seem to affect the information flow intensity. Thursdays seem to be the most informative MICEX days.

Chapter Two: General Literature Review

Chapter 2: General Literature Review

2.1 *Overview*

The emerging equity markets are rapidly expanding, not only domestically but also globally. The expansion manifests itself by the increased volume of the order flow across the equity markets, domestically and internationally in the form of cross-border listings and Russian stock market index tracking funds (ETFs). The emerging equity market of Russia itself, however, and specifically the growing relationship between the London and Moscow stock markets, seems to be neglected by the market microstructure research literature.

Despite numerous papers in the research field of cross-listing market microstructure, there is not a single study that has investigated the relationship between the Russian stock markets, despite a growing relationship between the London and Moscow stock exchanges. The objective and the motivation of this study is to examine the price discovery process, and contribute to the cross-listing market microstructure research literature and limit order book reconstruction methodology. This thesis aims to provide insight into information flow and transmission between the competing domestic and cross-border markets, by examining the eight most liquid cross-listed shares of Russian companies in 2006; Gazprom (GAZP), RAO UES (EESR), MMC Norilisk Nickel (GMNK), Lukoil (LKOH), Rostelecom (RTKM), Sibneft (SIBN), Surgutneftgaz (SNGS), Tatneft (TATN), traded in order-driven mode on MICEX, RTS, and its ADR equivalents traded in London on the LSE market. The research is based on limit order books reconstructed from intraday databases. It is hypothesised that the price discovery would occur to a larger extent in the more order flow intensive home market.

The nature of cross-listed stock makes the market dynamics process more complicated by enabling market participants from more than one market to compete for order flow. While it appears that the home market plays a major role in price discovery, some studies support the notion that new markets, especially those abroad, are playing an increasingly important role. The trading environment itself may be an important consideration for cross-sectional variation across markets. Generally, a stylised fact can be formulated as following: the contribution of a market to price discovery is greater if the fraction of global trading volume which takes place in the new market is higher. This statement is supported in studies by amongst others, Karolyi (2002), Harris et al. (2003), Eun and Sabherwal (2003), Gagnon and Karolyi (2004), Baruch et al. (2005), Grammig et al. (2005), and Phylaktis and Korczak (2005 and 2007).

However, whether this relationship has been characterised by a more permanent or merely transitory effect in the markets, the causality of that relationship still remains an open question. There is a vast research literature devoted to the issues of the cross-listed securities. Karolyi (2006) may be the primary reference in a detailed review of this growing branch of literature. The market microstructure research field in cross-listed securities could be categorised into certain main areas: price discovery, multi-market trading and arbitrage opportunities, liquidity-volatility aspects of multi-market trading. According to Karolyi (2006), the impact on multi-market trading, liquidity and the joint dynamics of equity returns in the competing markets are dependent on two categories of factors: firm level and country level specific. Firm specific factors related to the information environment of the firm are size, ownership structure and analyst coverage. Country level factors include market and exchange rate volatility and investment restrictions, together with gross and net transactions costs.

2.2 *Price Discovery*

Three major directions in research on studies of price discovery can be identified within market microstructure literature. The first focuses on theoretical research and is predominantly based on a framework for addressing issues related to the adjustment of pricing process to information. The second examines the relationship between the pricing of cross-listed homogenous equity securities on a national or international scale, as well as the relationship between the informationally linked securities traded on different trading systems e.g. dark pools, ECNs and various exchanges. The third direction could be categorized as multi-asset price discovery i.e. how information is dispersed and transmitted among heterogeneous, informationally linked securities in fragmented market segments. The third direction is the most extensive, with studies examining price discovery relationships between multiple asset classes. For instance some studies investigate a combination between equity and derivatives markets, while others focus on combinations of foreign currency exchange, fixed income and derivatives markets.

This price discovery literature review considers mainly studies in the first and second direction. The focus is on the price discovery issue within the cross-listed equity asset class on a national and international scale. The following literature review presents a summarised overview of seminal studies in each category, and the detailed literature review is illustrated in the empirical Chapters 7, 8 and 9. This price discovery review section is structured in three categories: theoretical and empirical studies on national and international cross-listed equity price discovery. Overall, this thesis aims to enrich the second direction of price discovery literature, a relationship between cross-listed equity with the previously unstudied Russian equity market.

Theoretical Background

The explanation for a relationship between price and quantity is not offered by the efficient market hypothesis (EMH). The EMH contradicts the notion of the trading size effect on trades because it does not explicitly reflect the price discovery or formation process, which is theoretically and empirically documented, for instance in Easley and O'Hara (1987) and in Hasbrouck (1991), respectively. The following information models stipulate that the informed investors inevitably reveal their more-precise value perception to the market when their trade intentions are communicated.

The trading process itself plays a vital part in price discovery. Uninformed traders and market makers are able to infer the perception of asset value from more informed investors, indirectly from observed trading parameters. Grossman and Stiglitz (1980) suggest that competitive trading might cause prices to be revealed; in such a way that one price formation would be sufficient to reveal a true value of a security, if the only uncertainty concerns the private information value of an informed investor.

The information costs to market makers of trading against informed investors are considered in the model of Copeland and Galai (1983). The assumption of the model is that any private signal is fully revealed after each trade. However, with this assumption, a market maker is precluded from dynamically adjusting his quotes over a series of trades. Trading parameters may become visible from transitory liquidity effects and in contrast to private signals, indirect evidence of value is constituted. This may lead to currently observed trading parameters of a value of an asset being less revealing than the history of trading parameters.

Sequential trade models are the theoretical extensions of information models based on their predecessors mentioned above. The models of Kyle (1985) consider the strategic behavior of an informed trader under different trading mechanisms. In the framework of Glosten and Milgrom (1985) the Bayesian learning models, which consider multiple rounds of trading and quote adjustments are applied. The signals are drawn from the price of each trade rather than from a sequence of prices over a series of trades, which, nevertheless, model price adjustment. The framework allows market makers to set bids and ask quotes, which results in transaction prices which ought to reflect the information of the trade transacted by the traders.

Multi- market Price Discovery

A fundamental question that remains unanswered is: which of the competing markets contributes on average most to the price? There are numerous studies that have attempted to address this issue however these papers seem not to reach a consensus because of different methodologies and the quality of data utilised. The field of multi-market equity price discovery literature could be ordered into categories which address the relationship between locally listed equity securities and the relationship between international cross- listings.

There are two pioneer studies by Harris et al. (1995) and Hasbrouck (1995) in the field of national multiple cross-listed equity market price discovery, which examine the relative contribution to price discovery between NYSE and regional exchanges of domestic stocks trading on these exchanges. The market with the highest informational contribution is called the central or the information dominant market, that which makes substantially less of a contribution is called the periphery or satellite market, and the studies of Harris et al. (1995) and Hasbrouck (1995) reveal significant price discovery in both. In order to measure the extent of differences in prices between exchanges reacting to the cross-market information flows, the Harris et al. (1995, 2002) study employs the common factor error-correction (ECM) estimation methods of Engle and Granger (1987) and the Gonzalo and Granger (1995) framework. Hasbrouck (1995), on the other hand, employs a common-trends vector auto-regression (VAR) representation utilising in essence Johansen's (1988) procedure. He defines the information share as the fraction of long-term total variation of returns explained by each market from a variance-decomposition analysis.

A sub-strand of national market price discovery literature is concerned with market fragmentation between the electronic crossing network (ECN) an order-driven and dealer market segments. For instance, Huang (2002) and Barclay et al. (2003) find that ECNs have the dominant price discovery share in the NASDAQ market. On the UK equity market, LSE SETS traded securities are studied by Friederich and Payne (2001), Lai (2003) and Cai and Dufour (2003). These studies find that the price discovery process occurs mainly on the order driven SETS LOB. In sum, the electronic order driven market segment leads the price discovery process.

Cross-border Price Discovery

The research in the area of international multi market price discovery suggests that the prices of stocks traded on the home market lead relative to their foreign listed "derivative" securities market, if the home market has higher trading volume than the foreign market. The studies mainly concentrate on a variety of different markets. Earlier studies employ low frequency daily data, testing only for informational linkages between the underlying securities and their markets. For instance, Kato et al. (1991) examine UK, Japanese and Australian stocks traded in New York and found evidence that the price in the home country market leads the price in the New York market. Lau and Diltz (1994) study Japanese stocks traded in New York, and find bi-directional causality but a stronger impact of NYSE returns on Tokyo returns than the reverse. Wang et al. (2002) examine a group of Hong Kong stocks which are also traded in London. Their findings indicate a bi-directional causality for local market returns between the two markets, but with Hong Kong the dominant market. Although the earlier price discovery studies are pioneering and informative, they differ in their data sets and quality of data utilised. Moreover, they also use exchange rates to convert equity prices into common units across countries, but do not explicitly model the exchange rate process.

The majority of the studies, which utilise high frequency data reveal significant price discovery in the home market. For instance, Ding et al. (1999) examine the links between Singapore and Malaysia trading for one Malaysian firm and Eun and Sabherwal (2003) the links between US and Canadian trading for a sample of Canadian companies. The estimated relative contributions of the two markets from cross-sectional regressions show that the most important variable is the proportion of total trading volume: the higher the fraction of total trading taking place in the US market the higher the contribution of the US market to price discovery.

Grammig et al. (2005) investigate the issue of international price discovery for cross-listed equity by applying the Hasbrouck (1995) methodology to German companies as well as to stocks from Canada, France and the UK cross-listed on the NYSE based on intraday data. They find that price discovery occurs largely in the home market, but their results differ across three firms between the German (XETRA) and US (NYSE) markets. Moreover, even though the exchange rates are modelled, their impact on price discovery seems to be insignificant. The results are similar to those of Phylaktis and Korczak (2005 and 2007) who examine the contribution of US trading to the price discovery process of British and French companies cross-listed on NYSE. Like Eun and Sabherwal (2003), both studies show that the liquidity of US trading discovery is positively related to the extent of the US price by exploiting a large cross-section of stocks. They find strong evidence that the concentration of stocks from a given country in an individual specialist has increased the share of US trading in price discovery through the reduction in information asymmetries. These studies confirm that the intraday exchange rate effect on price discovery is not statistically significant. Overall, the price discovery largely occurs in the home market despite the globalisation trends of equity markets.

Grammig and Peter (2008) study the price discovery relationship between Canada and US for Canadian cross-listed securities. They employ a data set similar to Eun and Sabherwal (2003), but their work indicates that the role of the foreign market may have been underestimated. This has been attributed to a potential bias of estimated information shares by microstructure effects, in papers which apply the Hasbrouck (1995) framework, by relying on high frequency data. The avoidance of large bounds of information shares at lower sampling frequency comes at the cost of potential bias of the estimated information shares at higher sampling frequency. This is the first price discovery study that addresses and attempts to resolve the issue of the optimal sampling frequency.

Harris et al. (2003) investigate the high-frequency spread and transaction price dynamics for Daimler-Chrysler after the creation of the global ordinary (GRS) shares. Their study and that of Karolyi (2002), illustrate how US interest in DCX trading decreased in the first six months following the merger of Chrysler and Daimler-Benz. Harris et al. (2003) provide a link between liquidity, information, and home bias in international investment. They conclude that domestic investors may be better informed about and better able to monitor local firms than foreign firms.

2.3 *Liquidity and Volatility*

The liquidity issue in the context of price discovery was first analysed by Pulatkonak and Sofianos (1999). Their analysis includes global trading data on NYSE cross-listed foreign stocks, and they find that, on average, one third of trading takes place on the NYSE. Forster and George (1995), Chan et al. (1996) and Werner and Kleidon (1996) examine the patterns in bid-ask spreads, price volatility and trading volumes in ADRs after cross-listing on US markets. Werner and Kleidon (1996) discover unusually high volatility and trading volume at the opening for Japanese ADRs in the period after Tokyo closing and for UK ADRs when London had closed. Gagnon and Karolyi (2004) demonstrate that the distribution of the trading volume is important, by evaluating a wider range of firm and country-level attributes. In particular, higher excess co-movements of the ADR shares with the US market index returns have been attributed to stocks for which the US trading volume is proportionally higher.

Baruch et al. (2005) provide a theoretical model and empirical support for the claim that trading volume of cross-listed firms is concentrated in the market with the highest correlation of cross-listed asset returns and other asset returns in that market. It is to be expected that the liquidity of each market should be a major factor in determining the location of price discovery as well as the trading volume.

Liquidity in markets, especially in emerging markets, is a significant factor in return distributions analysis. Market liquidity may play an important role in the empirical results. For example, Park and Tavakkolb (1994) indicate that ADRs are traded in a much more liquid market than their corresponding shares, but the opposite may also be true. Many local emerging markets trade under capital flow restrictions, which by themselves may create low trading liquidity and may provoke home bias, and some bias of the analysis, on foreign capital flows in and out of the market. However, if there is less capital restriction, the local market may become more efficient and a higher level of liquidity is expected, ceteris paribus. Furthermore, Park and Tavakkol (1994) exhibit some evidence that returns of Japanese ADRs are not significantly different from the returns on the underlying stocks traded in Japan. They found that the return of the underlying stock volatility is smaller than the volatility of ADRs. They have concluded, however, that this larger volatility of ADRs is the result of the covariance between the stock, the currency returns and the volatility currency returns. After all, the difference in hours of trading causes a lead-lag relationship in flow and dissemination of information between the ADR and the local markets. The arbitrage activity may be hindered, because some uncertainty induced by non-synchronous trading hours of the ADRs and their underlying security is shown by the study of Kim et al. (2000).

The liquidity impact of the listing decision itself has been considered by several studies. Noronha et al. (1996) provide evidence of no measurable difference in daily weighted average spreads for US firms after listing in Tokyo or London. On the other hand Foerster and Karolyi (1998) show an increase in intraday volume and decline in intraday effective spreads for Canadian firms which have been listed in the US. Domowitz et al. (1998) offer an interpretation which is related to the degree of transparency between the order flow competing markets, by examining weekly returns, volatility and their volumes of cross-listed Mexican stocks on the US market. It is established that lower market impact costs and higher volume have resulted only for those firms with no foreign ownership restrictions.

The aspect of the trading volume-volatility relationship is addressed by Lamoureux and Lastrapes (1990), who apply stochastic time series models of conditional heteroscedasticity to explore the contemporaneous relationship between volatility and volume data. They find the persistence in stock return variance mostly vanishes when trading volume is included in the conditional variance Equation. If trading volume is considered to be an appropriate measure for the flow of information into the market, this finding is consistent with the mixture of distributions hypothesis (MDH). The observation by Lamoureux and Lastrapes (1990) indicates that trading volume and return volatility are driven by identical factors, leaving the question of the source of the joint process largely unresolved.

The relationship between the underlying stock market volatility and the trading activities of the Korea Stock Price Index (SPI) 200 derivatives contracts is studied by Kim et al. (2004). They find a positive contemporaneous relationship between stock market volatility and the volume for both futures and options contracts. This confirms that the derivatives volume, which largely proxies speculative trading activities, tends to increase the underlying stock market volatility, while the open interest, which mainly reflects hedging activities, tends to stabilise the cash market. They also find that the lagged futures volume causes the current stock market volatility, and that the lagged cash volatility also causes the current trading volume.

Chatrath et al. (1995) examine a relationship between cash market volatility and option market activity on the S&P 100 index. Their evidence suggests that while increased cash market volatility is followed by an increase in the level of option market activity, an increase in option market activity is followed by a decline in cash market volatility. They use a bivariate VAR with options trading volume and spot price volatility and executed conventional causality tests, providing evidence that there is strongly significant feedback between the two variables. An increase in cash market volatility seems to cause an increase in the level of options trading, whereas an increase in options trading is followed by a decrease in spot market volatility.

The relationship between derivatives trading activity and spot market volatility is investigated by Kyriacou and Sarno (1999). Their study is based on daily data for the UK market. The dynamic relationship between spot market volatility, futures trading and options trading, is investigated. Their results provide strong evidence that significant simultaneity and feedback characterise the relationship between the spot market volatility and derivatives trading. In the structural model proposed, futures trading and options trading are found to have an opposite effect on spot market volatility. The results suggest that the failure to account for any contemporaneous interaction between the variables under consideration, as well as the omission of any of the derivatives trading activities examined in their study, may generate serious misspecification and ultimately produce misleading estimation results and statistical inferences.

2.4 *Arbitrage Opportunities and Multi-Market Trading*

The relationship between prices of informationally linked or cross-listed securities traded in multiple markets are of interest to researchers for a following reason. A central notion in fundamental financial theory of market efficiency, law of one price and arbitrage theory states that: In perfectly efficient markets, the arbitrage free assumption would imply that all new information transmitted into the market should be immediately reflected in all of the markets simultaneously as prices would adjust instantaneously and fully to all relevant information. When transaction costs are taken into account, there should be no systematic lagged responses large enough or long enough, to be economically exploited. However there is evidence in the empirical market- microstructure literature that markets are imperfect. For instance, DeJong and Donders (1998) illustrate the issue in the study of a relationship between cash index, futures and call options. They find that futures lead cash index and options markets and that there is lag of approximately ten minutes between futures returns and both options and cash index returns. The relationship between options and the cash market is not exclusively unidirectional.

Gagnon and Karolyi (2004), Ji (2004) are the studies that research a broad cross-sectional sample of foreign cross-listed stocks on US exchanges. Gagnon and Karolyi (2004) compare the synchronous, intraday prices of ADRs cross-listed securities in US markets relative to their home-market on a currency-adjusted basis. They examine the magnitude of the deviations from parity, their persistence and their systematic co-movements with market indexes and currencies.
Gagnon and Karolyi (2005) uncover the band of deviations that fluctuated significantly from a premium to a discount for some ADRs. Gagnon and Karolyi (2004) demonstrate that the distribution of the trading volume matters by evaluating a wider range of firm- and country-level attributes. In particular, higher excess co-movements of the ADR shares with the US market

index returns have been attributed to stocks for which the US trading volume is proportionally higher. Ji (2004) finds that larger systematic deviations from parity could be attributed to a higher US institutional lag explained by these excess co-movements in terms of the ownership structure of the stocks. Both studies find substantial systematic excess co-movements patterns in the deviations.

There are studies that find arbitrage opportunities between ADRs and underlying equity. Wahab et al. (1992) and Rabinovitch et al. (2003) analyse markets in Chile and Argentina. It has been shown that the estimated arbitrage trading cost or average daily returns spreads in Argentina have been on average significantly lower than in Chile. Furthermore, dramatic mean reversion to relatively large spreads in Argentina has been demonstrated. A follow up confirmation on these findings has been offered by two studies of the effect on the ADR market of the elimination of the US dollar peg of the Argentinian currency board in 2001. Melvin (2004), Auguste et al. (2002) indicate that the capital controls that were imposed by the government and with the expectation of a peso devaluation lead to significant arbitrage spreads which arose in the form of an ADR premium.

The Stulz (1999) critique is a catch up to the research interest in multi-market trading and liquidity, unlike the bonding hypothesis, information asymmetry and agency conflicts problems. Technological developments such as the more rigorous research methodologies researchers have at their disposal, and higher frequency data available for more markets around the world, provide increasing insight into liquidity such as spreads, volume and volatility changes for newly cross-listed firms, that may be related closely to changes in the information environment, the corporate governance systems and ownership structure of a firm. Despite the progress made, a question remains about the causality relationship between market intermediaries such as brokers and traders, and the liquidity that arises in the markets competing for their shares.

2.5 *Conclusion*

To summarise, in the context of price discovery, market microstructure literature considers numerous securities, market combinations and methodologies. The Asian and Latin-American emerging markets have been studied, but the Russian market and specifically the growing relationship between the London and Moscow equity markets has not been investigated in the literature reviewed above. On the Russian equity market as well as on other emerging markets, there is no consensus about the price discovery role of the domestic market in the presence of microstructure effects. Furthermore, in addition to the research gap on the cross-listed Russian equity market, the price discovery segment requires specialty high-frequency data. In addition, there is no agreement in the literature which data type i.e. quotes or transaction prices, are optimal for price discovery. Also, the optimal sampling frequency issue is a unique feature of each sample, and therefore remains an unanswered question. A more detailed review of literature is presented in Chapters 7, 8 and 9.

Overall, the following key questions have been addressed in this thesis:

- Is there an unobservable equilibrium price as a result of the order flow competition from multiple (fragmented) market trading?
- Which of the markets leads/lags by discovering the equilibrium efficient price?
- What is the relative contribution of the individual market to the common efficient price?
- Does the home market price discovery dominate the foreign market?
- How sensitive are the results to the type of data, methodology and sampling frequencies?
- How stable is the price discovery as conditioned upon daytime, weekday and information conditions such as trading volume and volatility?

The studies such as Harris et al. (1995, 2002) and Hasbrouck (1995, 2002) address the question of price discovery between central and satellite trading venues in the national markets. There is research into the established market, but the Moscow stock market is distinct, not only micro-structurally but due to the fact that it is a still an emerging market. The capitalisation of the Russian equity market has grown over the years so that it is in the world top ten stock markets in terms of trading volume. Despite this, there is a lack of research on the relationship between the RTS and MICEX. Is the price discovery relationship on the national Russian equity market comparable to the central-satellite relationship on the national US market? The issue of national price discovery is addressed in the Chapter 7.

The internationally cross-listed price discovery literature seems to have reached a consensus, firstly that the home market is usually dominant in price discovery, and secondly that the degree of dominance is dependent on the degree of relative liquidity between the home and the foreign market. The question which however remains is: given the presence of microstructure effects in the high frequency sampled data, does the home market dominate its foreign counterpart in the price discovery? Surprisingly, there is only the Grammig and Peter (2008, 2010) study which addresses the issue of microstructure effects relative to international price discovery. All other studies seem to utilise one single sampling frequency. Furthermore, there is a gap in the research literature on price discovery between the Moscow- London stock exchanges despite a substantial number of cross-listings. The question of cross-border price discovery between home and foreign markets is addressed in the Chapter 8.

The price discovery literature seems to focus on average price discovery contributions. There is a lack of literature on specific regimes or conditions in which the price discovery process takes place. In addition, the price discovery literature that focuses on equity market with respect to trading volume and volatility conditions is limited. The use of intraday data is found usually only in recent studies, such as that of Taylor (2008). There is limited evidence of the indirect approach of measuring the effect of volatility and trading volume on price discovery proportions, and the temporal aspect of price discovery is still an under researched sub area.

This thesis aims to close the identified research gaps of price discovery literature by bringing new insight into information flow and transmission in the cross-listed Russian equity markets. Chapter 7 aims to contribute to the cross-listed equity price discovery literature on the national scale, while Chapter 8 aims to contribute to the literature on the international scale. Chapter 9 aims to contribute to the limited field of conditional price discovery literature. Market structure is presented in the next chapter. The price discovery framework is reviewed in the following chapter on data processing, and in the chapters dealing with limit order book reconstruction.

Chapter Three: Market Structure Overview

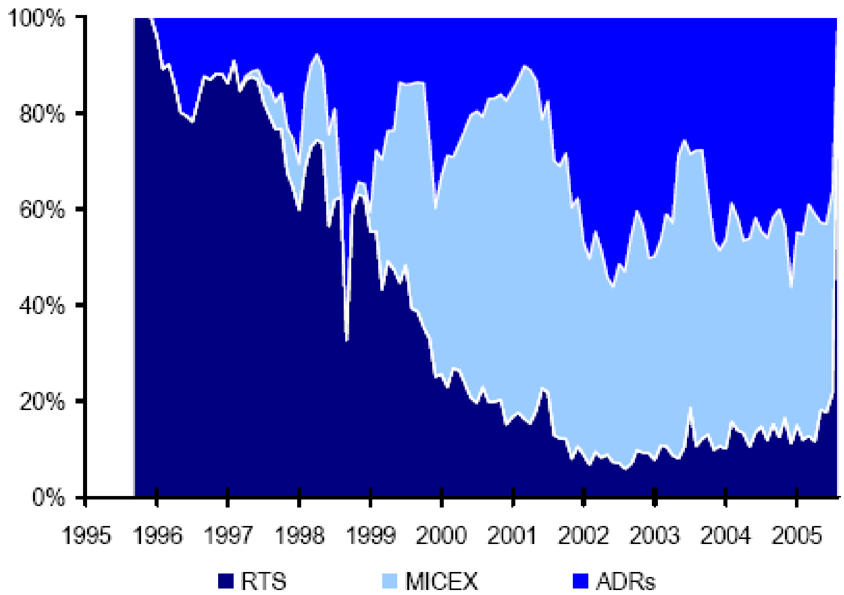

Figure 1 Total trading volume shares of the competing markets

(Source:http://www.nes.ru/~agoriaev/FMI4%20primary%20and%20secondary%20markets.pdf)

Stock markets, which facilitate trading of Russian equity securities, can be categorised into three main segments: home markets such as the Russian Trading System (RTS), the Moscow Interbank Currency Exchange (MICEX) and markets abroad which deal with American Depository Receipts (ADRs) such as the London Stock Exchange (LSE) and the Frankfurt Stock Exchange. Figure 1 and Table 2 exhibit the trading capacity of the stocks markets competing for order flow. Most stocks are still traded in RTS yet the trading volume has migrated from RTS to MICEX and foreign exchanges such as LSE and FSE. MICEX is a more liquid market than RTS. The trading volume of these two markets in December 2006 was expressed in a ratio of 20 to 1. Although trading on MICEX is concentrated on blue chips, which make up more than 80% of all equity trading (Gazprom, Lukoil, Norilsk Nickel and RAO UES), the RTS index still remains the benchmark for the Russian equity market. The other non visible, albeit equally important common competitor, is over-the-counter (OTC) which has comparable trading volumes.

	2003	2004	2005	Jan-May 2006
MICEX SE	99.1	151.2	225.6	164.4
% of total market	88.20%	85.30%	85.60%	83.20%
RTS	13.3	26.1	38	33.1
% of total market	11.80%	14.70%	14.40%	16.80%

The table presents the historic amount of trading volume in USD and the total market share of the Moscow equity market of MICEX and RTS exchanges

Table 1 Turnover of the Russian exchanges 2003- 2006, bln USD

(Source: MICEX)

Historically, RTS originated in 1993 almost from scratch, whereas the MICEX exchange was created from a former Soviet institution in 1995. RTS has been established from a private and foreign banking conglomerate. The MICEX exchange, however, evolved with the help of state funding. Table 2 shows the position of the MICEX market in the world league. On the basis of the ratio of trading volume per issuer, MICEX surpasses all emerging market exchanges.

	USD Billions	Number of Issuers	Average Volume/ Issuer
NYSE	6991.9	2176	3.21
NASDAQ	4081.3	3150	1.3
London SE	2432.3	3169	0.77
Tokyo SE	2168.5	2372	0.91
Euronext	1214.6	1225	0.99
Deutsche Boerse	877.0	757	1.16
Hong Kong Ex	266.7	1143	0.23
Shanghai SE	143.2	831	0.17
MICEX SE	120.4	184	0.65
Singapore Ex	60.8	680	0.09
Wiener Boerse	24.0	110	0.22
Warsaw SE	17.1	240	0.07

The table illustrates the overall amount of trading volume in USD, number of listed securities and an average traded volume per listed securities for the major stock exchanges relative to MICEX for January-April 2006

Table 2 Equities trading volume

(Source: MICEX)

Chapter 3: Market Structure Overview

3.1 *Moscow Interbank Currency Exchange (MICEX)*

The Moscow Interbank Currency Exchange (MICEX) is a fully electronic high-technology exchange. MICEX is the largest currency exchange in Russia. Since the reorganisation of Russia, the Central Bank of the Russian Federation has defined an official RUB rate based on the results of currency trading in MICEX. The United trading session for the realisation of export revenues is implemented in the MICEX System of Electronic Trading as well as the usual trading session in 11 foreign currencies, including the USD and EURO. The securities are traded in order driven mode. Trading hours are from 10:00-18:30 Moscow time[1].

3.2 *Russian Trading System (RTS)*

The Russian Trading System (RTS) was the first regulated stock market established in Russia as a fully electronic exchange, based originally on NASDAQs technology. The RTS exchange currently trades the full range of financial instruments from cash equities to commodity futures. The RTS Group operates the central counterparty, the settlement securities depository and the settlement house for RUB and foreign currencies. RTS is the only trading platform in Russia that allows for settlement in both Roubles and foreign currency (USD). The RTS Classic market is equally accessible to both Russian and foreign investors. There is no requirement to deposit securities and cash before a trade. The classic market consists of the eight most liquid stocks which have been traded since 2005 in order driven mode and are available for direct market access. Trading hours are from 10:30-18:00 Moscow time[2].

[1] The stated facts about the exchange trading, opening times and trading rules were valid for the sample period of 01.01.2006- 28.04.2006

[2] ibid

RTS	MICEX
Created in 1995 as a stock market	Started in 1992 as FX market Stock market – since 1997
• Hybrid Dealership system • Quotes in US dollars • 230 listed stocks – 40 actively traded stocks • 250 brokers/dealers	• Order- driven system • Quotes in Roubles • 130 listed stocks – 80 actively traded stocks • 530 brokers/dealers

The table presents a comparison of the main features between MICEX and RTS markets

Table 3 Comparison between the two Russian exchanges

Table 3 summarises the main trading rules differences between the MICEX and RTS exchanges valid for the sample period in 2006. The stock exchanges in Moscow are electronically fully automated and are quite similar to the developed markets equivalents. Nevertheless, some differences with the major order- driven exchanges do exist and can be summarised as follows.

1. MICEX is a purely order-driven market whereas RTS is hybrid, which is quote and order driven.
2. There are no hidden orders. The quote and quantity of an order are fully displayed and are obligatory in auction order-driven mode on both MICEX and RTS, but the counter parties are anonymous. The RTS system in the quote-driven mode accepts only limit orders with stated price. It also supports GOC (Good Till Cancelled) orders, FOK (Fill Or Kill) and Iceberg orders.
3. On RTS all quotes are accepted through the RTS workstation. There is a minimal trading lot of 5000 USD. Over-the-counter transactions executed over the telephone may also be reported. On MICEX, it is possible to register off-system deals indicating counterparty. There is also no minimum size requirement. The minimum price move is one tick, 0.01 USD on RTS and 0.01 RUB on MICEX.
4. Trading is continuous from the opening, but there is no overnight trading or call auction at the opening or closing. On MICEX there is a pre- opening session.

5. Order revision is unlimited unless an order is fully matched. The price of an order can be bettered and worsened, i.e. raised if it is a buy order and lowered if a sell order, a rule which facilitates trade execution. Order split is allowed.
6. An order hit occurs when two orders posted by the counter parties match. In this case, the trade would take place soon, according to settlement regulation, if no better order arrives and transaction is executed. If another order at the same price level and direction arrives, both orders are executed, if possible, by the “walking the book” process; otherwise the waiting limit order is shared according to specific rules between these competitive market orders.
7. On RTS, the names of brokerage houses in buy and sell sides of a transaction are displayed in the screens in quote-driven mode, which facilitates a high level of post-trade transparency. Both exchanges have central clearing counterparty. The settlement can be delayed by four trading days on RTS, but not on MICEX.
8. There are no market orders de juro. Only marketable limit orders, i.e. buy orders at the ask price or higher and sell orders at the bid price or lower, can be given to accomplish an immediate transaction.
9. No short-selling is permitted on both markets, in complete contrast to established exchanges such as LSE or NYSE

In sum, the available order types on MICEX and RTS are:

- limit buy or sell orders;
- market buy or sell orders existing only de facto;
- special bloc orders with limited value: special orders with or without limited price, but with a specified limited value;
- special negotiation orders with a limited price on RTS: similar to a market buy or sell order that satisfies all the waiting orders up or down to the specified price level.

3.3 *London Stock Exchange (LSE)*

The London Stock Exchange (LSE) is a dealer market with an electronic order book, SETS, used to trade blue-chip stocks. Large trades are executed on exchange, but can also be negotiated by telephone or executed through the order book. There is an obligation to quote bid-ask prices for normal quantities during official trading hours for the market makers allocated to particular stocks. Except for ADRs and other forms of DRs on the international order book (IOB), trading occurs in British pounds and the minimum price increment depends upon the price of a security. The ADR trading is facilitated on the IOB. The ADRs of the underlying foreign stock are issued by a depositary bank where the shares are accumulated and taken into custody. The fungibility of securities differs across ADRs, as some are issued at a fixed multiple relative to the underlying shares, unlike others which have a multiple of a unit (presented in Chapter 5, Table 8). They are priced in US dollars, therefore trade and settle just as any other stock in the UK and US. The dollar price of the ADR will differ from the home market price by at least a factor incorporating the exchange rate. Trading hours are from 8:00-16:30 and continuous trading session on the IOB for Russian ADRs was from 9:00- 15:30 London time[3].

The trading mechanism on LSE IOB is similar to MICEX and to RTS electronic order book trading. In a continuous trading session it is an order driven double-sided continuous auction with an automated matching trading mechanism. However, in contrast to MICEX and RTS, there are de juro market orders on LSE. The trading is characterised by the possibility of short selling and a minimum order size of 50. One tick, 0.01 USD is the minimum price move for most Russian cross-listed securities.

In sum, available order types on LSE are:

- limit buy or sell orders;
- market buy or sell orders existing de juro;
- iceberg orders;
- FOK (Fill Or Kill) orders;
- hidden limit (no display of price or size for orders greater than USD 14k);
- stop loss and stop limit orders

[3] The stated facts about the exchange trading, opening times and trading rules were valid for the sample period of 01.01.2006- 28.04.2006

The limit order book reconstruction process requires knowledge of the trading rules and mechanism. The trading rules are similar across these markets, but the differences mentioned above should be considered when working with the orders databases and order books on MICEX, RTS and LSE.

3.4 *Continuous Trading Time Overlap*

As illustrated by Figure 2, the trading on both Moscow exchanges overlaps for almost the entire trading day. MICEX starts to trade from 10:00 and closes at 18:30 Moscow time. RTS start to trade at 10:30 and closes at 18:00 Moscow time. Although MICEX covers RTS, trading time indicates that the intersection of the continuous trading hours of both exchanges is from 10:30-18:00 Moscow time, that is a continuous seven and a half hours per day.

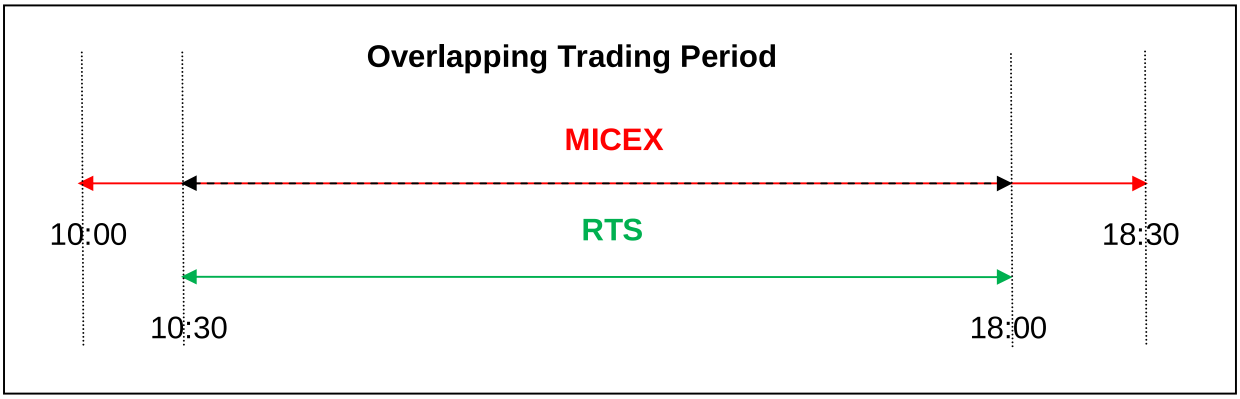

Figure 1 Overlapping trading time on the domestic market

Besides the competition of these two markets, one should not ignore the fact that international markets, where the stock ADRs are also listed, do compete with each other, as well as other available ADRs, are also internationally traded. MICEX and RTS trading times do overlap completely with the other exchange such as the Frankfurt Stock Exchange (FSE) and the London Stock Exchange (LSE), which directly compete with the home markets, but they also contribute to some extent to the price discovery process. On an international scale there is FSE, the first foreign market. It has a one hour advantage over LSE in time lag terms, starts to compete earlier with MICEX and RTS, and shares one overlapping hour with LSE before the trading day closes there. This competition between markets and alternative instruments demonstrates that in fact the existence of a multi-dimensional contribution to the price discovery, is not just a uni- or bi-directional, but possibly a multi-directional relationship. However this is an issue for further research.

The cross-border analysis provides the opportunity to have six overlapping trading hours for trivariate or even six and half hours for bivariate modelling. Although MICEX covers LSE trading time, the intersection of the continuous trading hours of both exchanges is from 12:00-18:30 for bivariate or from 12:00- 18:00 Moscow time for trivariate analysis (please refer to Figure 3). There is a three hours time differences between the two time zones. MICEX starts to trade from 10:00 and closes at 18:30 Moscow time. LSE start to trade at 9:00 and closes at 15:30 London, Central European Time (CET). RTS overlaps completely with MICEX and LSE.

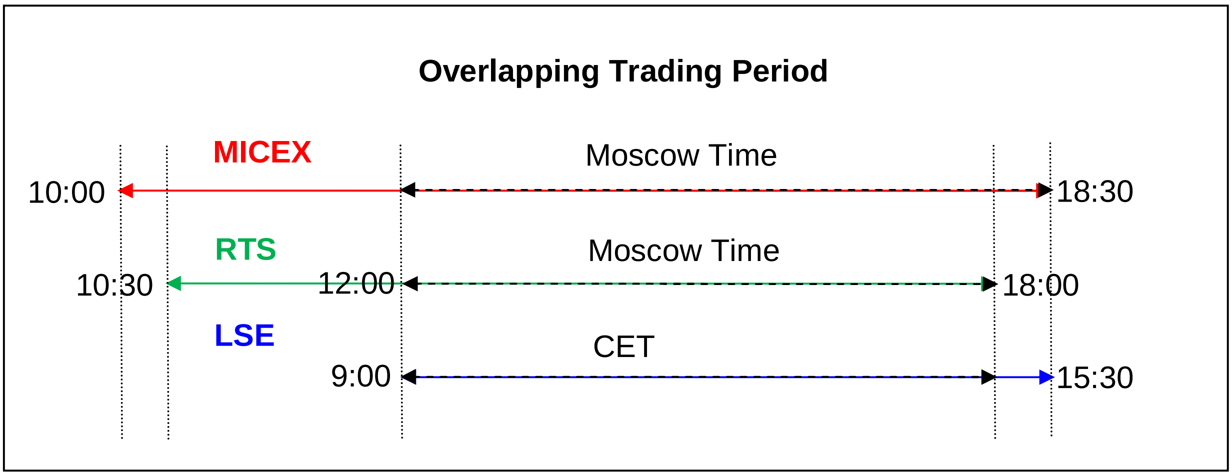

Figure 2 Overlapping trading time of the cross-border markets

The focus of this empirical study is on the continuously traded overlapping period of the MICEX, RTS and LSE markets. Trading of Russian stocks occurs in US Dollars on LSE and on RTS yet not on MICEX, where trading is only permitted in the Russian Rouble. Changes in exchange rates require a change on RTS and LSE and MICEX stock prices, in order to preserve the law of one price and avoid arbitrage opportunities. However, the Russian economy operated under capital flow restrictions and therefore the Rouble exchange rate is fixed overnight, based on central bank policy and the closing results on MICEX.

In order to avoid the problem of infrequent quoting, this thesis proposes to investigate pricing dynamics based on the reconstruction of the limit order books, with a range of sampling frequencies, from the highest resolution of 1 second up to 1920 seconds. The focus is directed on the eight most heavily traded stocks with the highest trading volume on the home market and abroad, which are a good representation of the chosen markets. All these stocks are traded in the auction mode which has been, with liquidity, the other criterion of choice. Despite RTS being essentially a quote-driven market, the RTS classic (recently renamed to RTS Standard) market operates in order- driven mode, so these differences could be mitigated. Furthermore, if far fewer liquid stocks were considered, then there would be a problem of in-signal asymmetries between the markets which would bias the results, due to less synchronous quoting in the home markets and in London. The reconstructed limit order books and the interpolated trade data sets started each day with observations on the actual trading times, no overnight quotes or prices were used.

The focus of this thesis is the analysis of the data set derived from the limit order books (LOBs) of the eight most liquid, cross-listed Russian securities: RAO UES (EESR), Gazprom (GAZP), Norilsk Nickel (GMNK), Lukoil (LKOH), Rostelecom (RTKM), Sibneft (SIBN), Surgutneftgaz (SNGS) and Tatneft (TATN). All these securities were traded electronically and order driven in similar fashion across the three stock exchanges. The trading mechanism is a continuous trading session, an order driven double sided continuous auction with automated matching for all the above listed securities.

Table 4 presents the summary of USD trading volumes for the eight securities. The total trading volumes ratio of LSE and RTS together with MICEX is approximately 1/10 because of EESR which has the largest trading volume. If the EESR trading volume is excluded from MICEX, the proportions of RTS and LSE to MICEX are ½. LSE trading is similar to RTS, but it is the lowest trading volume market. EESR is by far the most traded security across all three stock exchanges. The trading volume proportion of EESR is above 50% for all three markets. The trading volume of MICEX dominates most securities with the exception of GMNK, LKOH, whose total LSE trading volumes are in similar proportions to MICEX.

	MICEX	% Total	RTS	% Total	LSE	% Total
EESR	49,715,018,100	89.07%	1,580,064,214	73.28%	937,682,928	55.56%
GAZP	1,449,095,979	2.60%	401,976,300	18.64%	218,069,550	12.92%
GMNK	49,013,041	0.09%	3,130,258	0.15%	54,153,883	3.21%
LKOH	237,876,240	0.43%	12,626,761	0.59%	303,070,864	17.96%
RTKM	1,498,663,163	2.68%	33,601,418	1.56%	51,379,729	3.04%
SIBN	113,147,513	0.20%	6,388,948	0.30%	31,208,163	1.85%
SNGS	2,611,038,800	4.68%	113,788,777	5.28%	86,392,820	5.12%
TATN	149,051,429	0.27%	4,567,891	0.21%	5,663,499	0.34%
Total	55,817,536,248		2,156,054,567		1,687,621,436	

The table reports the amount of trading volume in USD for the eight securities in the first four months of 2006

Table 4 Summary of USD Trading Volume

The MICEX market total trading result for the first four months of 2006 is “thicker” than RTS and LSE trading, despite the fact that overall trading volume on LSE is slightly larger than on MICEX for GMNK and LKOH. The MICEX set has on average twenty thousand transactions per trading day. With much lower liquidity, LSE, in contrast, has on average only five hundred transactions per trading day, where RTS has even fewer. These are the major liquidity differences.

3.5 *Outlook*

Given the Russian cross-listed equity market structure constellation, the superior market liquidity of MICEX may determine the superior price discovery contribution of MICEX. This may be taken into account in the initial analysis of Chapter 4, and 5, and when interpreting the findings after the empirical analysis is performed in Chapters 7, 8, 9 and 10. It is expected that the price discovery contribution of MICEX is superior to RTS and LSE. In order to examine the price discovery relationship empirically between the cross-listed equity on MICEX, RTS and LSE markets, the data from these exchanges must be processed to a necessary format. The data processing is described in following Chapter 4 and the data set is presented in Chapter 5.

Generally there two types of data available: trades and quotes. Both types of data have been extracted from the MICEX, RTS and LSE order books. Each type of data requires a different processing approach. One approach in the price discovery literature utilising high frequency data, is the trades (transaction prices) based sampling {e.g. Harris et al. (2002a), Phylaktis and Korczak (2005, 2007)}. The other is an order quotes based approach {e.g. Hasbrouck (1995), Eun and Sabherwal (2003), Grammig et al. (2005)}. Both approaches have their merits and shortcomings. Neither method is mutually exclusive, but a transaction based approach is easier and quicker to implement, while data processing tends to be more accurate, because there is usually less room for mistake. The drawback associated with trades is, however, that there is less informational completeness relative to quotes. On the other hand, the quotes based or complete order book reconstruction approach usually results in more information, and requires a careful and more sophisticated reconstruction process in order to extract the relevant information. Therefore, it tends to be slower and more complex to implement. By reconstructing the limit order books, both types of data and approaches are utilised in this study.

Chapter Four: Limit Order Book Reconstruction Methodology

Chapter 4: Limit Order Book Reconstruction Methodology

This chapter describes the process of limit order book (LOB) reconstruction. It also discusses the derivation of the best prevailing quote, and the data sampling procedure. The empirical foundation of this study is based on the reconstruction of three limit order books. It is possible to skip the LOB reconstruction, and base the empirical analysis on the interpolated transaction tick data. However, since the information content of the transaction data is restricted relative to the quotes data, the resulting empirical findings may not provide firm enough evidence to illustrate the price discovery relationship at higher sampling frequencies. The transaction or trades tick data is an informational compromise, because the information provided by each tick is incomplete compared to the breadth of quotes derived from a LOB. Incompleteness is characterised by the absence of observations between ticks, and that is crucial to the lesser liquid securities which may remain untraded for multiple minutes. Given the incompleteness, if the sampling frequency is chosen fairly high (beyond a minute), the absence of trade observations for each sampling interval becomes substantial. In sum, sampling transaction based data at higher frequencies is insufficient to provide the necessary information about pricing behaviour. This happens because the discrete nature of the transaction data contributes to the widening of the observationless periods at higher sampling frequencies. Deriving the best prevailing quotes from the LOB largely overcomes the problem of missing observations.

Utilising inter-temporally aggregated low frequency data does not allow an insight into the dynamics of market microstructure. Market microstructure dynamics only become significantly visible with the use of high frequency data (HF). At daily sampling frequencies, meaningful inferences cannot be made about the actual trading process. If closing prices from different markets are used, there is an issue of non-synchronous quotes arising from different market closing times. If lower frequency data is employed, the pattern of adjustment of security prices to information shocks may dissolve, due to inter-temporal aggregation. However, higher frequency is associated with rising microstructure effects such as bid-ask bounce, within the impounded information {see Grammig et al. (2002 and 2008)}.

The main benefit of using high-frequency data is that it reveals microstructure dynamics. At a high sampling frequency there may be unidirectional causality among variables, which would tend to disappear into contemporaneous correlation at a lower sampling frequency. Changes in information flow cause traders to respond quickly to new information, therefore the data must be examined immediately in order to be able to make any inferences about the security price response. The issue arising from optimum sampling frequency can also only be investigated with high quality specialty data reconstructed from a limit order book. The trade-off between the fundamental price components (signal) and microstructure effects (noise) can then be directly examined. This issue will be analysed in Chapter 8.

The main research focus of this study is the price discovery relationship between LSE, RTS and MICEX. In order to investigate the multiple market relationship, the best quote or trade based time series were derived from the reconstructed LOBs of the three underlying markets. The RUB denominated prices of MICEX stocks were converted into USD prices as quoted on RTS, with officially set daily exchange rates obtained from MICEX. All relevant LSE ADR instruments were denominated in US Dollars.

4.1 *Function of a Limit Order Book*

An electronic LOB is essentially a “black box”, which stores a threaded list of all orders submitted by the traders. From the list of all submitted and prevailing (active) orders, the best order quotes are defined as the best (maximum) bid price and the best (minimum) ask price. The prevailing quote for an exchange is the most recent valid quote on that exchange. If a submitted market order is for a smaller quantity than the quantity at the best quote in the limit order book, the market order will be completely filled at a price equal to the best quote. If a market order cannot be filled completely at the best quote, it will transact with multiple quotes by “walking” in the book until it is either completely filled, or the book is empty. Any unfilled portion of a market order converts into a limit order.

Marketable limit orders are submitted limit orders which cross the best quote of the corresponding order on the opposite side of the LOB. The electronic limit order book stores all submitted, but unfilled, limit orders. The stored limit or market orders are automatically filled by market or marketable orders if the order quotes match. The unfilled limit orders in the order book are prioritised first by price, then by time, followed by size of the order submission. The prices of the sell limit orders in the book are called ask quotes and the prices of the buy limit orders in the book are called bid quotes. The electronic LOB trading in Moscow and the trading on LSE's International Order Book (IOB) is essentially a double sided auction with automatic order matching. Unlike London where market orders exist, the Moscow LOB contains only marketable limit orders.

The unprocessed LOB database contains a list of historically submitted orders. These orders appear unsorted, but each order usually contains a time stamp to the nearest second and a uniquely assigned number. In reconstructing the order book, it was necessary to keep track of incoming limit buy and sell orders. If an incoming limit buy order is greater than or equal to the ask, then it is classified as a market buy order and if an incoming limit sell order is less than or equal to the bid, then it is classified as a market sell order. Market orders are placed by those demanding liquidity, since they allow for immediate transactions. The flow of limit and market orders constantly updates the electronic order book.

The LOB reconstruction has several advantages over the simple reproduction of a time series of trades based on transaction data. The first and main advantage is that the order quote data provides a more complete picture of the behaviour of the market participants. There is an opportunity to analyse, for instance, the bid-ask spread and the associated indirect costs of trading, risk, inter-trade duration and many other important aspects of financial research interests. The other advantage is that orders are posted more frequently than transactions occur, because a transaction is the result of an executed trade based on a match of bid and ask orders. This eliminates the need for interpolation, which arises with the discrete nature of transaction data-missing observations in a given time period, which happen due to asynchronous and infrequent transacting, and the liquidity of a particular equity instrument on the particular market. In respect of the lead-lag relationship in price discovery, the results are very sensitive to the way the datasets are manipulated. Employing transactions data requires different assumptions to be made as to what is happening in the time intervals where there are no observations. Different missing data filling methods may lead to different and sometimes ambiguous inference results. Depending on the assumption of the interpolation technique, it could sometimes be a costly compromise, possibly resulting in complete ambiguity of a lead-lag relationship. On the other hand, interpolation can be mitigated if the data set can be reduced (inter-temporally aggregated) to a lower sampling frequency. The advantage of inter-temporal aggregation is that the data set also requires less interpolation to fill the missing values. This solution, however, comes with the disadvantage of data censorship, since scaling to larger intervals would lead to less informational completeness.

4.2 *Literature Review*

Although the literature strand studying the limit order book has grown over the years, the strand of order book reconstructing literature is still in the development stage. Recent technological advances enable the high frequency specialty data to be more readily available to researchers and easier to process, but despite the commonalities in auction designs across security markets, it seems that each market limit order book requires its own complex and unique reconstruction procedure. Furthermore, information about LOB reconstruction technique is limited.

There have been attempts to illustrate the procedure for reconstructing the limit order book. Following the pioneering works of Hasbrouck (1991) and Harris (1995), Kavajecz (1999) construct an estimate of the NYSE limit order book in four steps, using the TORQ database: limit orders at the start of the sample are identified; the current orders are added to the pre-book; order records are matched with execution records and cancellations. As a result, snapshots at 30 minute intervals are obtained. Goldstein and Kavajecz (2000, 2004) replicate this methodology.

Hall and Hautsch (2004) reconstruct the complete Australian Stock Exchange order book at real time frequency. Auguy and Le Saoût (2001) and Auguy et al. (2000), briefly describe the reconstruction procedure prepared in SAS, in their papers on the LOB analysis of the Paris Bourse. Beltran et al. (2005) and Frey and Grammig (2005) perform the LOB reconstruction for DAX stocks with the same dataset from the XETRA system. They reconstruct two separate limit order books based on the Gauss program, using a method similar to that used by Auguy and Le Saoût (2001). One of the books is visible to traders, and the other contains Iceberg orders, with snapshots each time a trade takes place. In a similar fashion, De Winne and D'Hondt (2005) reconstruct the LOB for eighty-two selected stocks from Paris, Amsterdam and Brussels.

Based on the literature above, Ekinci (2005) discusses the use of the limit order book as a source of information and shows step by step, the procedure for its reconstruction, in this case of the Istanbul Stock Exchange. The study offers an innovative approach by incorporating trades into the order book. The proposed approach consequently links trades to orders at defined snapshot periods.

Hasbrouck (2010) describes how to determine the best bid and offer (BBO) from the NYSE's monthly TAQ data by employing SAS. The quote reconstruction technique is in three stages: 1. Filtering; 2. Order Sequencing and 3. Derivation of BBO. The BBO derivation differs from the definition of Wharton Research Data System (WRDS) documentation. He explains the problems associated with order sequencing. The accuracy of BBO sampling is dependent on the correct ordering of the quote records. He concludes that incorrect sequencing within a LOB is much more profound than incorrect sequencing between exchanges.

The LOB reconstruction algorithm of this study incorporates five stages, but contains essentially the three step procedure of Hasbrouck (2010) plus the order sequencing suggestions of Ekinci (2005). This limit order book reconstruction of the Moscow and London stock exchanges contributes to the literature of order book reconstruction. By generating new variables, it contributes to understanding the complex behaviour of multi-market trading and the price discovery process of the MICEX, RTS and LSE exchanges. This is the first and the only study that reconstructs LOBs of two Russian stock exchanges. This is also one of the few studies that combines three reconstructed LOBs for eight cross-listed securities. The reconstruction approach utilised in this study, methodologically links trades to orders, i.e. marketable limit/market orders, and leaves only valid limit orders in the LOB. The best prevailing quotes are derived from the LOB at a range of discrete sampling intervals. Reconstructing the LOB by using varying sampling frequencies to derive the best prevailing quotes is a best quote sorted alternative to other simpler methods of reconstructing limit order books.

4.3 *LOB Reconstruction and Best Quote Sampling Algorithm*

The goal of the following algorithm is to restore the chronological sequence of the continuous double sided auction in regularly spaced snapshots, in essence a time interval sampling procedure, as accurately as possible. Since the electronic LOBs of the MICEX, RTS and LSE exchanges operate according to similar principles, the reconstruction algorithm is common to all three markets. The emphasis is placed on the derivation of the best prevailing bid-ask offer quote in a chosen sampling interval for each LOB. Best bid and best offer mean the highest priced bid and the lowest priced offer prevailing in the snapshot period. The reconstruction procedure results in a scalable moving picture, sampling frequency defined sequence of snapshots, of the order flow activity, which in the end contains the time series of best prevailing quotes of the trading session for chosen market(s). The essence of the algorithm is structured in the following consecutive stages:

Stage 0: Data Preparation: All databases, including the daily exchange rates time series, are uploaded and stored in one common uniform database. However, each market is reconstructed individually, since all markets are unique in their data record nomenclature and topology. For each market LOB, there are filtering options to choose: instrument name, date and time period, exchange rate and ADR rate conversion, sampling frequency, order depth, trade prices and how many markets are to be included in the final database. One must choose the sampling period as well as the sampling frequency, which defines the sampling time stamp (clock). This sampling clock is essential to all subsequent procedures. Stages 1 - 4 occur subsequently in one process.

Stage 1: Database Querying: All orders relevant to the chosen instrument related fields such as order ID, order type with corresponding bid-ask quotes in a chosen time period, are queried and filtered. In this Stage all bid and ask orders are filtered out. The bid and ask side of orders are from this point on processed separately.

Stage 2: Sequence ordering: There are two time stamps: that historically assigned to an order by exchange and sampling frequency, and the specified time stamp, referred to here as a sampling clock. The sampling clock is the base according to which snapshots are subordinated.

A snapshot is a fixed point in time, which cross-sectionally captures all valid and sequentially sorted orders sharing an equal time point (Figure 4). Fundamental to all subsequent procedures is the continuous sampling clock specified in Stage 0. The sampling clock is the reference time stamp for all sequence ordered snapshots. All orders contained in the relevant period of LOB are linked by their assigned order numbers (IDs) as they are found in separate databases. Order quote validity is clearly defined by the order's LOB entry and exit time points for each order. Each valid order quote is made up of the sequences captured in any given time snapshot. All valid orders captured by time snapshots are ordered according to best prevailing quote criteria, which are stated in the 3rd Stage (sampling). All quote ordered snapshots are assigned to the defined sampling clock, which forms a base for a sampling procedure in the next Stage.

When ordering snapshots, besides the originally recorded time stamp, which defines when the order has been submitted, matched, modified or cancelled in the LOB system, there is a historic action field which indicates the previously mentioned state of the order (status) at the given time point. Consequently, for all orders captured in each snapshot, there is a combination of scenarios for each order: full order match with counterparty order, order partial match, order deletion, size modification or expiry of an order. Normally, there is a clear indication of what happened to an order at the beginning of its valid period with its corresponding status (the full status list is in the Appendix) e.g. for an accepted order submission until the end of order validity, when the submitted order leaves the LOB in the multiple case scenario as described below. There are two major scenarios:

Scenario A: In the case of a full order match, deletion or order expiry, the result is simple: the order leaves the LOB system. In other words, a particular order that has been placed in the auction has been valid in a clearly defined time frame and is invalid for other time periods. An order match means a transaction occurred and the trade is reported in a separate trades data base. A match is the case in which the size of either bid or ask orders or both, matches fully at a given price level. If this event occurs, the orders are normally automatically executed, and this results in a transaction or a trade; both counterparties are bound to exchange the order size matched quantities at the executed price. So, matched market orders are trades, but the reverse may not necessarily be true. Once orders are matched, remaining quotes variations are limit, modification and cancellation orders.

Order cancellation (order kill or withdrawal) occurs, provided there is no full match, when the trading party decides either to change the quote of the submitted order or simply kills the order. During the normal daily trading session, a posted order usually expires at the end of the session, or the specified order expiration. However, on some markets, an order could have been posted outside the opening or closing periods in the extended session periods, and some orders may stay in the system for prolonged session periods of time. When Scenario A occurs, once the order leaves the system, it is therefore invalid outside its time period and not relevant for the remaining periods, particularly in the following sampling procedure.

Scenario B: Usually not all orders match fully, and therefore partial match of orders occurs. This means that usually one or other of the counter orders, or even both, hit each other, but the size matches incompletely. A trade occurs, one or both order sides simply changes the size, but remain active and stay in the LOB. So, the usual result may be one order match and the counter order partial match, or both orders partially matched at the given price level. In both cases, a transaction occurs, which is reported in the trades database.

Order modification occurs when the existing order price remains unchanged, but the size changes. The order does not normally change the priority in the queue and the order number does not change. The order may result in deletion status if the order price is changed and therefore loses queue priority. When Scenario B occurs, once orders fully match, they exit the LOB trading system, and are therefore invalid, as in Scenario A. Beyond order validity, orders are irrelevant for the other time periods, particularly in the sampling procedure. However, those orders which match only partially remain in the system and are valid until a further event occurs.

The presence of cancellations, deletions and modifications is a further complication in reconstructing the order book. Order cancellations and modifications are usually trader initiated, while order deletions are trading system initiated. If the order is not executed or is partially executed, traders have an option to cancel or to modify the submitted order parameters. In the data set utilised, cancellations, deletions and modifications are noted with a time stamp, identified by a historic action code and lastly by the order number. The process of dealing with cancellations and modifications is as follows: when a new order modification or cancellation arrives, the identified historic action code, usually C or W, D or M, depending on the trading system nomenclature, with its order number, are jointly checked for links in the trades database. If the transaction linked to the considered order appears in the trades database, then the order has been partially executed and is still active. If that order had not already been executed and left the LOB, then the order is active and can be modified or cancelled. In the case of a modification, if the order has not already been executed, the order is treated as a valid active order. If subsequent modification causes this order to be executed, the order may receive priority in execution {see Harris (2003)}.

Stage 3: Best Bid/ Ask Quote Sampling: The sampling procedure takes place in combination with the order sequencing stage described in Stage 2. The best quote selection procedure is looped for each snapshot located in each sampling clock moment specified in Stage 0. The procedure selects the best quote according to the best prevailing quote criteria outlined below. Best quotes of each snapshot, containing sequentially sorted orders created in Stage 2, are allocated to an a priori specified sampling time point of the sampling clock. As in Hasbrouck (2010), the SELECT procedure occurs in conjunction with ORDER BY statement, choosing order quote values by the best prevailing quote criteria for each specified time point of the sampling clock. The best prevailing bid-ask quote in the LOB system is:

For each defined sampling interval snapshot there is a maximum valid Buy or Bid order with a quote B(t)

$$B(t) = \max_{i=1,\dots,n} b_i(t)$$

For each defined sampling interval snapshot there is a minimum valid Sell or Ask order with a quote A(t)

$$A(t) = \min_{i=1,\dots,n} a_i(t)$$

If buy/sell orders match, then the orders are executed. If full or partial bid-ask order match leads to execution and transaction, resulting in trade, then these orders are excluded and not considered for other sampling intervals. If there are aggressive limit orders, which are posted above/below the best ask/bid quote, which cause the bid/ ask quote curves to cross over at that particular point of time, then their valid order quote is initially considered. However when the matched orders are executed, resulting in a trade, orders leave the LOB. So, the best prevailing quote reduces itself to the transaction price. If both quote curves only tangentially touch each other at the trade price of both order sides, the executed orders exit the LOB system.

For the sampling procedure of the best prevailing quote, only valid orders that stay in the LOB are the point of interest for LOB sampled reconstruction; the ones which, for example, are executed in a trade or are expired orders, and so have left the system, are of less concern for the best prevailing bid-ask time series, but are vital for accuracy and verification purposes.

Stage 4: Variable Creation: In the last reconstruction Stage, new variable are added, based on the reconstruction and sampling results given, such as mid-quote between the best prevailing bid and the ask, spreads of bid-ask, new order time delay, quantity depth and currency and ADR rate conversions. The most essential variables for undertaking this study are mid-quote and bid /ask spread. Let a(t) be the ask quote and b(t) be the bid quote at time t. The mid- quote M(t) is defined as:

$$M(t) = \frac{a(t) + b(t)}{2}$$

and the bid-ask spread S(t) at time t is defined as:

$$S(t) = a(t) - b(t)$$

Additionally, it is possible to calculate the aggregate depth of an a priori chosen level for all valid orders in each snapshot. The level of order depth must be chosen in Stage 0.

Stage 5: Synchronisation: This procedure synchronises the matrices of the sampled LOBs according to the equally defined sampling clocks of each market. The condition for synchronisation is that each market LOB must contain an equal number of rows. Once each LOB market is reconstructed in its identically defined time/ date period, the already separately reconstructed and LOB derived time series can be merged into one common database. In the end, the most relevant columns of all time series are summarised at the chosen sampling frequency. All the relevant data fields have been synchronised according to the a priori chosen sampling reference clock. The resulting matrix of variables consists effectively of multiple time series, and one can now export the database for analysis or continue with the procedures described above with additional markets.

The objective of the synchronisation stage is to create one final database which would contain a summary of all important variables in a uniform, chronologically synchronised, continuous format. There is a choice of which markets to merge, at which frequency and for which time/date period. However, some less order flow intensive markets such as RTS and LSE, regardless of how liquid some instruments were, would occasionally contain order-less snapshot periods. If there is an observationless period, in the derived best prevailing quote time series, it is interpolated with the Last-tick assumption (see Section 4.4). This was especially true for high frequency sampling intervals under one minute and lower liquidity instruments such as Sibneft. This issue is discussed in detail in the Reconstruction Issues Section 4.7.

Stage 6: Error Checking and Filtering: Once the individually reconstructed samples of best bid-ask quote series, with the corresponding variables of each LOB, are merged into one single database, one can proceed to check the joint time series evolution graphically. This procedure is carried out on a manual basis. The strictness of the filtering depends on the ultimate purpose of the calculation. Only extreme and economically meaningless outlying quotes are excluded. It has also been common practice in the literature e.g. Hasbrouck (2010) to exclude bids quoted near the minimum amount e.g. 0.01 USD, on the assumption that no transactions can occur at such a price.

When the chosen limit order books are reconstructed, it becomes possible to follow the evolution of behaviour of a market or a market combination at each moment. Several variables can now be deduced at each point of time including bid and ask quotes, quantities and order IDs of the bid and ask sides, as well as the balance of bid and ask variables. The reconstruction results example for LKOH for all three LOBs are depicted in Figure 19 and Figure 20 in the Appendix.

4.4 *Reconstruction Procedure*

The main objective of data processing is to reconstruct the LOB systematically and to derive the best prevailing bid-ask quotes at a chosen sampling frequency. The derivation of the best prevailing quote accords with the proposition of Hasbrouck (2010). This process requires the accurate retrieval and restoration of the recorded orders and realised transactions from their original unsorted state, into a chronologically and sequentially sorted snapshot aligned to the chosen sampling clock in daily intervals. The reconstruction process involves a sampling interval scaling feature, which allows observation of the reflected information flow in such a way that the information about the variables is reproduced in their original order, similar to the way in which traders would have observed uninterrupted the trading process, live in front of the screens. The reconstruction approach is similar to that of Ekinci (2005), and the validity of orders is determined by establishing the order history i.e. linking orders to trades.

The sampling frequency is defined by the sampling clock, which is set at the beginning of the reconstruction procedure. The smallest increment of the recorded time stamp is one second for all data bases. The sampling clock time stamp and the recorded time stamp coincide if orders are executed within a single second of the time stamp, and the sampling frequency is, for instance, one second. The sampling frequency is dependent on how frequently the snapshots are taken. The sampling scaling principle is illustrated by Figure 14 and Figure 15, where, Figure 15 displays a bid quote evolution at lower sampling frequency, while Figure 14 presents bid quotes at higher frequency.

The nature of ultra high frequency (UHF) data and issues associated with modelling are described in detail by Engle and Russell (2004). It is common in LOB trading that the orders posted by traders, and the resulting transaction price, arrive in discrete and unequally spaced time intervals. This poses a problem for later stages when modelling such samples, particularly with models which assume continuous variables. In order to transform the discrete data type into a continuous form, either inter-temporal aggregation or interpolation of the missing intermediate values becomes a necessity. The issues associated with inter-temporal aggregation, i.e. sampling at lower sampling frequencies are discussed in Chapter 8. Figure 21 illustrates issues of interpolation associated with the transaction data. In order to overcome the discreteness of data, it is essential to make assumptions about the missing observations. One possible assumption is that information about asset value evolves continuously, and is independent of quoting and transacting. That implies that the information observable in form of quotes and prices is not necessary complete. Therefore, even if there is an absence of a quote or a price in a given moment of time, there may still be an intermediate value. These intermediate values can be interpolated according, for instance, to the last-tick method.

A missing value of an observationless period can be interpolated in various ways. The application of interpolation methods is debatable, as illustrated by Figure 21. Between snapshots S3 and S5 there is a period, S4, which has no observation. How should be the missing observation be interpolated? An assumption about the observationless period would determine the value of the missing observation. Specifically for the transaction time series the transactionless periods become a serious challenge. This issue is discussed in the Reconstruction Issues section. Various interpolation methods are proposed by Dacorogna et al. (2001). The previous point or last-tick method or interpolation seems to be one of the viable solutions. However, there at least three simple ways to interpolate: 1. Ceteris paribus, interpolate until the new transaction happens (last-tick method), 2. Interpolate the missing values with the values from the other market (which becomes a problem if more than two markets are involved) and 3. Interpolate retrospectively (next-tick method), by interpolating the next executed transaction retrospectively until the current one (which is opposite to assumption 1, the last-tick method). Regardless of which interpolation assumption is more adequate in reality, an interpolation is still a missing value invention technique. Interpolation can be seen as having the potential to be an artefact and, therefore, it may be a problematic solution tending to alienate the missing values, and possibly lead to misleading inferences.

On the other hand, there is not much that can be done if no transactions occur. Interpolation itself is a problem, and overcoming it might be the only solution. That can only be achieved if order quotes databases are included for complete order book reconstruction. Here, the problem of interpolation does not exist, because there are usually order quotes posted in the trading system without the need for a transaction to happen. In order to overcome the problems associated with interpolation, this study, instead of inventing (interpolating) missing values, utilises best prevailing bid and ask quotes in the trading system, as an alternative way of filling the missing values.

As opposed to the missing observation issue, there is the occurrence of multiple transactions at the identical time stamp point. However, such events during the sample period were rare and took place mainly on the MICEX market for the most liquid securities such as EESR, LKOH and RTKM. If such an event occurred, the aggregated average value was chosen. However, one could compute an average price weighted by volume, as suggested by Engle and Russell (1998).

Prior to the synchronisation of individually reconstructed LOBs into a common database, one should consider some idiosyncratic peculiarities of traded securities. Each of them requires a unique approach in choosing an optimal sampling frequency, because of the differences in information expressed in the frequency with which initial orders are posted for each security across markets. That poses a problem for the stage at which inferences are made, because of the trade-off between signal (new information) and noise. For example, in the initial analysis, the time series of LKOH stock traded on RTS displayed the absence of a unit root at 1 second sampling frequency, despite the presence of it on MICEX. However, the unit root became strongly significant at thirty seconds frequency and with a larger sampling period. One possible explanation for that could be the presence of a weak signal or its complete absence, because of less frequent order posting and therefore less bid-ask bounce on RTS than on MICEX. The optimum sampling frequency choice and the associated issues are discussed in Chapter 8.

Alternative sampling frequencies of more than five minutes are also considered for suitability, relative to higher frequencies such as one minute, ten or five seconds, in the initial analysis. Due to inter-temporal aggregation, the accuracy diminishes at lower frequencies, so that the correlation dynamics between the variables dissolve, indicated by falling statistical significance in their coefficients, as demonstrated, for instance, in Chapter 8. At higher sampling frequencies than thirty seconds there would probably be no gain in terms of increase in the significance of correlation between the variables. However, there has been a trade-off with issues such as microstructure noise, signal (impounded information) and non synchronism of observations, which may lead to the conclusion that the thirty seconds interval is the optimal. The issue of optimal sampling frequencies is discussed in Chapter 8.

In Stage 6, Filtering and Error Checking, great attention has been paid to bid-ask quote crossovers and large outliers. While bid-ask quote crossovers are majorly attributed to incorrect order sequencing within snapshots, substantial deviations, often multiples of best prevailing quotes, are subject to LOB trading peculiarities. Figure 13 presents a picture of snapshots capturing best prevailing bid and ask quotes sampled at a continuous sampling clock. Filtering, according to Hasbrouck (2010), is a complex subject, because any filtering implies a trade-off between type-I and type-II errors, and this trade-off is dependent on the sampling frequency and the sample. In order to keep the integrity of the LOB microstructure, the reconstructed data has been mildly filtered in the last stage i.e. only substantial outliers have been removed. The removal of economically meaningless outlier quotes makes sense if one intends to derive the mid-quotes over each interval. Mid-quotes are sensitive to outliers and missing quote observations. Since the quote spread is positive, the resulting mid-quotes are not symmetrically distorted. Furthermore, subjecting quotes to a quote filter by removing quotes with spreads greater than a dollar, for instance, is considered normal.

4.5 *Reconstruction Program*

The unprocessed databases stemming from the exchanges are fundamental to limit order book reproduction. Only programmed data processing is feasible because of the size of the original databases. The original data base specifications are presented in the data chapter. Moreover, the time required by the software to reconstruct a single LOB and to derive the best quote variables, depends on the power of the computer and the liquidity of the underlying security in the LOB itself. For instance, a PC with a Quad core CPU (2.4 GHz), 4 GB of RAM with a SATA hard drive in a Windows 64-bit environment can take many minutes simply to filter the database. In order to process a single day's LOB and to sample the related data set at a frequency of one second, the PC might need up to 30 - 45 minutes for a single MICEX instrument. The required processing time depends mainly on the number of orders and trades on that day, and their combined complexity.

The data processing has been developed based on the Structured Query Language (SQL) programming language, which follows the algorithm stated in Section 4.3. In essence, the software program first links database files of transaction and order data. Then, queries are created which sort the raw data chronologically by security ID, sorting bid and ask quotes separately and filtering the unnecessary noise values out, for instance orders with zero quotes. Next, a procedure creates a clock (time stamp), which is the foundation for a sequence of sorted best quote snapshots chosen in the multiple markets overlapping time period. This initialises the sampling procedure, which is a combined process happening alongside LOB reconstruction. The program orders the information of overlapping entry and exit times of orders (validity) in each snapshot, for which at least two database files (orders and transactions) are required. Each snapshot requires the right values chosen according to selection criteria (maximum quote value for bids and minimum for asks). If orders match and are executed, they are first taken into account in the snapshot, since they are in the trading system, and then as they lose validity they are eliminated from the LOB. Each snapshot row may contain orders with an active, matched, modified or cancelled status. All valid (active) orders in each snapshot are processed consecutively, according to the priority rules and best quote criteria in the order book. In the end, each of the resulting arrays of best prevailing order quotes is allocated to the specific time point, according to the clock, in the chosen sampling intervals.

The LOB reconstruction, sampling and best quote derivation process occurs for each market individually, before all relevant markets are synchronised in one common database. This common database is finally exported in a format suitable for the econometric analysis. Transactions only data is processed separately. The multiple transaction price-time series must be synchronous. Furthermore, the time series is transformed into a continuous form by means of selectable interpolation methods. There is the possibility of uploading and linking databases into one common database by indicating to the software the paths where individual databases for quotes, trades and RUB/USD exchange rates are located. All databases relevant to the reconstruction process can be uploaded individually and checked for completeness. Furthermore, an ADR conversion ratio is an option for the LSE securities.

The most critical stage of the LOB reconstruction is the order sequence sorting stage followed by the sampling procedure. According to Hasbrouck (2010), incorrect sequencing within LOB snapshots is much more serious than incorrect sequencing between LOBs. The consequence of incorrect order sequence may result, for example, in an incorrect best quote being based on a cancelled or matched order and may cause bid-ask crossover. Therefore, it is crucial to have valid orders located in each snapshot with an ORDER BY clause in conjunction with a SELECT procedure as illustrated by Hasbrouck (2010). The snapshot order sorting principle for buy orders is illustrated in Figure 4. For instance, snapshot S1 at time period t2 captures all valid orders 1- 6 prevailing in the LOB after sorting. If the sequence sorting is correct, then only 6 orders are captured by the snapshot S1. The best prevailing bid quote from the valid buy order Ord6 for the snapshot S1 is Q6.

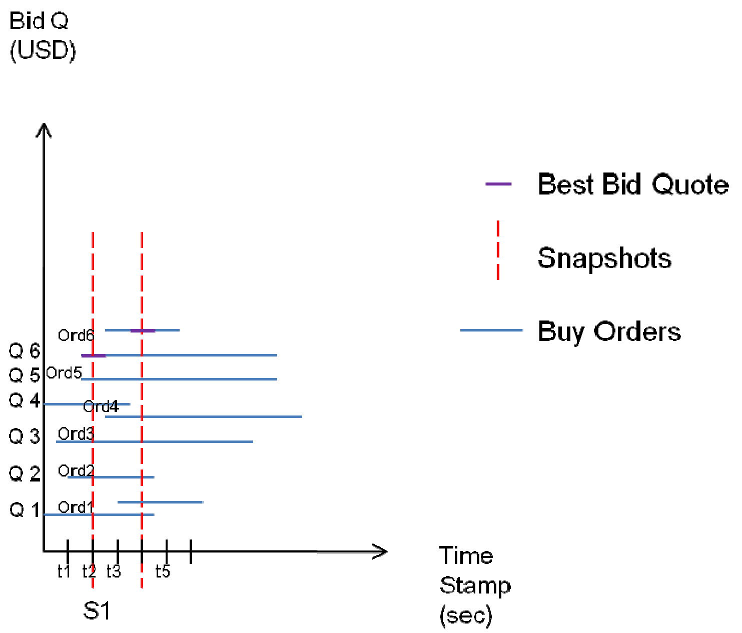

Figure 4 Snapshot Best Quote selection

Like Figure 4, Figure 11 shows an evolution of an order snapshot sequence, with selected best prevailing bid quotes. A similar sorting procedure for sell orders results in the snapshot sequence presented in Figure 12. These snapshot sequences are combined in Figure 13.

One can choose the scale of sampling interval in the sampling procedure. Sampling at lower than recorded time stamp frequency, is in essence an inter-temporal aggregation of time series. Flexibility of the sampling frequency can be a helpful feature to test consistency of the results, as opposed to sampling at the highest possible frequency and filtering the intermediate values at a later stage. Different sampling frequencies could also be obtained by choosing reconstruction at 1 second intervals, and by applying filtering at the later stage, omitting the intermediate intervals. There is an option of choosing the sampling frequency in a minimum recorded time of one second until infinity in a discretely-continuously inter-temporally aggregate in 1 second steps. However, 1, 5, 15, 30, 60, 120, 240, 480, 960 and 1920 second intervals were arbitrarily chosen without making any assumptions about the optimal sampling frequency for Chapter 7, for example. Also, each trading day is sampled individually in respect of the best prevailing quote of given snapshots, partly because there is no overnight trading on any of the investigated trading venues. Altogether, sampling at various frequencies, results in a range of new data sets containing variables for empirical analysis.

A characteristic feature, which differentiates the reconstructed LOB from the observations made on screens of traders, is that the marketable orders which resulted in transaction can be derived from the LOB in a similar fashion to Ekinci (2005). In order to detect whether an order is a limit order or marketable order, it is possible to check the actual bid- and ask quotes. If an arriving order in which the bid (ask) quote equals or overlaps the ask (bid) prevailing quote, the order is identified as a marketable order. When a marketable order arrives, instead of ignoring, the matching order in the LOB, the SQL program initially considers the quote in order to see the exit moment from the LOB system, but the order is then identified as invalid in the snapshot. Graphically, the bid-ask spread in this case drops to zero or causes a crossover for an instant. As a consequence, since the point of interest is the best prevailing quotes, crossovers caused by such quotes are consistently eliminated. Such an approach separates marketable and limit orders into separate baskets, while reflecting the prevailing demand or supply for securities more precisely.

The major challenge, however, appeared to be dealing with bid-ask order crossovers, which imply that the order quotes are matched at least in the part of the spread which is negative. The quote crossover results in fully or partially executed transactions at a price and quantity reported in the LOB trading system in the trades database, with allocated transaction IDs and time stamp point. The most complicated part of the reconstruction process is to define and identify trading scenarios (Section 4.3, 2nd Stage), which are, for instance, full order match, partial order match or order cancellation. The buy and sell orders in the quotes data are checked against the executed orders in the trades database. In order to prevent the crossover of bid and ask quotes, the orders resulting in trades are eliminated from the LOB.

Accuracy is an important aspect of the LOB reconstruction. It applies particularly to the data sequence ordering and sampling process across markets, as well as to each individual market. Following the order quotes sequential sorting in each snapshot, each sampling period is filled according the best prevailing quote criteria. Accuracy is crucial at this stage because of its consequences. When comparing pricing across the markets, the pricing should provide fairly close results; strong deviations could indicate reconstruction inaccuracy.

In the final stage, after all market LOBs are reconstructed individually, the equal frequency sampled databases containing all LOB variables must be synchronously combined in one final database. Because the number of variables for each reconstructed LOB is usually large, only the variables such as time stamp, order numbers, bid-ask quotes and order depths which are relevant to the research objective are transferred. At this stage, there are options for dealing with the missing quote or price observations which have occurred across the markets for the lesser liquid securities.

4.6 *Transaction Tick Data Processing*

An alternative to the proposed order book reconstruction method is the interpolation of a transaction price-time series based on the trades data, which is an additional test of robustness.

Given the discrete nature of transaction occurrence, there are relatively more missing observations in the periods between each transaction than between the best prevailing quotes. The microstructure literature offers two major solutions to the problem of missing observations: either continuous interpolation by the last-tick method or discrete sampling as conceptualised by Harris et al. (1995, 2002). The main drawback of the Harris et al. (1995, 2002) discrete data methodology is that it becomes difficult to resample the data set at different sampling frequencies once the multiple markets have been “tulped”. Though there is a range of implicit interpolation techniques, Chapter 7 and Chapter 9 of this thesis support the last-tick interpolation methodology. Assuming the price does not deviate significantly during the shorter time intervals e.g. under one minute, this way of interpolating price tick series should ensure the preservation of the intraday trading dynamics without sacrificing accuracy.

It is possible to use other techniques of interpolation, but the end result would be a trade-off between type-I and type-II errors. However, an alternative interpolation method would be, for example, to use the prevailing tick from another market, or assume that the missing observation consecutive price tick is the last missing value. The major argument against the complexity of interpolation is that the more sophisticated the invented missing data, the more difficult it becomes to support the assumption upon which manipulations have been made. Furthermore, the reconstruction results are more comparable across the different types of data if a similar interpolation method is used. Complex price extraction methods are best avoided, since the time lead-lag relationship in price discovery is sensitive to the way the datasets are manipulated. Different interpolation, may lead to different results and hence inferences. Therefore, the transaction tick data of this study relies on the simplicity of the last-tick interpolation technique.

The following steps were undertaken to process the data:

1. a query with filtering securities individually in the LSE, RTS and MICEX trades databases;
2. allocating the time stamps of the transaction prices to a common sampling clock;
3. interpolating the missing values with the last known price tick;
4. one option for comparison is merging rebuild trades with the best prevailing quotes

The merit of using prices based on trades data is that they eliminate the possibility that quotes are being revised on only one side of the market or the other to reflect positions. It is unlikely that the choice of execution versus mid-point prices will have any essential effect on the results. Since only the prices of executed transactions were considered, bid-ask quote mid-point conversions were not necessary. The transaction prices are not the theoretical mid-point of the bid-ask tick quotes, and may arguably better reflect the arrival of new information than the theoretical mid-quotes as advocated by Harris et al. (2002a).

The main disadvantage of transaction prices, however, is that the time series, by their very nature, contain fewer prices per observed interval than the best prevailing bid-ask quote series. This is expressed firstly in the more frequent and larger observation gaps, and secondly in more discreteness. The less liquid RTS and LSE data set is interpolated to fill the missing values on the assumption that the last observed price would remain constant until the next observation. This is the most conservative method since it assumes that the prices do not change over an unobservable period. However, it may not be true (subject to type I error) with respect to theoretical price levels derived from the quotes of an order book.

The price-time series have been sampled with varying sampling interval periods similar to the limited order book. On the one hand, sampling at shorter intervals avoids data censorship, on the other it requires more interpolation to fill the missing values which arise when no observations exist for a given interval. Moreover, there is evidence that these data gaps, provided that they are kept in reasonable proportions do not substantially affect the quality of inferences {see Grammig et al. (2002, 2005)}. The MICEX, RTS or LSE data samples may contain a high number of transactions during the sampling interval, but may have none during the next. In the case of the RTS and LSE data sample, such a transaction-less observation “gap” could last from several minutes to several hours or even days, depending on the given liquidity.

Among the necessary conditions for the multiple data sets is the synchronicity of data. In order to synchronise the overlapping continuous trading time between the two exchanges, the differences in liquidity, expressed in the number of observations, require a solution as previously mentioned in the case of limit order book reconstruction. The sampling procedure requires the time series during the overlapping trading times to be continuous and synchronous. So the number of observations must be equal. Most RTS and LSE samples have been manipulated by means of interpolation, and because MICEX is more liquid (more immediate), the sample interpolation has been negligibly minor.

4.7 *Reconstruction Issues*

This section discusses issues associated with time periods in which no valid quotes on one or both sides were present, or no transactions took place. Like error filtering, this issue is subject to a trade-off between type-I and type-II errors, if the time series are assumed to be continuous. Theoretically, the missing observation of a quote or price value could be either equal to zero or infinity, yet in empirical practice it is a missing observation. Filling unknown and unobserved values requires assumptions to be made about the missing values. If the missing observation only occurred on one side on the order book, then for instance, the mid-quote is affected, resulting in the value of a quote being halved. In this case, depending on the research purpose and desired accuracy, there may be no necessity to manipulate the data set in any way. However, if no transaction took place, or the quotes are missing on both sides of the market, then missing observations may become a serious issue.

Generally, the missing observation is not an issue for the LOB derived quotes. It becomes more of an issue for trades based securities, and particularly for lower liquidity securities sampled at the highest frequencies. Table 5 and Table 6 can be used to compare the degree of missing observations which could be cured by interpolation. Relative to trades based data, the LOB derived best prevailing quotes on the MICEX market require none or in exceptional cases some degree of interpolation on the RTS and LSE markets. Interpolation based on the transaction data, on the other hand, is not an exception but a necessity. The superior liquidity of the MICEX market suggests that only lesser liquid securities require heavy interpolation. These securities are SIBN, SNGS and TATN. GAZP required 51% interpolation, but given that the security was listed for the first time on MICEX at the beginning of the sample period, it may be less surprising. However, the transaction prices of all securities traded on the RTS and LSE markets, as a rule, required on average, 99% interpolation. That may be seen as a serious issue if the sampling frequency is 1 second, because most of the observations are seemingly invented. This issue is addressed in Chapters 7 and 9. The interpolation of transaction prices at the highest sampling frequency biases the price discovery results by assigning higher information shares to the lesser liquid market.

			RTS		LSE	
		Total Obs	Total Inter	% Interpol	Total Inter	% Interpol
EESR	Bid Quotes		2,109	0.12%	685	0.04%
	Ask Quotes		356	0.02%	5,999	0.35%
	Both Quotes	1,727,183	0	0.00%	110	0.01%
GAZP	Bid Quotes		0	0.00%	0	0.00%
	Ask Quotes		0	0.00%	0	0.00%
	Both Quotes	1,404,065	0	0.00%	0	0.00%
GMNK	Bid Quotes		45,757	2.65%	749	0.04%
	Ask Quotes		81,589	4.72%	1,965	0.11%
	Both Quotes	1,727,811	9,030	0.52%	0	0.00%
LKOH	Bid Quotes		5,995	0.35%	1,320	0.08%
	Ask Quotes		0	0.00%	290	0.02%
	Both Quotes	1,728,080	0	0.00%	0	0.00%
RTKM	Bid Quotes		1,874	0.11%	16,715	0.98%
	Ask Quotes		1,274	0.07%	23,704	1.39%
	Both Quotes	1,701,031	7	0.00%	12,089	0.71%
SIBN	Bid Quotes		425,516	26.71%	16,783	1.05%
	Ask Quotes		260,974	16.38%	3,233	0.20%
	Both Quotes	1,593,045	126,182	7.92%	567	0.04%
SNGS	Bid Quotes		90,706	5.25%	7	0.00%
	Ask Quotes		43,656	2.53%	1,133	0.07%
	Both Quotes	1,728,080	42,020	2.43%	0	0.00%
TATN	Bid Quotes		256,634	38.34%	79	0.01%
	Ask Quotes		239,370	35.76%	127	0.02%
	Both Quotes	669,439	162,517	24.28%	0	0.00%

The table shows the degree of linear interpolation required to transform the quotes based data set into continuous form

Table 5 Interpolation based on Quotes

How shall a time period be treated if there is a missing observation in this period, particularly in the case of transaction price-time series? There is no first best solution to this problem, but there are at least 3 options that can be implemented; a) interpolating these periods with for example, the last known value (last-tick method), b) leaving all the observationless periods with missing or zero values or c) deleting the row in effect the time period across the chosen markets, if the values are missing on either market side. As outlined above, each option has its merits and shortcomings. Keeping missing observations filled with zero values may appear to be the truest and least distorted recreation of the original event, yet it may introduce serious distortions in the price discovery modelling process. The introduced zero values, which are more likely to occur on the less liquid market, would seriously bias the contributions of the less liquid market in favour of the most liquid. The equilibrium adjustments of the less liquid market would look more dramatic, and at times completely undermine its role in price discovery. Interpolation is the subject of data invention assumptions as discussed in the next paragraph.

MICEX	EESR	GAZP	GMNK	LKOH	RTKM	SIBN	SNGS	TATN
Num. of Trades	1,651,364	1,296,073	1,727,369	1,728,019	1,402,831	761,900	298,111	50,474
Req. Observations	1,651,364	1,296,073	1,727,369	1,728,019	1,714,957	1,538,197	1,749,190	727,360
Interpolated	0	0	0	0	312,126	776,297	1,451,079	676,886
% Interpolated	0.00%	0.00%	0.00%	0.00%	18.20%	50.47%	82.96%	93.06%
RTS	**EESR**	**GAZP**	**GMNK**	**LKOH**	**RTKM**	**SIBN**	**SNGS**	**TATN**
Num. of Trades	6,047	10,924	2,660	5,940	876	137	1,984	736
Req. Observations	1,651,364	1,296,073	1,727,369	1,728,019	1,714,957	1,538,197	1,749,190	727,360
Interpolated	1,645,317	1,285,149	1,724,709	1,722,079	1,714,081	1,538,060	1,747,206	726,624
% Interpolated	99.63%	99.16%	99.85%	99.66%	99.95%	99.99%	99.89%	99.90%
LSE	**EESR**	**GAZP**	**GMNK**	**LKOH**	**RTKM**	**SIBN**	**SNGS**	**TATN**
Num. of Trades	12,564	37,624	12,985	42,372	4,152	3,290	14,679	1,401
Req. Observations	1,651,364	1,296,073	1,727,369	1,728,019	1,714,957	1,538,197	1,749,190	727,360
Interpolated	1,638,800	1,258,449	1,714,384	1,685,647	1,710,805	1,534,907	1,734,511	725,959
% Interpolated	99.24%	97.10%	99.25%	97.55%	99.76%	99.79%	99.16%	99.81%

The table shows the degree of linear interpolation required to transform the trades based data set into continuous form

Table 6 Interpolation based on Trades

One of the possible solutions to the missing observation problem is interpolation. That means connecting the observation points with each other, assuming that pricing is a continuous process, despite the lack of observational evidence. Substitution of the missing value with the last known value of the previous time period (last-tick method), could be regarded as one possible way of interpolating the data set, forcing it to become continuous. The major benefit of interpolation is that, while keeping the time series continuous, no valid order book quotes or prices are lost. The drawback to this particular type of interpolation is that the missing price or quote connected to the last quote value is assumed, which might encourage a type-I error. The assumption of last known value leads the corresponding market to react more slowly, because the old quote is repeated. An alternative to the last-tick method is the next-tick method. The assumption behind this interpolation method is that a new price or quote value is already formed before the next observation is recorded. This assumption might, however, give an advantage to the less liquid market. By the same token, this method becomes subject to a type-II error. There are other interpolation assumptions possible, but their presence merely changes the nature of the less liquid market reaction. This is discussed in the section dealing with transaction time series reconstruction, based on the trades data set.

In essence, the underlying problem of interpolation is a potential creation of artefacts, which can be regarded as a compromise between the extremes of deletion and having zeroed or missing values. The reservation with the last or next tick interpolation approach is that the missing values are chosen and substituted artificially. That has a direct effect on how markets react to information. The issue of the interpolation of a missing observation is directly illustrated in Chapter 7, which shows that price discovery is highly sensitive to the degree of interpolation associated with a trades based data set.

On the other hand, substituting missing observations with zero values can lead to an artificial overreaction of the less liquid market, while the presence of zero values minimises the bias of the less liquid market. However, zero value assumption ignores the opposite extreme, which is in theory infinity. In practice, the presence of multiple zero values may lead to a serious distortion of the results, as happened in the preliminary analysis. Introducing zero values on the bid or ask quote side of the market, leads to a half mid-quote value which is not a true reflection of the theoretically derived price.

Another possible way of treating the moments which have no observations is to delete the entire period. It could be argued that when the rows containing missing observation are deleted, the remaining analysis is made on the available information only. If the data is sampled at high frequency, then it is available in sufficiently large amounts to estimate a model and deletion may be feasible. The data span with even the lowest sampling frequency contains sufficient number of observations even after deletion; it may seem to be an appropriate compromise. The deletion is plausible provided the missing observations occur in parallel to all markets and the row deletion is equally spaced. Deletion seems to be the appropriate option since it eliminates the most liquid market bias. It is also arguably a feasible option because there is no chance left to interpolate, but it comes at a price, since the deletion occurs across all markets even if one market has a missing value, leading to larger deletions of data rows for the more liquid securities.

If the deletion occurs across all combined markets, there is also a tendency to bias towards the less liquid market. By deleting rows containing missing observations, valid prices (quotes) for markets that are transacting (quoting) are lost, merely because one or a few markets are not transacting (quoting). However, the alternative of deleting the rows does not force one market to be slower in responding than the others, so it is arguably a fairer solution. Though in Chapter 8, where the Moscow and London markets are analysed together, deleting the rows is a counterproductive measure because the lesser liquid market forces the other markets to behave as if they were less informative. The argument here is that row deletions according to the lesser liquid market or security, simply interfere with the natural relationship of the other two markets. In short, row deletion within a multiple market setting creates more selective bias than within a dual market setting. This is the main reason the observations should not be dropped when both other markets were trading well in the context of multiple market price discovery. However, the potential for biases would be induced if the missing observations were substituted for zero values, or left with missing values, in the context of the multi-market price discovery methodology of, for example of Engle and Granger (1987), which assumes the time series to be continuous. Furthermore, in the error-correction model (ECM), the lagged error correction term has the potential to induce serial correlation because of the measurement errors caused by missing or substituted values.

Further option is to stay with discrete time series, or lower the sampling frequency, as opposed to forcing the discrete data to become continuous. However, estimating models which assume continuity of the data with discrete time series such as transaction prices, introduces the risk of serial correlation caused by measurement errors in the form of missing values. An econometric solution for the problem of discrete data, would be to employ autoregressive-conditional-duration model type, e. g. the (ACD) family of models by Engle and Russell (1998), and Dufour and Engle (2000). There are studies on price discovery, which utilise the autoregressive conditional intensity (ACI) model, for instance Grammig and Peter (2010) and Kehrle and Peter (2010). However, data discreteness may also complicate the simultaneous sampling procedure across multiple markets, and may not be feasible with a high degree of asymmetrical inter-market liquidity. Lowering the sampling frequency, on the other hand, with a large degree of asymmetrical inter-market liquidity may reduce the number of observation gaps, but on the other hand it leads to inter-temporal aggregation and data censoring of the more liquid market, which is undesirable in the context of price discovery.

In the end, it could be argued that any data set manipulated by substituting or interpolating missing values with zeros or assumed values or row deletion, induces bias, which may distort the estimated results. However, the presence of bias should not undermine the overall results, if the nature and the extent of the bias are known. The degree of interpolation in the quotes based data is presented in Table 6. There are fewer than 3% missing observations across the three order books during the whole time period for most stocks, with the exception of two. It must be pointed out that the quoteless periods occur mainly for lower liquidity securities quoted on RTS and LSE. The MICEX market has no quoting issues. The LSE market has negligibly minor quotation gaps, usually around one percent. On RTS, however, two stocks (SIBN and TATN) indicated more profound observation gaps in the order book, presenting 27% to 36% missing observations at the highest sampling frequency (1s) in the researched timed period. Yet, the quotation issue is less critical because quotation gaps occur less on both sides of the market than on one side only. Quoteless periods present on both quote sides account for a maximum of 24% for TATN and 8% for SIBN compared to 36% and 27% respectively, on either quote side only.

Despite provisions for FOK and Iceberg orders on LSE and RTS, no FOK or Iceberg orders were detected in the given research sample period. A FOK order is essentially a limit order valid until execution, with an option to immediate execution at a given price and size. An Iceberg order, as examined in depth by Frey and Sandas (2008), is also a limit order that specifies a price, a total order size and a visible peak size. However the remaining size of the Iceberg order is not displayed to the counterparty traders. The visible part is immediately refilled by a size equal to the peak size, if the first peak size has been fully executed. Irrespective of the order entry times, all displayed order depth in the LOB has time priority relative to any hidden depth, at a given price level. These orders are usually not visible to counter-party traders but are by default recorded in the LOB database.

The presence of FOK orders would not have made deriving the best prevailing quote more difficult, because no special programming provision is required; it would have been treated as a normal order, but with very short and conditional validity. Iceberg orders, on the other hand would have required a special provision because of the possible discrepancy between execution price and the best offer. Normally the best quote offer match would have resulted in execution, and orders would leave the LOB. However with Iceberg or hidden orders, it would not be the case. If the orders Iceberg were present in the data, and no provision for these special types of orders existed, the LOB reconstructed sample would, as a result, have contained numerous crossovers between bid and ask quotes.

It must be pointed out that there are possible limitations in the electronic trading mechanism: imperfect time stamps and latency in publishing trades, as demonstrated by Toke (2010). There is a possibility of trading report timing inaccuracies e.g. orders entering or matching. Unlike UHF data, where time stamps are accurate up to fractions of a second, the highest LOB recording resolution is one second on all three LOBs. There is a growing strand of recent market microstructure literature on UHF data and trading for example Hasbrouck and Saar (2010), Zhang (2010) and Brogaard (2012).

Altogether, in the context of this study, it could be argued, that the option with the last-tick interpolation might be the more feasible 2nd best solution for at least three reasons: Firstly, no data is omitted, mitigating the liquidity based market selection bias. Secondly, equally spaced time intervals are not distorted, but deleted observationless periods would cause an asymmetric time frame compression of the liquid market. The asymmetry of time frames across markets could induce bias with respect to serial correlation when models are estimated with the proposed econometric methodology in Chapter 6 {for further details see the appendix of Harris et al.

(2002a)}. Finally, the last-tick interpolation method should not always bias the results unless it coincides with information shocks.

4.8 *Reconstruction Results*

This section presents the best prevailing quote and executed trades derived outputs in graphical form. The presentation of the reconstructed output focuses on the best prevailing order quotes, as well as on continuously sampled transaction prices. A better overview of the best quote time series outputs, given the space limitations of a computer screen, is a graph, since the convenience of the overview enables the evolution of the data span to be followed more easily. The partial extract from the processed output of LKOH for 31st of January 2006, sampled at five second frequency, is presented in Appendix Table 7. Because of the space constraints the presentation of this section is limited to a few examples of LKOH security.

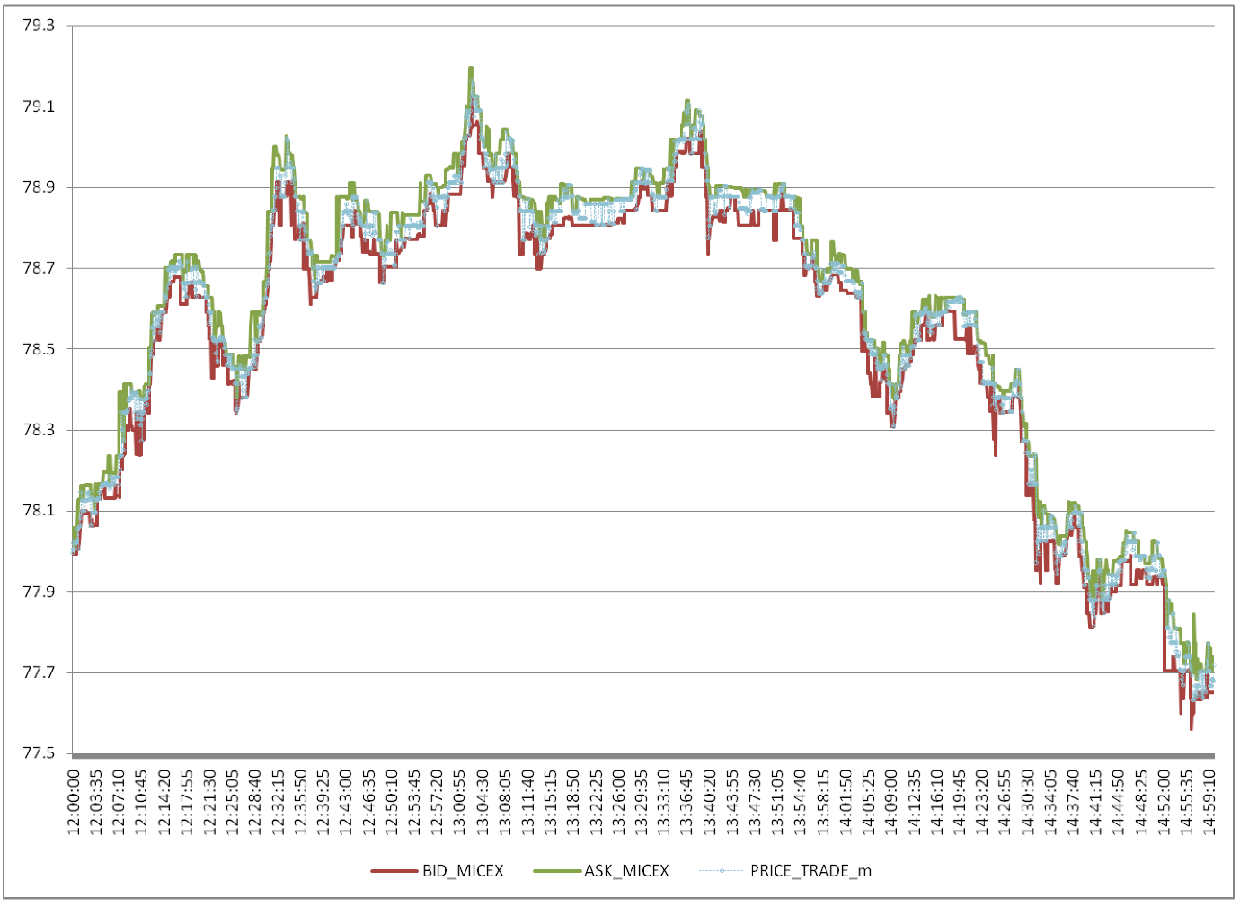

Figure 5 MICEX Best Bid/Ask Quotes with Trades 31st January for the first 3 trading hours at 5s frequency

Figure 5, Figure 6 and Figure 7 display part of one reconstructed trading day, 31st January 2006, with the first three overlapping trading hours of MICEX, RTS and LSE respectively. The combined quote time series are exhibited in Figure 8. The degree of LOB trading activity is clearly visible if Figure 5, Figure 6 and Figure 7 are compared. MICEX LOB derived quotes have the finest degree of quote evolution increments relative to RTS and LSE. The density of these increments is indicative of the degree of market activity. Judging by the example of LKOH, it is to be expected that the MICEX market is the most innovative and therefore the most informative market. Figure 5 presents the best bid-ask quote evolution on MICEX sampled at five second frequency. The degree of reconstruction accuracy is high: The bid and ask quotes do not cross, micro bid-ask bounce movements are clearly visible and transactions occur clearly inside the bid-ask spread. A more detailed view of the best quotes and trades of MICEX, RTS and LSE LOBs, sampled at 1s frequency, is presented in Figures 16 - 19 in the Appendix.

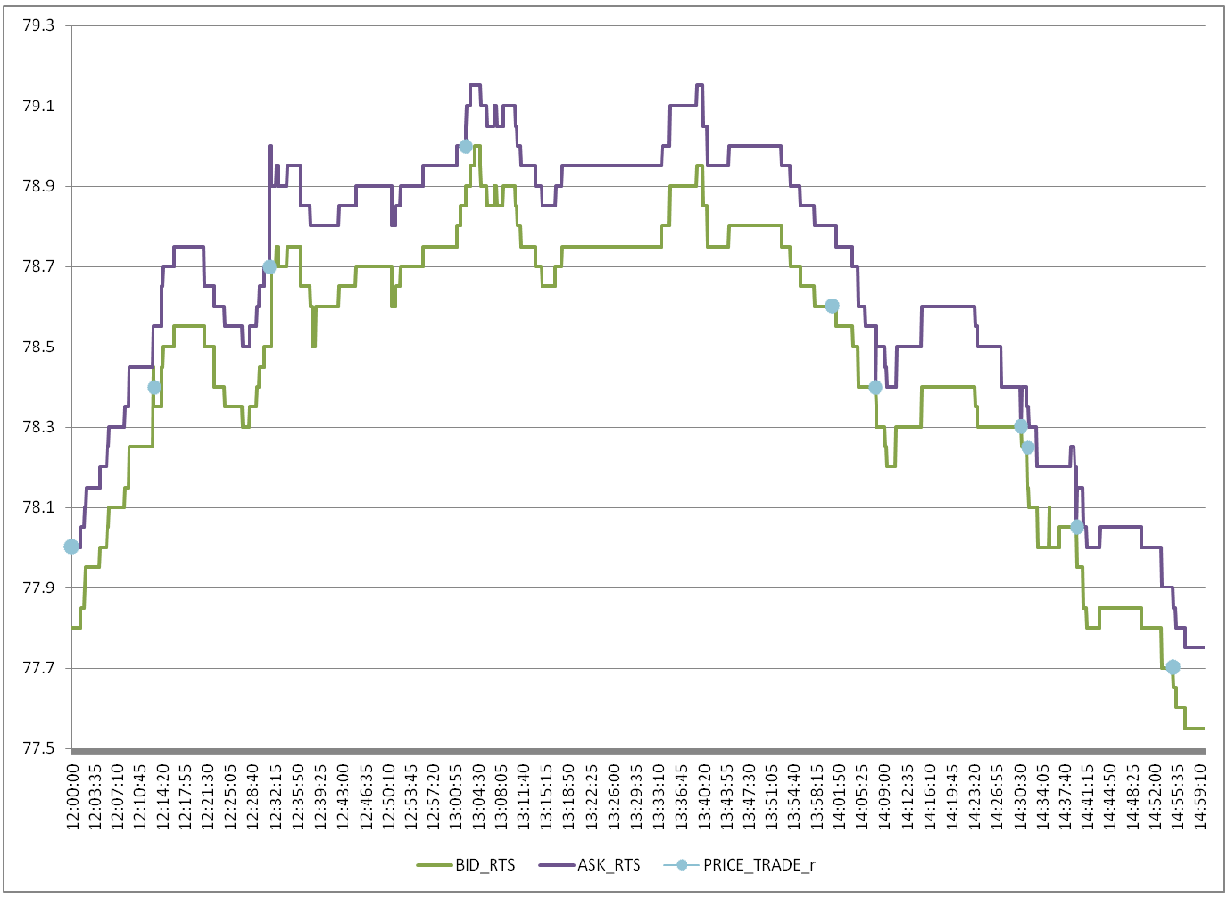

Figure 6 LKOH on RTS Best Bid/Ask Quotes with Trades 31st January for the first 3 trading hours at 5s frequency

The bid-ask quote time series graph of the RTS market (Figure 6) also displays the trades time series. It is observable that the trades occur less frequently than quotes are updated. Furthermore, the trades occur inside the bid-ask quote spread. The best prevailing quote evolution displays a good degree of variation but is not as innovative as on MICEX. The bid-ask spread is clearly wider on RTS than on MICEX. This observation, and the observation of a smaller number of innovations based on quotes, point to less liquidity for LKOH on RTS than on MICEX.

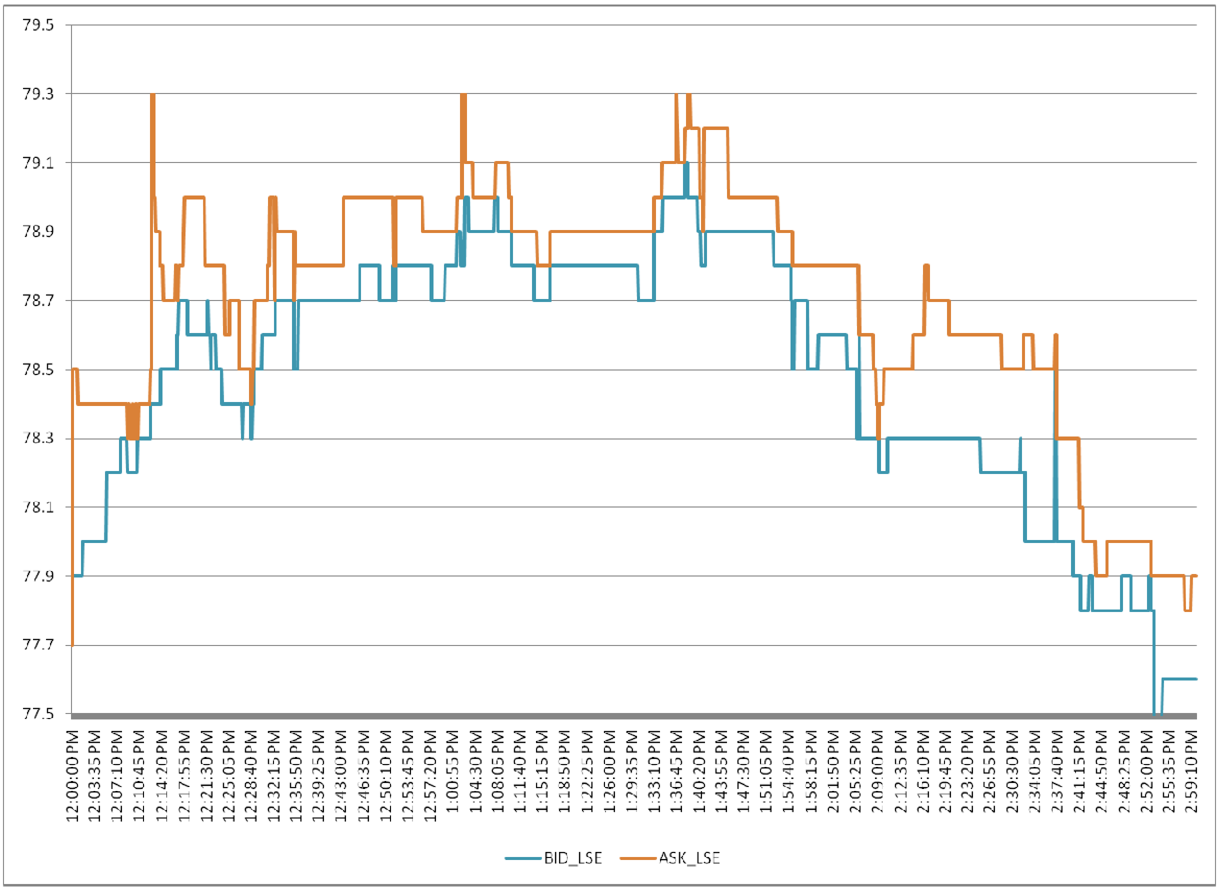

Figure 7 LKOH on LSE Best Bid/Ask Quotes with Trades 31st January for the first 3 trading hours at 5s frequency

Figure 7 illustrates the best bid-ask quote evolution derived from the LSE IOB LOB sampled at 5s frequency. The degree of accuracy is similar to MICEX and RTS. However, the bid-ask quote spread is relatively less stable compared to the spreads on both Moscow exchanges. This may be attributed to a higher degree of risk and to increased frictions in the flow of cross-border information. Nevertheless, the degree of LOB quote updating activity is comparable to RTS.

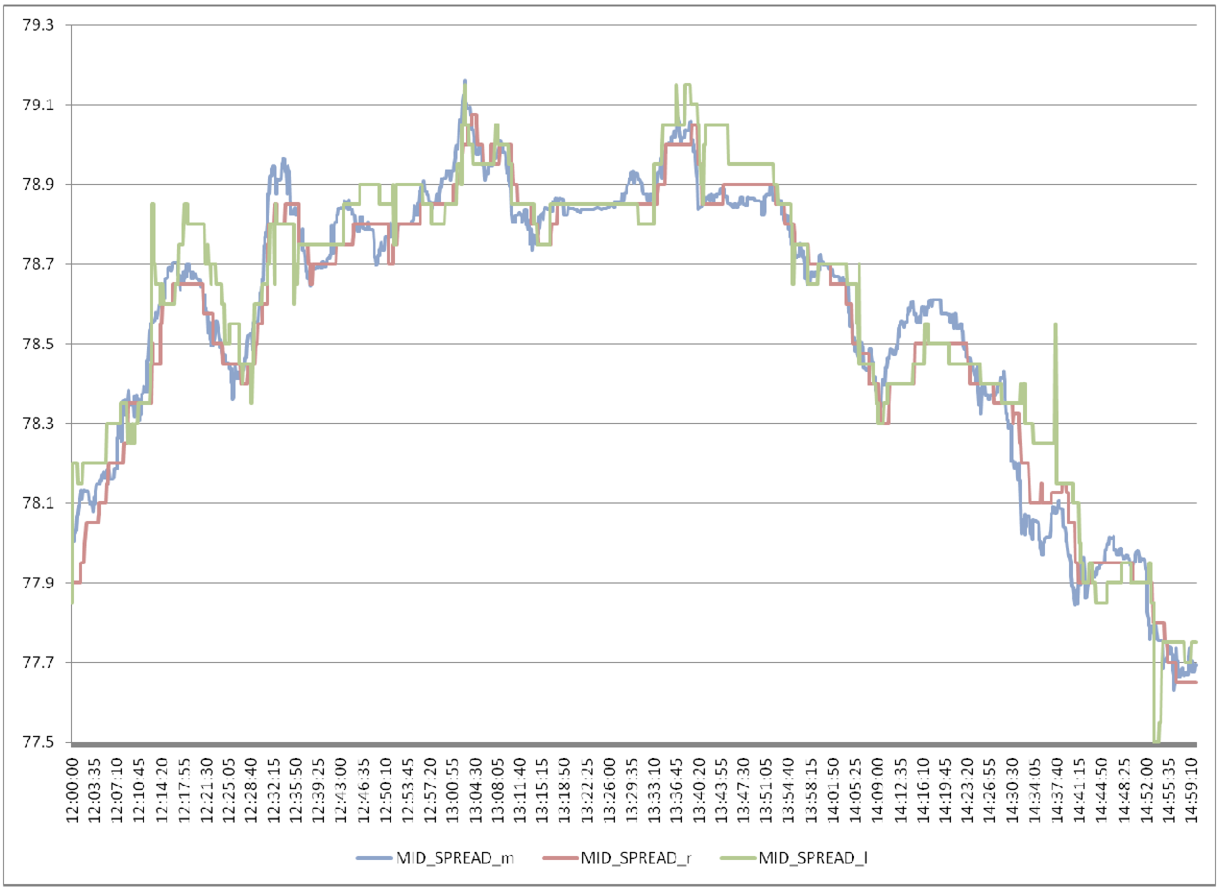

Figure 8 LKOH Mid-Quotes of MICEX, RTS and LSE 31st January for the first 3 trading hours at 5s frequency

Figure 8 presents the MICEX, RTS and LSE mid-quote time series after they have been synchronised. In the time series graphs of all mid-quotes combined, it can be seen that the theoretical pricing of each market behaves in a cointegrated fashion. Should arbitrage gaps between the three markets occur at one moment, they are likely to be corrected in the following moments. Overall, a degree of variation in quoting across the three markets is observable: RTS and LSE quoting is clearly “coarser” than that of MICEX, which is very “fine” in contrast. The quoting on RTS and LSE markets is “coarser” because of the less frequent quote updates reported in Chapter 5, Table 11 and partly because of a difference in the minimum tick sizes. Although, the minimum tick sizes are 0.01 on all three markets, LKOH ADR has a minimum tick size of 0.05 USD on LSE. Also, the exchange rate of RUB to USD behaves in the approximate ratio of 30:1. This may explain as to why the quoting on MICEX is about 30 times finer than those of RTS and LSE.

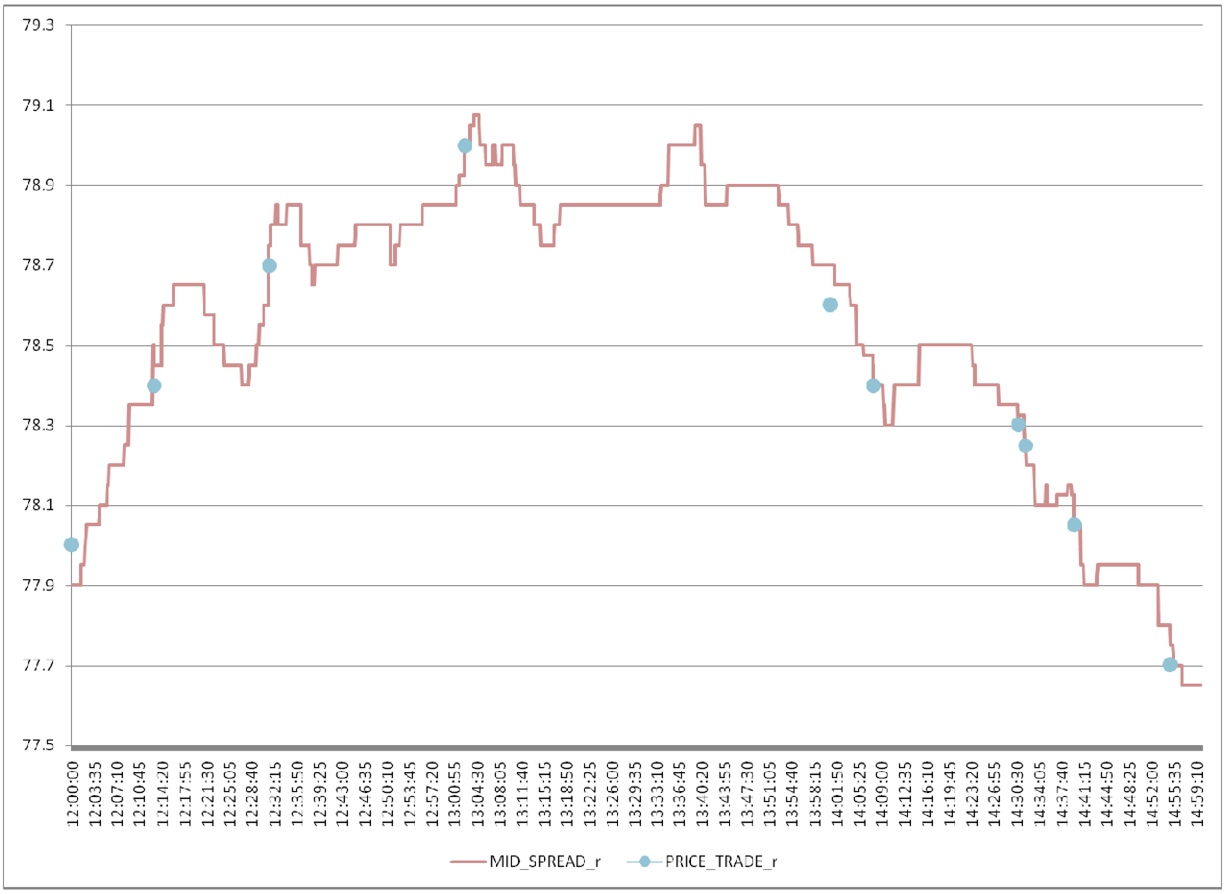

Figure 9 LKOH on RTS Comparison between Mid-quotes and actual Trades

Figure 9 displays mid-quote and interpolated trades evolution on the RTS market sampled at 5s frequency. The graph clearly shows the advantage of the LOB best quotes derived sampling over an interpolated transaction time series. The resulting mid-quotes reveal more incremental changes and therefore reflect more information about LKOH security at a higher sampling frequency, because the quotes are updated more frequently than transactions take place. This graph is a good example of why LOB derived best prevailing quotes are more suitable than the transaction prices for the analysis at higher sampling frequencies on the RTS market in particular.

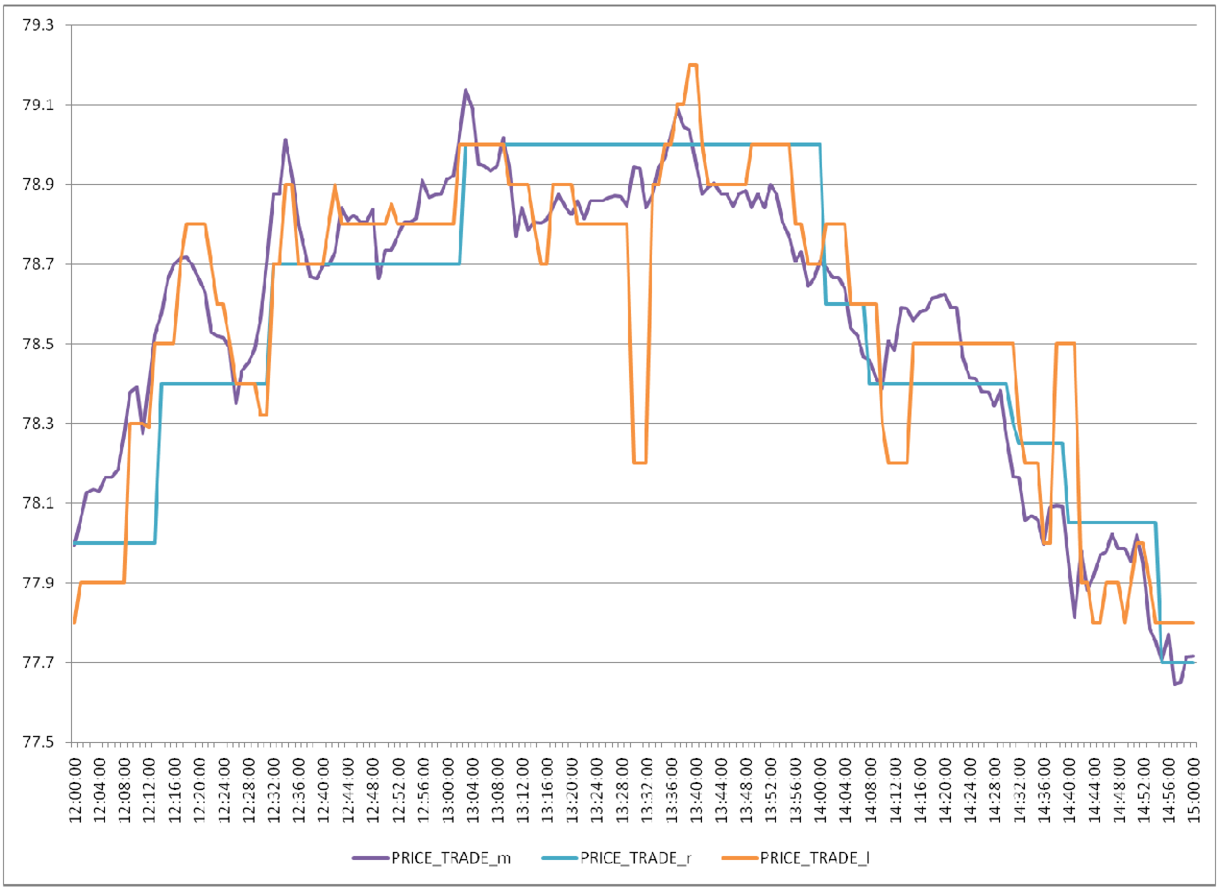

Figure 10 Trades of MICEX, RTS and LSE 31st January for the first 3 trading hours at 30s frequency

Figure 10 shows the evolution of interpolated trades synchronised across MICEX, RTS and LSE. The sampling frequency is 30s. The degree of trading intensity and interpolation is clearly comparable. Trading on MICEX facilitates the highest liquidity; the pricing evolution displays the most variation and the least amount of interpolation. At the other extreme, RTS trading is somewhat less frequent and a high degree of interpolation is necessary to keep up with the continuousness of MICEX pricing. The duration between the transactions on RTS can take from minutes up to one hour during the lunch time period. Overall, the pricing of all three markets combined displays a cointegrated behaviour, similar to the quote based data (please refer to Figure 8).

4.9 *Conclusion*

Limit order book reconstruction is a highly complex, iterative and time-consuming procedure. However, LOB reconstruction can be very rewarding, as it allows the creation of near lossless information variables which the general public would find difficult to access, yet which are essential for understanding the functioning of order-driven markets. While the general methodology of reconstruction remains similar for all order driven markets, exchange specific trading rules such as the absence of de juro market orders on MICEX and RTS require a modified approach.

This chapter aims to contribute to the literature of the limit order book by reconstructing and sampling a unique data set. This is the first study that reconstructs three LOBs for Russian cross-listed securities. For the eight most liquid cross-listed securities, MICEX seems to be the most trading active market relative to RTS and LSE. This observation is not only supported by the larger number of trades occurring on MICEX, but also by the gapless continuity of quotation in the LOB of MICEX. The RTS and LSE markets are both lacking in continuity of quotes, though this is not as severe as on the transaction side, which required interpolation in the form of the last-tick method. The degree of interpolation on RTS and LSE is dependent on the relative liquidity of the cross-listed security. Overall, EESR, GAZP, GMNK, LKOH and RTKM are the most liquid securities in terms of market immediacy.

The best prevailing quotes derived from the LOB are more suitable for analysis at higher sampling frequencies, and are more informative than transaction prices. The main reason for that is the difference in frequency of occurrence and their nature: quotes prevail continuously until cancelled or matched in the LOB and are more frequently updated than the transactions, which occur discretely. The variables of primary interest in the context of price discovery analysis are the mid-quotes derived from the best prevailing quotes and transaction prices, which become available for research once the LOB is reconstructed correctly and the underlying variables are sampled. However, since the reconstruction process is highly iterative, there is always a possibility of programming inaccuracy, when some temporary deviations might occur due to order crossovers. The cause of a few permanent deviations could not always be detected. This might be attributed to data errors contained in the source database. This fact does not undermine the empirical approach, but may negligibly bias the variables which are utilised in this study.

Appendix

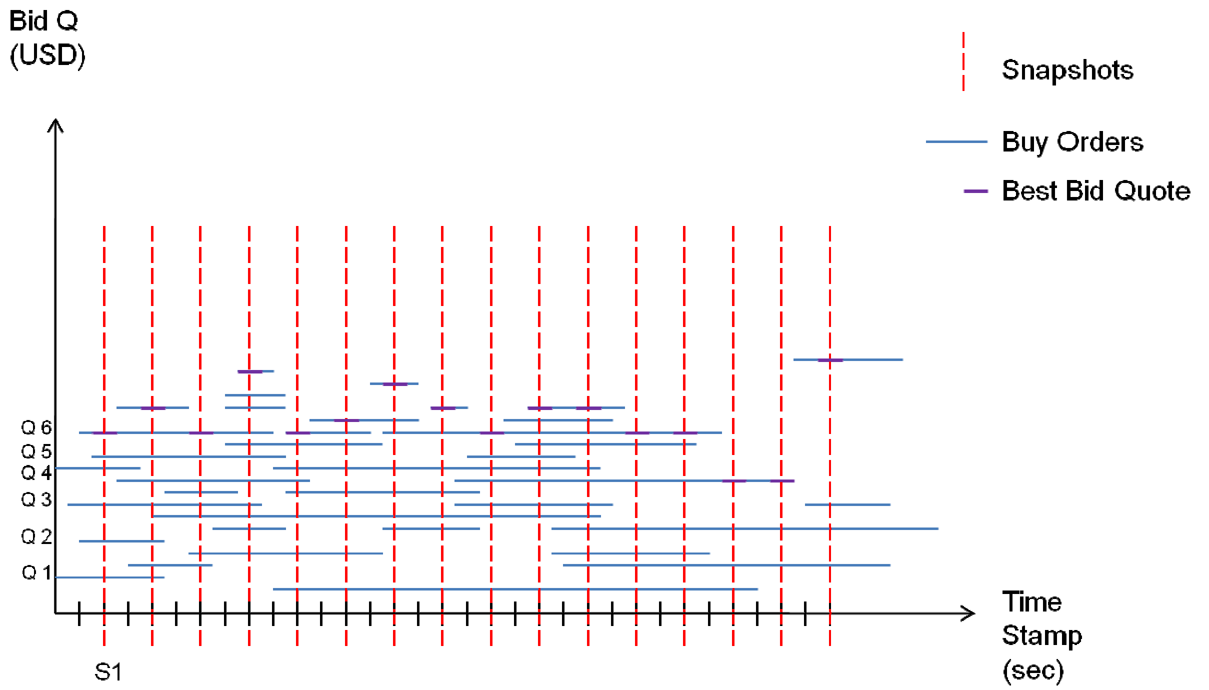

Figure 11 Snapshots of Best Bid Quotes

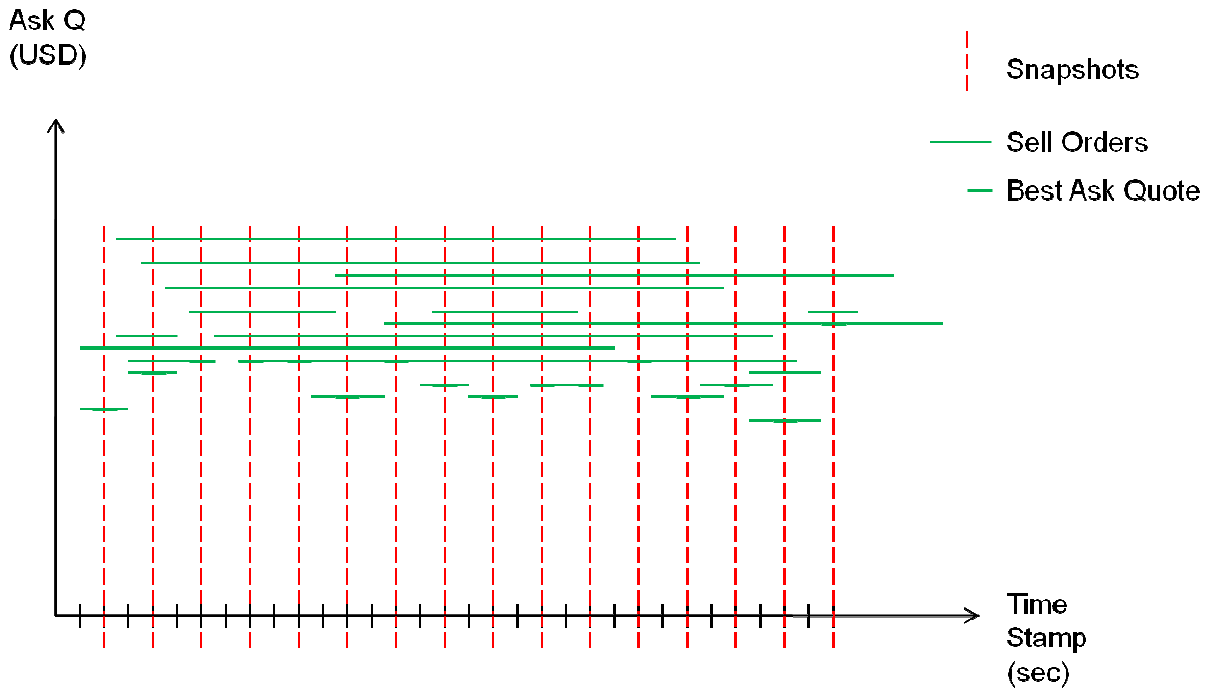

Figure 12 Snapshots of Best Ask Quotes

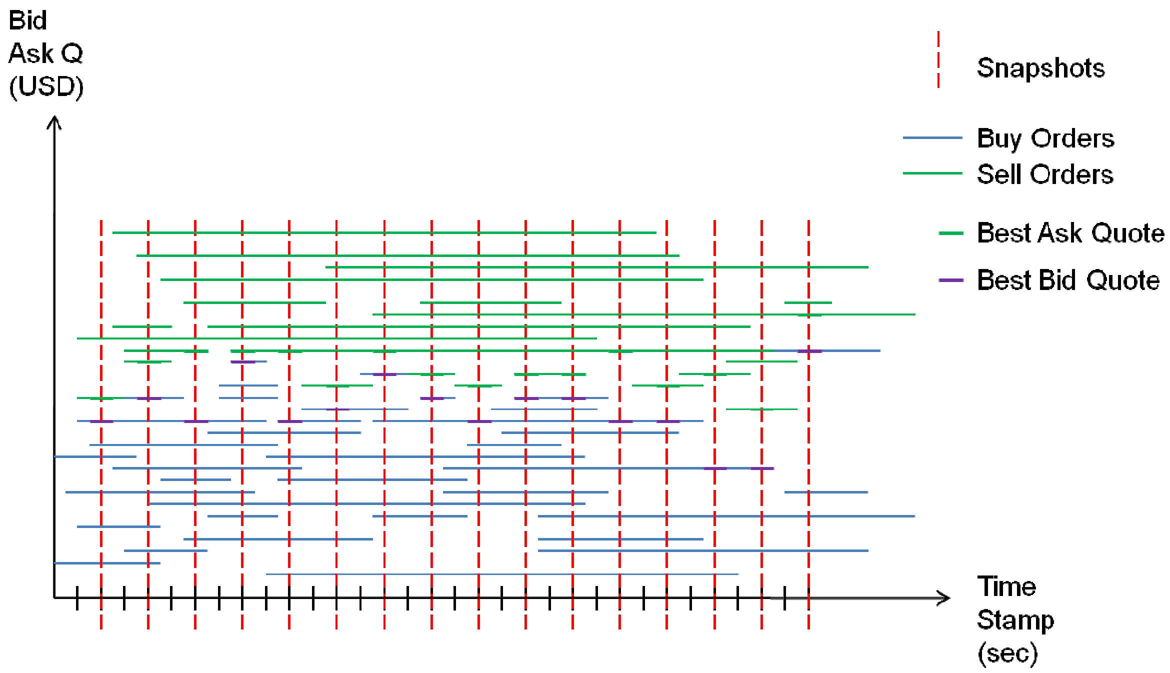

Figure 13 Snapshots of Best Bid and Ask Quotes

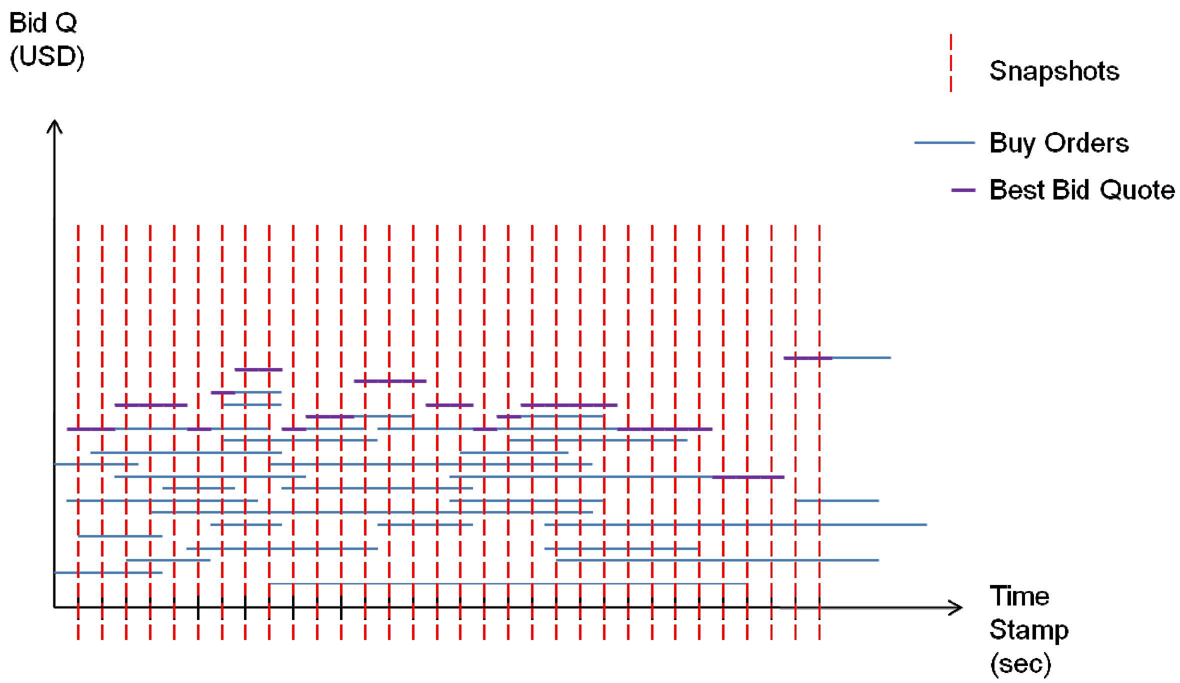

Figure 14 Snapshots of higher Sampling Frequency Best Bid Quotes

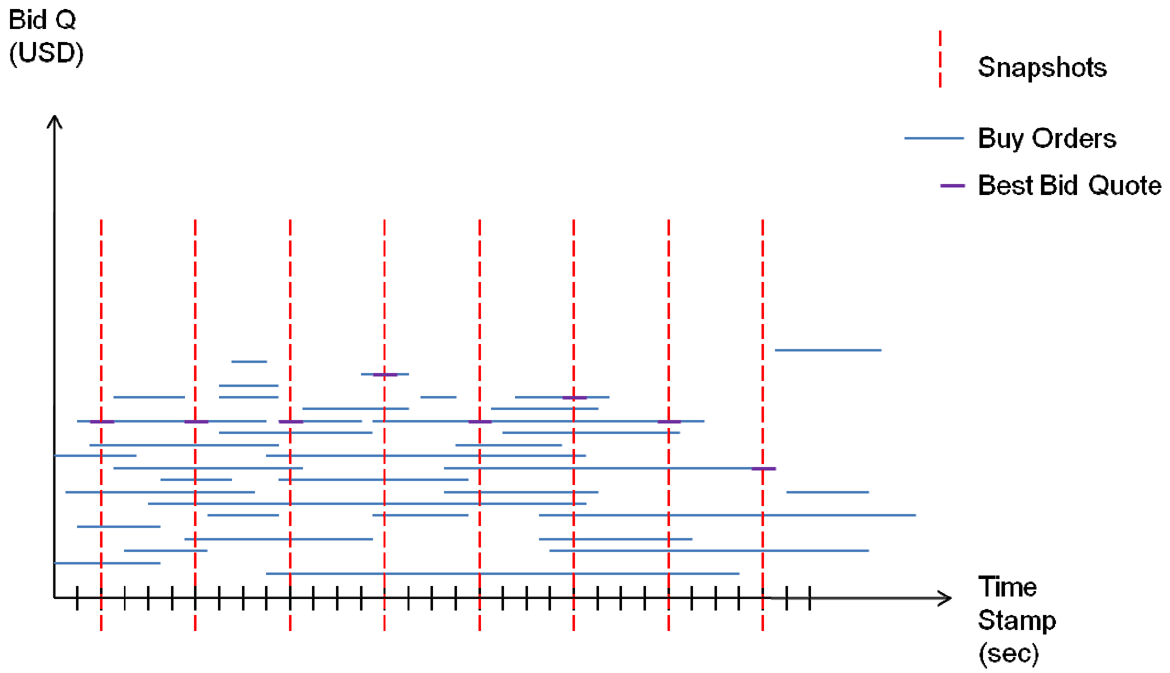

Figure 15 Snapshots of lower Sampling Frequency Best Bid Quotes

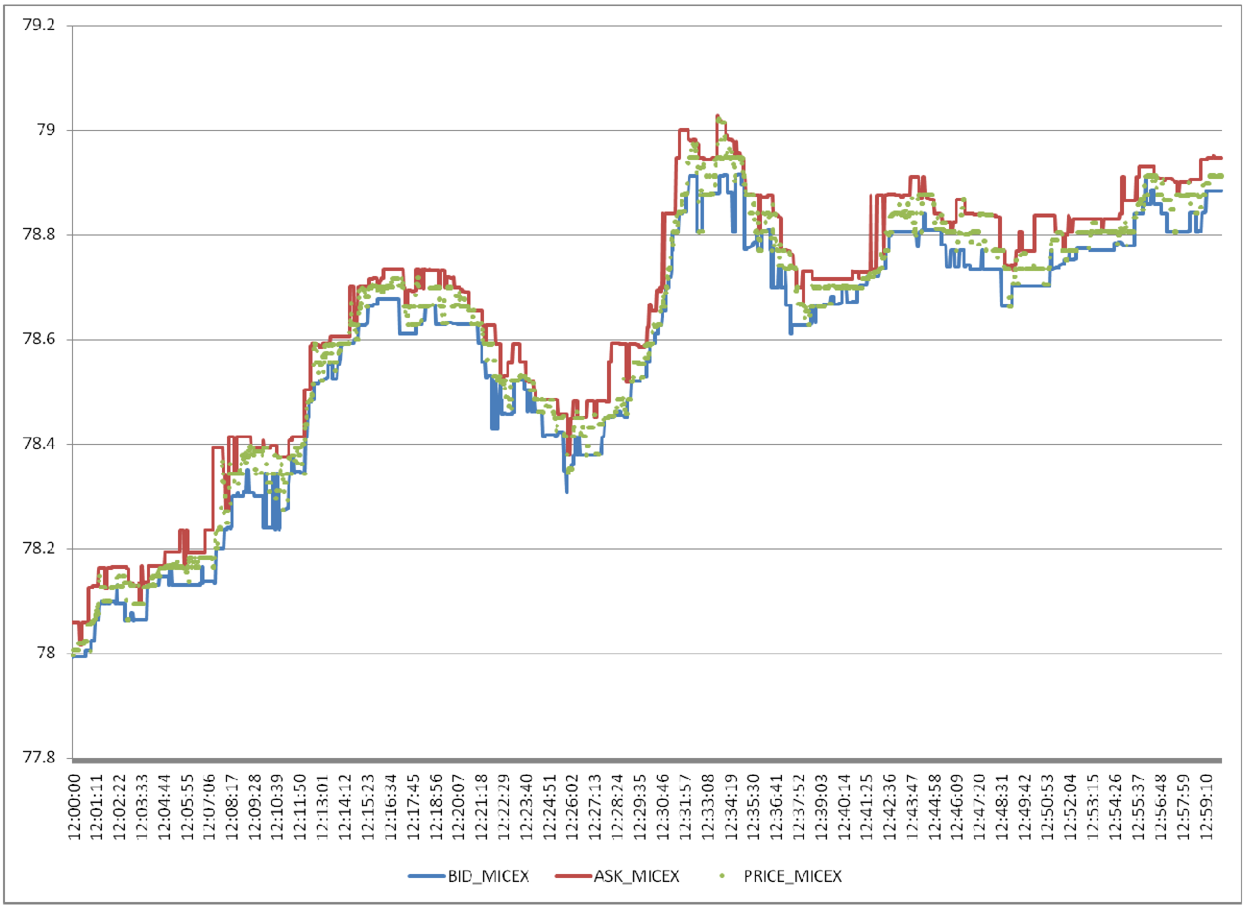

Figure 16 LKOH on MICEX Best Bid/Ask Quotes with Trades 31st January for the first trading hour at 1s frequency

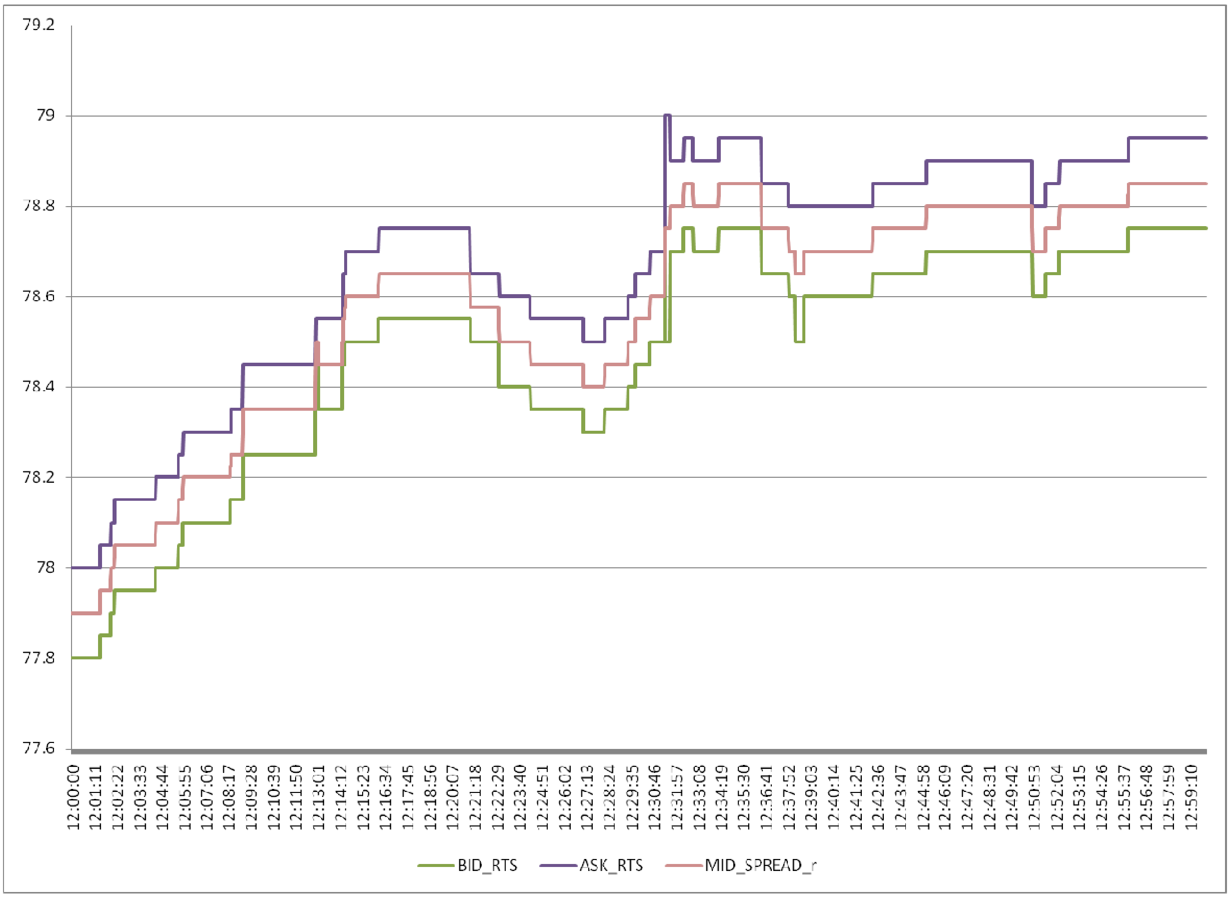

Figure 17 LKOH on RTS Best Bid/Ask Quotes with Mid-quotes 31st January for the first trading hour at 1s frequency

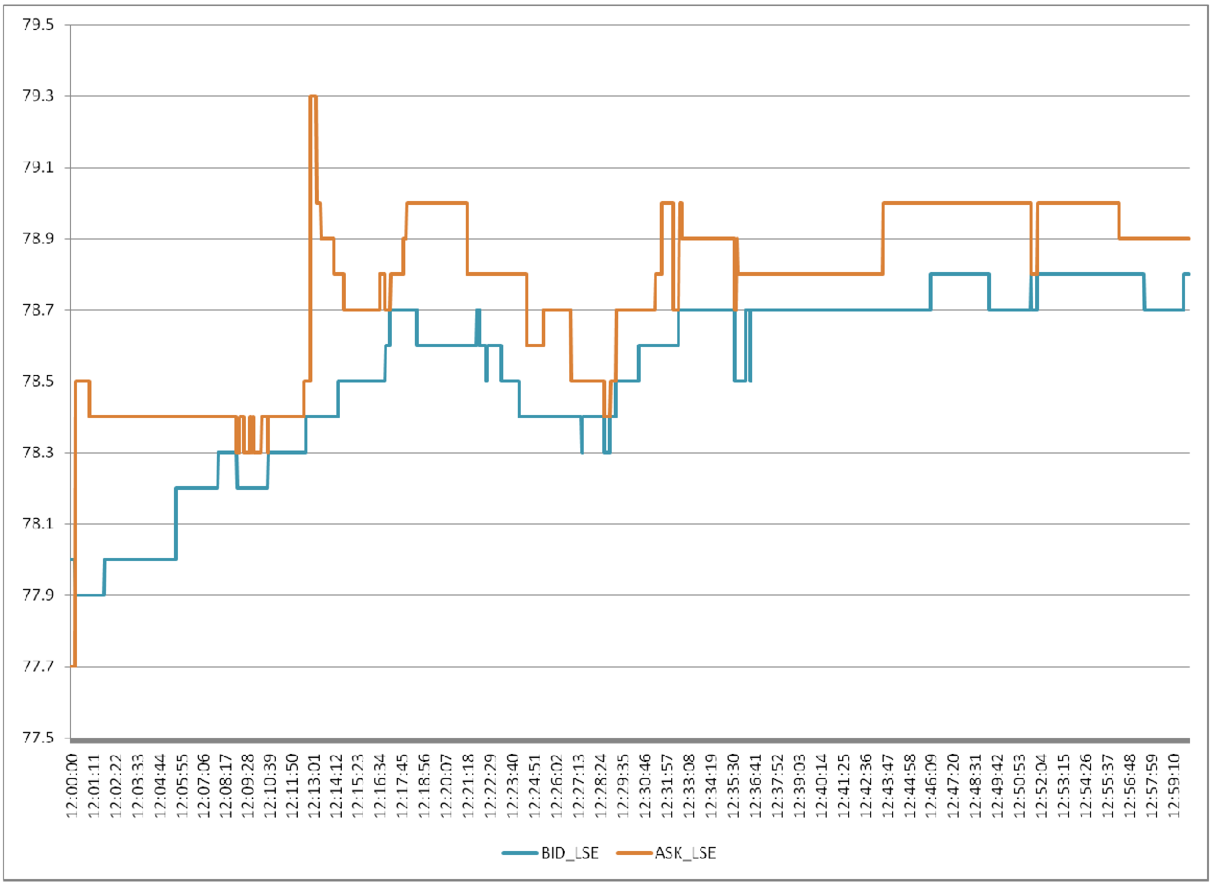

Figure 18 LKOH on LSE Best Bid/Ask Quotes 31st January for the first trading hour at 1s frequency

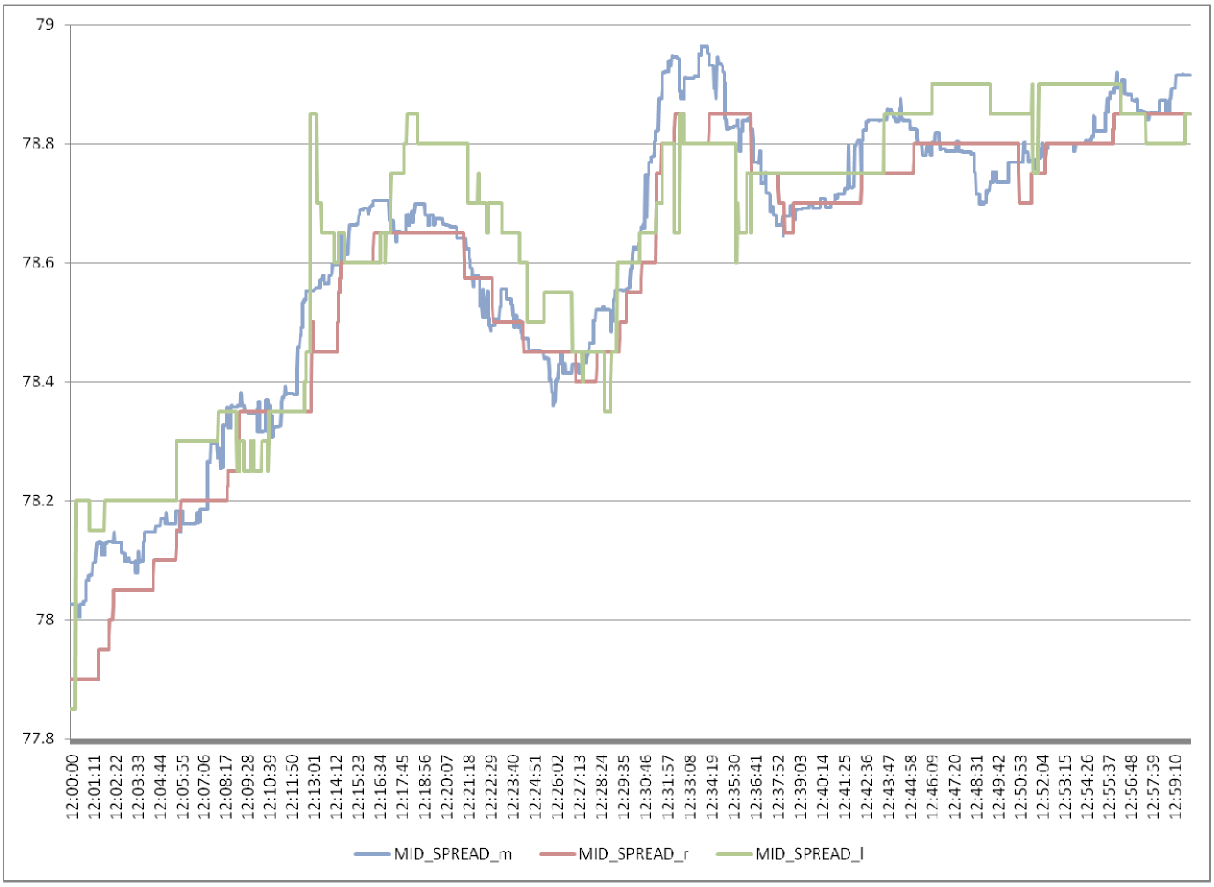

Figure 19 LKOH Mid-Quotes of MICEX, RTS and LSE 31st January for the first trading hour at 1s frequency

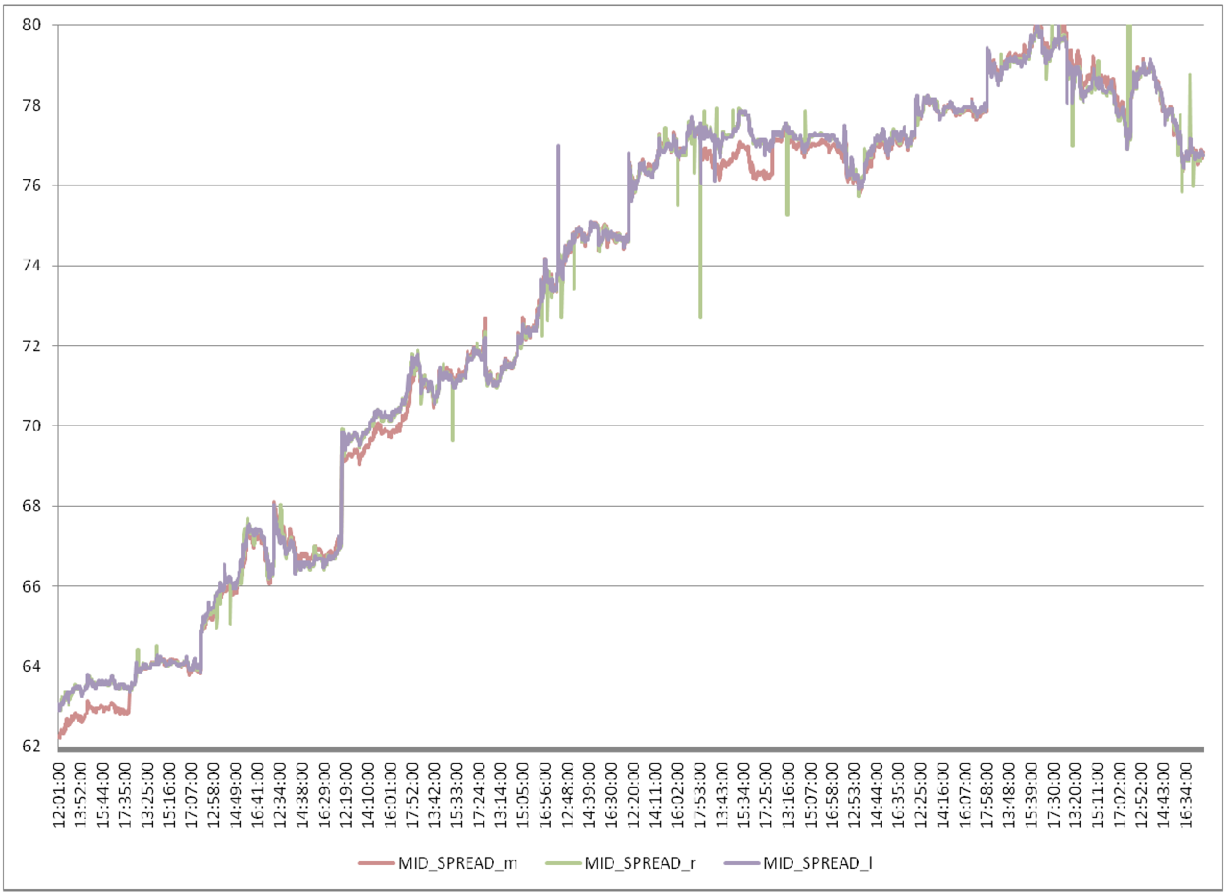

Figure 20 LKOH Mid-quotes of MICEX, RTS and LSE January at 60s frequency

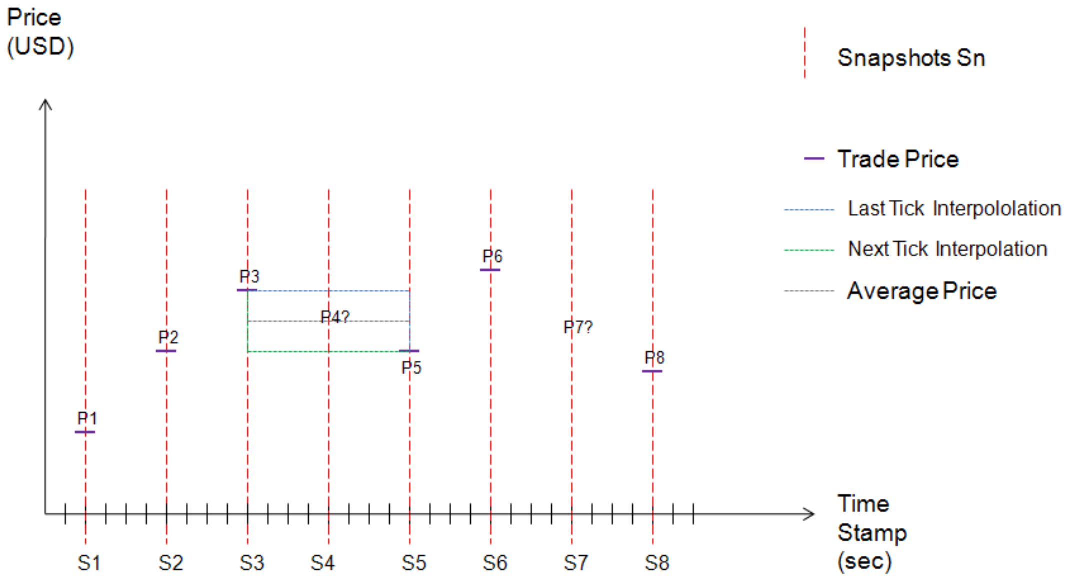

Figure 21 Interpolation Assumptions

DATE_TIME	BID_MICEX	ASK_MICEX	BID_RTS	ASK_RTS	BID_LSE	ASK_LSE	MID_SPREAD_m	MID_SPREAD_r	MID_SPREAD_l
12:00:00	77.99	78.06	77.8	78	78	77.7	78.03	77.9	77.85
12:00:05	77.99	78.06	77.8	78	78	77.7	78.03	77.9	77.85
12:00:10	77.99	78.06	77.8	78	78	77.7	78.03	77.9	77.85
12:00:15	77.99	78.06	77.8	78	77.9	78.5	78.03	77.9	78.2
12:00:20	77.99	78.02	77.8	78	77.9	78.5	78.00	77.9	78.2
12:00:25	77.99	78.02	77.8	78	77.9	78.5	78.00	77.9	78.2
12:00:30	77.99	78.06	77.8	78	77.9	78.5	78.03	77.9	78.2
12:00:35	77.99	78.06	77.8	78	77.9	78.5	78.03	77.9	78.2
12:00:40	78.00	78.06	77.8	78	77.9	78.5	78.03	77.9	78.2
12:00:45	78.00	78.06	77.8	78	77.9	78.5	78.03	77.9	78.2
12:00:50	78.00	78.13	77.8	78	77.9	78.5	78.07	77.9	78.2
12:00:55	78.00	78.13	77.8	78	77.9	78.5	78.07	77.9	78.2
12:01:00	78.02	78.13	77.8	78	77.9	78.4	78.07	77.9	78.15
12:01:05	78.02	78.13	77.8	78	77.9	78.4	78.08	77.9	78.15
12:01:10	78.06	78.13	77.8	78	77.9	78.4	78.09	77.9	78.15
12:01:15	78.06	78.13	77.8	78	77.9	78.4	78.10	77.9	78.15
12:01:20	78.06	78.16	77.8	78	77.9	78.4	78.11	77.9	78.15
12:01:25	78.09	78.16	77.8	78	77.9	78.4	78.13	77.9	78.15
12:01:30	78.10	78.16	77.85	78.05	77.9	78.4	78.13	77.95	78.15
12:01:35	78.10	78.16	77.85	78.05	77.9	78.4	78.13	77.95	78.15
12:01:40	78.09	78.16	77.85	78.05	77.9	78.4	78.13	77.95	78.15
12:01:45	78.10	78.12	77.85	78.05	77.9	78.4	78.11	77.95	78.15
12:01:50	78.09	78.16	77.85	78.05	78	78.4	78.13	77.95	78.2
12:01:55	78.09	78.16	77.85	78.05	78	78.4	78.13	77.95	78.2
12:02:00	78.10	78.16	77.85	78.05	78	78.4	78.13	77.95	78.2
12:02:05	78.10	78.17	77.9	78.1	78	78.4	78.13	78	78.2
12:02:10	78.10	78.17	77.9	78.1	78	78.4	78.13	78	78.2
12:02:15	78.09	78.17	77.95	78.1	78	78.4	78.13	78.025	78.2
12:02:20	78.09	78.17	77.95	78.15	78	78.4	78.13	78.05	78.2
12:02:25	78.09	78.17	77.95	78.15	78	78.4	78.13	78.05	78.2
12:02:30	78.09	78.17	77.95	78.15	78	78.4	78.13	78.05	78.2
12:02:35	78.09	78.17	77.95	78.15	78	78.4	78.13	78.05	78.2
12:02:40	78.09	78.17	77.95	78.15	78	78.4	78.13	78.05	78.2
12:02:45	78.06	78.17	77.95	78.15	78	78.4	78.11	78.05	78.2
12:02:50	78.06	78.16	77.95	78.15	78	78.4	78.11	78.05	78.2
12:02:55	78.06	78.13	77.95	78.15	78	78.4	78.10	78.05	78.2
12:03:00	78.06	78.13	77.95	78.15	78	78.4	78.10	78.05	78.2
12:03:05	78.08	78.13	77.95	78.15	78	78.4	78.10	78.05	78.2
12:03:10	78.06	78.13	77.95	78.15	78	78.4	78.10	78.05	78.2
12:03:15	78.06	78.13	77.95	78.15	78	78.4	78.10	78.05	78.2
12:03:20	78.06	78.13	77.95	78.15	78	78.4	78.10	78.05	78.2
12:03:25	78.06	78.13	77.95	78.15	78	78.4	78.10	78.05	78.2
12:03:30	78.06	78.09	77.95	78.15	78	78.4	78.08	78.05	78.2

The table displays an extract of best bid-ask time series derived from the reconstructed LOBs for the first 3 and ½ minutes

Table 7 Reconstructed and synchronised Output for MICEX, RTS and LSE LKOH 31st January

Definitions on the MICEX Order Data Fields:

ORDERNO: order number
ENTRYDATE: date of order placing
ENTRYTIME: time of order placing
SECURITYID: identification of the security
BUYSELL: direction of the order (B- bid- buy, S- ask- sell)
PRICE: order price in RUB
QUANTITY: quantity of the order in units
BALANCE: rest of the securities in order (part of QUANTITY) if part of securities had been taken by trade
AMENDTIME: time when the order was closed (only for C and W status)
PERIOD: trading period of the day (O- open period, N- normal trading, C- closing period)
VAL: value of the order in RUB (PRICE * QUANTITY)
STATUS - order status*

***Status of the order:**

C: cancelled by the trading system (normally before the close period)
M: matched (this order was ended by the trade)
O: open (this order left active to the end of the day)
R: rejected (this order was not taken by the trading system due to some system restrictions, e.g. price limits)
W: order was withdrawn by the trader

Definitions on the MICEX Trade Data Fields:

TRADENO: trade number
BUYSELL: direction of the trade (B- bid- buy, S- ask- sell)
TRADEDATE: date of the trade
TRADETIME: time of the trade

ORDERNO: number of the order the current trade was initiated by
SECURITYID: identification of the security
PRICE: trade price in roubles
QUANTITY: quantity of the trade in units
VAL: value of the trade in roubles (PRICE * QUANTITY)
PERIOD: trading period of the day (O- open period, N- normal trading, C- closing period)

Definitions of the RTS Order Data

HISTORY_ ID: identity (ID) number of the order
REP_DATE: date of the order reported
ISSUE_NAME: security identification of stock
MOMENT: date and time of the order placing
TYPE: type of the order
A: ask quote- sell order
B: bid quote- buy order

QTY: quantity of shares to be bought or sold
PRICE: price of the order
HIST_ACT: historic action is
A: accept
D: delete
U: update

STATUS: status of an order
A: accepted
D: declined
ACC_MOMENT: date and time the order left the trading system

Definitions of the RTS Trade Data

ID: identity number of the trade
AFFIRM_MOM: moment of date and time of the trade
ISSUE_NAME: name of the stock
PRICE: transaction price
QTY: Number of shares bought or sold
INIT_ORD_ID: ID number of the order which is on the involved in the transaction
CONF_ORD_ID: ID number of the order which is on the involved in the transaction

LSE original Database Field Definitions

LSE ORDER DETAIL:	all initially posted orders
OrderCode	unique number
StockCode	ISIN
MarketSectorCode	mostly IOB
ParticipantCode	anonymous unique number of the trading party
BuySellInd	B or S: buy or sell order
MarketMechanismType	order driven or other
Price	price of the order posted
AggregateSize	size of the order posted
OrderType	LO, MO or IB: limit, market or Iceberg order
Date	date of order posted
Time	time of order posted
MessageSequenceNumber	order priority number

LSE ORDER HISTORY:	all historically amended orders
OrderCode	unique number from o detail
OrderActionType	M: full match, P:partial, D: deleted, E: expired
MatchingOrderCode	counter order if M or P
TradeSize	executed trade size

TradeCode	unique number to t report
ParticipantCode	anonymous unique number of the trading party
StockCode	ISIN
AggregateSize	change in size
BuySellInd	B or S: buy or sell order
MarketMechanismType	order driven or other
MessageSequenceNumber	order priority number
Date	date of order change
Time	time of order change

LSE TRADE REPORT:	all consequently executed orders
MessageSequenceNumber	order priority number
ParticipantCode	anonymous unique number of the trading party
StockCode	ISIN
TradeCode	resulted transaction from O history
TradePrice	resulted price of the transaction
TradeSize	resulted size of the transaction
TradeDate	date when the trade occurred
TradeTime	time when the trade occurred
PublicationDate	date when the trade published
PublicationTime	time when the trade published

Definitions of the Output Data Fields for MICEX, RTS and LSE

SecurityID: see above

StateID: Any new situation receives an assigned ID number

Date: Date of the State

Time: Time in seconds of the State

Time_D: Difference in time between order placing

Quantity: Shares of the order or the trade

OrderNo_B: OrderID at best bid price

OrderNo_A: OrderID at best ask price

Price: Price of the trade

Value: Value of the trade

BID: Best Bid Price or quote

ASK: Best Ask Price or quote

Spread: Difference between best ask and best bid quotes (actual spread)

Mid_Spread: Mid Spread, i.e. (ASK+BID)/2

Perc_Spread:%age Spread (or Relative Spread), i.e. [200x(ASK-BID)/(ASK+BID)]

Quantity_B: Quantity of shares at the best bid price (becomes the volume at the two best bid prices if the actual order is a buy and causes a transaction)

Quantity_A: Quantity of shares at the best ask price (becomes the volume at the two best ask prices if the actual order is a sell and causes a transaction)

Depth_B: Sum of the volume at all bid prices (the volume of the actual order is included if this is a buy order and causes a transaction)

Depth_A: Sum of the volume at all ask prices (the volume of the actual order is included if this is a sell order and causes a transaction)

Depth_Spread: Total Bid Volume- Total Ask Volume

Chapter Five: Data

5.1 *Data Set Specifications*

The data set employed in this study originated from the databases which have been obtained from the MICEX, RTS and LSE exchanges directly. The original databases cover the period of one trading year between January 10th and December 27th, 2006. The MICEX, RTS and the LSE databases contain both quotes and transaction prices. The chosen sample consists of eight cross-listed Russian "blue chip" stocks: RAO UES, Gazprom, Norilsk Nickel, Lukoil, Rostelecom, Sibneft, Surgutneftgaz, Tatneft. The overview is provided by Table 8. Although RTS is characterised by the most diversity of listed equity securities, the main reason for the choice of the eight stocks is that there is no cross-availability of lesser liquid cross-listed securities on MICEX and in particular on LSE in this sample. Furthermore, these are the only securities, which were traded in a similar order driven mechanism across the three trading venues. In sum, the trading mechanism of the stock exchanges in Russia is similar to that of London Stock Exchange. Both Moscow and London trading for these securities operate in pure order-driven trading mechanism on electronic LOBs. Trading occurs from Monday to Friday, except holidays. Each trading day, there is a continuous session with 6 hours time overlap between the three exchanges.

Name	MICEX CODE	Currency	RTS CODE	Currency	LSE CODE	ISIN	Currency	ADR Ratio
RAO UES	EESR	RUB	EESR	USD	UESD	US9046882075	USD	100
GAZPROM	GAZP	RUB	GAZP	USD	OGZD	US3682872078	USD	4
MMC NORNICKEL	RU14GMKN0507	RUB	GMKN	USD	MNOD	US46626D1081	USD	10
LUKOIL	LKOH	RUB	LKOH	USD	LKOD	US6778621044	USD	1
ROSTELEKOM	RTKM	RUB	RTKM	USD	RKMD	US7785291078	USD	6
SIBNEFT	SIBN	RUB	SIBN	USD	SIF	US8257311022	USD	6
SURGUTNEFT	SNGS	RUB	SNGS	USD	SGGD	US8688612048	USD	10
TATNEFT	RU14TATN3006	RUB	TATN	USD	ATAD	US6708312052	USD	6

The table provides an overview of the cross-listed securities, denominated in the traded currency and the corresponding ADR to underlying shares ratio

Table 8 List of cross-listed stocks by their trading venues

Table 9 presents an overview of sample time periods for the securities of choice. The sample time period is essentially made up of three data panels. For all securities except TATN and

GAZP, the LOB derived samples cover the period of four trading months between January 10th and April, 2006. For GAZP and TATN, the sample period is between January 23rd and April 28th and between November 14th and December 29th 2006, respectively. The data sample resulted in 77 trading days for most securities with a minimum of 31 trading days for TATN.

	EESR RAO UES	GAZP GAZPROM	GMKN NORNICKEL	LKOH LUKOIL	RTKM ROSTELEKOM	SIBN SIBNEFT	SNGS SURGUTNEFT	TATN TATNEFT
Sample Beginning	10th Jan	23rd Jan	10th Jan	10th Jan	10th Jan	10th Jan	10th Jan	14th Nov
Sample Period End	28th Apr	28th Apr	28th Apr	28th Apr	28th Apr	28th Apr	28th Apr	29th Dec
Total Trading Days	77	67	77	77	77	77	77	31

The table presents the sample periods and the number of the total trading days of the cross-listed securities

Table 9 Overview of sample periods for all securities

5.2 *Database Descriptive Statistics*

This section aims to present summary descriptive statistics of the queried and filtered but unprocessed original data base samples. Tables 10 and 11 provide a summary of the processed transactions and orders, respectively. The most trading intensive market is MICEX, followed by LSE and RTS. The number of transactions on MICEX is substantially larger than RTS and LSE trading combined. Table 10 shows that MICEX has over 15 million transactions compared to RTS and LSE, which combined are under 300 thousand. The most traded securities on MICEX are EESR followed by GAZP, GMNK and LKOH. The trading constellation on RTS is similar to MICEX. GAZP and LKOH are the most traded securities on LSE followed by EESR and GMNK. Consequently, GAZP and LKOH are the most actively traded securities across the three trading venues.

	EESR	GAZP	GMKN	LKOH	RTKM	SIBN	SNGS	TATN	Total
MICEX	4925132	3293563	3013236	1784212	1402831	761900	298111	50474	15529458
RTS	6047	10924	2660	5940	876	137	1984	736	29304
LSE	22003	92983	25133	72804	7663	4410	26833	1401	253230

The table reports the number of rows in trades based data samples processed for all securities in each market

Table 10 Summary of the samples containing Trades

Table 11 presents a summary of all processed orders in order to reconstruct the LOB and to derive the best prevailing quotes. Overall, just fewer than 12 mil orders have been processed. The constellation of order flow intensity is similar to the trading intensity of the transaction samples: MICEX has the most dense order flow, followed by RTS and LSE. The proportion of order flow is very similar to the trading intensity; MICEX is a 20 times more order flow concentrated market than RTS and LSE combined. The order flow is dominated by EESR, GAZP, GMNK and LKOH orders across the three markets. Similar to transaction based data, EESR is the most order flow intensive stock on MICEX.

		MICEX			RTS			LSE		
		Buy Orders	Sell Orders	Total	Buy Orders	Sell Orders	Total	Buy Orders	Sell Orders	Total
EESR	Total	1867265	1796406	3663671	20716	20666	41382	8387	7525	15912
	Aver. Quote	17	17		1	1		61	62	
	Aver. Size	51468	51700		389615	401408		5118	4818	
GAZP	Total	679097	570686	1249783	22257	20385	42642	18200	15673	33873
	Aver. Quote	240	243		9	10		79	81	
	Aver. Size	4437	4556		42037	43711		4114	5050	
GMNK	Total	504717	468579	973296	8886	10216	19102	7726	6638	14364
	Aver. Quote	2521	2542		106	109		95	97	
	Aver. Size	197	215		1916	2051		2745	3107	
LKOH	Total	1240328	1174509	2414837	22317	21061	43378	20083	19082	39165
	Aver. Quote	2136	2147		79	79		78	79	
	Aver. Size	377	392		2996	2948		4691	5275	
RTKM	Total	793550	858813	1652363	8294	9283	17577	2191	2937	5128
	Aver. Quote	80	81		3	3		18	18	
	Aver. Size	3560	3288		41534	41301		6593	6755	
SIBN	Total	101033	90404	191437	2305	2144	4449	2349	1956	4305
	Aver. Quote	127	128		4	5		23	23	
	Aver. Size	3300	3363		43818	39792		4225	4424	
SNGS	Total	401201	383870	785071	7662	9972	17634	10639	9539	20178
	Aver. Quote	40	40		1	1		72	73	
	Aver. Size	14658	14928		82488	88052		3203	3734	
TATN	Total	247194	232011	479205	3056	4143	7199	888	904	1792
	Aver. Quote	121	124		5	5		93	95	
	Aver. Size	1961	1945		18994	18060		1952	25821	
Total				11409663			193363			134717

The table presents the total number of quotes, average quote size and average quote processed for all securities in each market

Table 11 Summary of Orders in the three LOBs

According to the original order based data, Tatneft (TATN) and Sibneft (SIBN) are the least liquid stocks in the sample, where RAO UES (EESR) and Gazprom (GAZP) are the most liquid. The daily exchange rate data has been provided by the MICEX exchange. Table 12 presents summary description statistics of the daily USD/RUB exchange rates for the three panels of securities.

	USD/RUB (all except GAZP and TANT)	USD/RUB (GAZP)	USD/RUB (TATN)
Mean	27.96	27.89	26.38
Median	27.99	27.93	26.33
Maximum	28.78	28.26	26.69
Minimum	27.36	27.36	26.18
Std. Dev.	0.31	0.26	0.17
Skewness	0.01	-0.26	0.71
Kurtosis	2.41	1.88	2.05
Observations	77	67	31

The table displays the descriptive statistics of the daily USD/RUB FX rate for the three data sample periods

Table 12 USD Exchange rates sample

5.3 *Processed Samples Statistics*

This section presents a summary of descriptive statistics of the processed samples, which have been derived from the original data bases. These are the samples on which the econometric methodology (presented in Chapter 6) has been applied. The most important variables in economic meaning terms are bid-ask spreads (Table 13), size of the trades (Table 14) of the three underlying markets. Tables 15 and 16 exhibit the number of observations for mid quotes and trades samples given the sampling frequency for all securities contained in the sampling period of the year 2006. The number of observations obtained for each sampling frequency is lower than the maximum achievable. The number of observations is generally lower the achievable because of error filtering and exclusion of the first observations in each trading day.

		Mean	Median	Maximum	Std. Dev.	Skewness	Kurtosis	Observations
EESR	MICEX	0.0007	0.0006	0.0555	0.0005	22.4114	2384.1750	1727183
	RTS	0.0036	0.0030	0.0600	0.0028	4.3627	46.0782	1727183
	LSE	0.0044	0.0030	0.2970	0.0080	18.8940	491.5411	1727183
GAZP	MICEX	0.0098	0.0089	0.1745	0.0060	1.7782	17.7658	1404065
	RTS	0.0268	0.0250	0.9800	0.0223	6.8397	117.2923	1404065
	LSE	0.0221	0.0182	2.4546	0.0214	20.1804	1548.9030	1404065
GMNK	MICEX	0.1873	0.1731	1.5699	0.1058	1.1685	6.7367	1727811
	RTS	1.2074	1.0000	17.0000	1.1917	4.2411	34.9002	1727811
	LSE	0.5355	0.4000	43.9000	0.6855	19.6279	945.2105	1727811
LKOH	MICEX	0.0696	0.0653	0.7928	0.0452	1.4914	9.4653	1728080
	RTS	0.3440	0.2000	10.0000	0.4367	8.0543	106.4240	1728080
	LSE	0.1815	0.2000	14.5000	0.1486	15.0912	921.6820	1728080
RTKM	MICEX	0.0052	0.0046	0.1579	0.0036	3.3116	51.5628	1701031
	RTS	0.0559	0.0400	0.4800	0.0540	1.7327	7.1603	1701031
	LSE	0.0350	0.0316	0.9750	0.0294	5.3254	116.8746	1701031
SIBN	MICEX	0.0217	0.0204	0.2676	0.0120	1.2631	9.4326	1593045
	RTS	0.0666	0.0000	0.7300	0.1236	2.4589	9.7506	1593045
	LSE	0.0538	0.0400	0.7800	0.0484	2.5850	15.4983	1593045
SNGS	MICEX	0.0033	0.0031	0.0298	0.0019	1.4861	9.9972	1728080
	RTS	0.0171	0.0150	0.1400	0.0165	2.7285	15.4575	1728080
	LSE	0.0070	0.0060	0.7260	0.0105	27.3326	1356.9370	1728080
TATN	MICEX	0.0081	0.0076	0.0758	0.0043	1.1401	7.4957	669439
	RTS	0.0426	0.0000	0.2500	0.0474	0.3056	1.2570	669439
	LSE	0.0400	0.0250	0.2250	0.0336	1.3521	4.5764	669439

The table reports the descriptive statistics of the bid-ask spreads for all securities

Table 13 Summary of the bid-ask spread statistics across the three markets

Table 13 reports statistics on a bid-ask spread for the eight cross-listed securities. These statistics indicate that MICEX is the least transaction costly market. The average transaction costs on MICEX in terms of the bid-ask spreads are the lowest relative to the RTS and LSE markets. The average bid-ask spread on MICEX is clearly narrower than on RTS and LSE. The mean, median, maximum of the spreads on MICEX is the smallest relative to LSE and RTS. The spreads in terms of the mean and median on LSE are either approximately equal or smaller than on RTS. In general, the transaction cost differences across the three markets denote heterogeneity of market structure, which can be explained by existing trading and regulatory restrictions and information asymmetry between the cross-border markets.

		Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Total Turnover	Observations
EESR	MICEX	158249	16000	27601600	200	491092	6	74	25839000000	1651065
	RTS	811819	500000	50000000	10000	2226280	14	256	4906812000	1651065
	LSE	22727	5000	3570000	2	84561	7	96	2853000000	1651065
GAZP	MICEX	6718	890	1440000	2	24381	15	522	425048000	1295976
	RTS	95688	50000	15500000	1000	422103	34	1247	104513400	1295976
	LSE	4782	2000	663678	1	12222	17	535	179924000	1295976
GMNK	MICEX	331	50	150304	2	1124	27	2524	31524000	1714261
	RTS	3717	2000	27500	68	3921	3	16	9555000	1714261
	LSE	5006	2000	250000	1	10543	6	66	6435000	1714261
LKOH	MICEX	677	100	194422	2	1930	10	267	115830000	1727978
	RTS	4768	5000	150000	100	6419	13	221	28016000	1727978
	LSE	9186	3920	1917455	1	29792	23	909	38986800	1727978
	MICEX	4857	464	4000400	2	22847	34	2797	824670000	1714957
RTKM	RTS	56284	50000	1200000	2000	95811	7	67	49215000	1714957
	LSE	12166	5000	466000	20	27479	5	36	50578000	1714957
SIBN	MICEX	5708	1000	10559982	2	33980	235	72614	61108800	1538197
	RTS	87815	50000	500000	5000	121974	3	10	12015000	1538197
	LSE	8656	3000	269610	5	21017	7	69	28329000	1538197
SNGS	MICEX	21538	2800	15000000	200	71126	17	1443	1560403000	1749190
	RTS	149116	100000	5000000	10000	299402	9	86	295974000	1749190
	LSE	5345	2700	745000	1	12216	18	723	776050000	1749190
TATN	MICEX	4997	400	400004	2	15889	6	54	116160000	727360
	RTS	10577	10000	100000	800	10945	3	12	7690000	727360
	LSE	3616	1478	64500	26	7870	5	32	4997000	727360

The table reports the descriptive statistics of the trades including total number of securities exchanged for all markets

Table 14 Summary of trading size statistics across the three markets

Table 14 displays the statistics of trading sizes. MICEX leads indisputably both RTS and LSE in terms of the total absolute number of securities exchanged. However, with the exception of EESR and SNGS securities, the median of the trading size on MICEX is the lowest relative to RTS and LSE. The notion that trading on MICEX occurs more frequently is supported by the larger aggregate number of securities exchanged with a minimum median in each transaction.

This argument is in line with conclusions of the Chapter 4. The minimum trading sizes on RTS are the largest relative to MICEX and LSE. This statistic is explained by the minimum trading size rule on RTS as defined in Chapter 3.

In sum, the descriptive statistics of Tables 13 and 14 reveal a superior trading activity of the MICEX market. For all securities on average, the MICEX market has about 80% of total securities turnover, which is partly consistent with more than 60% market share average of an overall trading volume (Figure 1). Furthermore, the cost of trading in terms of average bid-ask spreads on MICEX are about 60% and 80% lower than on LSE and RTS markets, respectively. In addition, the average median of a transaction on MICEX is about 90% of the LSE transaction. However, relative to the RTS market, the median size of a transaction on MICEX is under 5% of RTS, which may be indicative of the minimum order size rule on RTS and the presence of the larger trading size of institutional investors. Given the largest overall turnover of MICEX, the smallest median size of these trades on MICEX are reflective of the highest trading intensity of the MICEX market. These statistics are in line with the findings of Chapter 4, that MICEX market has the highest number of trades relative to the RTS and LSE markets. Overall, the descriptive statistics are supportive of the null hypothesis that MICEX is the central price discovery market.

Tables 15 and 16 represent a summary of descriptive statistics of the processed sample based on quotes for 1s and 1920s sampling frequency, respectively, while Tables 17, 18 report the statistics of the quotes based data and Tables 19, 20 and 21 represent the processed output based on the trades based data. This section presents the statistical properties of the frequency extremes, i.e. 1s and 1920s for quotes and trades based samples utilised in Chapters 7 and 8, and 300s trades based sample utilised in the Chapter 9. The intermediate sampling frequency statistics for each sample type are similar within the chosen sampling range because the statistical properties of the quote and price variables do not change significantly across the sampling frequency spectrum. This can be seen in the Tables 19, 20 and 21 by comparing statistical properties of the transaction prices at the sampling frequencies of 1s, 300s and 1920s.

	sampling frequency (s)								
	1	15	30	60	120	240	480	960	1920
EESR	1,727,183	115,146	57,573	28,786	14,393	7,197	3,598	1,799	1,037
GAZP	1,404,065	93,604	46,802	23,401	11,701	5,850	2,925	1,463	845
GMNK	1,727,811	115,187	57,594	28,797	14,398	7,199	3,600	1,800	1,038
LKOH	1,728,080	115,205	57,603	28,801	14,401	7,200	3,600	1,800	1,040
RTKM	1,701,031	113,402	56,701	28,351	14,175	7,088	3,544	1,772	1,019
SIBN	1,593,045	106,203	53,102	26,551	13,275	6,638	3,319	1,659	956
SNGS	1,728,080	115,205	57,603	28,801	14,401	7,200	3,600	1,800	1,040
TATN	669,439	44,629	22,315	11,157	5,579	2,789	1,395	697	402

The table shows the number of observations contained in each sample depending on sampling frequency

Table 15 Number of observations with sampling frequencies (seconds) derived from Quotes based data

	sampling frequency (s)									
	1	15	30	60	120	240	300	480	960	1920
EESR	1,651,065	110,071	55,036	27,518	13,759	6,879	5,505	3,440	1,720	993
GAZP	1,295,976	86,398	43,199	21,600	10,800	5,400	4,321	2,700	1,350	779
GMNK	1,714,261	114,284	57,142	28,571	14,286	7,143	5,715	3,571	1,786	1,030
LKOH	1,727,978	115,199	57,599	28,800	14,400	7,200	5,759	3,600	1,800	1,039
RTKM	1,714,957	114,330	57,165	28,583	14,291	7,146	5,719	3,573	1,786	1,030
SIBN	1,538,197	102,546	51,273	25,637	12,818	6,409	5,128	3,205	1,602	927
SNGS	1,749,190	116,613	58,306	29,153	14,577	7,288	5,831	3,644	1,822	1,050
TATN	727,360	48,491	24,245	12,123	6,061	3,031	2,425	1,515	758	438

The table shows the number of observations contained in each sample depending on sampling frequency

Table 16 Number of observations with sampling frequencies (seconds) derived from Trades based data

		Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Observations
EESR	M_LSE	0.63	0.65	0.86	0.44	0.11	-0.44	1.80	1727183
	M_RTS	0.63	0.65	0.80	0.44	0.11	-0.44	1.79	1727183
	M_MICEX	0.63	0.65	0.80	0.43	0.11	-0.45	1.81	1727183
GAZP	M_LSE	8.36	8.04	11.70	6.64	0.88	1.89	5.88	1404065
	M_RTS	8.41	8.09	11.80	7.65	0.87	1.86	5.55	1404065
	M_MICEX	8.41	8.08	11.66	7.64	0.86	1.86	5.53	1404065
GMNK	M_LSE	95.79	91.75	134.50	73.00	13.45	1.27	3.76	1727811
	M_RTS	93.22	89.60	130.25	74.88	12.40	1.24	3.72	1727811
	M_MICEX	93.24	89.60	129.71	75.10	12.43	1.25	3.76	1727811
LKOH	M_LSE	80.53	79.90	96.85	61.70	6.53	-0.09	3.22	1728080
	M_RTS	80.66	80.03	96.15	62.90	6.61	-0.08	3.17	1728080
	M_MICEX	80.62	79.73	94.02	62.20	6.58	-0.13	3.24	1728080
RTKM	M_LSE	2.96	3.18	3.70	2.25	0.48	-0.28	1.42	1701031
	M_RTS	2.98	3.21	3.67	2.24	0.49	-0.31	1.40	1701031
	M_MICEX	2.98	3.23	3.68	2.23	0.49	-0.34	1.40	1701031
SIBN	M_LSE	4.65	4.65	5.43	3.81	0.35	-0.13	3.21	1593045
	M_RTS	4.65	4.67	5.48	3.82	0.34	-0.11	3.22	1593045
	M_MICEX	4.65	4.65	5.38	3.83	0.34	-0.08	3.23	1593045
SNGS	M_LSE	1.48	1.46	2.04	1.19	0.15	0.47	2.43	1728080
	M_RTS	1.48	1.46	1.82	1.19	0.15	0.46	2.39	1728080
	M_MICEX	1.48	1.46	1.82	1.18	0.15	0.43	2.38	1728080
TATN	M_LSE	4.80	4.81	5.11	4.45	0.12	-0.17	1.66	669439
	M_RTS	4.81	4.83	5.09	4.55	0.12	0.14	2.09	669439

The table reports the descriptive statistics of quotes based samples sampled at 1s frequency

Table 17 Sample based on Best Quotes sampled at 1s frequency

		Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Observations
EESR	M_LSE	0.63	0.65	0.80	0.44	0.10	-0.44	1.81	1037
	M_RTS	0.63	0.65	0.79	0.44	0.11	-0.44	1.80	1037
	M_MICEX	0.63	0.65	0.79	0.44	0.11	-0.45	1.81	1037
GAZP	M_LSE	8.36	8.05	11.50	7.20	0.89	1.89	5.84	845
	M_RTS	8.41	8.09	11.53	7.70	0.87	1.86	5.52	845
	M_MICEX	8.41	8.08	11.55	7.67	0.86	1.86	5.53	845
GMNK	M_LSE	95.81	91.83	134.25	75.60	13.46	1.28	3.77	1038
	M_RTS	93.22	89.61	128.75	74.88	12.42	1.24	3.71	1038
	M_MICEX	93.24	89.61	128.88	75.19	12.45	1.25	3.75	1038
LKOH	M_LSE	80.53	79.95	93.75	62.95	6.53	-0.09	3.23	1040
	M_RTS	80.66	80.01	95.93	63.00	6.62	-0.08	3.18	1040
	M_MICEX	80.62	79.80	93.78	62.30	6.58	-0.13	3.25	1040
RTKM	M_LSE	2.96	3.17	3.66	2.25	0.48	-0.27	1.42	1019
	M_RTS	2.97	3.21	3.65	2.24	0.49	-0.30	1.40	1019
	M_MICEX	2.98	3.23	3.65	2.24	0.49	-0.34	1.39	1019
SIBN	M_LSE	4.65	4.65	5.43	3.82	0.35	-0.12	3.21	956
	M_RTS	4.65	4.68	5.43	3.82	0.34	-0.11	3.23	956
	M_MICEX	4.65	4.65	5.38	3.84	0.34	-0.08	3.23	956
SNGS	M_LSE	1.48	1.46	1.82	1.20	0.15	0.47	2.44	1040
	M_RTS	1.48	1.46	1.82	1.19	0.15	0.46	2.40	1040
	M_MICEX	1.48	1.46	1.81	1.18	0.15	0.44	2.38	1040
TATN	M_LSE	4.80	4.81	5.09	4.55	0.12	-0.14	1.65	402
	M_RTS	4.81	4.83	5.09	4.55	0.12	0.13	2.09	402

The table reports the descriptive statistics of quotes based samples sampled at 1920s frequency

Table 18 Sample based on Best Quotes sampled at 1920s frequency

		Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Observations
EESR	LSE_P	0.64	0.65	0.80	0.41	0.10	-0.52	1.95	1651065
	RTS_P	0.64	0.65	0.79	0.45	0.10	-0.52	1.95	1651065
	MIC_P	0.64	0.65	0.80	0.45	0.10	-0.53	1.96	1651065
GAZP	LSE_P	8.09	8.00	9.41	3.36	0.43	1.06	4.93	1295976
	RTS_P	8.18	8.02	9.79	7.65	0.48	1.89	5.80	1295976
	MIC_P	8.17	8.02	9.83	7.63	0.48	1.92	5.90	1295976
GMNK	LSE_P	95.58	91.68	135.00	20.51	14.20	0.65	5.66	1714261
	RTS_P	93.22	89.00	129.50	75.80	12.51	1.25	3.76	1714261
	MIC_P	93.24	89.61	129.78	75.02	12.48	1.24	3.73	1714261
LKOH	LSE_P	80.56	79.95	94.00	3.30	6.65	-0.18	3.93	1727978
	RTS_P	80.61	80.00	94.00	62.80	6.60	-0.08	3.17	1727978
	MIC_P	80.61	79.73	94.05	62.20	6.59	-0.13	3.22	1727978
RTKM	LSE_P	2.96	3.17	3.65	2.24	0.48	-0.31	1.44	1714957
	RTS_P	2.98	3.24	3.65	2.25	0.49	-0.36	1.42	1714957
	MIC_P	2.99	3.24	3.68	2.22	0.49	-0.37	1.42	1714957
SIBN	LSE_P	4.65	4.62	5.40	3.82	0.35	0.05	3.14	1538197
	RTS_P	4.67	4.67	5.50	3.85	0.37	0.21	3.12	1538197
	MIC_P	4.65	4.64	5.39	3.83	0.34	0.07	3.17	1538197
SNGS	LSE_P	1.48	1.46	2.10	1.20	0.15	0.47	2.39	1749190
	RTS_P	1.48	1.46	1.81	1.19	0.15	0.44	2.32	1749190
	MIC_P	1.48	1.46	1.82	1.18	0.16	0.43	2.32	1749190
TATN	LSE_P	4.80	4.81	5.05	4.35	0.11	-0.16	2.11	727360
	RTS_P	4.79	4.80	5.07	4.60	0.11	0.00	2.03	727360

The table reports the descriptive statistics of trades based samples sampled at 1s frequency

Table 19 Sample based on Last-tick interpolated Trades sampled at 1s frequency

		Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Observations
EESR	LSE_P	0.64	0.65	0.80	0.41	0.10	-0.52	1.95	5505
	RTS_P	0.64	0.65	0.79	0.45	0.10	-0.52	1.95	5505
	MIC_P	0.64	0.65	0.80	0.45	0.10	-0.53	1.96	5505
GAZP	LSE_P	8.09	8.00	9.41	7.45	0.43	1.18	3.89	4321
	RTS_P	8.18	8.02	9.79	7.65	0.48	1.89	5.79	4321
	MIC_P	8.17	8.02	9.80	7.64	0.48	1.92	5.90	4321
GMNK	LSE_P	95.59	91.68	134.00	20.51	14.18	0.67	5.61	5715
	RTS_P	93.22	89.00	129.50	75.80	12.51	1.25	3.76	5715
	MIC_P	93.24	89.60	129.38	75.11	12.48	1.24	3.73	5715
LKOH	LSE_P	80.57	80.00	94.00	59.70	6.61	-0.08	3.16	5759
	RTS_P	80.61	80.00	94.00	62.80	6.60	-0.08	3.17	5759
	MIC_P	80.61	79.73	93.96	62.20	6.59	-0.13	3.22	5759
RTKM	LSE_P	2.96	3.17	3.65	2.24	0.48	-0.31	1.44	5719
	RTS_P	2.98	3.24	3.65	2.25	0.49	-0.36	1.42	5719
	MIC_P	2.99	3.24	3.67	2.23	0.49	-0.37	1.42	5719
SIBN	LSE_P	4.65	4.62	5.40	3.82	0.35	0.06	3.14	5128
	RTS_P	4.67	4.67	5.50	3.85	0.37	0.21	3.12	5128
	MIC_P	4.65	4.63	5.39	3.83	0.34	0.07	3.17	5128
SNGS	LSE_P	1.48	1.46	1.81	1.20	0.15	0.46	2.38	5831
	RTS_P	1.48	1.46	1.81	1.19	0.15	0.44	2.32	5831
	MIC_P	1.48	1.46	1.82	1.18	0.16	0.43	2.33	5831
TATN	LSE_P	4.80	4.81	5.05	4.35	0.11	-0.16	2.11	2425
	RTS_P	4.79	4.80	5.07	4.60	0.11	0.00	2.02	2425

The table reports the descriptive statistics of trades based samples sampled at 300s frequency

Table 20 Sample based on Last-tick interpolated Trades sampled at 300s frequency

		Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Observations
EESR	LSE_P	0.64	0.65	0.80	0.45	0.10	-0.52	1.95	993
	RTS_P	0.64	0.65	0.79	0.45	0.10	-0.52	1.95	993
	MIC_P	0.64	0.65	0.79	0.45	0.10	-0.53	1.96	993
GAZP	LSE_P	8.09	8.00	9.38	7.46	0.43	1.17	3.88	779
	RTS_P	8.18	8.02	9.79	7.69	0.49	1.89	5.81	779
	MIC_P	8.17	8.02	9.79	7.69	0.48	1.92	5.91	779
GMNK	LSE_P	95.50	91.60	134.00	20.51	14.33	0.55	5.95	1030
	RTS_P	93.23	89.28	129.10	75.80	12.51	1.25	3.76	1030
	MIC_P	93.25	89.59	128.85	75.25	12.49	1.24	3.72	1030
LKOH	LSE_P	80.49	79.80	93.90	3.30	7.04	-1.31	16.39	1039
	RTS_P	80.63	80.10	94.00	63.25	6.59	-0.07	3.17	1039
	MIC_P	80.63	79.81	93.80	62.37	6.57	-0.12	3.22	1039
RTKM	LSE_P	2.96	3.17	3.65	2.24	0.48	-0.30	1.44	1030
	RTS_P	2.98	3.24	3.65	2.25	0.49	-0.36	1.42	1030
	MIC_P	2.99	3.24	3.66	2.23	0.49	-0.37	1.42	1030
SIBN	LSE_P	4.65	4.62	5.40	3.82	0.35	0.05	3.15	927
	RTS_P	4.67	4.67	5.50	3.85	0.37	0.21	3.13	927
	MIC_P	4.65	4.64	5.39	3.84	0.34	0.07	3.16	927
SNGS	LSE_P	1.48	1.46	2.10	1.20	0.16	0.53	2.67	1050
	RTS_P	1.48	1.46	1.81	1.19	0.15	0.44	2.32	1050
	MIC_P	1.48	1.46	1.81	1.19	0.16	0.43	2.32	1050
TATN	LSE_P	4.80	4.81	5.00	4.56	0.11	-0.14	2.01	438
	RTS_P	4.79	4.80	5.07	4.60	0.11	0.00	2.04	438

The table reports the descriptive statistics of trades based samples sampled at 1920s frequency

Table 21 Sample based on Last-tick interpolated Trades sampled at 1920s frequency

Chapter Six: Methodology

In order to investigate the subject of the price discovery relationship between multiple markets trading cross-listed securities, this study proposes to estimate models of cointegration/error-correction (ECM) in Engle and Granger (1987), Johansen (1988) cointegration/vector error-correction (VECM) frameworks, by applying Gonzalo and Granger (1995) and Hasbrouck (1995) methodologies. The main purpose of these models is to provide insight into the pricing relationship between the markets. The estimated models should reveal whether MICEX, RTS and LSE, are co-moving or cointegrated, whether there is a lead-lag relationship as well as on which market the information is concentrated and dispersed.

The methodology of this chapter is organised as follows: firstly, general assumptions and assumptions about market efficiency are reviewed. Secondly, tests are presented that can be used to test the order of integration and to test for a common stochastic component between time series. Thirdly, structural price discovery, VAR and VECM models are reviewed in order to investigate the price discovery relationship. Lastly, the methodology of price discovery contribution is presented and discussed.

Arithmetic vs. Logarithmic Returns

Arithmetic and logarithmic returns are approximately equal for small returns. The difference between them is large only when percentage changes are high. For example, an arithmetic return of +50% is equivalent to a logarithmic return of 40.55%, while an arithmetic return of -50% is equivalent to a logarithmic return of -69.31. The main advantage of logarithmic returns is that the continuously compounded return is symmetric, while the arithmetic return is not: positive and negative percentages of arithmetic returns are not equal. This means that an investment of 100 that yields an arithmetic return of 50% followed by an arithmetic return of -50% will result in 75, while an investment of 100 that yields a logarithmic return of 50% followed by an logarithmic return of -50% it will remain 100.

Log return is defined as:

$$r_t = \log \frac{P_t}{P_{t-1}} \quad (1)$$

Arithmetic return is defined as:

$$r_t = \frac{P_t - P_{t-1}}{P_{t-1}} \quad (2)$$

where P is the intra- daily price of a security.

Market Efficiency Conditions

Starting with the static analysis, if there is a form of weak market efficiency between the markets *x* and *y*, for instance between MICEX and RTS and if these markets are not cointegrated then it is expected that the market prices would satisfy the following conditions:

$$\rho\left[\Delta \log(P_{xt}), \Delta \log(P_{yt})\right] \approx 1 \quad (3)$$

$$\rho\left[\Delta \log(P_{x_t}), \Delta \log(P_{y_{t-k}})\right] \approx 0 \quad \forall k > 0 \quad (4)$$

$$\rho\left[\Delta \log(P_{x_{t-k}}), \Delta \log(P_{y_t})\right] \approx 0 \quad \forall k < 0 \quad (5)$$

That is changes in the log quotes or prices of a financial asset in one market and its corresponding changes in the other market on that asset are perfectly contemporaneously correlated. Furthermore there should be no cross- autocorrelation for example between P_{x_t} and $P_{y_{t-k}}$. If these conditions do not hold, then the markets do not function frictionless and are not perfectly efficient[4].

4 Brooks, C. (2002) "Introductory Econometrics for Finance", Cambridge University Press, p. 395

6.1 *Causality Relationship*

The following models represent the standard Granger (1969) causality test, which enables us to examine the co-movements of two price-time series. The direction of information flow as well as the weak exogeneity condition can be tested by applying the Granger (1969) causality model. One time series is regressed on its own lagged values and on the lagged values of the other time series. Broadly, if the two time series under study are specified, the formulated model takes this general form:

$$X_t = \sum_{k=1}^{q} \alpha_k X_{t-k} + \sum_{m=1}^{q} \beta_m Y_{t-m} + \varepsilon_t \tag{6}$$

$$Y_t = \sum_{k=1}^{q} \delta_k X_{t-k} + \sum_{m=1}^{q} \gamma_m Y_{t-m} + \tau_t \tag{7}$$

From (5) for instance, assuming *X* for MICEX and *Y* for RTS, if the coefficient on lagged values of MICEX in the regression of RTS on lagged variables of RTS and MICEX are statistically significant, it could be concluded that MICEX is the leading or MICEX Granges- causes RTS prices to follow. This would mean that lagged values of MICEX would contain relevant information for the current value of LSE. With this denotation it could be tested with Wald test, whether the coefficients δ and β are jointly significantly different from zero. This is symmetrically valid for the inversed hypothesis that RTS Granger- causes MICEX. All together, there are four possible outcomes: two cases of unidirectional causality (MICEX causes RTS or RTS causes MICEX however not vice versa) or causality resulting in either directions (bi-directional) or no causality.

In a specific case, the values for the two time series, MICEX, RTS and LSE would be the log prices of the locally traded stocks and their corresponding ADRs. In the case of returns, they are calculated as logarithmic price changes. It should be mentioned that the evidence of causality in either or both directions would indicate that the markets may be fragmented. In the case of no causality, the hypothesis that the markets are integrated and that new information is assimilated into prices instantly at the two exchanges cannot be rejected. However, there is also a possibility that the two price series are uncorrelated. This possibility is addressed in the next section, where the cointegration of the two time series and an error-correction model are estimated.

6.2 *Testing for Cointegration*

The variables combined are said to be cointegrated, if and only if there exists a stationary linear combination of non-stationary random variables. The components of the vector X_t are cointegrated of order *(d, b)*, denoted by X_t ~ *CI (d, b)*, if all components of X_t are *I(d)* and there exists a vector *b* such that *b x t* is *I(d- b)*, where *b > 0.*

It is necessary to investigate the degree of integration in order to proceed with the cointegration and error-correction models. The Granger Representation Theorem, {Engle and Granger (1987)} states that if there are cointegrating relations among the elements of *X*, there exists an error correction representation of the form:

$$\Delta X_t = \alpha + \beta Z_{t-1} + \delta_1 \Delta X_{t-1} + \delta_2 \Delta X_{t-2} + \ldots + \Delta X_{t-q+1} + \varepsilon_t \qquad (8)$$

where $Z_{t-1} = \alpha_1 ' X_{t-1}$ (9)

and all components of *X* are I(d) then $\alpha_1 ' X_{t-1}$ ~ *I(d - b)* are integrated in order *(d, b).*

Alternative integration testing procedures:

1. Determining whether all components are integrated of the same order *I(d).* This could be tested by applying the augmented Dickey- Fuller (ADF) or equivalent to determining whether or not variables contain unit roots.
2. Provided that the variables are both integrated to the same order, the parameters of the cointegrating relation could be estimated such as

$$Y_t = \beta_0 + \beta_1 X_t + u_t$$

3. Test by applying the ADF test to see whether the residuals u_t are stationary.

If the cointegration exists, that would imply that at least one of the markets adjusts to the other and that they display a common stochastic trend in the long run. That would also mean that market is not efficient since publicly available information causes the market to react.

Before the level of integration of the price-time series can be estimated, the stationarity of each price-time series has to be tested. It is expected, and this in fact turns out to be the case, that only the first differences of the price-time series will be stationary. This means that the domestic and foreign prices are both integrated of the order *I(1).* The augmented Dickey-Fuller (ADF) test has been used, in order to test for the unit root of time series integration. For any time series, denoted as *X*, this test would be used to estimate the regression

$$\Delta X_t = \mu_t + \alpha_1 X_{t-1} + \sum_{k=1}^{q-1} \beta_k X_{t-k} + \varepsilon_t \qquad (10)$$

and to test whether the coefficient α_1 from Equation (10) is significantly different from zero. The null hypothesis is that this coefficient equals zero, which means that there is a unit root in *X*. Therefore, rejecting the null hypothesis would enable to conclude that the time series are stationary. Moreover when the ADF test has been conducted, the optimal number of augmenting lags *(q)* has been determined according to the Akaike (AIC) and Schwarz Information Criteria (SIC).

6.3 *Roll (1984) Model and its Extensions*

A random walk process is the sum of independently and identically distributed *(i.i.d.)* random variables. Unlike fixed-income securities, equity prices, which have neither limiting conditions nor maturity, may be plausibly approximated by a random walk. A property of a random walk is that in the first differences $(p_t - p_{t-1})$ there is a stationary process, whereas the price process itself is not. Roll (1984) proposes following a random walk process:

$$m_t = m_{t-1} + \mu_t + u_t \qquad (11)$$

where *m* is the price at the time *t*, μ_t is the expected return and u_t is *i.i.d.* random variable. In order to be able to model the price-time series, however, it is necessary to take the bid-ask spread into account. This can be presented in the following way:

$$p_t = m_t + cq_t \tag{12}$$

where q_t is the trade indicator: *+1* for a buy, and *-1* for a sell; *c* is the half spread (1/2 of the difference of the bid and the ask prices). The standard Roll model makes it is possible to relate the cost of trading, defined as the bid-ask spread, to the first- order autocorrelation of the price series is given by:

$$Cov(\Delta p_t, \Delta p_{t-1}) = -c^2 \tag{13}$$

where Δp_t and Δp_{t-1} are the price changes in periods *t* and *t-1*, respectively. This could be a way of estimating the cost of trading, based solely on the autocorrelation of the observed prices. The model can be extended to include asymmetric information. Hasbrouck (2002) uses the term Generalized Roll model to describe this extension. In this extension, the trade indicator q_t is unobserved. The structural model according to Hasbrouck (2002) is now the following:

$$m_t = m_{t-1} + w_t \tag{14}$$

where w is an *i.i.d.* random variable, and λ is the information content of the trade (if there are no informed traders, λ=0).

$$w_t = \lambda q_t + u_t \tag{15}$$

If the order processing cost *c* (the half spread) is added and the following structural models are obtained:

$$ask_t = m_{t-1} + u_t + c + \lambda \tag{16}$$

$$bid_t = m_{t-1} + u_t - c - \lambda \tag{17}$$

where m_{t-1} is the quote mid-point in the previous period, u_t is an *i.i.d.* random variable, *c* is the half spread, and λ is the information content of the trade. The above defined Generalized Roll model can be extended to a multivariate linear model. Hasbrouck (2002) proposes a structural model, with an efficient price *mt* that is common to both price series. The first price reflects the Roll model with a bid-ask spread, whereas the second price is based on the lagged efficient price.

$$m_t = m_{t-1} + u_t \qquad (18)$$

$$p_{xt} = m_t + cq_t \qquad (19)$$

$$p_{yt} = m_{t-1} \qquad (20)$$

where m_t is the efficient price at time *t*, p_{xt} and p_{yt} are two price series, and q_t is the trade type indicator, *-1* or *+1*. The efficient unobserved price of the structural model is the key for all following price discovery models. The major objective of the decomposition analysis, as proposed by the Gonzalo-Granger (1995) Permanent-Transitory Component (GG) (PT) and the Hasbrouck (1995) Information Share (HIS) measures is to understand which market contributes most to the common unobserved efficient price in the cointegrating system.

6.4 *Models of Information and Price Discovery in Multiple Markets*

This section examines the existence of long-run equilibrium and the persistence of short- run differences. The ordinary least squares (OLS) estimator is used for testing the unit roots and cointegration, as well as for the error-correction model. The first proposed approach is the conditional two step residuals based approach. A level regression for both directions is estimated. The second approach is the unconditional model, which utilises the mispricing spread series, which are the differences between the log prices on the domestic or foreign markets. Finally, this study utilises the vector autoregressive (VAR) in conjunction with the maximum likelihood estimation method for consistent model dynamic specification and in order to measure the contributions of markets to price discovery.

6.4.1 Conditional Error Correction Model (ECM)

This method is a two step Engle and Granger (1987) procedure based on ordinary least squares (OLS) estimator. After testing for unit root, one can proceed to the first step, estimating the possible cointegration relationship in levels between the MICEX, RTS or LSE log prices. In the second step, based on these results, the ECM is estimated, based on the optimal lag structure determined according to SIC.

Firstly, the cointegration level regressions are estimated:

$$X_t = \alpha_t + \beta_1 Y_t + \varepsilon_t \quad (21)$$

and

$$Y_t = \alpha_t + \gamma_1 X_t + \tau_t \quad (22)$$

where X_t and Y_t may stand for prices on the Moscow and London markets.

Secondly the test for stationarity of the residuals from the regressions is executed again by using the augmented Dickey-Fuller test. If the null hypothesis of a unit root in the residuals from the above regressions can be rejected, that is, if the residuals are I(0), then it can be concluded that the time series are cointegrated. The coefficients β_1 and γ_1 express the equilibrium relationship between the two variables, and can be used to formulate the error-correction model.

According to the law of one price, it is expected, that the two prices should be the same, since the two securities are nearly identical, so the coefficients β_1 and γ_1 would be equal to one if the market efficiency condition holds. The difference in prices would then be the error or the deviation from the long-term equilibrium relationship. Both directions of the error-correction model, the local return as dependent variable are estimated as

$$\Delta X_t = \lambda \varepsilon_{t-1} + \beta_1 \Delta Y_{t-1} + \delta_1 \Delta X_{t-1} + \eta_t \quad (23)$$

and the cross-listed stock returns as the dependent variable.

$$\Delta Y_t = \theta \tau_{t-1} + \delta_2 \Delta Y_{t-1} + \beta_2 \Delta X_{t-1} + \pi_t \quad (24)$$

The coefficients of fundamental importance are λ and θ given by Equations (23) and (24) respectively. These coefficients indicate the direction in which the price series react to the short run deviations from the long run equilibrium relationship. Market efficiency and the assumption of no arbitrage do not exclude the possibility that random factors would cause the two price series to diverge from their equilibrium relationship. However, such random shocks should be quickly corrected by arbitrage restoring the equilibrium. Therefore, the notion of the existence of arbitrage opportunities is not excludable; however these opportunities should not persist over the long run.

The difference in denotation of error-correction coefficients λ and θ is deliberate, for the purpose of a detailed inquiry into the lead-lag relationship between the two markets. If a form of mispricing arises, the follower market would be expected to move at a faster rate towards the price on the other market rather than vice versa. A statistical significant in λ and θ coefficients would indicate a convergence of both markets in the long run.

The parameters β_2 and β_1 indicate a short run deviation from the equilibrium and are not expected to be significant. A positive significant parameter would indicate that one or the other market leads in the price discovery process persistently over the whole sampling period. The significance for both OLS estimators is mutually exclusive, otherwise it is contradictory to initial assumptions.

The no less important coefficients δ_2 and δ_1 explain the autocorrelation between the lagged and spot values. A positive and significant coefficient reveals positive autocorrelation and vice versa for negative autocorrelation. Significance in autocorrelation is an undesired property, since it can contribute to drawing false inferences about the importance of estimated variables. However, it also contributes to correct dynamic specification of the models.

6.4.2 Unconditional ECM

The second approach is the unconditional Engle-Granger model, which does not directly involve residuals of the levels, but the series of differences between log prices i.e. as a one step procedure, and the actual series spread is treated as a variable instead, and serves as a confirmation of the above stated model. If there is a causality relationship between MICEX, RTS and LSE, the inputs are defined as cointegrating regression and first differences respectively:

$$X_t = \alpha_t + \beta_t Y_t + \mu_t \tag{25}$$

$$\mu_t^* = X_t - Y_t \tag{26}$$

and vice versa for the opposite direction

$$Y_t = \gamma_t + \delta_k X_t + \lambda_t \tag{27}$$

$$\lambda_t^* = Y_t - X_t \tag{28}$$

Then, the ratio of residuals and their corresponding differences would be integrated with I(0).

$$\frac{\mu_t}{\mu_t^*} \sim I(0) \tag{29}$$

$$\frac{\lambda_t}{\lambda_t^*} \sim I(0) \tag{30}$$

The residuals and spreads of log prices must be $\mu_t \approx \mu_t^*$ and $\lambda_t^* \approx \lambda_t$ for the above statements (29) and (30) then to be valid. As a first step, the series of differences or spreads, denoted as μ_t^* and λ_t^* are computed for both directions respectively. The actual ECM regression would use these spreads instead of residuals from the level regression. The error correction model is estimated as follows:

$$\Delta X_t = \alpha + \Delta X_{t-1} + \Delta Y_{t-1} + \lambda \mu_{t-1}^* + \eta_t \tag{31}$$

and analogous

$$\Delta Y_t = \beta + \Delta Y_{t-1} + \Delta X_{t-1} + \theta \lambda_{t-1}^* + \pi_t \tag{32}$$

As the actual series of raw differences are used for the estimation instead of their deviations in the model, this analysis offers an alternative insight into the information discovery process. The parameters λ and θ are the indicators of a long run relationship similar to the representations in the previous ECM. These parameters describe the speed of adjustment if the disequilibrium occurs. Expressed in stricter terms, these parameters measure the proportions of the last equilibrium error[5]. A positive significance and higher degree of value in one these parameters is expected for a lagging market and vice versa. For instance if RTS or LSE lags MICEX, the prices on RTS or LSE are expected to catch up to MICEX prices at a higher speed than if the reverse were true . If MICEX follows RTS or LSE prices then the speed of adjustment in the prices of MICEX to equilibrium is expected to be higher than that of RTS or LSE.

Though arbitrage would result in the prices closely following the exchange rate adjusted home market price during the time of day when the two markets overlap, it is not expected that the time series would be equal at every point in time. There should be a no arbitrage band due to transaction costs. Additional factors, which counteract the arbitrage opportunity are time lags and associated exchange rate risk involved in conversions of home market shares into ADRs or the conversions in the opposite direction[6].

6.4.3 VAR and Vector Error Correction Models (VECM)

An alternative to ordinary least squares (OLS) estimation method as described above and more consistent methodology to model cointegration and error-correction would be the Johansen (1988) procedure. It assumes that all variables are endogenous and utilises maximum likelihood estimation (MLE) for determining the optimum lag structure. The procedure begins with an unrestricted VAR, involving potentially non-stationary variables. A key aspect of the approach is isolating and identifying the r cointegrating combinations among a set of *k* integrated variables and incorporating them into an empirical model.

The appropriate estimation procedure is:

Step 1: Identifying the optimal lag structure according to information criteria

Step 2: Estimating the unrestricted VAR

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5 Ibid, pp. 398- 399

6 Grammig, J. Melvin, M. and C. Schlag (2005) “Internationally cross-listed stock prices during overlapping trading hours: price discovery and exchange rate effects” Journal of Empirical Finance, vol. 12, issue 1, p. 8

Step 3: Performing the cointegration test

Step 4: Determining the cointegrating rank and the factorisation $\Pi = \alpha\beta^T$: Estimating the matrix of cointegrating vectors, β^T and the weighting matrix α .

Step 5: Estimating the VECM, incorporating the cointegrating relations and the lag structure from the previous steps.

Step 6: Imposing restrictions and testing.

Johansen's approach is based on MLE of the VECM, by step-wise eliminating the parameters out i.e., maximizing the likelihood function over a subset of parameters, treating the other parameters as known, given the number *r* of cointegrating vectors, where the matrix β^T is the last to be concentrated out. Let *X* to be a *1xn* vector of unit- root processes where it is assumed that there exist *1−n* cointegrating vectors, which would imply the existence of a single common stochastic trend according to Stock and Watson (1988). Based on Engle and Granger (1987), the series have the following vector autoregressive VAR (n) representation:

$$\Delta X_t = \alpha + \Pi X_{t-1} + \sum_{k=1}^{q-1} \Gamma \Delta X_{t-k} + \varepsilon_t \tag{33}$$

$$\varepsilon_t \sim NID(0, \sum \varepsilon)$$

$$x_t = A_0 + A_1 x_{t-1} + \ldots + A_p x_{t-q} + u_t$$

$$\Rightarrow \Delta X_t = \sum_{k=1}^{q-1} \Pi_i \Delta X_{t-k} + \Pi X_{t-q} + u_t$$

$$\Rightarrow \Delta X_t \text{ - } \Pi X_{t-q} = \sum_{k=1}^{q-1} \Pi_k X_{t-k} + \varepsilon_t$$

$$\text{where } \Pi_k = I + A_1 + \ldots + A_i; \quad \Pi = I - A_1 - A_2 - \ldots - A_q$$

are the matrices of coefficients determining the cointegration relationship between the variables.

Johansen also proposes a likelihood ratio test of parametric restrictions on β^T of the form $\beta = H\phi$, where *H* is a given *q x s* matrix of rank *k≦r* and ϕ is an unrestricted *k x r* matrix. For example, in the case *r = 1, k = 2,* it is possible to test whether β^T is proportional to *(1, −1) =*

H^T. The likelihood ratio test (LR) statistic $-2\ln\left[\sup_{\phi}\hat{L}\left(r,H\phi\right)\big/\hat{L}\left(r,\hat{\beta}_r\right)\right]$ has a limiting χ^2 null distribution with *r (q-s)* degrees of freedom.

Procedures for the Johansen cointegration test

Step 1: Perform an auxiliary regression of Δx_t on $\Delta x_{t-1},\Delta x_{t-2},\ldots\Delta x_{t-q+1}\Rightarrow residuals\_\varepsilon_{0t}$

and x_{t-q} on $\Delta x_{t-1},\Delta x_{t-2},\ldots\Delta x_{t-q+1}\Rightarrow residuals\_\varepsilon_{qt}$

Step 2: Compute S00, S0q, Sp0, and Sqq

$$S_{xy}=T^{-1}\sum_{t=1}^{T}\varepsilon_{it}\varepsilon'_{jt};x,y=0,q;T=sample\ size$$

Step 3: Solve the Equation: $\left|\lambda S_{qq}-S_{q0}S_{00}^{-1}S_{0q}\right|=0$

Find roots or eigenvalues of the polynomial Equation in step 1; the solution yields the eigenvalues: $\lambda_1>\lambda_2>\lambda_3\ldots>\lambda_k$ and associated eigenvector v_i

Step 4: Compute the likelihood ratio (LR) statistic $LR=-T\sum_{i=r+1}^{k}\ln(1-\hat{\lambda}_i)$

If rank = $r<k$, the first r eigenvectors are the cointegrating vectors – the columns of β^T

H_0: at most r cointegrating vectors

1. the rank of $\Pi=0\Rightarrow$ no cointegrating relationships
2. the rank of $\Pi=r<k\Rightarrow$ r cointegrated vectors
3. the rank of Π is full (r = k) $\Rightarrow$ the variables are stationary

The second case is of major interest for the initial hypothesis of this study. Once the cointegrating relationships have been confirmed by LR test, Π can now be substituted with factorised matrix $\Pi = \alpha\beta^T$, where β and α are *nx(n-1)* matrices of rank *(n-1)*. This transformation would result in following VECM

$$\Delta X_t = \alpha_0 + \alpha\beta^T X_{t-1} + \sum_{k=1}^{q-1} C\Delta X_{t-k} + \varepsilon_t \tag{34}$$

The columns of β consist of the (n-1) cointegrating vectors and each column of α consists of error-correction coefficients, which define the speed of adjustment back to equilibrium similar to bivariate ECM. The matrix *Π* is decomposed in such a way that $\beta^T X_t$ consists of *(n-1)* vector of stationary series. The covariance matrix of the error term is given by $E = \left[\varepsilon_t \varepsilon_t^T\right] = \Omega$.

6.4.4 Gonzalo-Granger (1995) Permanent- Transitory Component (GG)

The Gonzalo-Granger (1995) approach specifies the proportion of information shares discovered in either market. The basic idea is to decompose the cointegrated system X_t into a permanent, common factor component $A_1 f_t$ and a transitory, stationary component $X_t^{\sim}$:

$$X_t = A_1 f_t + X_t^{\sim} \tag{35}$$

where A_1 represents a factor loading matrix. By using the identifying restrictions that f_t is a linear combination of Y_t and that the transitory component $X_t^{\sim}$ does not Granger- cause X_t in the long-run Gonzalo and Granger (1995) definition, the dynamics above can be decomposed as:

$$X_t = \beta_\perp (\alpha_\perp ' \beta_\perp)^{-1} \alpha_\perp ' X_t + \alpha (\beta ' \alpha)^{-1} \beta X_t \tag{36}$$

Since f_t is given $\alpha_\perp ' X_t$ the elements of $\alpha_\perp$ ($\perp$ denotes orthogonality) are the common factor weights of the variables driving the cointegrated system. More precisely, Gonzalo and Granger (1995) show that in a *N*-variable system with r cointegrating restrictions the relevant vectors of common factor weights are given by the eigenvectors corresponding to the $N-r$ smallest eigenvalues determined in a reduced rank regression and generalized eigenvalue problem similar to those of Johansen (1988, 1991). Once $\alpha_\perp$ has been normalised so that its elements sum to unity, it measures the fraction of system innovations attributable to each variable. In a bivariate system, the Gonzalo-Granger measure is defined as a ratio of coefficient of errors over the difference in coefficients of errors θ and λ from Equations (37) and (38) between both markets:

$$GG_x = \frac{\alpha_{x\perp}}{\alpha_{x\perp} - \alpha_{y\perp}} \tag{37}$$

$$GG_y = \frac{\alpha_{y\perp}}{\alpha_{y\perp} - \alpha_{y\perp}} \tag{38}$$

Assuming market x to MICEX and y to be RTS, for instance from Equation (37), if the proportion of GG is higher than 50%, then MICEX contains higher proportion of information share in price discovery or vice versa indicating that RTS is a leader or a more dominant market.

6.4.5 Hasbrouck (1995) Information Share (HIS)

An alternative method of measuring the price discovery contribution is the information share method proposed by Hasbrouck (1995). This framework follows Stock and Watson (1988) decomposition by transforming the Equation (34) into the following vector moving average (VMA) representation:

$$\Delta X = \psi(L)\varepsilon_t \tag{39}$$

alternatively, $X_t = X_0 + \psi(1)\sum_{i=1}^{t} \varepsilon_t + \psi^*(L)\varepsilon_t$ (40)

Since the two series are cointegrated, the Engle- Granger representation theorem implies the following:

$$\beta^t \psi(1) = 0 \quad \text{and} \quad \alpha\psi(1) = 0 \tag{41}$$

Therefore, there is $\psi(1) = \alpha_{\perp}^{T}\beta_{\perp}$ where $\alpha\perp$ and $\beta\perp$ are orthogonal vectors to α and β respectively. Equation (23) could be expressed as

$$X_t = X_0 + \beta_\perp \alpha_\perp^T \psi(1) \sum_{i=1}^{t} \varepsilon_t + \psi^*(L)\varepsilon_t \tag{42}$$

The term $\alpha_\perp^T \sum_{i=1}^{t} \varepsilon_t$ represents the common stochastic trend component, which follows a random walk process. The $\psi(1)\varepsilon_t$ term represents the long-run impact of innovation on price. It is also clear that the existence of n-1 cointegrating vectors implies that the impact matrix *Ψ(1),* which is the sum of the moving average coefficients, has rank 1. *Ψ* represents the identical row of *Ψ(1).* Hasbrouck points out, that $\psi\varepsilon_t$ constitutes the long-run impact of the innovations on each of the prices and suggests the following measure of information share of market x for the case where the covariance matrix Ω is diagonal i.e., the innovations are independent:

$$S_x = \frac{\psi_x^2 \Omega_{xx}}{\psi \Omega \psi^T} \tag{43}$$

Here, the ψ is the x-th element of the identical row of the impact matrix *Ψ(1).* The information share measure when the covariance matrix is not diagonal is given by

$$HIS_x = \frac{\left([\psi F]_x\right)^2}{\psi \Omega \psi^T} \tag{44}$$

where *F* is the Cholesky factorisation of Ω and $[\psi F]_x$ represents the x-th element of the row vector *Fψ*. Since the Cholesky factorisation depends on the ordering, Equation (44) would provide an information share for a particular ordering. By considering all possible orderings it is possible to compute the upper and lower bounds of the information share. In Hasbrouck (1995), a different series corresponds to the prices of the same security being traded in multiple markets. Therefore, in equilibrium, all the prices are expected to be equal.

By utilising Cholesky decomposition of Ω following terms for upper and lower bounds of market *x*, information share are obtained:

$$HIS_{xu} = \frac{\left(\alpha_y \sigma_y + \rho \alpha_x \sigma_x\right)^2}{\left(\alpha_y \sigma_y + \rho \alpha_x \sigma_x\right)^2 + \alpha_x^2 \sigma_x^2 \left(1 - \rho^2\right)} \tag{45}$$

$$HIS_{xl} = \frac{\alpha_y^2\sigma_y^2\left(1-\rho^2\right)}{\left(\alpha_x\sigma_x + \rho\alpha_y\sigma_y\right)^2 + \alpha_y^2\sigma_y^2\left(1-\rho^2\right)} \qquad (46)$$

Baillie et al. (2002) argue that the mid-point average of the bounds is:

$$HIS_{x\varnothing} = \frac{1}{2}\left(S_{xu} + S_{xl}\right) \qquad (47)$$

DeJong (2002) proves that there is an interrelation between the two approaches of information contribution measures. The Gonzalo-Granger and Hasbrouck's measures seem to be competing approaches to detect leadership effects in cointegrated security markets. The approach of Hasbrouck (1995) captures variable innovations ε_t to the total variance of the common trend innovations. He defines the permanent component as a combination of current as well as lagged variables of interest, since the common stochastic trend is, and the transitory components are, driven by current and lagged innovations ε_t. However, this *I(1)* process is a random walk by definition.

On the other hand, Gonzalo and Granger (1995) measure the impact of ε_t on the innovation in the common factor and their permanent component only comprises current values of Y_t. Any non-stationary process could therefore form the permanent component in the Gonzalo and Granger decomposition. Thus, the efficient price process is non martingale and may be forecastable, according to Hasbrouck (2002). Nevertheless, the two methodologies are indirectly related to each other via the Gonzalo-Granger factor loadings which directly feed into the calculation of Hasbrouck's measure.

Chapter Seven: Price Discovery in the Moscow Equity Market: RTS vs. MICEX

7.1 *Overview*

This chapter investigates the subject of price discovery on the Moscow cross-listed equity market between the MICEX and RTS exchanges. Arbitrage activities should keep prices of cross-listed assets in the competing markets from diverging. Thus, the prices of cross-listings in the multiple markets are expected to be cointegrated and to be driven by one common factor or by the implicit efficient price. Hasbrouck (1995) states: "The information share associated with a particular market is defined as the proportional contribution of that market's innovations to the innovation in the common efficient price." The price discovery contributions in this chapter are measured by applying Hasbrouck (1995) and Gonzalo and Granger (1995) methodologies. Both methods are based on a decomposition of return time series into a permanent component associated with the efficient price of the asset and a transitory component which reflects microstructure effects. The efficient price should be identical in both markets, while the transitory component may differ. The goal is to establish which market's informational contribution is first impounded into the efficient price.

The findings of this chapter support the notion that price discovery occurs in the most trading active MICEX (central) market yet also with statistically significant results for the less active competitor RTS (satellite market). The results are also consistent with the hypothesis that the more active trading market is the central market and the less active one is the satellite market. These findings are in line with studies of Hasbrouck (1995, 2002) and Harris et al. (2002), which focus on the US national price discovery relationship between major and regional markets. On the one hand, the more trading intense MICEX market happens to be a dominant price discoverer, contributing to the major information share. On the other, both markets contribute to price discovery significantly, yet the RTS stock market plays rather a supportive role. These conclusions are based on transactions as well as on quotes based data samples.

In this chapter, the empirical analysis is based on both transaction and quotes data, unlike the one type of data usually found in the price discovery literature. For instance, the US market price discovery analysis of Hasbrouck (1995) is based on best quotes, while the analysis of Harris et al. (1995, 2002) is based on transaction prices. Despite the differences in the nature of the data, generally, both data types yield similar results, although they present some fine differences in the price discovery contributions to a common efficient price.

Another distinct feature of this study is that the findings are not just based on one arbitrarily chosen sampling frequency as usually presented in the literature {e.g. event time in Harris et al. (1995), 1s in Hasbrouck (1995), 600s in Eun and Sabherwal (2003), 10s in Grammig et al. (2005) or 60s and 600s in Phylaktis and Korczak (2007)}. The analysis of this study is based on a spectrum of frequencies for transaction and quotes data set types. Both types of data are continuously sampled, containing sub-samples of 1, 15, 30, 60,120, 240, 480, 960 and 1920 second intervals.

The sampling frequency range has been limited to the 1-1920s range because there is no better way to cope with the trade-off between the issues of contemporaneous correlation and non-quoting or trading. These trade-offs are stock and trading venue specific. By increasing the frequency to the highest level, there is a risk of picking up too much microstructure effects (as evidenced by e.g. Bandi and Russell (2008), Grammig and Peter (2008) and Chapter 8); such as bid-ask quote bounce, stale quotes or missing observations corrected by means of interpolation resulting from lesser trading intensity. On the other hand, at a longer sampling interval the likely information containing observations are lost, resulting in some parameters, still contemporaneously correlated but not statistically significant. The issue of the optimum sampling frequency will be addressed in Chapter 8.

Despite the enormous amount of existing literature on US market price discovery and the similarities in the market constellations between Russia and the US, the trading environment of the Russian equity market is distinct from its US counterpart. Firstly, unlike the US, the Russian equity market is still an emerging market. Secondly, in the given sample period, the Russian economy operated under capital flow restrictions unlike the US. At the same time, cross-listed equity trading on MICEX was denominated in RUB while in USD on RTS. The exchange rate was dynamically set by the Central Bank of Russia (CBR) based on the foreign exchange trading results T-1. Given that one of the markets is quoted in foreign currency, the exchange rate factor is assumed to be exogenous despite its effect on the dynamic pricing behaviour. The findings of Liebermann et al. (1999), Grammig et al. (2005) and Phylaktis and Korczak (2007) indicate that the contribution of the intraday exchange rate factor to the common component is negligible, providing support for the assumption of the exchange rate as an exogenous variable in this study.

The rest of the chapter is organised as follows: Firstly, price discovery literature on national cross-listed equity is illustrated and examined. Secondly, the two major frameworks of measuring price discovery in multiple markets are compared and discussed. Thirdly, empirical results are presented and their findings are discussed.

7.2 *Literature review*

Following the general literature review on price discovery of Chapter 2, this part of the literature review focuses exclusively on price discovery in the multiple national markets. Price discovery here has been defined as “the search for an equilibrium price”, which is also a purpose function of stock exchanges. Prices and quotes of homogenous equity securities traded on separate trading venues are informationally linked, thus forming a cointegrating system. The price discovery process, therefore, is supposed to be a function of a multi-lateral error-correction mechanism (ECM). This field has been pioneered by two studies of Harris et al. (1995) and Hasbrouck (1995) which have examined the relative contribution to price discovery in the US equity market, between NYSE and regional exchanges. These two studies are central to the subject of price discovery in multiple national equity markets, but they have also since been applied universally to the price discovery of informationally linked markets.

Harris et al. (1995) reveal the adjustment dynamics of the trading process implementing the cointegration/error-correction methodology of Engle and Granger (1987) based on transaction prices of one cross-listed IBM stock between the NYSE, Chicago and Pacific stock exchanges. Harris et al. (1995) demonstrate that the prices of IBM in 1990 on these three informationally linked markets are cointegrated and follow a multi-lateral error-correction process. They find a significant price discovery with multi-directional price adjustments on all three exchanges.

Hasbrouck (1995) proposes multiple cointegrated markets as a potential source of a common innovation variance for cross-listed stocks between NYSE and Boston, Chicago, Cincinnati and the Philadelphia exchanges. The researched data set is based on quotes at one second resolution, comprising thirty DJIA stocks for a period of three months in 1993. Hasbrouck (1995) proposes the concept of information share. Hasbrouck (1995) finds that 92% of the price discovery is attributable to the quoting on NYSE. This proportion exceeds 84% of the trading volume share on NYSE. The NYSE has been categorised as information dominant, the central market and regional exchanges as satellite markets.

The studies of Harris et al. (1995) and Hasbrouck (1995) reveal significant price discovery in both main and regional markets. The market with the highest informational contribution is called the information dominant or the central market and the market with substantially less contribution is called the periphery or satellite market. The Harris et al. (1995) study, on the one hand, employs the error-correction (ECM) estimation methods of Engle and Granger (1987) in order to measure the extent of differences in prices between exchanges, reacting to the cross-market information flows. Hasbrouck (1995), on the other hand, employs a common-trends vector auto-regression (VAR) representation utilising in essence the Johansen (1988) procedure. The fraction of long-term total variation of returns explained by each market from a variance-decomposition analysis is computed and is called the information share. The two models are illustrated in detail in the methodology chapter.

In order to estimate the informational contribution of each market, Hasbrouck (1995) proposes an information shares based model, while Gonzalo and Granger (1995) estimate price discovery contributions using a permanent transitory model. Price discovery is defined in terms of the variance of the innovations to the common factor by Hasbrouck (1995). The model of information shares measures the relative contribution to variance in the common efficient price of each market. The model of Gonzalo and Granger (1995) focuses only on the error-correction process. This process involves only permanent, not transitory shocks that result in a pricing disequilibrium, as opposed to Hasbrouck's (1995) definition. The pricing disequilibrium occurs because markets impound information at different rates in the context of price discovery. The permanent-transitory model of Gonzalo and Granger (1995) measures the contribution to the common factor of each market, where the price discovery contribution of each market is defined as a function of the market's error-correction coefficients of the estimated VECM.

As a follow up to Hasbrouck's (1995) study, Harris et al. (2002a) investigate price discovery for thirty DJIA stocks cross-listed between NYSE, Chicago and Pacific stock exchanges employing the Gonzalo and Granger (1995) methodology. The data set is based on transaction prices sampled at event time rather than clock time for the 1988-1995 period. Harris et al. (2002a) uncover varying and statistically significant price discovery over time for all exchanges. The central market NYSE was information dominant at the beginning of the sample period. The average common factor weight for the NYSE (72%) closely matched its share of the trades in 1988. By 1992 the proportion of the price discovery attributable to the NYSE had declined for 27 of the DJIA stocks, averaging 49.6%. However, the proportion of price discovery on NYSE had recovered substantially by 1995. These findings point to price discovery proportions not being constant, but varying substantially over time. The temporal aspects of price discovery as well as the variability attributable to trading are going to be examined in detail in Chapter 9.

The application of the two competing methodologies in the empirical literature results in a debate. The studies of Harris et al. (2002b) and Hasbrouck (2002) debate the performance of the two models. Hasbrouck's (2002) criticism is that the common factor method of Gonzalo and Granger (1995) or common component share as employed in Harris et al. (2002a) violates the condition of the efficient price, which should be a martingale. Harris et al. (2002b) respond to the critique by arguing that the subject is price discovery and not quote discovery. Therefore, even when a central trading venue leads on quote revision, without observable trading price divergence conditioned error correction, price discovery does not occur, if the quotes from regional and central exchanges are matched when trades are executed. DeJong (2002), Baillie et al. (2002) and Lehmann (2002) derive the relationship between the permanent-transitory model of Gonzalo and Granger (1995) and the information share of Hasbrouck (1995). The study of DeJong (2002) demonstrates that only the model of Hasbrouck (1995) takes the variability of the innovations in price of each market into account, although both Gonzalo and Granger (1995) and Hasbrouck (1995) offer a similar measure for the informational contribution of a market on the efficient price process. DeJong (2002) proves that the total variance of innovation is not considered with the common component method. In contrast, the Hasbrouck information share approach provides a relative measure of how much variation in the efficient price process is explained. The variation in the efficient price can be interpreted as new information impounded into the process of efficient price. The competing approaches of measuring the multiple market contribution to price discovery are compared and discussed in detail in section 7.3.

A sub-strand of national market price discovery literature is concerned with market fragmentation between the electronic order driven and dealer market segments. For instance, Huang (2002) and Barclay et al. (2003) find that ECNs have the dominant price discovery share in the NASDAQ market. On the UK equity market, LSE SETS traded securities are studied by Friederich and Payne (2001) and Lai (2003) and Cai and Dufour (2003). These studies find that the price discovery process occurs largely on the order driven SETS LOB. In sum, the electronic order driven- market segment leads the price discovery process.

The studies on multi-market price discovery address the question of price discovery between central and satellite trading venues in the national markets. Although there is already research on the established market (predominantly on the US market), the Moscow equity market is distinct, not only micro-structurally but by the fact that it is still an emerging market. The Russian equity market has grown over the years to be one of the world’s top ten stock markets in terms of trading volume. Despite this, there is a lack of research on the relationship between RTS and MICEX. Is the price discovery relationship on the national Russian equity market comparable to the central-satellite relationship in the national US market?

This study attempts to consolidate the price discovery relationship between central and satellite markets with the two major stock exchanges in Moscow: MICEX and RTS. The contribution of this study to the price discovery literature is achieved firstly by covering the lack of research on the Moscow market; secondly by utilising transaction and quotes based intraday data and applying both major price discovery measurements, then by presenting the estimation of results in a spectrum of sampling frequencies, and finally by seeking to reconcile the performance of the Hasbrouck (1995) and Harris et al. (2002a) approaches.

Chapter 7: Price Discovery in the Moscow Equity Market: RTS vs. MICEX

This chapter focuses on the following questions:

- Is there a long-run equilibrium relationship between the Moscow markets?
- If so, how is the price discovery lead-lag direction relationship characterised?
- How much does the individual market contribute to the common factor?
- Which type of methodology and data perform better?

The following null hypotheses have been established:

1. H_0: There is a long-run equilibrium relationship between MICEX and RTS pricing.
2. H_0: MICEX leads RTS, the price discovery relationship is uni-directional.
3. H_0: MICEX is the informationally dominant market.

7.3 *Price Discovery in Multiple Markets*

Chapter 6, Methodology, describes two major competing schools of thought in the price discovery research literature. Both schools propose a measurement of a market's contribution to price discovery in a cointegrated system: information shares {Hasbrouck (HIS), (1995 and 2002)}, and common factor components {Gonzalo and Granger (GG) (1995)} employed by Harris et al. (2002). Literature review section 7.2 illustrates similarities between those two approaches: Harris et al. (2002) view price discovery similarly to Hasbrouck (1995) in terms of innovations in the permanent components of the stochastic process in the underlying cointegrated time series. Both models use the vector error correction model (VECM) as their basis and Hasbrouck (1995) points out that the VECM is consistent with several market microstructure models in the existing literature. Both schools have extensively researched the price discovery relationship on the US national stock market, between NYSE and the regional exchanges, and arrived at similar findings; that the central market i.e. NYSE leads the price discovery with a contribution approximately 70-90%.

Despite this initial similarity, the information shares and permanent-transitory models use different definitions of price discovery. Hasbrouck defines the permanent component as a combination of current as well as lagged market variables (Equation 43). He measures markets innovation to the total variance of the common component (trend) innovations. The common stochastic trend and the transitory components are driven by current and lagged innovations in the residuals. Hasbrouck's (1995) methodology takes standard deviations and correlations of price innovations into account. The HIS measure provides upper and lower bounds of information share by means of ordering in Cholesky factorization. The arithmetic mean which is comparable to the GG measure is obtained from the bounds. Gonzalo and Granger (1995) on the other hand, measure the impact of long-run information arrival on the innovation in the common factor. Their permanent component comprises only current values of the observed prices (Equation 37). Gonzalo and Granger (1995) are concerned exclusively with the error-correction process, and this process involves only permanent shocks. The permanent-transitory model measures each market's contribution to the common factor, where the contribution is defined as a function of the market's error-correction coefficients. This very intuitive measure utilises the factor loadings of VECMs, while the values sum up to one. The HIS method measures, however, only the upper and lower bounds of the information shares.

Although the information share (HIS) and the permanent-transitory (GG) models are applied to the same subject of research, the two methodologies provide different views on the price discovery process. The Hasbrouck (1995) model extracts the price discovery process using the variance of innovations to the common factor. The Gonzalo and Granger (1995) approach focuses on the components of the common factor and the error correction process. This method involves only permanent as opposed to transitory shocks which result in disequilibrium.

However, the major difference between the two approaches is that, on the one hand, Harris et al. (2002a) applies the GG methodology to the transaction prices, and, on the other, Hasbrouck investigates price discovery by implementing his information share framework on the order quotes. Harris et al. (2002a) address permanent innovations in prices in near synchronous (time span minimised) trading time, which is dependent on event time frequency rather than clock time frequency, whereas the methodology of Hasbrouck addresses permanent innovations in the best prevailing quotes continuously sampled at one second frequency.

Hasbrouck (2002) shows with his simulation model, that when regional (satellite) markets cross uninformative trades at the stale quote mid-point of the central market, the Gonzalo- Granger (GG) approach may provide biased estimates of the true price discovery parameters. In contrast, the position of Harris et al. (2002a) is that the competition for order flow between the centralised and regional exchanges takes place in trades and not in quotes.

Harris et al. (2002a) believe that price discovery does not result from fast updating of the quotes to reflect an information event. According to Harris et al. (2002a), the price discovery process is initiated only when the limit order placers or market participants evaluate the information in a different way in order to execute a transaction, at a divergent price in error correcting fashion. Their argument is that regional exchanges do not compete on quotes because there is no requirement that the market with the best quote also automatically receives an order. Therefore, despite the satellite exchange revising their quotes more slowly even when a central trading venue leads on quote revision, price discovery does not occur without observable trading price divergence and error-correction, unless the quotes from regional and central exchanges are matched when trades are executed. Furthermore, Harris et al. (2002a) argue that “stale quotes on one market can provide evidence that another market has moved first to incorporate permanent innovations in the stock price”. Therefore, the information shares and impulse response functions of Hasbrouck (1995) demonstrate the relative speed of short-run order quote adjustment across exchanges. The analysis of Harris et al. (2002a) focuses on unequal price changes in near synchronous transactions, because of the presence of auto quotes and quotes with little or no depth in the inter market quote data. Assuming the one way price discovery hypothesis, a satellite market could trade at a new price before a trade in the central market, even though the central market updated the quotes first.

The debate about which methodology better measures the contribution to price discovery is resolved by DeJong (2002) for instance, who derives the indirect relationship between the information share and common factor component methodologies by demonstrating that the Stock-Watson (1988) common stochastic trend with idiosyncratic transitory disturbance and the GG permanent-transitory decomposition are closely related. According to DeJong (2002), transitory innovations associated with factors such as market imperfections, bid-ask bounce or reporting errors are ignored by both frameworks.

DeJong (2002) proves that the methodologies of Hasbrouck and Gonzalo and Granger are indirectly related to each other. The GG factor loadings (Equation 35) feed directly into the calculation of Hasbrouck's information share measure (Equation 44). Similarly, the GG common factor weight (Equations 37 and 38) measures the impact of information arrival (captured by ε_t) on innovation in the permanent component, whereas the information share measures the contribution of information to the total variance of innovation in the permanent component. The major difference between the two approaches is the role of the variance of innovations. The GG definition only works with the weights that innovation of markets have in the increment of the efficient price. This definition ignores the variance of ε_{it}. The information share measures the share in the total variance of the efficient price change contributed by each market.

The structural determinants of two established price discovery measures, the information share of Hasbrouck (1995) and the common component share employed in Harris et al. (2002a), are analysed by Yan and Zivot (2007). Using a structural cointegration model, they demonstrate that the two measures separately cannot differentiate between dynamics of price discovery on multiple markets. Furthermore, only the information share methodology measures the relative order flow of individual markets. The information share of one market is higher if it impounds less liquidity shocks and more new information. However, both the information share and component share measure the relative liquidity shocks and noise trading shocks. They conclude that the application of the information share along with the common component measure is complementary and can help differentiating between the interactive effects of the two types of shock.

Finally, where the views of Hasbrouck and Harris et al. (2002b) diverge is actually the nature of the information flow and which data type better reflects price discovery. The information flow is assumed to be discrete by Harris et al. (2002a) while it is continuous in Hasbrouck's framework. Harris et al. (2002a) assume that trading is endogenous to the information flow process. However, the information may still be flowing, even if placed orders are not matched and trades do not take place on any trading venues. Information flow may not be a discrete on/off event; a period in which no transaction occurs may also reflect a part of the information. This notion implies that executed transactions (even order revisions) do not happen frequently enough to reflect all the information flow. There is also a possibility that traders in the satellite market may react to the new information by not submitting an order until the information is fully absorbed in the dominant market. If the new information arrival is not captured by either proposed price discovery measuring approaches, it does not mean that the price discovery is not in process. Since trades occur mostly in a discrete fashion, even when the prices are not adjusting to the available information, there are undefined information periods between these transactions. Harris et al. (1995, 2002a) do not offer a direct provision for the transactionless periods. However, they attempt to minimize the time span of these periods because they believe that information only exists if there is a manifestation of it in a trade. Only Hasbrouck's, sampling methodology offers to overcome the issue by filling the seemingly "informationless" periods with the best prevailing limit order quote.

The major shortcoming of GG measure is the absence of lagged innovations in the common component. When the variances are contemporaneously correlated, the major disadvantage of Hasbrouck's (1995) information share approach is non uniqueness of the upper and lower bounds resulting from of permuted ordering in the Cholesky factorisation. Lower and upper bounds have the tendency to widen considerably at lower sampling frequencies, due to the rising contemporaneous correlation of innovations. More recent studies seek to correct the shortcomings of both frameworks. Grammig and Peter (2008, 2010) and Peter and Kehrle (2010) propose unique information shares based on distributional assumptions.

In order to measure price discovery, this study implements both major approaches: the information shares a model developed by Hasbrouck (1995) and the permanent-transitory model discussed by Gonzalo and Granger (1995). Hasbrouck (1995) uses a Stock-Watson (1988) common stochastic trend decomposition to decompose transaction prices into random walk, which Hasbrouck interprets as the efficient price and transitory disturbance, and measures the contribution of each market to the variance of the former. The information shares are not uniquely defined if the price innovations in the underlying markets are correlated. One has to compute upper and lower bounds for the information shares attributable to each market. The price discovery contribution measure of Gonzalo and Granger (1995) is uniquely defined. It decomposes transaction prices into a permanent component which is integrated of order I(1), and a transitory component which is stationary.

There is evidence that price discovery is not only conditional upon the choice of data type but also sensitive to the choice of the sampling frequency as illustrated by the study of Grammig and Peter (2008). Differences in the trading intensity of cross-listed securities between informationally linked markets are normal. The MICEX market is the most trading intensive market, and hence is expected to contribute most of the innovation to the common efficient price, and therefore lead price discovery. Therefore, the MICEX market is expected to be the most innovative market, but the degree of informational contribution of the MICEX market would be dependent on how frequently the data is sampled. Which sampling frequency should be used in order to measure price discovery contributions accurately? This question will be addressed in Chapter 8.

7.4 *Empirical Results*

This section reports the results of the price discovery analysis based on the Moscow cross-listed equity market. The analysis is characterised by the multi-dimensionality of the empirical results: sampling frequency, data type, price discovery contribution methodology and cross section of individual stock. Since the results are sensitive to the above mentioned factors, the spectrum of results is presented for the MICEX exchange (unless otherwise stated) grouped and then individually. Consequently, the resulting RTS contributions are 1-MICEX contribution. Firstly, the ADF and Johansen cointegration tests are applied to test stationarity of the time series. Secondly, the VARs and the error-correction models are estimated by Equations (33) and (34) respectively, in Chapter 6, in order to determine the lead/lag relationship between the MICEX and RTS stock markets. Finally, information share and permanent-transitory models are applied to estimate the contribution of each market to the common factor.

There is evidence that the MICEX market is a dominant price discoverer. Both the Hasbrouck (1995) and Gonzalo and Granger (1995) measures indicate MICEX is the central market, as it plays the primary role in price discovery. Despite sensitivity to the sampling frequency choice, the information share of MICEX is significantly larger than the satellite RTS market and the price discovery predominantly occurs in the central market. The results of price discovery share similarities with Harris et al. (1995) and the Hasbrouck (1995) studies. Like Harris et al. (1995) and Hasbrouck (1995), this study supports the notion that there is a central-satellite market relationship on the Moscow cross-listed equity market. MICEX is the central market, which is similar to NYSE. The MICEX price discovery contribution on average accounts for over 80%, matching the findings for NYSE of Hasbrouck and Harris et al. (1995). However, the findings of this chapter may differ from the findings of other studies which are either based on daily data or sampled at a lower sampling frequency (above 30 min).

In order to exclude the possibility of a spurious relationship between the underlying RTS and the MICEX variables, it is important to test the unit roots prior to testing for cointegration and the causal relationships, ensuring that the residuals of all ECM and VECM models are stationary. A series is said to be integrated of order I(1), if it has to be differentiated once before becoming stationary. Formal testing for stationarity has been performed with the Augmented Dickey-Fuller (ADF) (1979) unit root test and the Phillips-Perron (1988) test.

7.4.1 Stationarity and Order of Integration

Formal testing for stationarity can be performed with the Augmented Dickey-Fuller (ADF) Dickey and Fuller (1979, 1981) unit root test. Under the null of unit root, test results indicate that the time series are not stationary at levels, but they are stationary after the first difference. All ADF and PP level tests indicate a statistical significance at the 5% level under the null that there is a unit root. These results provide strong evidence that the price and quote time series are integrated in order one I(1). The augmented Dickey-Fuller test rejected the null in first differences, therefore the test indicate unit roots in time series for all eight securities, in all markets, for all sampling frequencies. Regardless of the sampling frequency, the overall results indicate unit root in level and I(0) in first difference, which fulfils the requirements of the cointegration assumption reported in Tables 22 and 23.

		Level Tests		1st Difference Tests	
EESR		ADF - Fisher	PP - Fisher Chi-square	ADF - Fisher Ch	PP - Fisher Chi-sq
	Statistic	2.78	3.17	491.16 *	310.51 *
	Prob.	0.84	0.79	0.00	0.00
	Obs	3104.00	3108.00	3102.00	3105.00
GAZP					
	Statistic	0.01	0.00	421.80 *	416.44 *
	Prob.	1.00	1.00	0.00	0.00
	Obs	2531.00	2532.00	2529.00	2529.00
GMNK					
	Statistic	0.04	0.04	366.42 *	227.57 *
	Prob.	1.00	1.00	0.00	0.00
	Obs	3108.00	3111.00	3107.00	3108.00
LKOH					
	Statistic	10.31	10.45	344.58 *	342.30 *
	Prob.	0.11	0.11	0.00	0.00
	Obs	3116.00	3117.00	3114.00	3114.00
RTKM					
	Statistic	1.69	1.69	310.17 *	311.71 *
	Prob.	0.95	0.95	0.00	0.00
	Obs	3053.00	3054.00	3051.00	3051.00
SIBN					
	Statistic	8.65	8.41	430.13 *	286.18 *
	Prob.	0.19	0.21	0.00	0.00
	Obs	2863.00	2865.00	2861.00	2862.00
SNGS					
	Statistic	3.42	3.45	397.51 *	257.78 *
	Prob.	0.75	0.75	0.00	0.00
	Obs	3115.00	3117.00	3113.00	3114.00
TATN					
	Statistic	5.70	4.46	471.76 *	472.02 *
	Prob.	0.46	0.61	0.00	0.00
	Obs	1203.00	1203.00	1200.00	1200.00

Table 22 Summary of Unit root Tests for Quotes based data

The table reports the statistics of ADF and PP tests of quotes based samples sampled at 1920s frequency. For any time series, denoted as *X*, this test would be used to estimate the regression $\Delta X_t = \mu_t + \alpha_1 X_{t-1} + \sum_{k=1}^{q-1} \beta_k X_{t-k} + \varepsilon_t$ and to test whether the coefficient α_1 is significantly different from zero. The null hypothesis is that this coefficient equals zero, which means that there is a unit root in *X*. The asterisks indicate a statistical significance at the 0.05 level.

		Level Tests		1st Difference Tests	
EESR		ADF - Fisher	PP - Fisher Chi-square	ADF - Fisher Ch	PP - Fisher Chi-square
	Statistic	3.27	3.19	366.32 *	357.82 *
	Prob.	0.77	0.78	0.00	0.00
	Obs	2975.00	2976.00	2973.00	2973.00
GAZP					
	Statistic	0.50	0.60	437.11 *	429.25 *
	Prob.	1.00	1.00	0.00	0.00
	Obs	2333.00	2334.00	2331.00	2331.00
GMNK					
	Statistic	0.23	8.58	425.11 *	301.17 *
	Prob.	1.00	0.20	0.00	0.00
	Obs	3075.00	3087.00	3073.00	3084.00
LKOH					
	Statistic	0.31	0.52	446.28 *	267.97 *
	Prob.	1.00	1.00	0.00	0.00
	Obs	3108.00	3114.00	3106.00	3111.00
RTKM					
	Statistic	1.85	1.89	324.81 *	318.61 *
	Prob.	0.93	0.93	0.00	0.00
	Obs	3086.00	3087.00	3084.00	3084.00
SIBN					
	Statistic	7.65	7.64	466.20 *	361.49 *
	Prob.	0.26	0.27	0.00	0.00
	Obs	2775.00	2778.00	2774.00	2775.00
SNGS					
	Statistic	3.81	10.63	436.38 *	257.01 *
	Prob.	0.70	0.10	0.00	0.00
	Obs	3142.00	3147.00	3140.00	3144.00
TATN					
	Statistic	8.69	7.02	482.21 *	475.13 *
	Prob.	0.19	0.32	0.00	0.00
	Obs	1311.00	1311.00	1308.00	1308.00

The table reports the statistics of ADF and PP tests of trades based samples sampled at 1920s frequency. For details see the annotation of Table 22. The asterisks indicate a statistical significance at the 0.05 level.

Table 23 Summary of Unit root Tests for Trades based data

7.4.2 Cointegration Test Results

Following the unit root test procedures gives the first step in the Engle-Granger (1987) methodology in testing for cointegration. Granger (1981) introduced the concept of cointegration in which two variables may move together, although individually they are non-stationary. Cointegration is based on the long run relationship between the variables. In the short run the variables may diverge from each other. This step would involve estimating the long run equilibrium (Equation 8) and conducting an ADF test on the residuals from the Equation 10. If the residuals are found to be stationary, then the MICEX and RTS time series are cointegrated.

The cointegration analysis is essential because if two non-stationary variables are cointegrated, a vector auto regression (VAR) model in the first difference is misspecified, due to the effect of a common trend. If a cointegration relationship is identified, the model should include residuals from the vectors, lagged at one period, in a dynamic vector error-correction mechanism (VECM). Granger (1986) and Engle and Granger (1987) have proven that, if Y (e.g. RTS) and X (e.g. MICEX) are both I(1) variables and are cointegrated, an error-correction model exists.

The Engle and Granger (1987) technique allows identification of only a single cointegration vector within a system. Alternatively, Johansen (1991, 1995) offers a formal cointegration test, enabling us to identify the maximum number of cointegrating vectors existing between a set of variables. The Johansen cointegration test checks whether, or not, there is any cointegration between the variables. It is, therefore, an alternative or supplementary test to those previously described. This approach also gives the maximum likelihood estimates for the cointegrating vectors. These estimates can be compared with those obtained through the application of ordinary least squares using the Engle and Granger two-step method. The error-correction mechanism (ECM) can be interpreted as showing there often exists a long run equilibrium relationship between two economic variables, but in the short run, however, there may be disequilibrium. With the error-correction mechanism, a proportional disequilibrium in one period is corrected in the next period. The testing procedure for causal relationships between multiple variables could be carried out by VAR and VECM modeling. The VECM allows the simultaneous estimation of short-term and long-term inter-market adjustments. The ECM and

VECM approaches require the time series to be non-stationary or integrated of an order bigger than zero, as well as being cointegrated.

The fundamental condition for the lead-lag relationship analysis is the cointegration between the price variables. If the residuals of the level regression between markets time series are not I(0) stationary unlike their corresponding price series, then the estimation results are spurious. However, the ADF test coefficients displayed significance at least at 5% significance level, meaning that the null hypothesis, that there is a unit root, should be rejected for all stocks and frequencies. Therefore, the residuals of the level regression are concluded to be stationary.

Johansen cointegration tests are performed under the assumption of no deterministic trend and no intercept in both VAR and VECM as suggested by Hasbrouck (1995). The results clearly reject the null of no cointegration and support the hypothesis of at least one cointegrating relationship vector among the two variables amongst all stock pairs and sampling frequencies. These findings are in line the with ADF residual test above. With the variables ordered as mid-point RTS and MICEX market prices, the estimated cointegrating vectors are close to the vector $\beta^T = (1, -1)'$ as indicated by theory. The results for the 1920 second sampling frequency for quotes are reported in Table 22.

		Cointegration Rank Test (Trace)		(Maximum Eigenvalue)	
EESR	No. of CE(s)	None	At most 1	None	At most 1
	Eigenvalue	0.0004	0.0000	0.0004	0.0000
	Statistic	726.2493 *	3.2630	722.9863 *	3.2630
	Critical Value	12.3209	4.1299	11.2248	4.1299
	Prob.	0.0001	0.0839	0.0001	0.0839
GAZP					
	Eigenvalue	0.0005	0.0000	0.0005	0.0000
	Statistic	682.2291 *	5.0803 *	677.1489 *	5.0803 *
	Critical Value	12.3209	4.1299	11.2248	4.1299
	Prob.	0.0001	0.0287	0.0001	0.0287
GMNK					
	Eigenvalue	0.0004	0.0000	0.0004	0.0000
	Statistic	704.8904 *	6.0604 *	698.8300 *	6.0604 *
	Critical Value	12.3209	4.1299	11.2248	4.1299
	Prob.	0.0001	0.0164	0.0001	0.0164
LKOH					
	Eigenvalue	0.0007	0.0000	0.0007	0.0000
	Statistic	1295.1350 *	3.1450	1291.9900 *	3.1450
	Critical Value	12.3209	4.1299	11.2248	4.1299
	Prob.	0.0000	0.0902	0.0000	0.0902
RTKM					
	Eigenvalue	0.0002	0.0000	0.0002	0.0000
	Statistic	297.5546 *	1.9226	295.6320 *	1.9226
	Critical Value	12.3209	4.1299	11.2248	4.1299
	Prob.	0.0001	0.1949	0.0001	0.1949
SIBN					
	Eigenvalue	0.0001	0.0000	0.0001	0.0000
	Statistic	90.6618 *	1.8380	88.8238 *	1.8380
	Critical Value	12.3209	4.1299	11.2248	4.1299
	Prob.	0.0001	0.2061	0.0001	0.2061
SNGS					
	Eigenvalue	0.0003	0.0000	0.0003	0.0000
	Statistic	540.6731 *	2.2082	538.4650 *	2.2082
	Critical Value	12.3209	4.1299	11.2248	4.1299
	Prob.	0.0001	0.1620	0.0001	0.1620
TATN					
	Eigenvalue	0.0001	0.0000	0.0001	0.0000
	Statistic	66.7561 *	0.5482	66.2079 *	0.5482
	Critical Value	12.3209	4.1299	11.2248	4.1299
	Prob.	0.0000	0.5213	0.0000	0.5213

The table reports the statistics of unrestricted cointegration tests (trace and maximum eigenvalue) based on quotes samples sampled at 1s frequency. The initial null hypothesis is that there is no common stochastic trend amongst 2 variables versus the alternative that one. The subsequent null is that there exists at least 1 common stochastic trend. The asterisks indicate a statistical significance at the 0.05 level.

Table 24 Johansen Cointegration Test Summary

The results of Johansen's unrestricted rank tests of Maximum Eigenvalue and Trace are presented in Table 24. The Johansen cointegration tests, when performed, revealed results which clearly support the hypothesis of one cointegrating vector among the two variables and hence one common stochastic trend. In Table 25, the return series of each market are cointegrated with one common stochastic trend. The cointegrating vector is close to the theoretical *(1, –1)*, indicating that the MICEX and RTS markets value the same underlying information differently over the long run.With the variables ordered as mid-point RTS and MICEX market prices, the estimated cointegrating vectors are close to the vector $\beta^T = (1, -1)'$ indicated by theory. Whether the practice has deviated significantly from the theory has been tested at a later stage in VECM by imposing restrictions.

		M_MICEX(-1)	M_RTS(-1)	Standard error	t-statistic
EESR	Cointegrating Vector	1	-0.9994	0.0001	[-6736.36]
GAZP	Cointegrating Vector	1	-0.9993	0.0001	[-10109.2]
GMNK	Cointegrating Vector	1	-1.0000	0.0002	[-4307.09]
LKOH	Cointegrating Vector	1	-0.9995	0.0001	[-10714.7]
RTKM	Cointegrating Vector	1	-1.0008	0.0006	[-1584.95]
SIBN	Cointegrating Vector	1	-0.9998	0.0019	[-530.820]
SNGS	Cointegrating Vector	1	-1.0016	0.0002	[-4041.06]
TATN	Cointegrating Vector	1	-0.9984	0.0009	[-1162.08]

The table reports the cointegrating vectors, their standard errors and t-statistics of the VECM (Equation 34) for quotes based samples, sampled at 1s frequency.

Table 25 Cointegrating Vectors based on Quotes 1s frequency

Almost all cointegrating vectors showed closeness to the theoretical $\beta^T = (1, -1)'$. However, most of the vectors deviated somewhat from the theoretical ideal. Therefore the restrictions for the VECM of the cointegrating vectors *(1, –1)'* were imposed. The purpose of the test is to determine whether the practice is significantly different from theory. The test results of the restricted models (reported in the Table 26) for all stock pairs indicate a non-rejection of null and that the imposed restriction of the theoretical *(1, – 1)* is not significantly different from the empirical. This finding is interesting because despite the difference of currencies quoted, the exogenous exchange rate and idiosyncratic trading rules, one could have expected a significantly constant equilibrium gap between the markets. The non-rejection of the restriction supports the notion that the exchange rate could be treated as exogenous, as previously assumed.

	MICEX vs RTS	beta= (1,-1)
EESR	Chi-square(1)	1.6202
	Probability	0.2031
GAZP	Chi-square(1)	0.6306
	Probability	0.4271
GMNK	Chi-square(1)	0.5057
	Probability	0.4770
LKOH	Chi-square(1)	1.0488
	Probability	0.3058
RTKM	Chi-square(1)	0.4467
	Probability	0.5039
SIBN	Chi-square(1)	0.0568
	Probability	0.8117
SNGS	Chi-square(1)	13.7020 *
	Probability	0.0002
TATN	Chi-square(1)	3.4603
	Probability	0.0629

The table presents the Chi-squared test statistics and their p-values for the imposed restriction of cointegration vector β^T = (1, –1)' from Equation 34 for all cross-listed securities based on quotes samples, sampled at 1s frequency. The asterisks indicate a statistical significance at the 0.05 level.

Table 26 Cointegration Restriction Test Summary

The cointegration tests of Engle Granger and Johansen evaluate long-run relationships between variables. Granger suggests the use of ECM to examine the dynamic short run relation and long-run equilibrium relation. The framework of ECM can also examine the Granger-causality relationship between variables. The analysis of causality between the time series provides an explanation of the short-run dynamic adjustments needed by each variable to reach positions of long-run equilibrium. The estimates of the cointegration models determining the cointegrating rank, the factorisation results in the matrix of one cointegrating vector, β^T and the weighting matrix α estimates of error correction adjustments for eight stocks in the sample, are more consistent estimates then the ECMs of Engle and Granger, but are in line with stated inferences.

7.4.3 VAR and VECM and Lead-Lag Estimation Results

A general to specific model formulation strategy leads to similar results, with the presence of cointegration being robust to the number of lags. The optimal lag structure for unrestricted VAR has been identified according to the minima of the Schwarz Information Criterion (SIC). The optimum lag range has been between fifty for 1 second and one lag for 1920 seconds sampling intervals. Closer to the event time frequency of one second, the lag structure tends to increase, whereas for lower frequencies to decrease. For VECM, the determinant of lag length choice has been the SIC.

The focus of the analysis in this chapter is the estimated VECM. The initial observation each day for each stock is determined by the first sampling interval following the RTS opening containing quotes in both markets. The more parsimonious choice of lag length for VECM has been finally determined by the SIC. The initial lag length is 60 lags, which represents a sample with observations at one second intervals. Then, using the same set of observations that was used for the estimation of the model with 60 lags, the VECM is estimated at each shorter lag length down to one lag to determine the lag structure that minimises the SIC. Lag lengths range from 1 for the lowest sampling frequency, up to 50 for the highest for all time series combinations.

Table 23 reports the estimation results of the VECM and causality. Estimation of the VECM shows the influence of the MICEX returns on the RTS returns sampled at 480s. Of particular interest are the estimates of error-correction coefficients. As shown in Table 27, the error-correction coefficients for the MICEX market are estimated using the Equation 34, which is also used to estimate the error-correction coefficients for the RTS market. The coefficient estimates of the MICEX market are negative and not statistically significant. However, the error-correction term for the RTS market is statistically significant at the 5% level or higher and is positive. This implies that adjustments to the disequilibrium take place mainly in one market. Noticeable differences in the adjustment process are observed between the RTS market and the MICEX market. The RTS market is responsive to the departures of the MICEX market, but not vice versa. This indicates that an information shock to the MICEX market would have a significant effect on the RTS market, but an information shock to the RTS market would not influence the MICEX market significantly.

	Error Correction term	Adj. Coeff. alpha	Standard error	t-statistic
EESR	D(M_MICEX)	-0.0001	0.0000	[-1.82480]
	D(M_RTS)	0.0010 *	0.0000	[22.7329]
GAZP	D(M_MICEX)	-0.0001 *	0.0001	[-2.49383]
	D(M_RTS)	0.0012 *	0.0001	[18.1746]
GMNK	D(M_MICEX)	0.0000	0.0000	[-1.35479]
	D(M_RTS)	0.0008 *	0.0000	[24.8904]
LKOH	D(M_MICEX)	0.0000	0.0000	[-0.81653]
	D(M_RTS)	0.0022 *	0.0001	[34.2277]
RTKM	D(M_MICEX)	0.0000	0.0000	[1.29994]
	D(M_RTS)	0.0004 *	0.0000	[17.0295]
SIBN	D(M_MICEX)	0.0000	0.0000	[-0.94587]
	D(M_RTS)	0.0001 *	0.0000	[9.26225]
SNGS	D(M_MICEX)	0.0000	0.0000	[-0.34418]
	D(M_RTS)	0.0007 *	0.0000	[21.4491]
TATN	D(M_MICEX)	0.0000	0.0000	[-0.97768]
	D(M_RTS)	0.0002 *	0.0000	[7.43666]

The table reports the adjustment coefficients α of the VECM from Equation 34, their standard error and t-test statistics for all cross-listed securities based on quotes samples, sampled at 1s frequency. The asterisks indicate a statistical significance at the 5% level.

Table 27 VECM Error-Correction Coefficients based on Quotes 1s frequency

7.4.4 Contribution to Price Discovery

There is evidence that MICEX trading dominates the Moscow cross-listed equity market, regardless of which price discovery estimation method, data type or sampling frequency is used. Figure 22 and Table 28 clearly support the hypothesis of MICEX market dominance in price discovery in the Moscow cross-listed equity market. The MICEX market contributes on average almost 90% to the common component for both GG and HIS methods. This finding and the proportion of the information share captured by the central market reveals a resemblance to the central NYSE market as documented by e.g. Hasbrouck (1995). The share of contribution for RTS price innovations should be regarded as a mirror image of the MICEX information shares.

The higher the information share of the MICEX price innovations in explaining MICEX price, the lower the share of RTS.

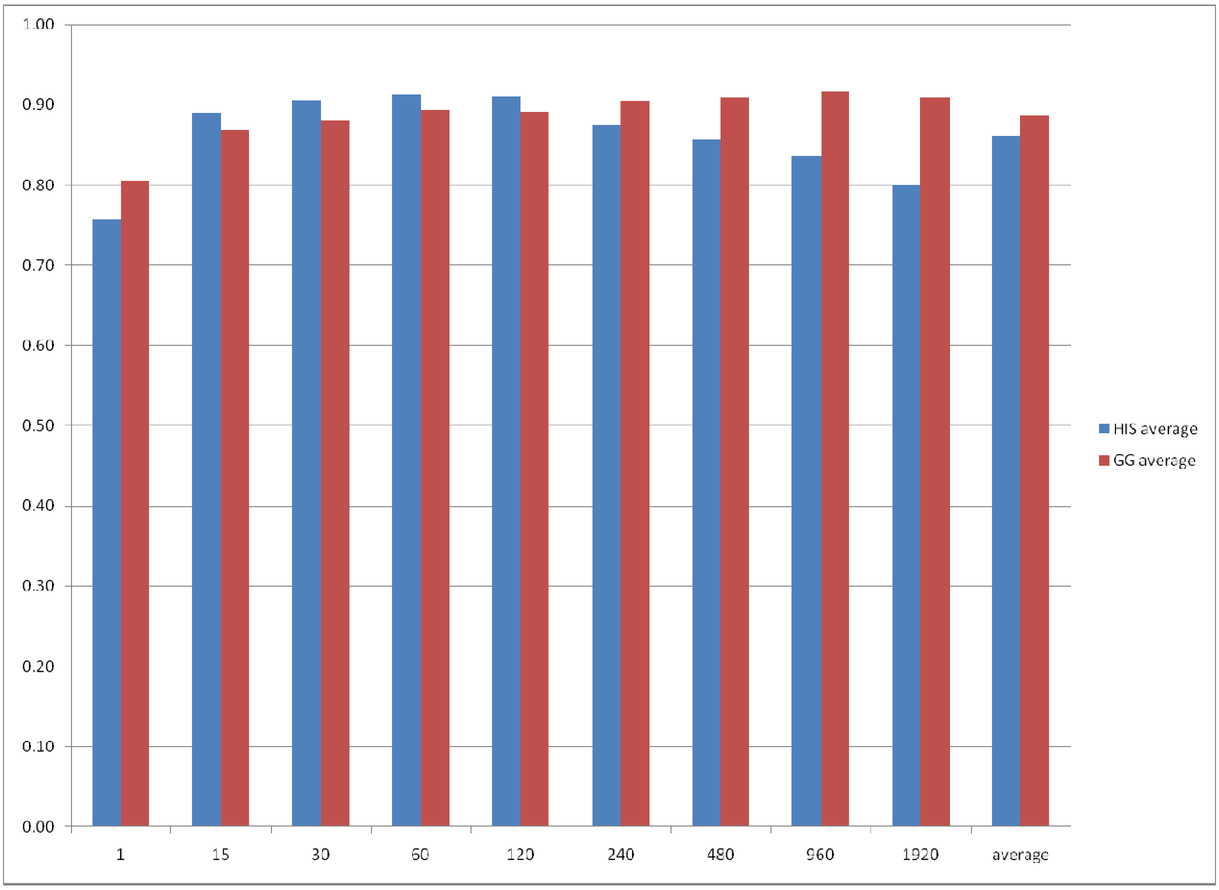

Figure 22 Summary of average HIS and GG for Trades and Quotes for MICEX

frequency (s)	1	15	30	60	120	240	480	960	1920	average
HIS average	0.76	0.89	0.91	0.91	0.91	0.87	0.86	0.84	0.80	0.86
GG average	0.81	0.87	0.88	0.89	0.89	0.90	0.91	0.92	0.91	0.89

The table summarises the Gonzalo and Granger measures and the mid-points of Hasbrouck information shares of MICEX market from Equations 37 and 46 respectively, as a function of sampling frequency, for all cross-listed securities on average based on quotes and trades samples.

Table 28 Summary of average HIS and GG for Trades and Quotes for MICEX

Price Discovery based on Quotes

Table 29, reports the upper and lower bounds, while Table 30 reports average mid-points of all permutations of the Cholesky factorisation of information shares. The MICEX exchange dominates with an average information share of 85.4%, and thus the RTS exchange yields an information share of 14.6%. The lower and the upper bounds differ increasingly with lower sampling frequencies, however Grammig (2008) demonstrates in similar fashion widening bounds in the Hasbrouck (1995) upper and lower bounds of information shares. Baillie et al. (2002) show in a bivariate case, using various examples, that the average of the information shares given by the two permutations is a reasonable estimate of the market's role in price discovery.

Table 31 presents the price discovery results of the RTS and MICEX market. The average contribution of MICEX to the common component resulted in 88.5% according to GG measure, across all stocks and all given sampling frequencies. These findings suggest that the MICEX market contributes most to the price discovery process. The factor weights are a measure of the markets' contribution to permanent information, and the greater a factor weight assigned to a market, the slower its speed of adjustment to equilibrium and the bigger its role in discovering equilibrium price.

frequency (s)		**1**	**15**	**30**	**60**	**120**	**240**	**480**	**960**	**1920**	**mean**
EESR	upper	1.00	1.00	0.99	0.98	0.96	0.84	0.82	0.83	0.69	0.90
	lower	0.81	0.76	0.78	0.76	0.71	0.75	0.69	0.60	0.67	0.73
GAZP	upper	1.00	0.99	0.99	0.98	0.98	0.97	0.59	0.68	0.96	0.90
	lower	0.64	0.62	0.58	0.47	0.36	0.32	0.76	0.09	0.00	0.43
GMNK	upper	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.99	1.00
	lower	0.92	0.88	0.87	0.87	0.87	0.84	0.79	0.75	0.64	0.83
LKOH	upper	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.97	0.99
	lower	0.92	0.89	0.87	0.80	0.76	0.65	0.48	0.42	0.37	0.68
RTKM	upper	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00
	lower	0.95	0.91	0.89	0.84	0.81	0.67	0.67	0.55	0.38	0.74
SIBN	upper	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	lower	1.00	1.00	0.99	0.99	0.99	0.98	0.97	0.94	0.90	0.97
SNGS	upper	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	lower	0.87	0.80	0.78	0.74	0.70	0.64	0.55	0.44	0.34	0.65
TATN	upper	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	lower	0.94	0.90	0.88	0.87	0.85	0.83	0.82	0.76	0.71	0.84
mean		0.94	0.92	0.91	0.89	0.87	0.84	0.82	0.75	0.73	0.85

The table summarises the upper and lower bounds of Hasbrouck information shares of MICEX market from Equation 46, as a function of sampling frequency, for all cross-listed securities based on quotes samples.

Table 29 MICEX Quotes based upper/lower bounds of Hasbrouck Information Shares

frequency (s)	1	15	30	60	120	240	480	960	1920	mean
EESR	0.90	0.88	0.88	0.87	0.84	0.79	0.75	0.71	0.68	0.81
GAZP	0.82	0.80	0.78	0.73	0.67	0.65	0.67	0.39	0.48	0.67
GMNK	0.96	0.94	0.94	0.93	0.93	0.92	0.89	0.87	0.81	0.91
LKOH	0.96	0.94	0.93	0.90	0.88	0.82	0.74	0.70	0.67	0.84
RTKM	0.97	0.95	0.95	0.92	0.90	0.84	0.84	0.78	0.69	0.87
SIBN	1.00	1.00	1.00	0.99	0.99	0.99	0.98	0.97	0.95	0.99
SNGS	0.93	0.90	0.89	0.87	0.85	0.82	0.77	0.72	0.67	0.82
TATN	0.97	0.95	0.94	0.93	0.92	0.92	0.91	0.88	0.86	0.92
mean	0.94	0.92	0.91	0.89	0.87	0.84	0.82	0.75	0.73	0.85

The table summarises the mid-points Hasbrouck information shares of MICEX market from Equation 46, as a function of sampling frequency, for all cross-listed securities based on quotes samples.

Table 30 MICEX Quotes based mid-points of Hasbrouck Information Shares

frequency (s)	1	15	30	60	120	240	480	960	1920	mean
EESR	0.94	0.92	0.86	0.83	0.79	0.70	0.67	0.65	0.59	0.77
GAZP	0.90	0.86	0.85	0.83	0.81	0.77	0.58	0.36	-0.26	0.63
GMNK	0.97	0.98	0.98	0.98	0.91	0.90	0.90	0.85	0.83	0.92
LKOH	0.99	0.97	0.97	0.93	0.91	0.90	0.89	0.81	0.74	0.90
RTKM	0.96	0.97	0.98	0.95	0.95	0.95	0.95	0.93	0.88	0.95
SIBN	0.92	0.95	0.96	1.00	1.00	1.00	1.00	0.97	0.94	0.97
SNGS	0.99	0.99	0.99	0.99	0.99	1.00	0.98	0.95	0.93	0.98
TATN	0.91	0.93	0.96	0.96	0.96	0.96	0.97	0.99	0.99	0.96
mean	0.95	0.95	0.94	0.93	0.91	0.90	0.87	0.81	0.71	0.88

The table summarises the Gonzalo and Granger measures of MICEX market from Equation 37, as a function of sampling frequency, for all cross-listed securities based on quotes samples.

Table 31 MICEX Quotes based Gonzalo and Granger Common Factor Weights

Price Discovery based on Transactions

Similar to the findings based on quotes data, Table 34 reports an average MICEX price discovery contribution of 82.6%, measured by GG across all sampling frequencies and for all stocks. These findings support the notion that the MICEX market is dominant in the price discovery process. One could only presume that the reason for clear values far from half is a relatively very large MICEX liquidity relative to RTS, and hence the informational contribution impounded in MICEX market, which is in line with the findings of Harris et al. (2002a).

Additionally, Table 32 reports the upper and lower bounds, and Table 33 reports averages of all permutations of the Cholesky factorisation of information shares. The MICEX exchange dominates with a mid-point information share of 83.4% and the RTS exchange sustains an information share of 16.6%. The lower and the upper bounds differ increasingly with lower sampling frequencies.

frequency (s)		**1**	**15**	**30**	**60**	**120**	**240**	**300**	**480**	**960**	**1920**	**mean**
ESSR	upper	0.77	0.96	0.97	0.98	0.97	0.96	0.96	0.98	0.96	0.76	0.93
	lower	0.80	0.86	0.82	0.77	0.75	0.71	0.70	0.61	0.55	0.74	0.73
GAZP	upper	0.50	0.91	0.94	0.96	0.98	0.97	0.95	0.97	0.99	0.59	0.88
	lower	0.90	0.94	0.88	0.82	0.71	0.67	0.70	0.57	0.37	0.84	0.74
GMNK	upper	0.43	0.76	0.84	0.90	0.93	0.96	0.95	0.98	0.98	0.99	0.87
	lower	0.71	0.96	0.99	1.00	0.98	0.92	0.93	0.84	0.75	0.65	0.87
LKOH	upper	0.46	0.92	0.96	0.97	0.96	0.96	0.95	0.95	0.97	0.95	0.90
	lower	0.83	0.95	0.88	0.84	0.80	0.77	0.76	0.74	0.58	0.52	0.77
RTKM	upper	0.86	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98
	lower	0.97	0.98	0.95	0.92	0.84	0.83	0.76	0.71	0.65	0.55	0.82
SIBN	upper	0.43	0.76	0.84	0.90	0.93	0.68	0.90	0.76	0.95	0.98	0.81
	lower	0.71	0.96	0.99	1.00	0.98	0.70	0.92	0.78	0.98	1.00	0.90
SNGS	upper	0.27	0.83	0.87	0.96	0.98	1.00	1.00	1.00	1.00	0.99	0.89
	lower	0.63	1.00	0.99	0.93	0.85	0.73	0.69	0.63	0.51	0.41	0.74
TATN	upper	0.10	0.37	0.50	0.65	0.80	0.90	0.91	0.96	0.98	0.99	0.72
	lower	0.17	0.49	0.64	0.78	0.91	0.98	0.99	1.00	0.99	0.95	0.79
mean		0.59	0.80	0.85	0.89	0.91	0.85	0.90	0.86	0.88	0.86	0.83

The table summarises the upper and lower bounds of Hasbrouck information shares of MICEX market from Equation 46, as a function of sampling frequency, for all cross-listed securities based on trades samples.

Table 32 MICEX Trades based upper/lower bounds of Hasbrouck Information Shares

frequency (s)	1	15	30	60	120	240	300	480	960	1920	mean
EESR	0.78	0.91	0.89	0.88	0.86	0.84	0.83	0.79	0.75	0.75	0.83
GAZP	0.70	0.92	0.91	0.89	0.85	0.82	0.83	0.77	0.68	0.72	0.81
GMNK	0.57	0.86	0.92	0.95	0.95	0.94	0.94	0.91	0.87	0.82	0.87
LKOH	0.65	0.94	0.92	0.90	0.88	0.86	0.86	0.84	0.77	0.73	0.84
RTKM	0.91	0.99	0.98	0.96	0.92	0.91	0.88	0.86	0.83	0.78	0.90
SIBN	0.57	0.86	0.92	0.95	0.95	0.69	0.91	0.77	0.97	0.99	0.86
SNGS	0.45	0.91	0.93	0.94	0.92	0.86	0.85	0.81	0.75	0.70	0.81
TATN	0.13	0.43	0.57	0.72	0.86	0.94	0.95	0.98	0.98	0.97	0.75
mean	0.59	0.85	0.88	0.90	0.90	0.86	0.88	0.84	0.83	0.81	0.83

The table summarises the mid-points Hasbrouck information shares of MICEX market from Equation 46, as a function of sampling frequency, for all cross-listed securities based on trades samples.

Table 33 MICEX Trades based mid-points of Hasbrouck Information Shares

frequency (s)	1	15	30	60	120	240	300	480	960	1920	mean
ESSR	0.68	0.84	0.86	0.87	0.85	0.83	0.82	0.85	0.80	0.65	0.80
GAZP	0.67	0.79	0.81	0.82	0.85	0.83	0.80	0.82	0.85	0.59	0.78
GMNK	0.64	0.73	0.75	0.79	0.80	0.83	0.82	0.87	0.89	0.91	0.80
LKOH	0.69	0.81	0.84	0.84	0.84	0.82	0.81	0.80	0.82	0.76	0.80
RTKM	0.84	0.93	0.96	0.97	0.95	1.03	0.99	0.97	0.99	1.00	0.96
SIBN	0.64	0.73	0.75	0.79	0.80	0.73	0.84	0.76	0.88	0.92	0.78
SNGS	0.63	0.78	0.79	0.85	0.89	0.96	0.99	1.02	1.11	1.19	0.92
TATN	0.51	0.64	0.66	0.70	0.74	0.79	0.80	0.84	0.88	0.92	0.75
mean	0.66	0.78	0.80	0.83	0.84	0.85	0.86	0.87	0.90	0.87	0.83

The table summarises the Gonzalo and Granger measures of MICEX market from Equation 37, as a function of sampling frequency, for all cross-listed securities based on trades samples.

Table 34 MICEX Trades based Gonzalo and Granger Common Factor Weights

The overall findings indicate that the MICEX market does have a dominant role in price discovery on the national cross-listed securities market. This finding may be explained by the overall superiority of liquidity of the MICEX equity market. The hypothesis that the MICEX market is the primary market and RTS the supportive market would be consistent with a larger role for price discovery on the MICEX market than on RTS. Figures 23, 24 and 25, 26, presented in the Appendix, indicate that this is clearly true for all the stocks in the sample. However, all stocks have a considerable average information share, greater than the 10% role for RTS price discovery, but none of the stocks display a larger information share for RTS price innovations than the MICEX market price innovations. The findings are similar to the study of Hasbrouck (1995), where the main or central market contributes around 90% to the implicit efficient price, and the regional market provides a supportive role in that process. The interesting question of what explains the differences across stocks will be addressed in the cross-section analysis below.

Comparison of Results

The evidence suggests that both the Hasbrouck (1995) and Gonzalo and Granger (1995) price discovery contribution methodologies perform similarly when these measures are based on a homogenous data type. However, the major difference in performance is attributable to the choice of data type and sampling frequency, rather than the price discovery methodology. Figures 32 and 33 report the average GG and HIS across all stocks and data types. Although the distributions of GG and HIS differ across the sampling frequencies, they display a similar “bell” shape (Figure 32). However, if the results based on data type are compared, differences in price discovery proportions are visible at the frequency extremes between MICEX and RTS (Figure 33). Looking at quotes based data, average HIS and GG display an identical, monotonously falling and rising sampling intervals behaviour with very similar values across the rising sampling frequency range. With trades based data, on the other hand, the behaviour is almost the opposite: GG and HIS rise with rising sampling frequency until they reach a plateau, and even display a diminishing HIS above a 120 second sampling interval, which is in line with the finding of Phylaktis and Korczak (2007). The continuously falling and rising sampling intervals behaviour could be explained by censorship of MICEX innovativeness and therefore an increased bias towards a slower RTS market. This is an interesting feature, since the two competing price discovery methodologies become progressively more controversial at the sampling frequency extremes across the data types. Hasbrouck information shares are smaller for transactions at the highest frequency; however at the 1920 second sampling frequency, HIS is smaller for quotes. The GG measures display the opposite behaviour; they are smaller for transactions at the 1 second and larger for quotes at 1920 seconds frequency. This behaviour might be explained by the fact that the price discovery frameworks are applied on the chosen data type. Harris et al. (2002a) focus on the transaction based data and followed the GG methodology, whereas Hasbrouck formulates his methodology based on continuously sampled best mid quotes. Figure 27 and Figure 28 and Tables 35 and 36 show the results of price discovery; and if they are compared across the different nature of data type, it becomes evident that the measure of price discovery is generally higher for quotes than for trades. This can be observed from the graphs; all price discovery contributions in the trades for MICEX are lower by 10-20%.

frequency (s)	1	15	30	60	120	240	480	960	1920	mean
EESR T	0.78	0.91	0.89	0.88	0.86	0.84	0.79	0.75	0.75	0.83
EESR Q	0.90	0.88	0.88	0.87	0.84	0.79	0.75	0.71	0.68	0.81
GAZP T	0.70	0.92	0.91	0.89	0.85	0.82	0.77	0.68	0.72	0.81
GAZP Q	0.82	0.80	0.78	0.73	0.67	0.65	0.67	0.39	0.48	0.67
GMNK T	0.57	0.86	0.92	0.95	0.95	0.94	0.91	0.87	0.82	0.86
GMNK Q	0.96	0.94	0.94	0.93	0.93	0.92	0.89	0.87	0.81	0.91
LKOH T	0.65	0.94	0.92	0.90	0.88	0.86	0.84	0.77	0.73	0.83
LKOH Q	0.96	0.94	0.93	0.90	0.88	0.82	0.74	0.70	0.67	0.84
RTKM T	0.91	0.99	0.98	0.96	0.92	0.91	0.86	0.83	0.78	0.90
RTKM Q	0.97	0.95	0.95	0.92	0.90	0.84	0.84	0.78	0.69	0.87
SIBN T	0.57	0.86	0.92	0.95	0.95	0.69	0.77	0.97	0.99	0.85
SIBN Q	1.00	1.00	1.00	0.99	0.99	0.99	0.98	0.97	0.95	0.99
SNGS T	0.45	0.91	0.93	0.94	0.92	0.86	0.81	0.75	0.70	0.81
SNGS Q	0.93	0.90	0.89	0.87	0.85	0.82	0.77	0.72	0.67	0.82
TATN T	0.13	0.43	0.57	0.72	0.86	0.94	0.98	0.98	0.97	0.73
TATN Q	0.97	0.95	0.94	0.93	0.92	0.92	0.91	0.88	0.86	0.92
mean	0.77	0.89	0.90	0.90	0.89	0.85	0.83	0.79	0.77	0.84

The table presents a comparison between the mid-points Hasbrouck information shares based on quotes and trades samples of MICEX market from Equation 46, as a function of sampling frequency, for all cross-listed securities. T stands for trades and Q for quotes based samples.

Table 35 MICEX Quotes and Trades averaged Hasbrouck Information Shares

The price discovery contribution of GG and HIS as a function of sampling frequency, displays differences in values usually when based on the different data type. This may be the major factor, which sparked the debate between Hasbrouck (2002) and Harris et al. (2002a). Figure 29 and Figure 30 display the price discovery contribution estimates for GG and HIS methods for all securities and frequencies. For instance, with higher sampling frequencies, the HIS share of MICEX is substantially lower compared to GG (Figure 29) and this is in line with the finding of e.g. Phylaktis and Korczak (2007). In contrast, with lower frequencies the MICEX share of GG seems to fall less steeply than in the case of HIS for the range of sampling frequencies between 240 and 920 seconds. Quotes based data of the GG as a function of time generally rises monotonously while for transactions it falls. Apart from the monotonous decay, it takes roughly the shape of a parabola; the price discovery contribution is larger for the lagging market at the lowest frequency i.e. 1s. Intuitively, this characteristic may be most likely attributed to the interpolation of missing price observations, keeping in mind that the more interpolated market is biased to have a higher informational contribution. Also worth mentioning is that, besides the overstated HIS for MICEX, there are more discrepancies in price discovery contribution results across trades than across quotes. It seems that the trades are far inferior to reconstructed and to continuously sampled best prevailing quotes for the price discovery contribution computations, because there is less informational content in the transaction prices.

frequency (s)	1	15	30	60	120	240	480	960	1920	mean
EESR T	0.68	0.84	0.86	0.87	0.85	0.83	0.85	0.80	0.65	0.80
EESR Q	0.94	0.92	0.86	0.83	0.79	0.70	0.67	0.65	0.59	0.77
GAZP T	0.67	0.79	0.81	0.82	0.85	0.83	0.82	0.85	0.59	0.78
GAZP Q	0.90	0.86	0.85	0.83	0.81	0.77	0.58	0.36	-0.26	0.63
GMNK T	0.64	0.73	0.75	0.79	0.80	0.83	0.87	0.89	0.91	0.80
GMNK Q	0.97	0.98	0.98	0.98	0.91	0.90	0.90	0.85	0.83	0.92
LKOH T	0.69	0.81	0.84	0.84	0.84	0.82	0.80	0.82	0.76	0.80
LKOH Q	0.99	0.97	0.97	0.93	0.91	0.90	0.89	0.81	0.74	0.90
RTKM T	0.84	0.93	0.96	0.97	0.95	1.03	0.97	0.99	1.00	0.96
RTKM Q	0.96	0.97	0.98	0.95	0.95	0.95	0.95	0.93	0.88	0.95
SIBN T	0.64	0.73	0.75	0.79	0.80	0.73	0.76	0.88	0.92	0.78
SIBN Q	0.92	0.95	0.96	1.00	1.00	1.00	1.00	0.97	0.94	0.97
SNGS T	0.63	0.78	0.79	0.85	0.89	0.96	1.02	1.11	1.19	0.91
SNGS Q	0.99	0.99	0.99	0.99	0.99	1.00	0.98	0.95	0.93	0.98
TATN T	0.51	0.64	0.66	0.70	0.74	0.79	0.84	0.88	0.92	0.74
TATN Q	0.91	0.93	0.96	0.96	0.96	0.96	0.97	0.99	0.99	0.96
mean	0.80	0.86	0.87	0.88	0.88	0.87	0.87	0.86	0.79	0.85

The table presents a comparison between the Gonzalo and Granger measures based on quotes and trades samples of MICEX market from Equation 37, as a function of sampling frequency, for all cross-listed securities. T stands for trades and Q for quotes based samples.

Table 36 MICEX Quotes and Trades averaged Gonzalo-Granger measures

Which framework performs better at estimating the price discovery relationship? The methodologies are complementary; they can both be accurate, if applied on the appropriate data type, and the sampling frequency is carefully chosen. The proportion of contribution to the price discovery between the two types of data appears to be in a similar range at a 2-5 min sampling frequency. This finding is in line with Yan and Zivot (2007). However, the HIS approach seems to work better when applied on continuously sampled higher sampling frequencies, but with a lower sampling frequency above 5min, the precision of the average HIS declines progressively because of the widening upper and lower bounds. The GG model seems to perform better when applied on the lower sampling frequency trades based data. The GG model behaves in the reverse way to HIS if they are compared on transaction data, particularly when the sampling frequency rises above 1min. As seen in Figure 29 and Figure 30, both price discovery measures tend to conflict at the sampling frequency extremes. The conflict could be explained by the combination of two factors: the nature of the data, and the way Hasbrouck and GG define price discovery. The data type with an appropriate sampling frequency has a more profound effect on the measuring performance.

On the one hand, the Hasbrouck model is based on the contribution to the variance of the innovations to the common factor from each market. The researched data contains the best prevailing limit order quotes, which per se are revised relatively more frequently than transactions are occurring. Therefore, at higher sampling frequencies, the nature of the quote time series is relatively continuous and innovative compared to transactions. So, the relatively more innovative data type and the way Hasbrouck views price discovery, results in a relatively accurate price discovery measure at a given sampling frequency. At lower sampling frequencies, on the other hand, the nature of quotes becomes increasingly discrete because of the truncation of inter period observations. This process is in essence a form of inter-temporal aggregation, which leads to “data thinning”, which “censors” the information contents of the pricing pattern, as discussed by Hasbrouck (2002). The degree of information censoring is dependent on whether the trading occurs in exogenous or endogenous fashion to the information flow process. This notion contrasts with Harris et al. (2002a) who argue that trading is an exclusively endogenous information process. According to Hasbrouck, the possibilities of misleading inference may increase further, if occurrence of trades is endogenous to the information process.

On the other hand, when the GG method is applied to the transactions based data, the nature of the trades simply complements the price discovery definition of GG. In comparison with Hasbrouck, the Gonzalo and Granger model focuses on the innovations in the common factor rather than in variances of innovations of the common component. The stress is on the current new information impact on the common factor, rather the lagged variance behavior of innovations in the common component. As opposed to HIS method, only when the transactions are occurring is the impact of innovation revealed and registered by the permanent factor component, which ignores all inter-period history. The GG method based on trades data displays no superior performance relative to the HIS method based on quotes data. This may be explained by the fact that the trade data is less innovative in the nature and the definition of the permanent component of GG, where lagged innovations are not included.

However, with the increasing sampling frequency and the type of data, the choice of price discovery methodology starts to gain importance (Figure 27 and Figure 28). This is particularly true for the trades based data at higher sampling frequencies. From Figure 28, it becomes apparent that at higher (below 5min) sampling frequency both GG and HIS measures are misleading. The trades are relatively more discrete than quotes by nature; the amount of interpolation employed starts to influence the price discovery proportions in a biased fashion as discussed in the data chapter. The nature of the trades based data type translates itself into a behaviour displayed by Figures 23, 24, 25 and 26. The amount of the interpolation bias effect is greatest at the lowest sampling frequency since the amount of interpolation is highest. A rising amount of interpolation makes the trades data appear continuous, despite originally being discrete. On the other hand, the continuous nature of quotes data becomes more discrete as a result of data thinning.

The combination of GG methodology applied on a higher sampling frequency as well as HIS applied on lower sampling frequencies, ceteris paribus, should be avoided, because it may lead to misleading inferences. The reasons for that are widening bounds of HIS at lower sampling frequency and the absence of lagged innovations in the permanent component of GG per se. One should also treat transaction based data with caution, especially at the highest sampling intervals. Misleading inferences may result from an increased degree of interpolation in trades of infrequently traded stock combined with the highest sampling frequencies.

Cross-security Analysis

From Figure 33 it can be seen that there are sampling frequency points for both price discovery measures, where contribution of trades and quotes cross each other: between 240s and 480s for quotes and trades. These crossing points could be considered as equilibrium price discovery contributions with corresponding sampling frequency. For quotes at 240s sampling frequency, the MICEX market average contribution mid HIS is 89.3%. Based on Table 35, the average HIS values range from a maximum of 99.4% (SNGS) to the minimum of 72.8% (GAZP). The MICEX average contribution measured by GG is 86.8% at 480 second intervals. The range of the average GG measure (Table 36) presents a range of between a maximum of 100% (SNGS) and a minimum of 57.9% (GAZP). These results are indicative of similar price discovery measures, and identical outcomes for quotes are suggestive of accurate and robust measurements for the quotes data.

Although the average HIS and GG are similar between quotes and trades, the measurement accuracy for trades not only yields different price discovery contributions, but also conflicting results compared to quotes. Like the quotes average of 89.3% at 60s sampling frequency, the MICEX market average contribution mid HIS is 89.8% for trades. The average HIS values range from a maximum of 96.0% (RTKM) to a minimum of 71.6% (TATN). Almost identical to quotes, the MICEX average contribution measured by GG is 86.6% at 480 second frequency. The range of an average GG measure is characterised by a maximum of 100% (SIBN) and minimum of 75.6% (SNGS). The trades GG price discovery contribution of SNGS conflicts somewhat with the results of HIS and GG for quotes based data. This inconsistent result for SNGS is suggestive of a substantial asymmetry between infrequent trading associated with a high degree of interpolation, and the quote revision in the two data types at the 480s sampling frequency. Similar result discrepancies are found for all lesser liquid stock including SNGS for TATN and SIBN. However, the discrepancy between price discovery methods and across the data types starts to “settle down” at the 960s frequency, which indicates that the asymmetry between quote revisions, and occurrence of trades diminishes by means of the data sampling censorship in the quotes.

The interpretation of the cross-sectional variation of contribution to price discovery measures across securities leads to ambiguous results. The measurement extremes of SNGS in informational contribution and the inferiority of price discovery on the RTS market may be explained by lower liquidity (Table 14) on RTS and particularly wider average bid-ask spreads as reported in Table 13. Yet, these explanations potentially all reflect the same underlying issue, namely, that MICEX is an information dominant market. Both broader interpretation and implications of the finding that MICEX dominates the multi-market price discovery in Moscow is suggested in the last section of this chapter. However, the larger information share of GAZP security on the RTS market can be explained by the fact that the GAZP stock was only listed on MICEX at the end of January 2006. Beforehand, GAZP stock was only available on RTS. The higher information share of RTS for GAZP trading can be attributed to the historically prevailing concentration of GAZP trading participants on RTS.

At which sampling frequency should the price discovery results be compared? The HIS measure for MICEX tends to decline with rising sampling intervals, the GG price discovery contribution tends to rise even at a 1920 second sampling interval for quotes and trades based data. Based on the results of market price discovery contributions for 1-1920 seconds sampling range, it is inconclusive, which is the better sampling frequency, despite an observable equilibrium between GG and HIS at 240s and 480s. However, since the GG on trades based data still displays a rise at 1920 second frequency, it may be argued that the plateau has still not been reached i.e. it lies beyond the 1920 seconds frequency.

It could be argued that sampling frequency affects the information shares on MICEX for most securities only to a minor extent. However, for EESR and GAZP, the information shares fall monotonically as the frequency reduces. The tendency of information shares to fall monotonically can be explained by two factors: the effect of informational censorship in the data caused by inter-temporal aggregation, and the rising degree of contemporaneous correlation between the cointegrated markets. Contemporaneous correlation, in particular, contributes to the sharp decrease of the lower bound in Hasbrouck's (1995) definition of information shares. Inter-temporal aggregation comes with a loss of observations (information) particularly in the more actively trading market. The lower the sampling frequency, the higher the informational censorship, which makes the more active market look less informative and increasingly correlated with the lesser active market. The steeper the reduction in information shares, the stronger is the effect of both informational censorship and contemporaneous correlation on the initial informational asymmetry between the markets. This effect may be particularly true for EESR and to a lesser degree for GAZP cross-listings, which are the most actively traded securities on MICEX and less active on RTS at the highest sampling frequencies. The question of which sampling frequency is optimal is addressed in Chapter 8. In order to resolve the issue of sampling frequency choice, Chapter 8 seeks to analyse, the trade-off between microstructure effects at the highest sampling frequencies and informational censorship at the lowest, on the one hand and the choice of sampling frequency in the context of market microstructure, on the other.

HIS Bounds Analysis

The Hasbrouck upper and lower bounds of information shares tend to widen with lower sampling frequencies. This is true for all stocks in the sample as presented by Figure 29 and Figure 30. This finding is in line with the findings in the literature of Hasbrouck (1995), Grammig et al. (2005) and Grammig (2008). By definition, the information shares are estimated with permuting ordering of markets. The width of the bounds depends on the contemporaneous correlation of innovations in the residuals of the VECM. The bound widening is mostly determined by the lower bound, which assumption rules out the contemporaneous effect of market Y (e.g. RTS) price on market X (e.g. MICEX) price. Since contemporaneous correlation increases with lower sampling frequency, the lower bound decreases more rapidly than the upper. Consequently, the precision of the price discovery parameter estimation depreciates, driving the mid-point of information share of the central market down relative to the initial higher sampling frequency.

Figure 29 and Figure 30 present the upper and lower bounds of Hasbrouck information share. The information shares tend to be narrower for quotes than for trades. A possible explanation for this is that quotes are more innovative than trades. HIS focuses on the lagged innovations in the permanent component. These innovations are better captured by HIS because of the relatively greater informational completeness (innovativeness) of the quotes data, expressed by a lower degree of contemporaneous correlation. Trades based information share bounds tend to cross each other at the highest sampling frequency, due to the interpolation effect of the transactions, as opposed to quotes based data, which do not cross.

Figure 29 demonstrates the GG measure fitted into HIS upper and lower bounds. Looking at the quotes based data results, for most stocks the GG stays inside the upper and lower bounds of HIS. Only occasionally are there exceptions. Similar behaviour is observable for trades data, although, there are more exceptions here, particularly for higher sampling frequencies, i.e. 1-60s. However, if transaction based data is utilised, the results become less clear. For trades, the HIS bounds become very narrow, sometimes even inversed, and GG could be found outside these bounds. That could indicate that the transaction based data is less information containing and may therefore be less accurate in terms of measuring the price discovery contribution, particularly at lower sampling frequencies.

Lukoil (LKOH) case example

The cross-listed Lukoil security could be considered a representative example. Along with EESR, GAZP and GMNK, LKOH is considered one of the most actively traded stocks on the Moscow stock market. As observable from Figure 31, Figure 34 and Figure 35, the price discovery results based on the HIS method do not differ substantially across the sampling frequency spectrum. With the exception of the high sampling frequency (1s and 15s) trades based price discovery measurement; all price discovery measures display a slowly declining MICEX price discovery proportion with rising sampling intervals. Based on quotes, the average HIS (90%) is close to the average GG (88%) at 60s sampling frequency. These high price discovery contributions are supportive of the MICEX information dominance notion. Figure 29 and Figure 30 show GG fitted between the upper and lower bounds of HIS for quotes and trades respectively. The bounds widen with lower sampling frequencies. The upper and lower bounds of HIS are close to the GG values, in line with the rising price discovery contributions reported above. The largest discrepancies in results are observable at the highest sampling frequency. The discrepancy is explained by the differences in the nature of trades data (discreteness) and the resulting bias induced by the interpolation.

To summarise results so far, price discovery for all eight cross-listed securities occurs largely in the MICEX market with a smaller, economically significant but statistically insignificant role for RTS. This is consistent with the MICEX market being the primary market for all considered cross-listed securities, with RTS trading following the MICEX market. However, RTS has significantly less than a half information share for all stocks and has more than a 10% information share for five securities.

Interpretation of the Findings

The central-satellite market constellation in Moscow could be compared to the established market in the US and explained by at least two hypotheses suggested by the literature in e.g.

Harris et al. (2002a): the trading-practices hypothesis e.g. Keim and Madhavan (1996) and the spread-sensitive-uninformed order-flow hypothesis e.g. Benveniste et al. (1992). The spread-sensitive-uninformed order-flow hypothesis may offer the most plausible explanation as to why MICEX overtook RTS in attracting a higher level of order flow and therefore gained the status of information dominant market. Following the spread-sensitive-uninformed order-flow hypothesis, MICEX managed to attract a higher proportion of liquidity traders. Consequently, MICEX attracted more uninformed order flow by outcompeting the RTS market with lower equilibrium spreads, which is consistent with the average lower bid-ask spread statistics in Table 13 and the finding that the average spreads on MICEX were overall lower by 60-80% in 2006.

The trading-practices hypothesis can offer an explanation as to why RTS, despite being statistically insignificant in price discovery, remained an economically significant exchange given the importance of institutional trading practice differences across RTS and MICEX. It could be argued that RTS managed to retain its economic significance by being attractive to institutional traders due to special quote-driven features, such as special negation orders, delayed settlement and settlement in foreign currency, which MICEX did not offer. Generally, the match making feature of RTS is the main advantage that most likely offered the price improvement, which institutional trading are assumed to be seeking for {Keim and Madhavan (1996)}. Besides that RTS also offered a better developed derivative securities segment, the feature in which MICEX was lagging. Overall, it could be generalised that MICEX simply lacked the features that made RTS attractive to the institutional investors, who kept the price discovery function on RTS alive. The competition for cross-listed securities on two Moscow exchanges resulted in one- way price discovery, i.e. both markets offered competitive advantage in complementary segments. Finally, growing competition from abroad e.g. LSE, which is going to be investigated in the Chapter 8 and the declined competition in price discovery on the Moscow market might have been the motives for a merger between MICEX and RTS. Further implications of the overall findings are discussed in detail in section 10.3, Implications of the Findings, in Conclusions, Chapter 10.

7.5 *Conclusion*

Regardless of which dimension is considered, the findings suggest that MICEX is the central market where most of the price discovery takes place. RTS is a satellite market and has a supportive role. The complexity of the analysis is characterised by the multi-dimensionality of the empirical results: sampling frequency, data type, price discovery contribution methodology and the cross section of individual stock. The findings of Chapter 7 can be summarised in the following way: all time series cointegrate at least at 5% significance level; the pricing on MICEX generally does not adjust to RTS pricing; more than 80% of innovations are impounded into the common factor by MICEX. These findings are consistent with the notion of a central-satellite market relationship, as documented by Harris et al. (1995) and Hasbrouck (1995). The central market informational domination of MICEX resembles that of NYSE. The Russian central-satellite market constellation is comparable to the one in the US.

MICEX is the overall and cross-sectionally consistent price discovery leader followed by RTS. Although RTS trading represents a relatively small portion of stock trading, it is an important contributing factor in Moscow price discovery. The findings are more sensitive to the type of data and to the sampling frequency utilised, than to the choice of the price discovery contribution methodology. The discrepancies in results between the alternatives measures of GG and HIS, when applied to trades and quotes based data, can be attributed to differences in the nature of the data type rather to the price discovery methodology. These differences in results, based on the alternative data types and price discovery methodologies, are consistent with the deviations in results found in the Harris et al. (2002) and Hasbrouck (1995, 2002) studies on the US market.

The implementation of trades based data is sufficient for price discovery measuring purposes, if transactions occur frequently enough and the sampling frequency chosen is not at the highest level. It can be concluded that the transaction data is a less informational source for measuring the contribution of price discovery at a sampling interval of under 120s, because of its discrete nature which requires a higher degree of interpolation. Otherwise, with lower sampling frequencies it is adequate for the purpose of measuring price discovery proportions. The quotes based data set is to be implemented in Chapter 8. In order to evaluate the price discovery contribution on the international scale, the next chapter will look at securities in the form of cross-listed ADRs on the London Stock Exchange.

Further findings are: the proportion of price discovery contribution between the two types of data is similar at 2-5 min sampling frequency, but there are also distinct differences in the informational contributions associated with sampling frequency; HIS appears to be larger for transactions, a finding which is in line with Yan and Zivot (2007), but smaller for orders, and vice versa: price discovery contribution is generally higher for quotes than for trades; the GG and HIS, as functions of sampling frequency, generally fall continuously for the quotes based data, while for transactions they rise and fall, because of the interpolation effect. As indicated by Baruch et al. (2005), liquidity of a security may affect the cross market price discovery proportions. The effect of daily trading volume as an indicator of liquidity is investigated in the conditional price discovery in Chapter 9.

This chapter is the key contribution of this thesis. It is the first study that addresses the price discovery issue on the Russian cross-listed equity market. There are central-satellite market constellation similarities between the Russian and US cross-listed equity markets. However, the data set of this investigation is distinctively different from US market data, because the price discovery issue addressed here, is in the context of an emerging market. The price discovery relationship between the Moscow markets is unique, because of their equally unique economic, political and regulatory environment. Despite the similarity of the Russian and the US cross-listed equity market constellations, there are no studies in the price discovery literature that have touched on the subject of the Russian cross-listed equity markets. Regardless of differences in the economic and regulatory environment, the findings of this chapter are in line with the existing research on cross-listed securities in the US markets, analysed by Hasbrouck (1995, 2002) and Harris et al. (1995, 2002).

Appendix

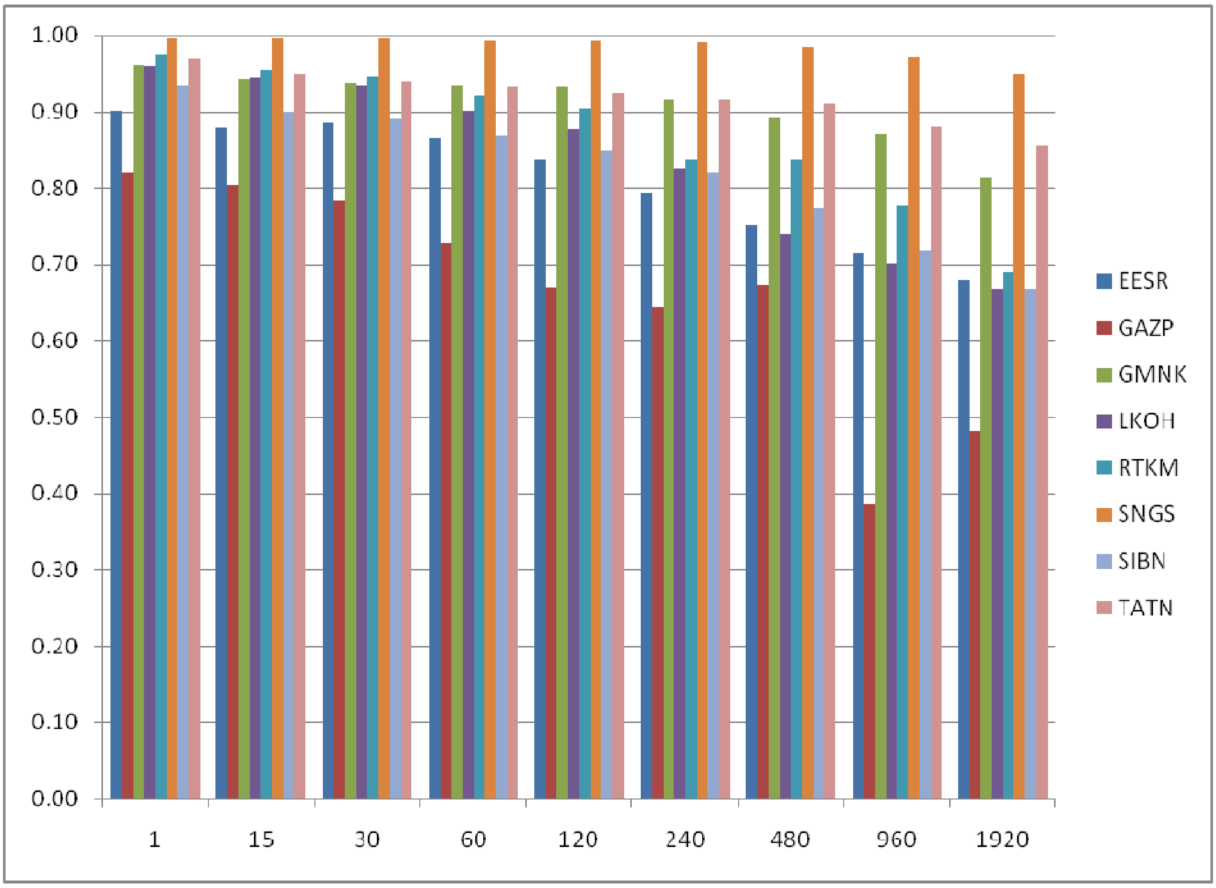

Figure 23 MICEX Quotes based mid-point Hasbrouck Information Shares

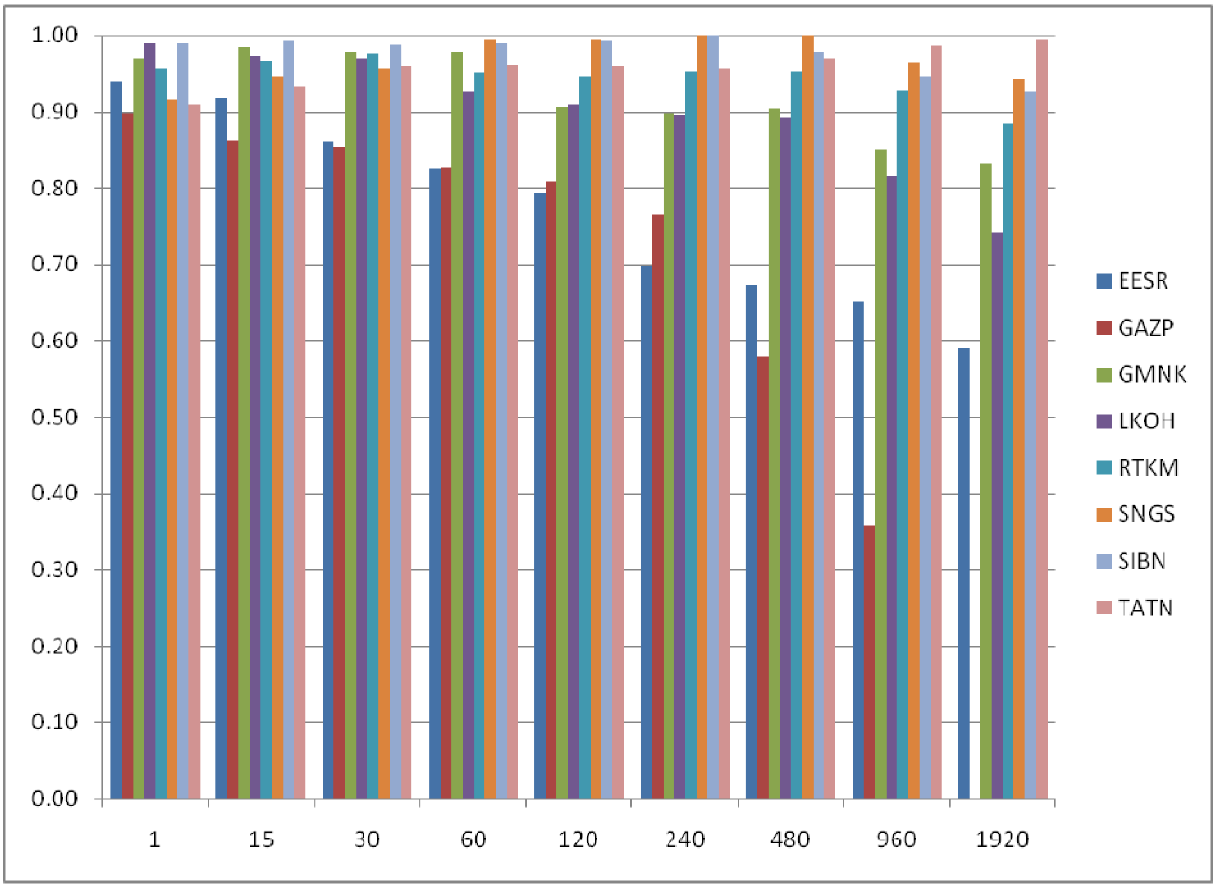

Figure 24 MICEX Quotes based Gonzalo and Granger PT measures

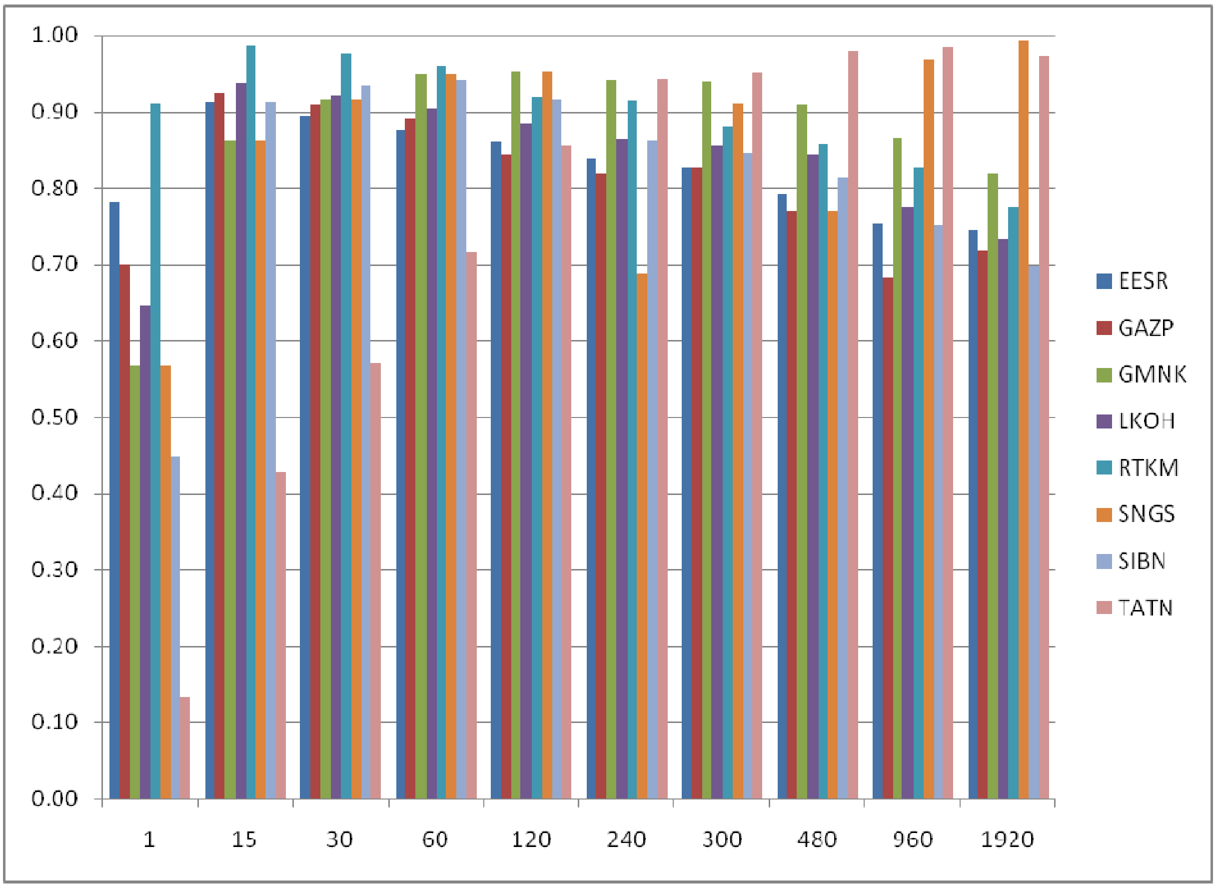

Figure 25 MICEX Trades based mid-point Hasbrouck Information Shares

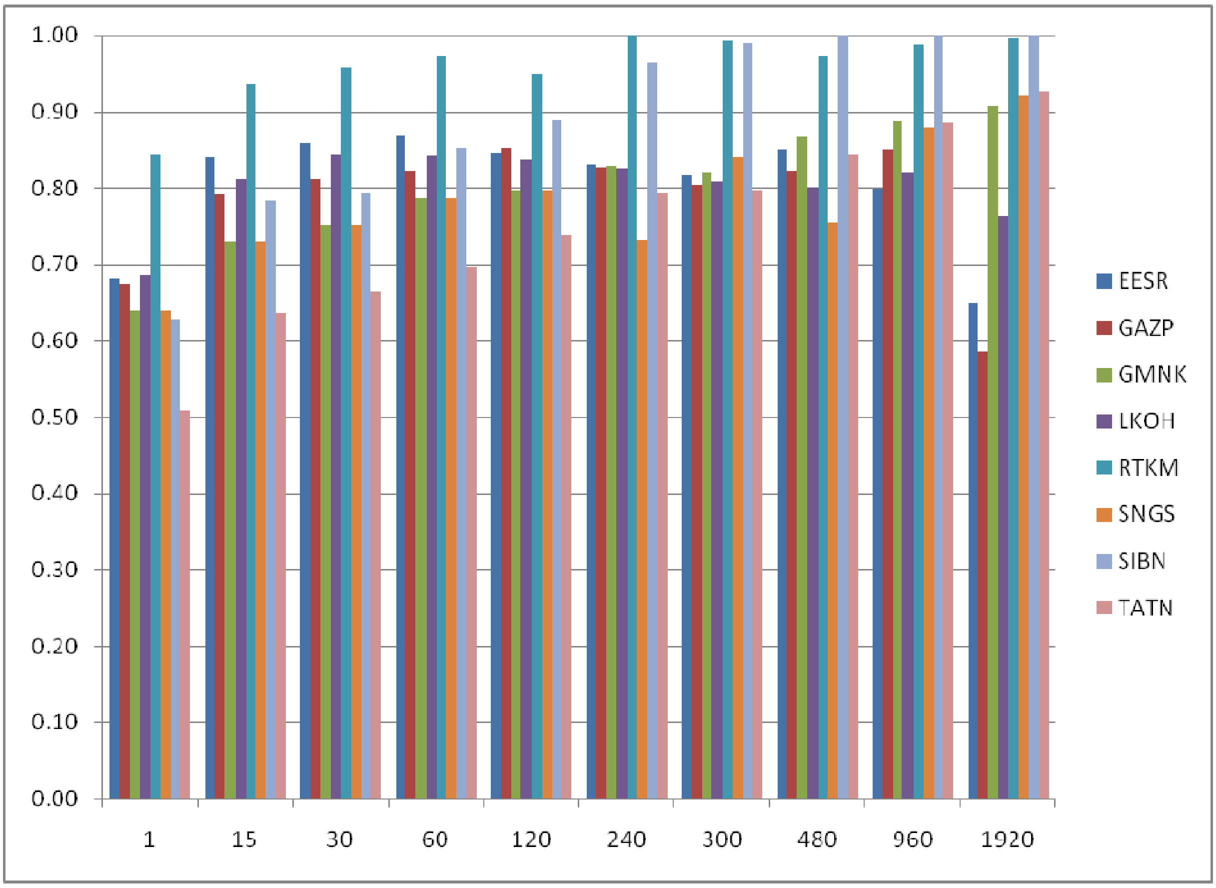

Figure 26 MICEX Trades based Gonzalo and Granger PT measures

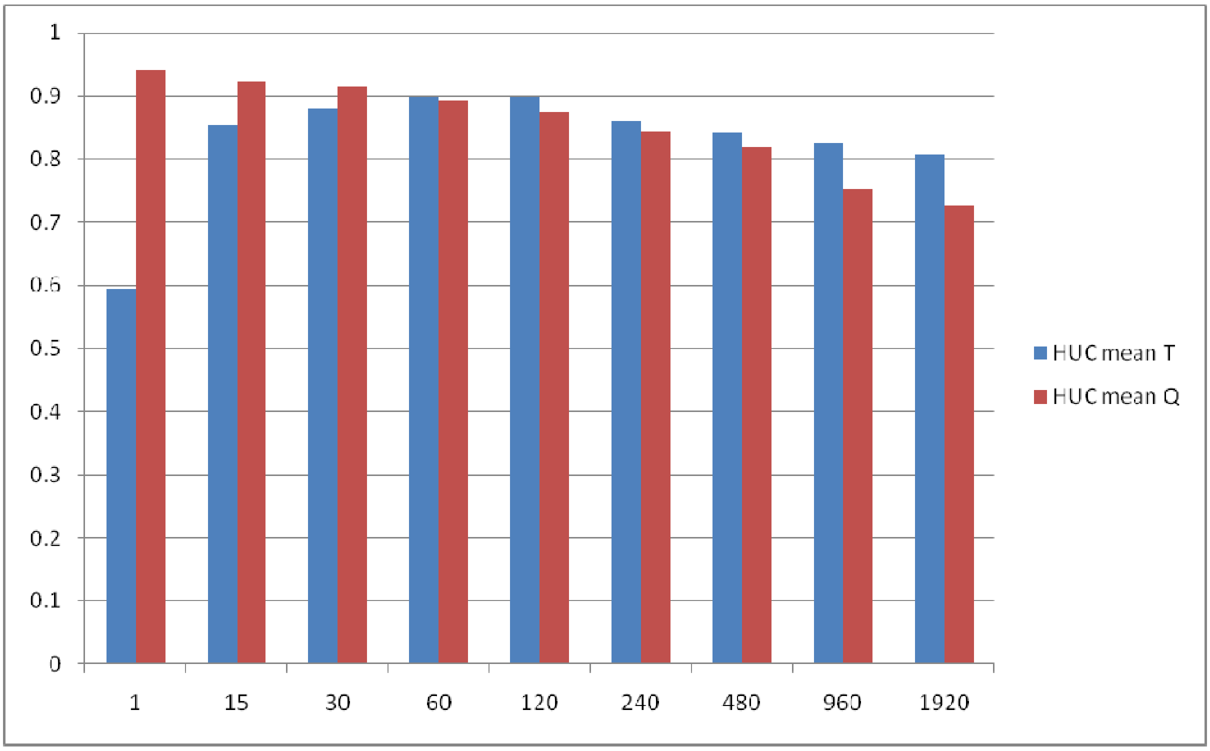

Figure 27 MICEX Quotes vs. Trades mid-point Hasbrouck Information Shares

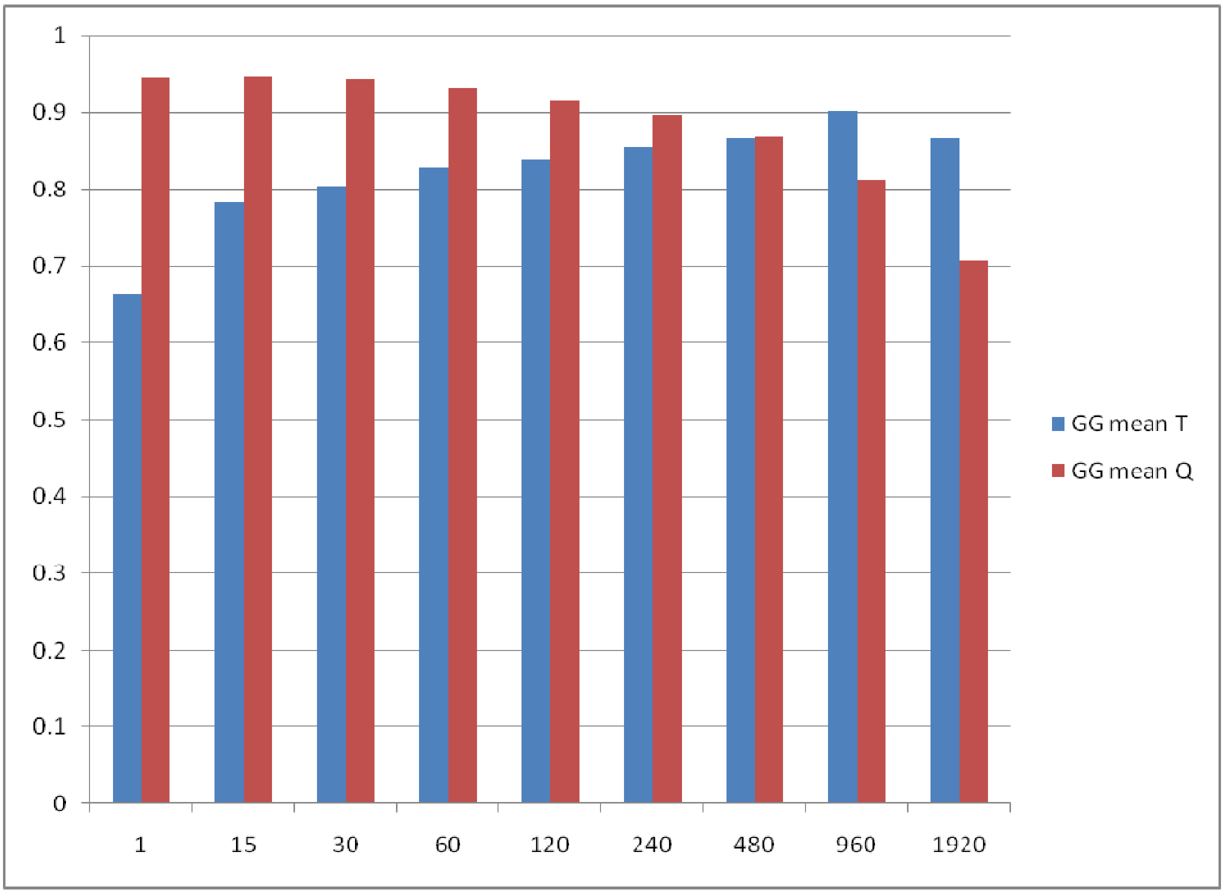

Figure 28 MICEX Quotes vs. Trades Gonzalo and Granger PT Weights

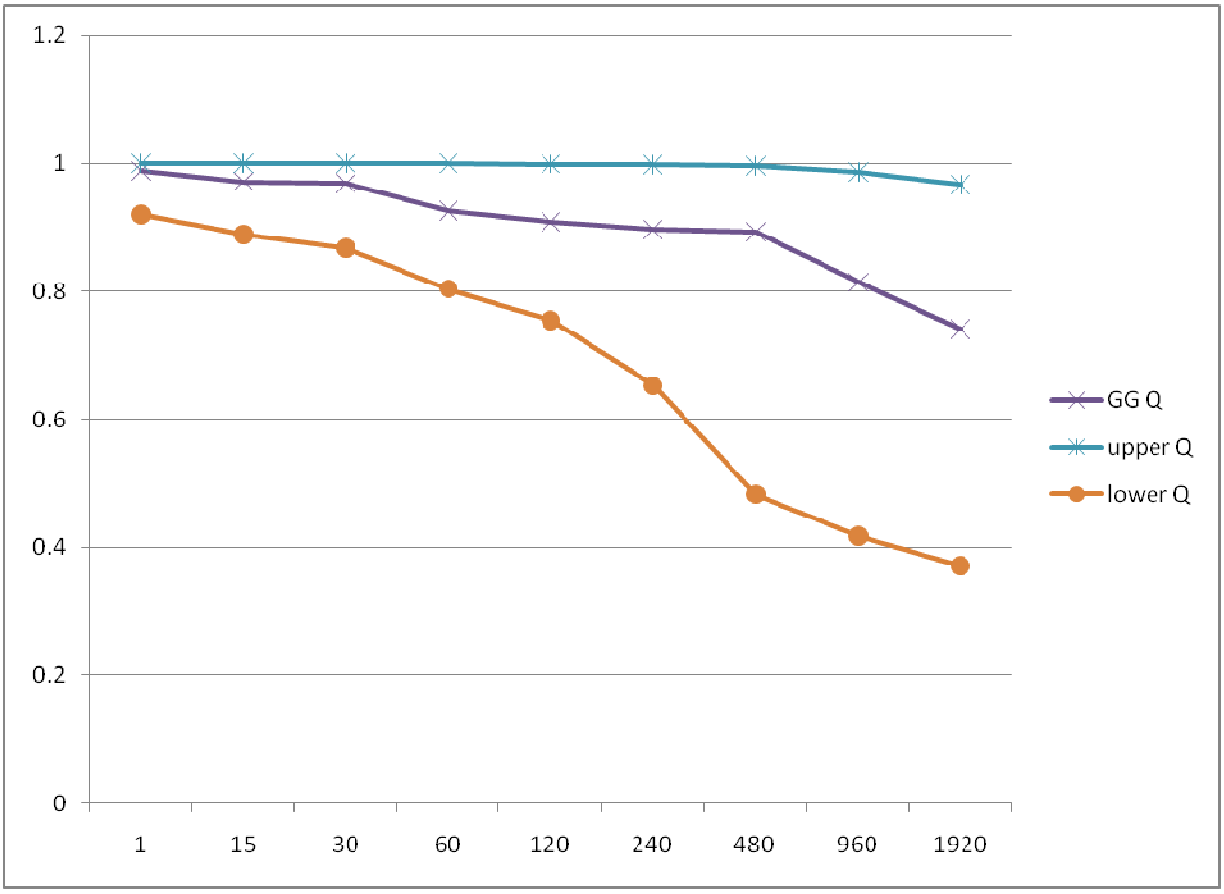

Figure 29 MICEX Quotes based Hasbrouck bounds vs. Gonzalo and Granger measure

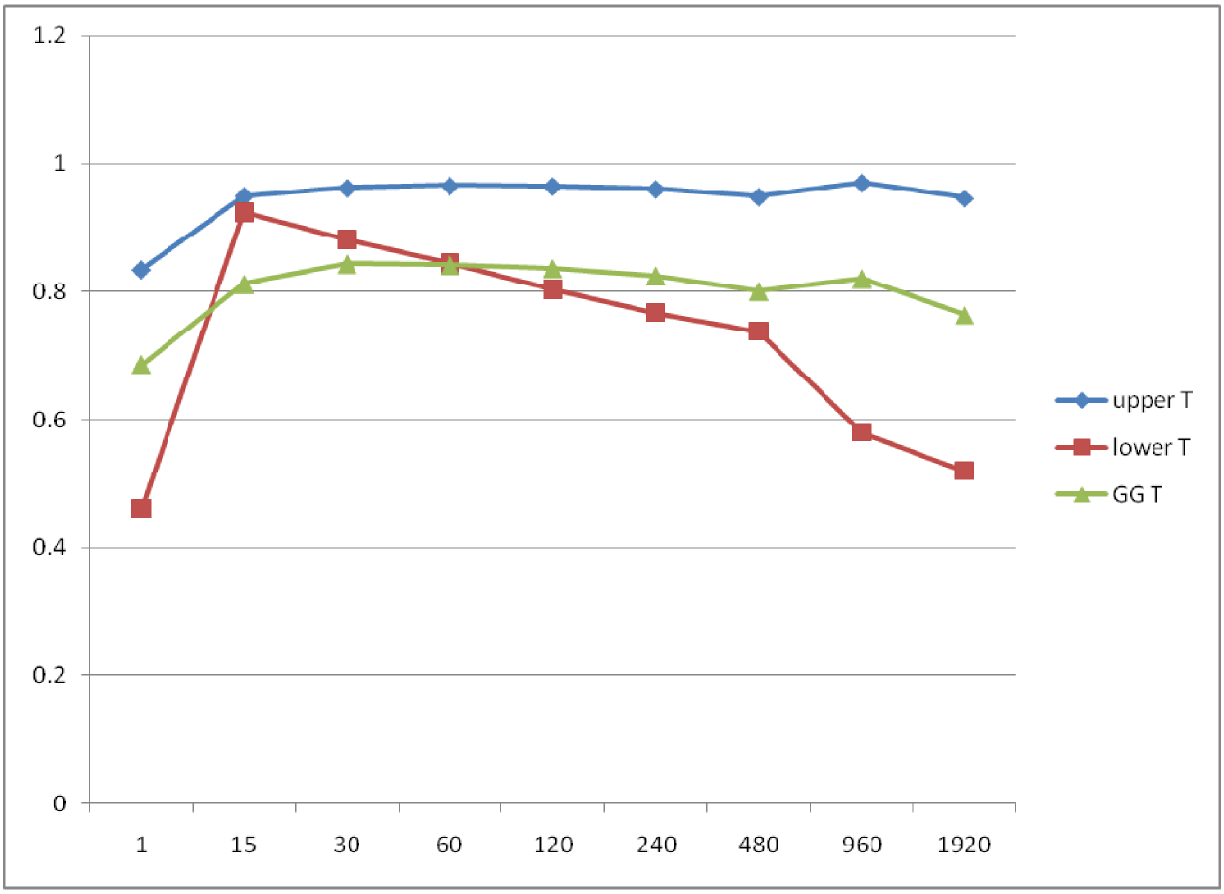

Figure 30 MICEX Trades based Hasbrouck bounds vs. Gonzalo and Granger measure

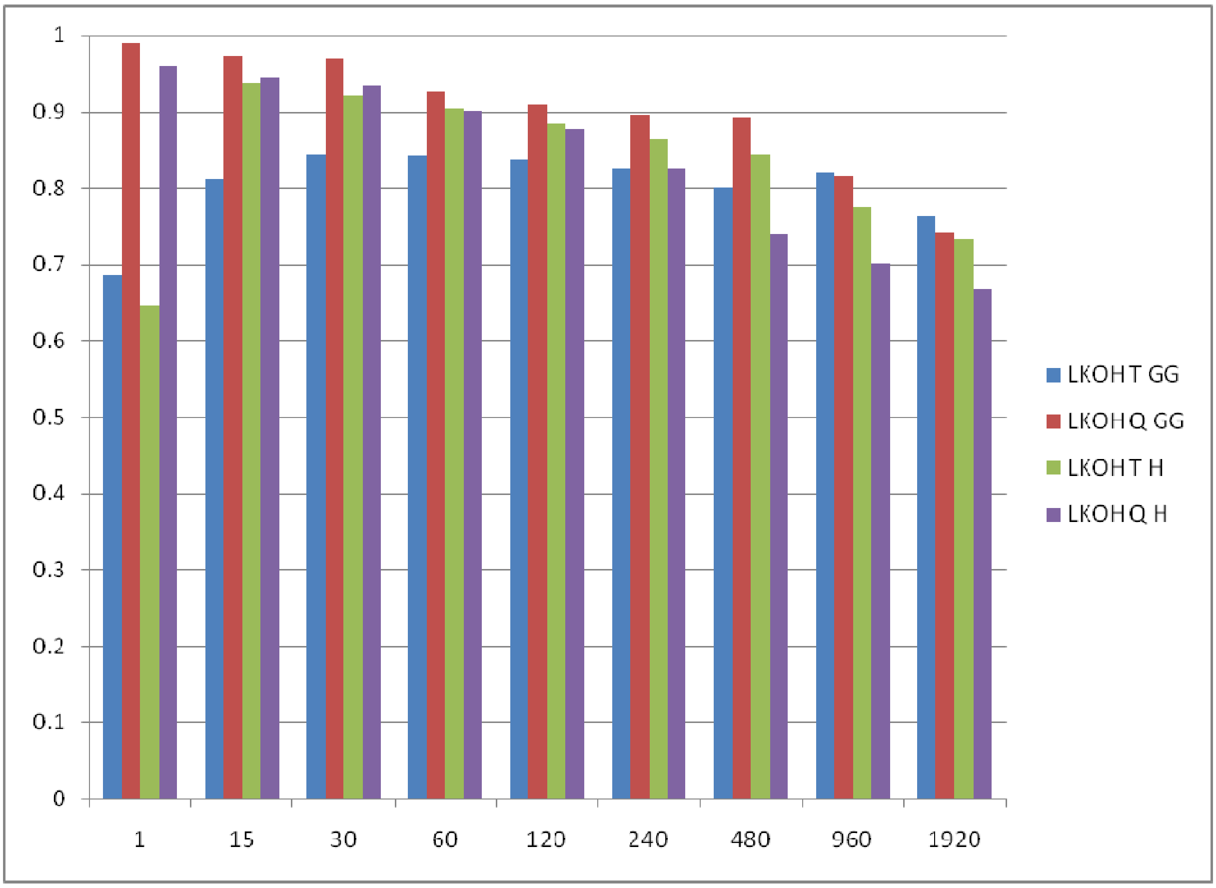

Figure 31 Summary MICEX LKOH GG and HIS measures

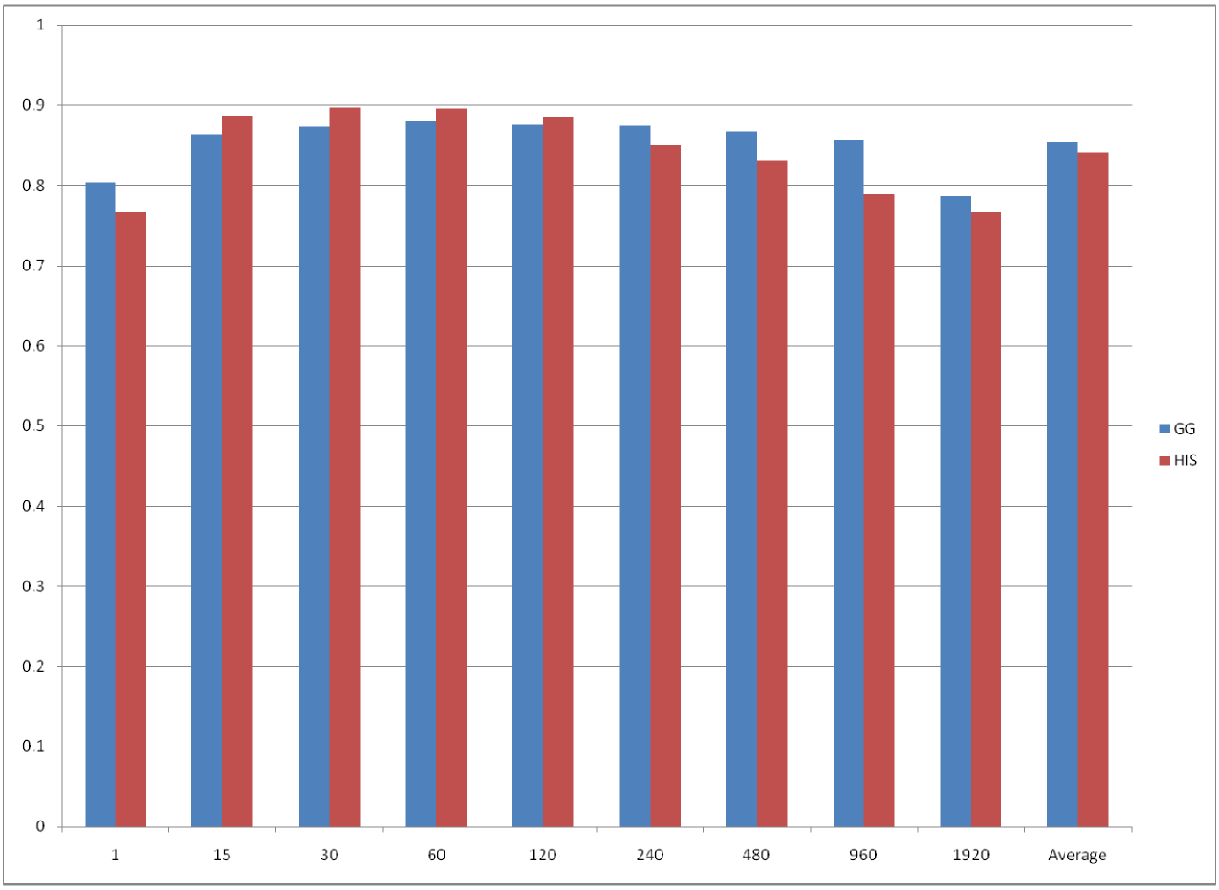

Figure 32 Summary of GG vs. HIS measures average

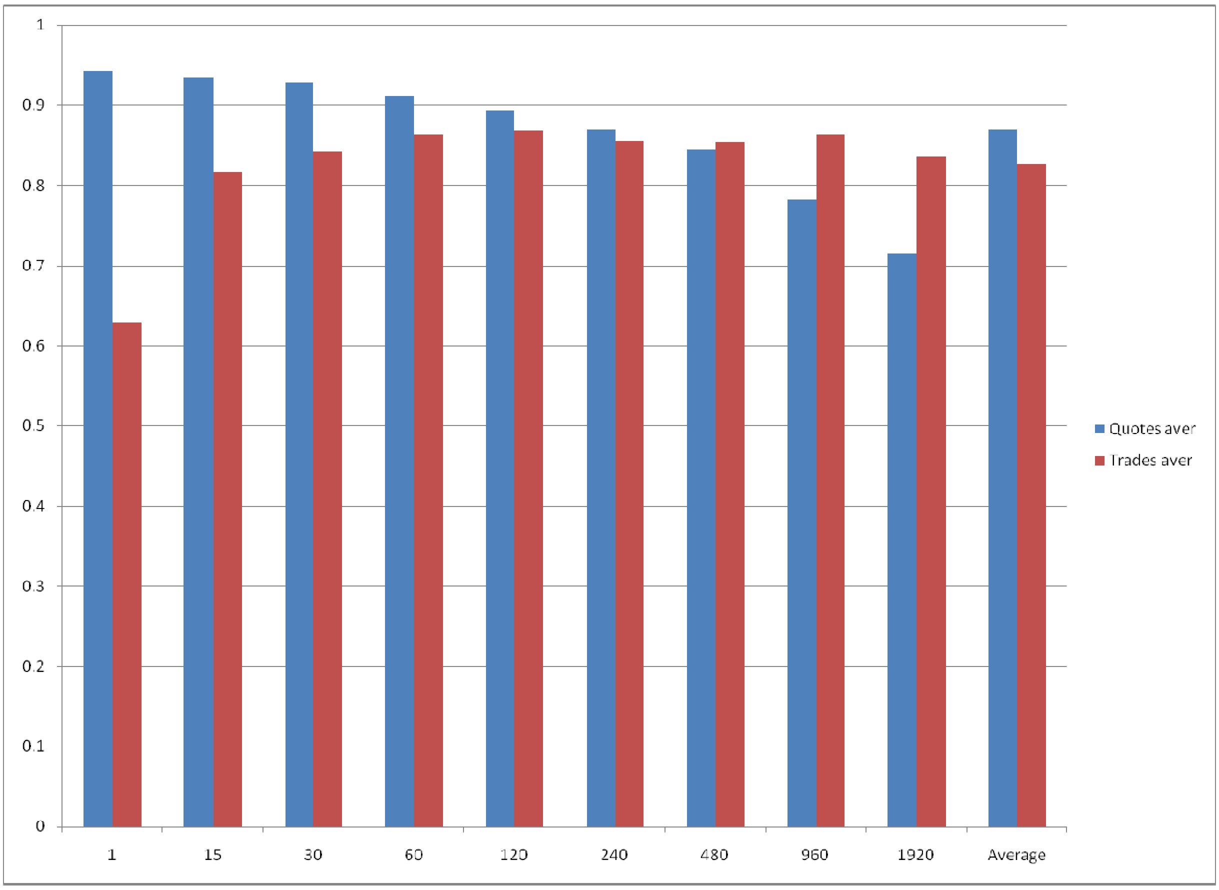

Figure 33 Summary of Quotes vs. Trades average

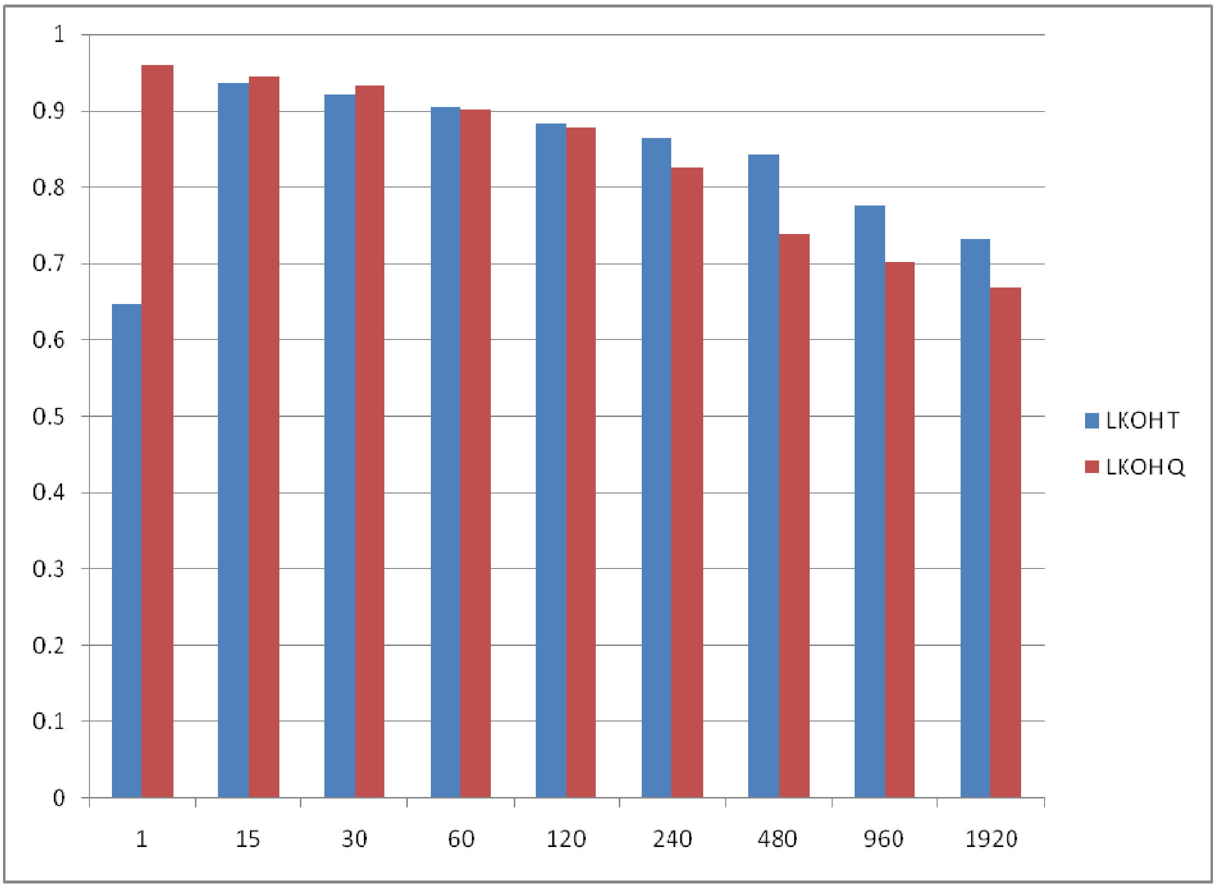

Figure 34 MICEX LKOH Quotes vs. Trades based Hasbrouck Information Shares

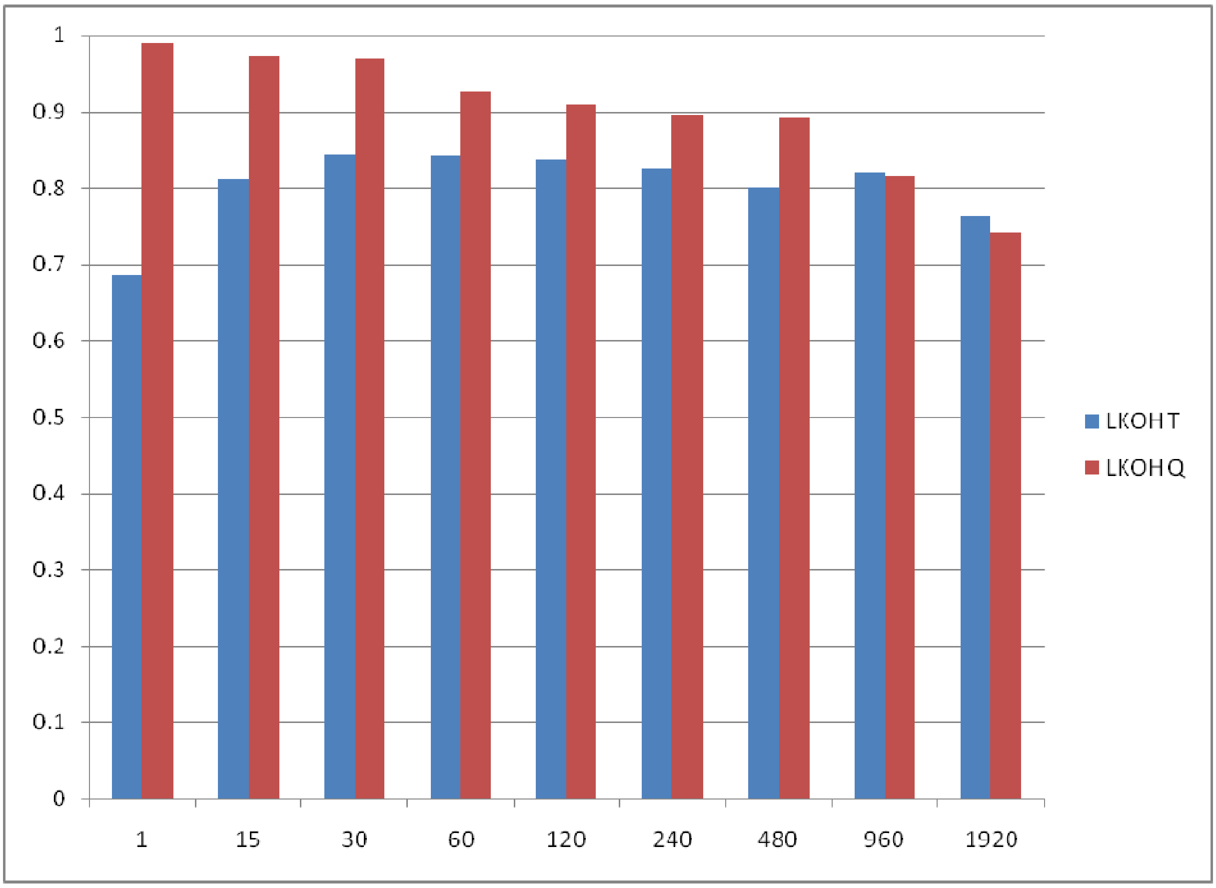

Figure 35 MICEX LKOH Quotes vs. Trades based Gonzalo and Granger PT measures

Chapter Eight: Cross-border Price Discovery: Moscow and London Stock Exchange

Chapter 8: Cross-border Price Discovery: Moscow and London Stock Exchange

8.1 *Overview*

The research subject of this chapter is price discovery on the international cross-listed equity markets: the Moscow stock market versus the London Stock Exchange (LSE). This chapter is an extension of Chapter 7, with the difference that the data set in this chapter includes a cross-border trading venue, LSE. In 2006, LSE IOB competed with the two Moscow stock exchanges, RTS and MICEX for six continuous overlapping trading hours, by facilitating trading for the eight most liquid equity securities in the form of ADR. As in Chapter 7, it is expected that the more trading intensive market, in this case the Moscow home market, would have the edge in price discovery contribution relative to the foreign LSE market.

The issue of price discovery for internationally listed stocks between London and Moscow has not been addressed in the literature. The role of London trading relative to the Moscow market is unknown. Besides the previously unexplored data set, the value added in this chapter is the notion of optimising the sampling frequency, as opposed to randomly choosing one or a range of sampling frequencies, in order to estimate the price discovery contributions more accurately. The nature of the intraday data is characterised by the choice of sampling frequency, which is a trade-off between the microstructure effects at the highest sampling frequencies and the rising contemporaneous correlation with decreasing sampling frequencies. The main objective of sampling frequency optimisation is the minimisation of bias in the information shares caused by transitory component, if the sampling frequency is chosen too high or by the rising proportion of contemporaneous correlation when the sampling frequency is chosen too low. Here, the study attempts to address and resolve the problems caused by microstructure effects and contemporaneous correlation, when measuring the relative importance of the Moscow and London markets in the price discovery process of internationally cross-listed stocks. The major difference between Chapter 7 and Chapter 8, besides the geographical, political and economic differences in the trading environments, is that Chapter 8 deals with stock equivalent ADRs, rather than the underlying cross-listed stocks.

Since the HIS and GG price discovery shares vary with the sampling frequency, as presented in Chapter 7, it is vital to determine the optimum observation (sampling) frequency. The optimum is the time interval across observations, at which the efficient price-transitory component trade-off between contemporaneous correlation and microstructure effects is minimised. On the one hand, in the case of low frequencies, the HIS bounds diverge considerably due to the increasing contemporaneous correlation of the price series. The commonly reported mid-point of upper and lower bounds then becomes rather unreliable as a proxy for the true information share. On the other hand, using high frequency data, the information share estimates are prone to a distortion by microstructure effects, as documented in Grammig and Peter (2008). This chapter extends the sampling frequency analysis of the previous chapter by seeking to optimise the sampling frequency choice based on the data set of Chapter 7 and by investigating the cross-border market, LSE.

As demonstrated in the previous chapter on the MICEX-RTS relationship case, if the sampling frequency is chosen at random, without taking into account the trade-off between the informational contribution of the market microstructure and the microstructure effects i.e. contribution to the fundamental or efficient price process (common component) and trading mechanism related process (transitory effects), the resulting information shares of a market may be biased. The objective of the HF data analysis in this chapter is to approximate a sampling frequency optimum in order to minimise the bias in information measures. The cross-listing price discovery literature on the local domestic stock market suggests that the more order flow intensive MICEX exchange leads over the less active RTS exchange. Is it still the case that MICEX will maintain the central position relative to LSE?

The rest of Chapter 8 is organised as follows: Firstly, the literature on international cross-listed equity price discovery is reviewed. Secondly, the existing literature on optimal sampling is presented and discussed. Thirdly, the results of the analysis are reported and the findings are discussed. The last section summarises the main findings and points to a potential area of further research.

8.2 *Literature Review*

Following the general literature review of Chapter 2, this section reviews the literature of price discovery in the context of internationally cross-listed equity. The early literature concentrates mainly on low-frequency daily returns, In the early research stage, tests of price parity or arbitrage were conducted between the cross-listed security prices, and between those in the home market and abroad, on a currency-adjusted basis. Earlier studies such as Kato et al. (1991), Wahab et al. (1992), Park and Tabakkol (1994), Lau and Diltz (1994), Miller and Morey (1996) have not found deviations from price parity while moderately small samples are used. Early studies simply apply a multi-market price discovery framework to non-synchronous closing prices across markets. However, newer studies utilise specialty high-frequency data, based on either transactions or quotes.

Generally, the studies based on daily low-frequency data, do not conduct tests for price discovery in the lead-lag relationship sense, but examine links in pricing across markets. The majority of low-frequency daily data based studies, such as Wang et al. (2002), indicate that the home market is the dominant source of pricing. For instance, they examine links between twenty-two cross-listed securities on the Hong Kong SEHK and LSE markets, and find that there is a bi-directional return and volatility spill-over relationship between these markets. Lieberman et al. (1999) examine six Israeli securities that are listed in New York, and find that price discovery appears to occur in the home Israel market for five securities, while one security has a dominant role in the foreign US market. The evidence from low-frequency daily data indicates that the issue of price discovery for cross-listed securities remains unresolved. In order to capture the trade dynamics, and to provide firm evidence of the price discovery relationship, an analysis based on intraday data is required. The lower-frequency data, fails to capture the trade dynamics; it only indicates an independent effect of the markets.

As opposed to the above mentioned studies, the following studies reveal significant price discovery in both the home and foreign market, but although the majority are informative, they differ in their analysis and the quality of data utilised. The studies, in which intraday data on individual securities have been implemented, have mainly concentrated on the relationship between the US and a variety of different markets. The evidence from the mixed data sets suggests that price discovery occurs significantly on both home and foreign markets, the home market being the leader. However, the proportions of price discovery contributions vary depending on the data set. For instance, Ding et al. (1999) investigate the relationship between Singapore and Malaysia trading for one Malaysian firm, and Ding et al. (1999) find that the majority of the price discovery (approximately 70%) occurs in the home country, Malaysia. The finding is supported by the argument that the Malaysian market trading volume exceeds the Singapore share in price discovery.

The application of different data sets, sampling frequencies and methodologies, has resulted in a mixture of findings. On the one hand, there are studies that support the notion that the foreign market has the highest share in price discovery. For instance, Hedvall et al. (1998) find a consistent result for Nokia cross-listing between Helsinki and NYSE, implementing the Gonzalo-Granger (1995) methodology based on a two year sample period. There is evidence that the NYSE plays the dominant price discovery role. This finding, however, is explained by the 60% proportion of trading volume of the NYSE market.

Flad and Jung (2005) investigate the relationships between the US and the German equity markets during overlapping trading hours. They employ the framework of the bivariate common factor model of Harris et al. (2002a). In order to establish a permanent-transitory decomposition between the two major equity indices DAX and DJIA, the empirical analysis is based on high frequency data. They find that the DJIA contributes as much as 95% to the total innovation of the common factor, clearly demonstrating the dominant role played by the foreign US market during overlapping trading hours.

On the other hand, there are studies that support the notion, that the home market makes the highest contribution to price discovery. These studies suggest that the cross-listed securities traded on the home market prices lead, relative to their foreign listed “derivative” securities market. For instance, Pascual et al. (2005) investigate a relationship between SSE and NYSE for six Spanish stocks using the Hasbrouck (1995) methodology. They find that the contribution of NYSE is marginal, while the SSE contribution to price discovery is between 60% and 80%.

Menkveld et al. (2007) examine seven major US-listed Dutch securities. They reveal significant price and quote activity around the NYSE opening. However, they find that NYSE plays a minor role in price discovery. In sum, the more liquid home market leads the price discovery process.

More recent studies offer evidence that price discovery proportions are dependent on the relative liquidity of the home and the foreign market. Eun and Sabherwal (2003) implement the methodology of Harris et al. (2002a) to quotes and trades data for sixty-two Canadian securities cross-listed on the TSX and the NASDAQ or NYSE. Overall, they find strong evidence that substantial price discovery takes place in both Canada and the US. Furthermore, they find that the most important variable explaining the price discovery relationship is the proportion of total trading volume between the US and Canada. That is, the higher the fraction of total trading taking place in Canada, the higher the contribution of the Canadian market to price discovery and vice versa.

Grammig et al. (2005) investigate the issue of price discovery by applying the Hasbrouck (1995) methodology to three German companies as well as fourteen stocks from Canada, France and the UK cross-listed on the NYSE, based on intraday data. They find that price discovery occurs largely in the home market. However, their results differ for three firms across the German (XETRA) and US (NYSE) markets. Moreover, the exchange rates are modelled, but their impact on price discovery seems to be insignificant. The results are similar to Phylaktis and Korczak (2007) who examine the contribution of US trading to the price discovery process of sixty-four British and French companies, cross-listed on NYSE. Similar to Eun and Sabherwal (2003), both studies show that the extent of the US price discovery contribution is positively related to the liquidity of US trading. They find strong evidence that the concentration of stocks from a given country increased the proportion of US trading in price discovery through the reduction in information asymmetries. The estimated relative contributions of the markets from cross-sectional regressions show that the most important variable is the proportion of total trading volume - the higher the fraction of total trading taking place in the US market, the higher the contribution of the US market to price discovery.

As a follow up to the studies of Eun and Sabherwal (2003) and Phylaktis and Korczak (2007), Grammig and Peter (2008) investigate the price discovery relationship of sixty-nine Canadian securities cross-listed on TSX and NYSE. Their analysis is based on quotes data performed on a range of sampling frequencies, and they employ a modified version of Hasbrouck (1995) information share methodology. Grammig and Peter (2008) indicate that the role of the foreign market may have been underestimated. This has been attributed to a potential bias of estimated information shares by microstructure effects, in papers which apply the Hasbrouck (1995) framework, relying on high frequency data. The avoidance of imprecision of information share mid-points, resulting from the widening bounds at a lower sampling frequency, comes at the cost of potential bias of the estimated information share at a higher sampling frequency. This is the first paper that addresses and attempts to resolve the issue of the optimal sampling frequency.

The internationally cross-listed price discovery literature based on high frequency data seems to have reached a consensus; firstly, the home market is usually dominant in price discovery found in studies by e.g. Grammig et al. (2005), Menkveld et al. (2007); secondly, the degree of dominance is dependent on the degree of relative liquidity between the home and the foreign market e.g. Eun and Sabherwal (2003), Phylaktis and Korczak (2005); finally, the intraday exchange rate influence on price discovery contribution is statistically insignificant. According to the findings of Liebermann et al. (1999), Grammig et al. (2005) and Phylaktis and Korczak (2007), the contribution of the intraday exchange rate factor to the common component is negligible, supporting the assumption in this study of exchange rate as an exogenous variable.

The question remains, given the presence of microstructure effects in the high frequency sampled data, whether the home market dominates its foreign counterpart in price discovery. Surprisingly, there are only the Grammig and Peter (2008, 2010) studies which address the issue of microstructure effects relative to international price discovery. All other studies report their findings based on one single sampling frequency. Furthermore, there is a gap in the research literature on price discovery between the Moscow and London stock exchanges, despite a substantial number of cross-listings.

The main questions that are addressed in this chapter are:

- Which sampling frequency is optimum in the context of Moscow-London price discovery?
- Does the home market dominate price discovery relative to the market abroad?
- How do the quotes in the London and Moscow equity markets adjust in the short run?
- Is there a cointegrating relationship between home and foreign market pricing?

It has been hypothesised that price discovery would occur principally in the Moscow home market, since the trading activity in the home market is superior to the market abroad. There are no directly comparable findings, since there is no literature on the Moscow-London price discovery relationship. However, in conjunction with the cross-border price discovery literature, it is expected that the home market would maintain its leadership position.

1. H_0: The home market dominates the price discovery process over the foreign market.
2. H_0: MICEX leads RTS and LSE, and the relationship is multi-directional.
3. H_0: There is a cointegrating relationship between MICEX, RTS and LSE.

8.3 *Optimised Sampling Frequency*

So far the term “noise” in the context of microstructure has been used rather loosely. The use of this term needs to be defined more precisely, since the original goal is to understand how variation in the microstructure across trading venues affects contribution to the common efficient price. On the one hand, “noise” contained in the high frequency data may contribute to a bias when measuring the shares of price discovery across multiple markets. On the other, “noise” is an essential feature given that it defines the microstructure of a market mechanism. Instead of analysing solely the effects of microstructure that cause variation in the shares of price discovery, one of the main research objectives in this chapter is to find the sampling frequency optimum from the econometric perspective. The analysis aims to uncover any variation in the shares of price discovery across the spectrum of sampling frequencies. This can be achieved by minimising the side effects of microstructure when measuring the price discovery shares. The effect of sampling frequency choice on the estimation accuracy of integrated return volatility based on the high frequency data is documented in the literature e.g. Andersen et al. (2001 and 2003), Barndorff-Nielsen and Shephard (2002), Ait-Sahalia et al. (2005), Hansen and Lunde (2006), and Bandi and Russell (2005 and 2008). The overall main objective of sampling frequency optimisation is to minimise the bias in information shares, which may either be caused by the interference of microstructure effects contained in the high frequency data or by an increased proportion of contemporaneous correlation of innovations if the sampling frequency is chosen adversely. The optimum sampling frequency for determining the consistent information share of a market is a mid-point or a range within the trade-off bounds between idiosyncratic market microstructure effects and contemporaneous correlation. This scenario shares similarity to the type I and type II error, when making inferences. On the one hand, the sampling frequency should be as high as possible in order to capture all the information available; however it comes with a side effect when measuring the price discovery contribution: that is, the information share of a more active market may be biased up by microstructure effects. For example, Harris et al. (2002a) point out that a market may be misperceived as more innovative if its quotes are updated more frequently which may not necessarily reflect a contribution to the common efficient price. Frequently updated quotes may reflect innovations in the common efficient price however may also reflect higher degree of bid-ask bounce, which should be attributed to the transitory, rather to the permanent component when the variance of innovations is decomposed. On the other hand, if the sampling frequency is chosen too low, inter-temporal aggregation censors the information content, biasing the more innovative market down. The employed price discovery methodologies of Hasbrouck (1995) and Gonzalo-Granger (1995) are imperfect when it comes to differentiating between dynamics of price discovery on multiple markets. For example, Yan and Zivot (2007) demonstrate that the information share of one market is higher if it impounds less liquidity shocks and more new information. The effect of informational censorship in HF data is caused by inter-temporal aggregation, which ultimately results in the rising degree of contemporaneous correlation of price movements in the cointegrated markets. Grammig and Peter (2008) argue that contemporaneous correlation, in particular, contributes to the sharp decrease of lower bound in information shares as defined by Hasbrouck (1995). Inter-temporal aggregation comes with a loss of observations particularly in the more actively trading market. The lower the sampling frequency, the higher the informational censorship, which makes the more active market look less informative and increasingly contemporaneously correlated with the lesser active market. Overall, the microstructure effects in high frequency data and the contemporaneous correlation of innovations across markets may contribute to the distortion of accuracy when estimating the information shares of a cointegrated system.

Grammig and Peter (2008) state that the results of the Hasbrouck (1995) study, which is based on one second continuously sampled best quotes based data, might be biased despite the narrow bound of information shares. Hasbrouck's (1995) study avoids divergence of information share bounds, because it utilises data sampled at the highest possible frequency. However, sampling at the highest frequency possible may not be the best solution according to recent literature dealing with the estimation of return volatility using high frequency data. Ait-Sahalia et al. (2005) and Bandi and Russell (2008) assert that market microstructure effects interfere with the fundamental price process. These effects are negligible at longer sampling intervals, but dominate the realised variance estimate at high frequencies. Microstructure effects are transient price changes which are uninformative concerning the fundamental value of an asset. They arise from sources such as minimum tick-size, temporary inventory effects, liquidity shocks and bid-ask bounces.

A non-parametric and indirect way of measuring the relative degree of microstructure effects contained in the higher frequency data is performed by analysing the realised variance (RV) estimator as a function of sampling frequencies. Andersen et al. (2001 and 2003), Barndorff-Nielsen and Shephard (2002) advocate data sampling at high frequencies of five minutes optimum in order to estimate the integrated daily volatility of returns. The idea is to divide the trading day d into M equivalently spaced time intervals $\delta_i^* = h / M_i^*$, compute log price changes $r_{d,j}^2$ for each interval *j* and compute the realised variance estimator as

$$RV_d = \sum_j^M r_{d,j}^2 \qquad (48)$$

If the underlying price process is a diffusion process with stochastic volatility, then RV_d converges in probability to the integrated volatility for day *d*. However, in the presence of jumps and microstructure effects, the RV is an inconsistent estimator of integrated volatility. Shortening the sampling intervals, by increasing *M*, as opposed to aggregating the time series inter-temporary, should improve the precision of the estimator. However, Bandi and Russell (2008), Ait-Sahalia et al. (2005) indicate that aiming for accuracy by increasing the sampling frequency may be misleading. The studies demonstrate that the RV estimator can exhibit erratic behaviour, if the sampling frequency chosen is too high. The realised variance estimator displays stability up to a sampling frequency of approximately two minutes, but increases sharply at higher sampling frequencies.

Hansen and Lunde (2006) illustrate how the RV estimator is affected by market microstructure effects under a general specification for the noise that allows for various forms of stochastic dependencies. Market microstructure effects are time-dependent and correlated with efficient returns. For Dow 30 stocks, noise may be ignored when returns are sampled at low frequencies (e.g. 20 min). Microstructure effects are correlated with efficient price, are time dependent and are time variant.

How frequently should one sample, in order to avoid the measurement bias? The current literature on asset return volatility offers two major methodologies to derive the optimum sampling point: a parametric and non parametric method. The parametric optimum sampling frequency estimation method is proposed by Ait-Sahalia et al. (2005) and the non parametric estimation method by Bandi and Russell (2008) and Zhang et al. (2005). The focus of this chapter is on the non parametric Bandi and Russell (2005) methodology. The sampling optimum could be approximated by minimising the mean squared error (MSE) of variances between the sampled observations and the inter-temporally aggregated sample, as suggested by Ait-Sahalia et al. (2005) and Bandi and Russell (2008). The alternative method is to determine the optimum graphically by plotting the computed realised variance (RV) estimators, contemporaneous correlations and HIS bound differences as a function of their sampling frequency across the range of 1s - 1920s.

Bandi and Russell (2004, 2005 and 2008), define the optimal sampling frequency, $\delta_i^* = 1/M_i^*$ as a function of the ratio $\delta_i^* = q/m$ i.e. the ratio of microstructure noise to the number of interday observations (signal to noise ratio). The optimal sampling δ_i^* is defined as the minimum of the conditional MSE in Equation 49. The optimal sampling frequency minimizes the difference between realised variance and the integrated variance V_i. The intuition behind this equation is that the RV estimator is expected to be less biased when sampled at low frequencies, since microstructure effects play less of a role when δ_i^* is large.

$$\underset{\arg\min}{MSE}\left(\sum_{j=1}^{M}\tilde{r}_{j,i}^{2}, V_i\right) = E\sigma\left[\left(\sum_{j=1}^{M}\tilde{r}_{j,i}^{2} - V_i\right)^2\right] \tag{49}$$

Bandi and Russell (2004) provide a “rule of thumb” estimation procedure to isolate HF return data of microstructure components, and extract information on efficient return variance by sampling at optimal frequencies. They define observed price at time i_h as:

$$\tilde{p}_{ih} = p_{ih} + \eta_{ih} \tag{50}$$

Where p_{ih} is unobserved HF log efficient price, η_{ih} is unobserved microstructure noise and *h* denotes a trading day and *i = 1, . . . , n* trading days.

The *j*-th inter-daily log return for day *i* is defined by:

$$\tilde{r}_{j,i} = \tilde{p}_{(i-1)h+j\delta} - \tilde{p}_{(i-1)h+(j-1)\delta},\ j = 1, \ldots, M \tag{51}$$

The “rule of thumb” approximate δ_i^* expressed in equivalently spaced time intervals M_i^* is a ratio between moments of the unobserved efficient returns, represented by $\hat{Q}_i$, and moments of the unobserved noises in returns $\hat{a}$ as defined by Equation 52:

$$M_i^* = \left(\frac{\hat{Q}_i}{\hat{\alpha}}\right)^{1/3} \tag{52}$$

$$\hat{Q}_i = \frac{M^{low}}{3} \sum_{j=1}^{M^{low}} \hat{r}_{j,i}^{4} \qquad (53)$$

where M^{low} at low sampling frequency (960s)

$$\hat{\alpha} = \left(\frac{1}{nM^{high}} \sum_{i=1}^{n} \sum_{j=1}^{M^{high}} \tilde{r}_{j,i}^{2} \right)^2 \qquad (54)$$

and where M^{high} at highest sampling frequency (1s)

Both unobserved components of variance can be estimated using HF data sampled at different frequencies: high frequency sampling (1s) captures microstructure noise (effects), whereas low frequency sampling (960s) captures the efficient return variance.

8.4 *Empirical Results*

This section reports the findings of the price discovery relationship between the Moscow and London stock exchanges. The objective of this section is to analyse and to discuss the influence of the sampling frequency on the contribution to price discovery. As demonstrated in the findings of the previous chapter, the estimation accuracy of price discovery contribution depends on the following factors: the price discovery methodology, data type choice with associated sampling methodology and the choice of the sampling frequency. The price discovery methodology is a question of definition, while the data type choice is a question of availability and sampling methodology. This section focuses on the sampling frequency rather than on the data type or price discovery methodology choice. The analysis of this chapter has been narrowed down to continuously sampled best prevailing bid-ask quotes, comparable to Grammig and Peter (2008). As reported in the previous chapter, the trades based data proved to be less accurate at higher sampling frequencies because of infrequent trading, particularly in a less liquid market.

The overall findings indicate that MICEX is still the overall, but on this occasion, disputed price discovery leader, followed by RTS and LSE competing for second place. The optimal sampling frequency suggests that the foreign market price discovery share may be underestimated at the highest sampling frequency, as documented in the Grammig and Peter (2008) study.

The empirical results section 8.4 is organised as follows: Firstly, the ADF and Johansen cointegration tests are presented. Secondly, the error correction models expressed in Equation (34) are estimated in order to determine the lead-lag and the price discovery relationship between the LSE, MICEX and RTS markets. Thirdly, the main analysis is divided into two parts: On the one hand, section 8.4.4 analyses the factors associated with the optimum sampling frequency from the econometric perspective, which approximates the optimum choice of a sampling frequency. On the other, section 8.4.6 presents the analysis from the perspective of microstructure and seeks to offer a plausible economic interpretation of the findings from the section 8.4.4. At last, restriction tests are carried out in order to test when the extreme cases of price discovery are true. The final section suggests economic interpretation and discusses of the overall findings.

8.4.1 Cointegration Test Results

The fundamental condition for the lead-lag relationship analysis is the cointegration between the price variables. If the residuals of the level regression between market time series are not I(0) stationary, unlike their corresponding price series, then the estimation results are spurious. All of the LSE time series displayed integration of order I(1) at levels. However, in first differences, the ADF test coefficients displayed statistical significance at least at the 5% significance level. Consequently, the null hypothesis, that there is a unit root, has been rejected for all cross-listings and frequencies. Therefore, the residuals of the level regression are concluded to be stationary. The Johansen cointegration tests are performed assuming no deterministic trend and no intercept in VAR or VECM. The results clearly reject the null of no cointegration and support the hypothesis of at least one cointegrating relationship vector between the two variables amongst all stock pairs and sampling frequencies. With the variables ordered as mid-point RTS and MICEX market prices, the estimated cointegrating vectors are close to the vector $\beta^T = (1, -1)'$ as indicated by theory. The results of order of integration for 1920 second frequency for quotes are reported in Table 37 and the cointegration test results are presented by Table 38.

		Level Tests		**1st Difference Tests**	
EESR		ADF - Fisher	PP - Fisher Chi-square	ADF - Fisher Chi	PP - Fisher Chi-square
	Statistic	2.78	3.17	491.16 *	310.51 *
	Prob.	0.84	0.79	0.00	0.00
	Obs	3104.00	3108.00	3102.00	3105.00
GAZP					
	Statistic	0.01	0.00	421.80 *	416.44 *
	Prob.	1.00	1.00	0.00	0.00
	Obs	2531.00	2532.00	2529.00	2529.00
GMNK					
	Statistic	0.04	0.04	366.42 *	227.57 *
	Prob.**	1.00	1.00	0.00	0.00
	Obs	3108.00	3111.00	3107.00	3108.00
LKOH					
	Statistic	10.31	10.45	344.58 *	342.30 *
	Prob.	0.11	0.11	0.00	0.00
	Obs	3116.00	3117.00	3114.00	3114.00
RTKM					
	Statistic	1.69	1.69	310.17 *	311.71 *
	Prob.	0.95	0.95	0.00	0.00
	Obs	3053.00	3054.00	3051.00	3051.00
SIBN					
	Statistic	8.65	8.41	430.13 *	286.18 *
	Prob.	0.19	0.21	0.00	0.00
	Obs	2863.00	2865.00	2861.00	2862.00
SNGS					
	Statistic	3.42	3.45	397.51 *	257.78 *
	Prob.	0.75	0.75	0.00	0.00
	Obs	3115.00	3117.00	3113.00	3114.00
TATN					
	Statistic	5.70	4.46	471.76 *	472.02 *
	Prob.	0.46	0.61	0.00	0.00
	Obs	1203.00	1203.00	1200.00	1200.00

The table reports the statistics of ADF and PP tests of trades based samples of the LSE market sampled at 1920s frequency. For details see the annotation of Table 22. The asterisks indicate a statistical significance at the 0.05 level.

Table 37 Summary of Unit root Tests for Quotes based data from the LSE market

		Cointegration Rank Test (Trace)			(Maximum Eigenvalue)		
EESR	No. of CE(s)	None	At most 1	At most 2	None	At most 1	At most 2
	Eigenvalue	0.2558	0.1012	0.0029	0.2558	0.1012	0.0029
	Statistic	419.1474 *	113.4183 *	2.9642	305.7291 *	110.4541 *	2.9642
	Critical Value	24.2760	12.3209	4.1299	17.7973	11.2248	4.1299
	Prob.	0.0001	0.0001	0.1007	0.0001	0.0001	0.1007
GAZP							
	Eigenvalue	0.0856	0.0278	0.0054	0.0856	0.0278	0.0054
	Statistic	103.8327 *	28.3935 *	4.5970 *	75.4391 *	23.7966 *	4.5970 *
	Critical Value	24.2760	12.3209	4.1299	17.7973	11.2248	4.1299
	Prob.	0.0000	0.0001	0.0380	0.0000	0.0002	0.0380
GMNK							
	Eigenvalue	0.1949	0.0802	0.0052	0.1949	0.0802	0.0052
	Statistic	316.5782 *	92.0428 *	5.4455 *	224.5353 *	86.5973 *	5.4455 *
	Critical Value	24.2760	12.3209	4.1299	17.7973	11.2248	4.1299
	Prob.	0.0001	0.0001	0.0233	0.0001	0.0001	0.0233
LKOH							
	Eigenvalue	0.0670	0.0399	0.0032	0.0670	0.0399	0.0032
	Statistic	117.4362 *	45.4881 *	3.2836	71.9480 *	42.2045 *	3.2836
	Critical Value	24.2760	12.3209	4.1299	17.7973	11.2248	4.1299
	Prob.	0.0000	0.0000	0.0829	0.0000	0.0000	0.0829
RTKM							
	Eigenvalue	0.0901	0.0445	0.0018	0.0901	0.0445	0.0018
	Statistic	144.0483 *	48.0728 *	1.8232	95.9755 *	46.2496 *	1.8232
	Critical Value	24.2760	12.3209	4.1299	17.7973	11.2248	4.1299
	Prob.	0.0001	0.0000	0.2082	0.0000	0.0000	0.2082
SIBN							
	Eigenvalue	0.1391	0.0560	0.0022	0.1391	0.0560	0.0022
	Statistic	199.9376 *	57.0648 *	2.1157	142.8727 *	54.9491 *	2.1157
	Critical Value	24.2760	12.3209	4.1299	17.7973	11.2248	4.1299
	Prob.	0.0001	0.0000	0.1719	0.0001	0.0000	0.1719
SNGS							
	Eigenvalue	0.1280	0.0704	0.0022	0.1280	0.0704	0.0022
	Statistic	219.9331 *	77.9365 *	2.2602	141.9965 *	75.6763 *	2.2602
	Critical Value	24.2760	12.3209	4.1299	17.7973	11.2248	4.1299
	Prob.	0.0001	0.0001	0.1566	0.0001	0.0001	0.1566
TATN							
	Eigenvalue	0.1158	0.0275	0.0008	0.1158	0.0275	0.0008
	Statistic	60.7246 *	11.4942 *	0.3238	49.2305 *	11.1704 *	0.3238
	Critical Value	24.2760	12.3209	4.1299	17.7973	11.2248	4.1299
	Prob.	0.0000	0.0685	0.6316	0.0000	0.0511	0.6316

Table 38 Cointegration Test Summary across MICEX, RTS and LSE markets

The table 38 reports the statistics of unrestricted cointegration tests (trace and maximum eigenvalue) based on quotes samples sampled at 1s frequency. The initial null hypothesis is that there is no common stochastic trend amongst 3 variables versus the alternative that one. The subsequent null is that there exists at least 1 or maximum 2 common stochastic trends. The asterisks indicate a statistical significance at the 0.05 level.

	Cointegrating Vector	M_LSE(-1)	M_RTS(-1)	M_MICEX(-1)	Standard error	t-statistic
EESR	1	1	0	-0.9991	0.0005	[-2215.89]
	2	0	1	-1.0005	0.0003	[-3233.36]
GAZP	1	1	0	-0.9921	0.0036	[-275.435]
	2	0	1	-1.0005	0.0003	[-3440.38]
GMNK	1	1	0	-1.0272	0.0020	[-519.107]
	2	0	1	-0.9999	0.0003	[-3131.36]
LKOH	1	1	0	-0.9985	0.0012	[-859.625]
	2	0	1	-1.0004	0.0002	[-4073.67]
RTKM	1	1	0	-0.9950	0.0024	[-414.818]
	2	0	1	-0.9993	0.0011	[-892.382]
SIBN	1	1	0	-1.0005	0.0004	[-2261.38]
	2	0	1	-1.0005	0.0021	[-486.391]
SNGS	1	1	0	-0.9981	0.0010	[-1001.55]
	2	0	1	-0.9984	0.0004	[-2748.98]
TATN	1	1	0	-1.0005	0.0017	[-605.558]
	2	0	1	-1.0017	0.0009	[-1064.36]

The table reports the cointegrating vectors, their standard errors and t-statistics of the VECM (Equation 34) for quotes based samples, sampled at 1s frequency.

Table 39 Cointegration Vectors Summary

8.4.2 Cointegration Vector Restriction Test

Table 40 presents the estimated cointegrating vectors across the LSE, RTS and MICEX markets. All cointegrating vectors display closeness to the theoretical $\beta^T = (1, -1)'$. However, most of the vectors deviated somewhat from the theoretical ideal. Therefore the restrictions for the VECM of the cointegrating vectors *(1, – 1)'* are imposed to test whether the empirical estimates are significantly different from the theory. The null hypothesis is that the theoretical cointegrating vector is not significantly different from the empirical. The test results of the

Likelihood Ratio (LR) test of the jointly restricted (both cointegrating vectors must be β_i^T = *(1, – 1)'* models for all instruments across the three markets. Interestingly, for both LKOH and TATN, the theoretical ideal has not been rejected at 5% level, supporting the notion that the market for these instruments is fairly well integrated. The test results of securities such as EESR, GAZP, GMNK and SNGS indicate a rejection of null; the imposed restriction of the theoretical *(1, – 1)* is significantly different from the empirical at the 5% level, and for LKOH and RTKM at 10% level. Unlike the restriction test results reported in the previous MICEX versus RTS chapter, with the exception of SNGS, no other restrictions are rejected for the Moscow markets. There are clearly more LR test rejections than in Chapter 7. The rejections of the null are confirmed for the cases of EESR and GMNK in separate tests between the MICEX/LSE and RTS/LSE combinations. The increased rejection of the null may be caused by the differences on the cross-border level between MICEX/LSE and RTS/LSE. This finding suggests that the differences of quoted currencies, exogenous exchange rate and idiosyncratic trading rules (microstructure) may cause a long-run equilibrium difference between the markets. The rejection of the restriction on the international scale is indicative of the frictions and information asymmetry between the cross-border markets.

		MICEX vs RTS	MICEX vs LSE	RTS vs LSE	MICEX vs LSE/RTS
EESR	Chi-square(1)	1.6202	6.6014 *	10.7022 *	10.7222 *
	Probability	0.2031	0.0102	0.0011	0.0047
GAZP	Chi-square(1)	0.6306	3.5389	3.7187	9.6713 *
	Probability	0.4271	0.0599	0.0538	0.0079
GMNK	Chi-square(1)	0.5057	60.0099 *	75.6452 *	66.9498 *
	Probability	0.4770	0.0000	0.0000	0.0000
LKOH	Chi-square(1)	1.0488	1.5786	3.2390	4.7755
	Probability	0.3058	0.2090	0.0719	0.0918
RTKM	Chi-square(1)	0.4467	4.4494 *	6.2704 *	4.8749
	Probability	0.5039	0.0349	0.0123	0.0874
SIBN	Chi-square(1)	0.0568	0.7562	0.0047	0.7706
	Probability	0.8117	0.3845	0.9455	0.6802
SNGS	Chi-square(1)	13.7020 *	3.2906	0.4451	11.4543 *
	Probability	0.0002	0.0697	0.5047	0.0033
TATN	Chi-square(1)	3.4603	0.1945	1.1703	4.1785
	Probability	0.0629	0.6592	0.2793	0.1238

The table presents the Chi-squared test statistics and their p-values for the imposed restriction of cointegration vector β^T = (1, –1)' from Equation 34 for all cross-listed securities based on quotes samples, sampled at 1s frequency. The asterisks indicate a statistical significance at the 5% level.

Table 40 Cointegrating Vector Restriction Likelihood-Ratio Test Summary

8.4.3 VAR and VECM Estimation Results

A general to specific model formulation strategy leads to similar results, with the presence of cointegration being robust to the number of lags. The optimal lag structure for unrestricted VAR has been identified according to whatever minimises the Schwarz Information Criterion (SIC). The optimum lag range has been between over fifty for 1 second and one lag for 1920 seconds intervals. For event time frequency, the lag structure tends to increase, but for lower frequencies to decrease. For VECM, the determinant of lag length choice has been the SIC.

Table 41 reports the estimation results of the VECM at 480s sampling. Estimation of the VECM shows the influence of the MICEX returns on the LSE and RTS returns. Of particular interest are the estimates of error-correction coefficients from both cointegrating relationships. As shown in Table 41, the error-correction coefficients for the MICEX market are estimated using Equation (34). The Equation has been used to estimate the error-correction coefficients for the MICEX/LSE cointegrating relationship and MICEX/RTS cointegrating relationship. None of the coefficients of the MICEX market are statistically significant for the MICEX/RTS cointegrating relationship, but all the error-correction terms for the LSE market as well as RTS are statistically significant at the 5% level and are negative. However, in contrast to the MICEX/RTS relationship, with the exception of EESR and GAZP, MICEX adjusts to LSE innovations because, for the remaining instruments, the error-correction parameters are statistically significant at the 5% level and positive. This implies that adjustments to the disequilibrium take place not only in the satellite LSE and RTS markets but also in MICEX in relationship to LSE. Unlike RTS, the MICEX market is partly responsive to the deviations of the LSE market and vice versa. This indicates that an information shock to the MICEX market would have a significant effect on the satellite markets. However an information shock to the LSE satellite market in particular would influence the MICEX market significantly. Overall, the findings of the VECM estimation point out the importance of LSE in international price discovery relationship between London and Moscow.

	Error Correction:	MICEX/RTS	Std. error	t-stat	MICEX/LSE	Std. error	t-stat
EESR							
	D(M_LSE)	-0.3603 *	0.0179	[-20.1047]	0.1494	0.0443	[3.37216]
	D(M_RTS)	0.0131	0.0070	[1.88259]	-0.0799 *	0.0172	[-4.64569]
	D(M_MICEX)	0.0126	0.0072	[1.75529]	0.0295	0.0177	[1.66075]
GAZP							
	D(M_LSE)	-0.0159 *	0.0059	[-2.69750]	0.0300	0.0402	[0.74675]
	D(M_RTS)	0.0077	0.0043	[1.80640]	-0.0848 *	0.0291	[-2.91233]
	D(M_MICEX)	0.0034	0.0043	[0.79267]	0.0234	0.0293	[0.79943]
GMNK							
	D(M_LSE)	-0.0384 *	0.0071	[-5.37193]	0.0008	0.0197	[0.04165]
	D(M_RTS)	0.0178	0.0049	[3.62322]	-0.1862 *	0.0135	[-13.7625]
	D(M_MICEX)	0.0130 *	0.0037	[3.55763]	0.0165	0.0101	[1.62599]
LKOH							
	D(M_LSE)	-0.0134 *	0.0065	[-2.05863]	0.0090	0.0158	[0.56795]
	D(M_RTS)	0.0349	0.0078	[4.49356]	-0.1861 *	0.0188	[-9.90190]
	D(M_MICEX)	0.0145 *	0.0067	[2.15592]	0.0033	0.0162	[0.20503]
RTKM							
	D(M_LSE)	-0.0302 *	0.0060	[-5.03520]	0.0023	0.0092	[0.24672]
	D(M_RTS)	0.0190	0.0053	[3.56163]	-0.0755 *	0.0082	[-9.19947]
	D(M_MICEX)	0.0094 *	0.0046	[2.04795]	-0.0100	0.0071	[-1.42003]
SIBN							
	D(M_LSE)	-0.1308 *	0.0100	[-13.1317]	-0.0058	0.0040	[-1.45706]
	D(M_RTS)	0.0296	0.0100	[2.95187]	-0.0336 *	0.0040	[-8.38527]
	D(M_MICEX)	0.0333 *	0.0067	[4.97812]	-0.0010	0.0027	[-0.38749]
SNGS							
	D(M_LSE)	-0.0636 *	0.0101	[-6.27022]	-0.0348	0.0182	[-1.91265]
	D(M_RTS)	0.0250	0.0071	[3.49535]	-0.1478 *	0.0128	[-11.5410]
	D(M_MICEX)	0.0213 *	0.0063	[3.39581]	-0.0132	0.0112	[-1.17067]
TATN							
	D(M_LSE)	-0.0188 *	0.0080	[-2.36400]	-0.0048	0.0091	[-0.52913]
	D(M_RTS)	0.0118	0.0088	[1.34342]	-0.0670 *	0.0100	[-6.68305]
	D(M_MICEX)	0.0169 *	0.0070	[2.40985]	-0.0018	0.0080	[-0.21882]

The table reports the adjustment coefficients α of the VECM from Equation 34, their standard error and t-test statistics for all cross-listed securities based on quotes samples, sampled at 1s frequency. The asterisks indicate a statistical significance at the 5% level.

Table 41 VECM Error-Correction Coefficients of MICEX, RTS and LSE

As presented in Table 41, estimation of the VECM shows the influence of the RTS returns on the LSE returns sampled at 480s. The estimates of the LSE market are positive for six instruments (exceptions are GAZP and TATN) and statistically significant, however the error-correction term for the RTS market is also statistically significant at the 5% level and is negative. This implies that adjustments to the disequilibrium take place in both markets. If divergence from equilibrium occurs in one period in one market, it is error-corrected by the other market and vice versa. The RTS market is responsive to the departures of the LSE market and vice versa. This indicates that an information shock to the LSE market would have a significant effect on the RTS market and an information shock to the RTS market would influence the LSE market also significantly.

8.4.4 Optimum sampling frequency

In order to measure the price discovery relationship between the London and Moscow markets accurately, it is essential to identify a sampling frequency at which the interaction between the contemporaneous correlation and microstructure effects is minimised. The main objective of the sampling frequency analysis is to minimise the effects of the transitory component, while at the same time maintaining as much of the information in the common efficient price as possible. The objective function of optimisation is the minimisation of the bias in information shares caused by an increase in contemporaneous correlation or by the interference of transitory components when the sampling frequency is adversely chosen. This section seeks to identify an optimised sampling frequency by analysing the behaviour of the data in terms of Hasbrouck (1995) HIS bounds, the contemporaneous correlation measure suggested by DeJong (2002), the realised variance estimator of Anderson et al. (2003) and the Bandi and Russell (2005) rule of thumb method. Since the trading activity on all three markets for all eight cross-listed securities is substantially different, it is impossible to offer a universal "one fits all"- sampling frequency. However, it is more feasible to offer an optimum sampling frequency range solution. The inter-market optimum sampling has been identified as the range between 120s and 960 seconds for all cross-listed securities.

8.4.4.1 Hasbrouck (1995) HIS Bounds

Figure 43 and Figure 44 display the absolute differences between the upper and lower bounds of HIS for the LSE-MICEX and LSE-RTS markets. In the case of LSE-MICEX, with the exception of LKOH and TATN, the bound differences increase after 120s, while for LKOH and TATN the bounds start widening considerably after 30s. In the LSE-RTS case the HIS bounds start widening even earlier at 30s-60s, than in the LSE-MICEX case. These plots suggest that the LSE-RTS relationship is more symmetrical than that between LSE and MICEX, because the contemporaneous correlation starts earlier with a higher sampling frequency. This statement is also true for LKOH, GAZP and TATN stock in particular, because the bounds are generally wider and the widening starts earlier, with a higher sampling frequency around 30s for both market combinations.

8.4.4.2 Contemporaneous Correlation

Figure 37 and Figure 38 show the graph of contemporaneous correlations of innovations between MICEX and LSE. As expected, all contemporaneous correlations display a tendency to rise with higher sampling intervals. At 1s frequency, the correlations starts off as low as 0.05 and can rise as high as 0.82. These numbers suggest that the innovations can be almost uncorrelated at the highest sampling frequency due to the larger proportion of microstructure effects. At a low sampling frequency the innovations could become almost perfectly correlated, hereby censoring the informational contribution of each market. The correlation seems to increase above 120s sampling frequency considerably. Interestingly, there seems to be no relationship between asset liquidity and the degree of contemporaneous correlation. GAZP and LKOH, among the most liquid instruments, display a relatively high degree of contemporaneous correlation even at the highest sampling frequency. With GAZP in particular, correlations range from 0.42 at 1s to 0.69 at 1920s. These relatively high numbers could indicate a lower degree of idiosyncratic noise and therefore a more symmetric information arrival. This observation is also confirmed by the RV estimator differences across the markets: LKOH and GAZP trading is relatively less affected by microstructure effects between LSE and MICEX.

DeJong (2002) illustrates the dependence of HIS on variance of innovations ε_{it}. A simplified model of information shares assuming no contemporaneous correlation is:

$$IS_i = \frac{\sigma_i^2}{\sigma_1^2 + \sigma_2^2} \tag{55}$$

Where $\sigma_i^2 = Var(\varepsilon_{it})$

That is, a proportion of a market *i* innovation variance to the combined market variance. The closer is *IS* to 0.5, the greater the cross-correlation. Figure 25 illustrates the *IS* relationship of LSE-MICEX markets depending on sampling frequency. All graphs display a declining *IS* tendency with rising sampling intervals closer to 0.5. This implies that contemporaneous correlations are rising with lower sampling frequencies. After about 30s sampling, a sharper decline in IS is observable, indicating a spiking contemporaneous correlation in innovations.

8.4.4.3 Realised Variance (RV) Estimator Andersen et al. (2001)

The RV estimator plots for the eight securities on each market are presented separately in Figure 39, Figure 40 and Figure 41 for MICEX, RTS and LSE respectively. Looking at the RV graphs of each exchange separately, the differences in RV estimator dimensions are apparent. These differences are indicative of the fundamental heterogeneity in the microstructure of the underlying markets. Generally, MICEX seems to have the lowest RV values, followed by RTS and then by LSE. The RV values of eight stocks traded on MICEX range from 0.007 to 0.07; RTS RV range from 0.01 to 0.17; LSE RV range from 0.007 to 1.4. In the absence of jumps and microstructure noise, the RV estimator is an approximation of the integrated volatility of the returns. Assuming the presence of microstructure noise at higher sampling frequencies, however, RV can be used as a proxy indicator of a relative degree of effects in microstructure at chosen sampling frequencies. The lowest RV value ranges suggest that MICEX may be overall the market, which is least saturated with microstructure effects.

The relatively low RV estimator values of MICEX in comparison to the higher RV values of the RTS and LSE markets is an indication of the fundamental difference in the microstructure of the MICEX market. Interpreting Figure 39 from the perspective of the microstructure effects captured by the RV estimator, it can be said that a trading mechanism of the MICEX market has the least influence on the fundamental pricing process. This can be supported by that fact the slope of the RV decline, as a function of sampling frequency, is modest. Assuming that the efficient price is less affected by the trading process at lower sampling frequencies, the modest decrease in variance could mean that the degree of interference of transitory component at the highest sampling frequencies is low relative to the fundamental pricing process, or that the degree of information impounded into the efficient price is high relative to the microstructure effects of the trading process. The relative flatness of RV across the range of the chosen sampling frequencies is indicative of a balance between microstructure effects and the degree of impounded information into prices. In the context of price discovery, if one compared the range of values of the RV estimator with the other competing markets, it could be said that the pricing of MICEX market is the least influenced by its trading process, and likely to be the most informative market. This statement is in line with the overall findings.

Table 42 and Figure 49 portray the absolute differences in the RV estimator as a function of sampling frequency plots between the market combinations. The absolute differences in inter-market RV are an indicator of market information symmetry at a lower sampling frequency or idiosyncrasy of microstructure at the highest frequency. The absolute RV differences confirm the contemporaneous correlation observations: LKOH, GAZP and TATN have the lowest differences in microstructure effects as well as in informational symmetry, whereas the differences in microstructure effects tend to be larger than in informational symmetry. Furthermore, the differences are also, on average, larger between MICEX and LSE than between LSE and RTS, indicating that RTS and LSE are more alike than LSE and MICEX.

		frequency (s)									
	RV Difference	**1**	**15**	**30**	**60**	**120**	**240**	**480**	**960**	**1920**	**mean**
EESR	LSE- MICEX	0.20	0.21	0.20	0.17	0.08	0.07	0.07	0.05	0.04	0.12
	LSE-RTS	0.09	0.15	0.15	0.13	0.05	0.04	0.04	0.03	0.03	0.08
GAZP	LSE- MICEX	0.13	0.07	0.06	0.06	0.05	0.04	0.04	0.04	0.04	0.06
	LSE-RTS	0.11	0.05	0.04	0.05	0.05	0.04	0.04	0.04	0.04	0.05
GMNK	LSE- MICEX	0.37	0.36	0.36	0.27	0.16	0.14	0.14	0.11	0.10	0.22
	LSE-RTS	0.29	0.31	0.30	0.22	0.12	0.10	0.10	0.08	0.08	0.18
LKOH	LSE- MICEX	0.07	0.06	0.06	0.01	0.01	0.00	0.00	0.00	0.00	0.02
	LSE-RTS	0.04	0.03	0.02	0.03	0.04	0.03	0.02	0.01	0.01	0.03
RTKM	LSE- MICEX	1.38	1.39	1.07	0.94	0.74	0.58	0.46	0.41	0.42	0.82
	LSE-RTS	1.35	1.36	1.05	0.92	0.73	0.58	0.46	0.41	0.42	0.81
SIBN	LSE- MICEX	0.06	0.07	0.06	0.07	0.06	0.05	0.05	0.03	0.03	0.05
	LSE-RTS	0.04	0.04	0.03	0.03	0.02	0.01	0.01	0.01	0.01	0.02
SNGS	LSE- MICEX	0.46	0.33	0.31	0.24	0.18	0.13	0.12	0.10	0.10	0.22
	LSE-RTS	0.40	0.28	0.27	0.21	0.16	0.10	0.10	0.08	0.08	0.19
TATN	LSE- MICEX	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	LSE-RTS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
mean		0.31	0.30	0.25	0.21	0.15	0.12	0.10	0.09	0.09	0.18

The table portrays the absolute cross-market differences and their averages in the RV estimator as a function of sampling frequency between the market combinations. The lower the difference the more are the underlying markets alike.

Table 42 Absolute inter-market differences between RV estimators

The tendency of the RV estimator to decline with lower sampling frequencies is also observable, particularly in the cases of RTS and LSE. MICEX, on the contrary, has a tendency to be rather flat or even to rise with lower sampling frequencies. A sharp initial decline is observable in all plots, followed by less sharp declines and eventual flatness. The breaking point between the sharp initial decline and RV stabilising is security and market dependent. For the majority of MICEX stocks, the breaking point is about 15s. For RTS the breaking point is between 15s and 60s, while for LSE the breaking point can reach 120s. The breaking point at 15s is not surprising, because the sampling frequency decreases by a factor of 15, while the consecutive frequencies decrease only by a factor of 2. Like the results in the literature, for example Hansen and Lunde (2006), the RV estimators start to flatten out after 120s sampling frequency. For the majority of firms, sampling below 120s intervals would induce a substantial amount of microstructure effects, which would affect the inferences by biasing up the less noisy market, as documented by Grammig and Peter (2008).

The optimum point of trade-off in bias between microstructure effects and data censorship is most likely located where the RV estimator curves reach the point where graph plots have reached a relative flatness or display close to zero variation (Figure 39, Figure 40 and Figure 41). According to the RV estimator-sampling frequency plots, the more optimal sampling frequency for three companies GAZP, LKOH and TATN in all three markets is approximately 480s. The optimum sampling frequency for all other companies seems to be around or beyond 15 minutes (960s).

8.4.4.4 Rule of Thumb Method by Bandi and Russell (2005)

The non parametric estimation of optimal sampling frequency is provided by the "rule of thumb" method of Bandi and Russell (2005). As opposed to a single RV estimator measure, the "rule of thumb" approximation takes a variance of unobserved efficient price (signal) in the form of realised quarticity (RQ) proxy of an inter-temporally aggregated sample into account, usually sampled above 15min intervals. The proportion of RQ relative to RV (Equation 52) is a compact expression of signal to noise ratio. These ratios are in line with the graphical representation of the RV estimator-sampling frequency plots. Table 43 presents the optimum sampling points in minutes based on the Russell (2005) rule of thumb method for the given sample. The all stock average optimum sampling frequency is 28.73, 15.9 and 12.88 minutes for LSE, RTS and MICEX respectively. The numbers imply that MICEX and RTS optima are more alike, as opposed to MICEX and LSE, where LSE, according to the optimum, needs to be sampled more than half as often. These findings seem to be in conflict with those of the RV estimator and cross-correlation differences, hint that LSE and MICEX are more similar in their informational contribution. However, the differences in the results are plausible, since the method of Bandi and Russell (2008) also takes a variance of efficient price additionally into account, relative to single RV estimator (proxy for the relative microstructure effects) at the highest sampling frequency. Overall, the average sampling optimum frequency, based on signal to noise ratios, is 19.17 minutes across the three markets. This optimum average is similar to the findings of Bandi and Russell (2008), in which 15 minute sampling are considered the usual optimum.

	LSE	RTS	MICEX	Average
EESR	35.08	16.74	15.40	22.40
GAZP	34.41	19.03	21.62	25.02
GMNK	41.83	14.27	10.88	22.33
LKOH	24.72	20.18	11.88	18.93
RTKM	35.08	16.74	15.40	22.40
SIBN	14.15	16.58	8.43	13.05
SNGS	39.98	16.24	14.55	23.59
TATN	4.56	7.40	4.86	5.61

The table reports the sampling frequency optima of Bandi and Russell's rule of thumb measured in minutes for all markets and securities.

Table 43 Sampling Frequency Optima Bandi and Russell (2005) Rule of Thumb

Which sampling frequency is better in order to determine accurate price discovery shares? The current literature does not offer an inter-market optimum sampling frequency solution. Optimum sampling frequency range is probably a better solution than a single optimum point. A single point optimum is difficult to implement in practice because of the differences in each market structure resulting in differences in trading and quoting frequency, with the current methodology choice. There are options: choose the optimum from 1. the fastest market (MICEX), 2. the slowest market (LSE), 3. the intermediate market (RTS). There is a microstructure bias-aggregation trade-off; if the sampling interval is chosen from the fastest market, then the likelihood of microstructure bias increases in favour of the faster market. If on the other hand, the frequency of the slowest market is the choice, then there is a risk that the faster market contribution is under estimated. As reported above, the differences in the market microstructure and in the microstructure effects across the markets is substantial, especially between MICEX and LSE. However, based on the RV estimator plots, the "rule of thumb" and contemporaneous correlation plots, the optimum range for MICEX-LSE is, in the end, firm dependent.

In order to avoid misleading inferences, it is crucial to base the inferences rather on the sampling frequency range. On the one hand, making inferences on sampling below 60s is best avoided because of microstructure effects, according to the RV estimator results. The RV values begin to stabilise after 120s sampling intervals. A similar observation can be made about IS for the LSE-RTS case. On the other hand, the HIS bounds start to diverge substantially after 60s for LKOH, TANT and GAZP; HIS precision begins to fade less dramatically for the remaining stocks after

120s intervals. These findings are in line with Bandi and Russell (2008), Ait-Sahalia et al. (2005). The average "rule of thumb" method suggests an optimal sampling around 960s. Overall, it would be reasonable to define the range of the optimum frequency between 120s and 960s for all stocks and market combinations. Additionally, for those stocks which are closer to the lower frequency bound of the optimum sampling range, it would make sense to assign more weight to the GG method rather to HIS because of the precision loss due to widening HIS bounds.

8.4.5 Contribution to Price Discovery and the Sampling Frequency Choice

The null that the home market dominates the cross-border price discovery process should not be rejected. Figure 36 displays the MICEX, RTS and LSE market HIS contribution averages as a function of sampling frequency. The HIS of MICEX is the highest of the three markets and it remains significantly above the other two. The second highest HIS is attributable to RTS. The LSE market has the lowest average information share for all sampling frequencies. Noteworthy is HIS behaviour versus the sampling frequency: MICEX averages fall monotonously with rising sampling intervals, while the HIS averages of LSE rise monotonously. The HIS averages of RTS display both a decrease and increase, with a minima at 240s frequency. Overall, the findings clearly suggest that the MICEX market average price discovery contribution is superior to the RTS and LSE contributions within the optimum sampling frequency range between 120s and 960s. Given the information share behaviour of LSE in the context of microstructure effects, sampling only below 120s intervals would have lead to the even more contrasting finding that the home market is the vastly superior price discovery market relative to its foreign counterpart. This finding is in line with findings of Grammig and Peter (2008, 2010).

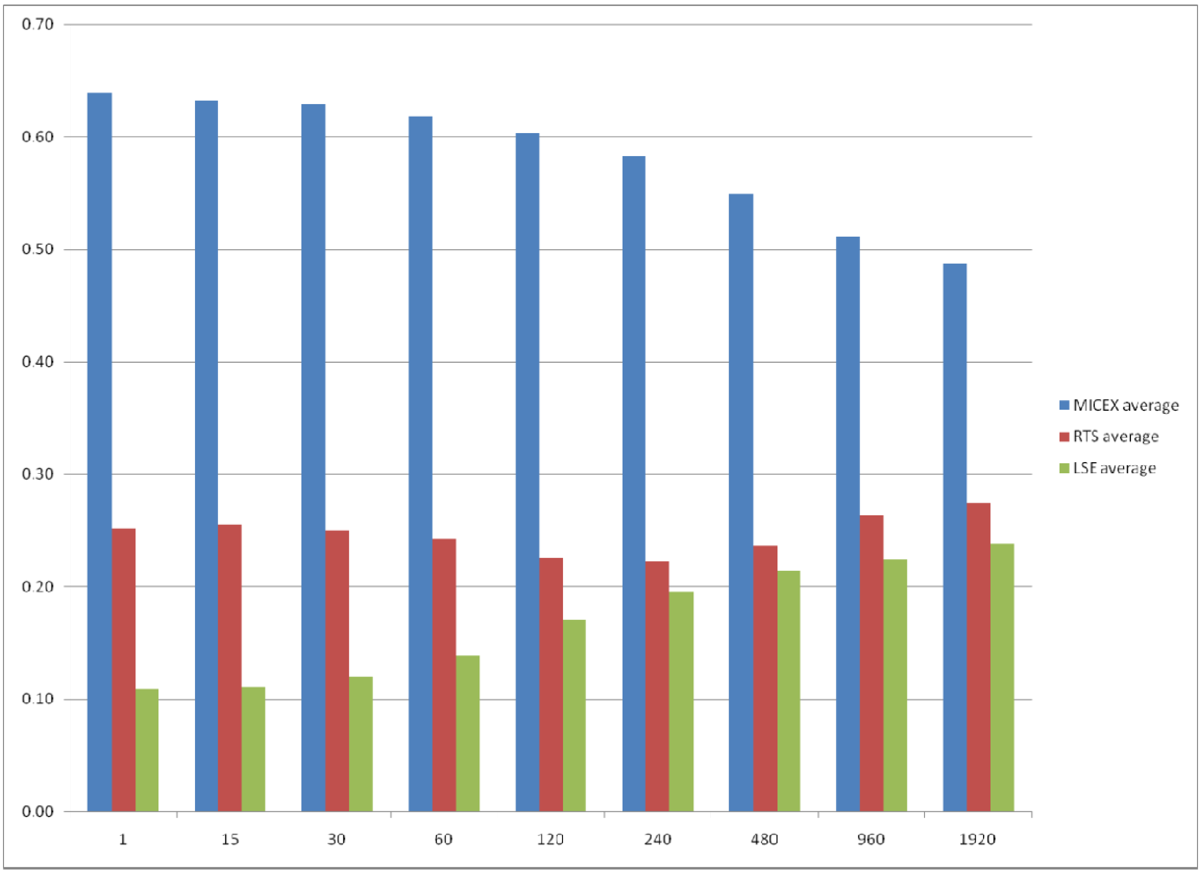

Figure 36 Summary of average normalised mid- point HIS for MICEX, RTS and LSE

Table 44 presents a summary of the normalised mid-point HIS for all sampling frequencies. Overall, the information share of MICEX is the highest. The informational contribution of MICEX accounts for approximately a 60% share of the three markets at for instance, 120s sampling frequency. The average IS of RTS and LSE taken together accounts for about 40%. The price discovery contributions of MICEX, RTS and LSE are in the ratio of approximately 60/20/20 on average, respectively. The finding, that the most liquid MICEX market is superior in price discovery is in line with expectations from Chapter 3. The proportions of the total trading volume (Table 4, Chapter 3) seem to be positively correlated with the information share averages.

		frequency (s)									
	security	**1**	**15**	**30**	**60**	**120**	**240**	**480**	**960**	**1920**	**mean**
MICEX	EESR	0.63	0.63	0.63	0.62	0.61	0.59	0.57	0.56	0.54	0.60
	GAZP	0.58	0.56	0.56	0.54	0.51	0.50	0.51	0.40	0.44	0.51
	GMNK	0.65	0.65	0.65	0.64	0.64	0.64	0.63	0.62	0.60	0.63
	LKOH	0.65	0.64	0.63	0.61	0.55	0.47	0.34	0.34	0.30	0.50
	RTKM	0.66	0.65	0.65	0.64	0.63	0.60	0.60	0.57	0.53	0.62
	SIBN	0.66	0.66	0.66	0.66	0.66	0.66	0.66	0.65	0.63	0.66
	SNGS	0.64	0.63	0.62	0.62	0.61	0.59	0.57	0.55	0.52	0.59
	TATN	0.64	0.64	0.64	0.62	0.62	0.61	0.52	0.41	0.35	0.56
	mean	0.64	0.63	0.63	0.62	0.60	0.58	0.55	0.51	0.49	0.58
RTS	EESR	0.37	0.37	0.37	0.37	0.38	0.39	0.40	0.41	0.42	0.39
	GAZP	0.38	0.38	0.39	0.39	0.40	0.40	0.39	0.47	0.43	0.40
	GMNK	0.34	0.35	0.34	0.32	0.28	0.31	0.33	0.36	0.39	0.34
	LKOH	0.03	0.03	0.03	0.04	0.06	0.09	0.13	0.15	0.17	0.08
	RTKM	0.31	0.31	0.31	0.31	0.25	0.25	0.23	0.25	0.25	0.27
	SIBN	0.21	0.18	0.14	0.08	0.06	0.02	0.03	0.02	0.02	0.08
	SNGS	0.35	0.36	0.36	0.36	0.33	0.28	0.34	0.39	0.42	0.36
	TATN	0.03	0.06	0.06	0.06	0.05	0.04	0.04	0.06	0.09	0.06
	mean	0.25	0.26	0.25	0.24	0.23	0.22	0.24	0.26	0.27	0.25
LSE	EESR	0.00	0.00	0.00	0.01	0.01	0.02	0.02	0.03	0.04	0.02
	GAZP	0.04	0.05	0.06	0.07	0.09	0.10	0.10	0.13	0.13	0.09
	GMNK	0.00	0.00	0.01	0.03	0.07	0.06	0.04	0.02	0.02	0.03
	LKOH	0.33	0.33	0.33	0.35	0.39	0.45	0.52	0.51	0.53	0.42
	RTKM	0.04	0.04	0.04	0.05	0.12	0.15	0.18	0.18	0.22	0.11
	SIBN	0.13	0.16	0.19	0.26	0.28	0.32	0.32	0.34	0.35	0.26
	SNGS	0.00	0.01	0.01	0.03	0.07	0.12	0.09	0.07	0.06	0.05
	TATN	0.33	0.30	0.30	0.31	0.34	0.35	0.44	0.53	0.57	0.38
	mean	0.11	0.11	0.12	0.14	0.17	0.20	0.21	0.22	0.24	0.17

The table summarises the normalised mid-points of Hasbrouck information shares of MICEX market from Equation 46, as a function of sampling frequency, for all cross-listed securities on average based on quotes samples.

Table 44 Hasbrouck Information Shares mid- point normalised

The general finding that the MICEX market is a superior price discoverer relative to RTS and LSE is in line with the hypothesis that the home market leads the foreign competitor market in price discovery. The Russian home market accounts for a combined 80% share relative to the foreign market, taking into account the superior trading volume of MICEX (Table 4) and its information share proportions. This finding is also consistent with the findings of Chapter 7, Ding et al. (1999), Eun and Sabherwal (2003) Menkveld et al. (2007), Grammig et al. (2005) and Phylaktis and Korczak (2005). The bivariate cases of MICEX vs. LSE and RTS vs. LSE are examined in detail in following paragraphs.

MICEX vs. LSE

frequency (s)		1	15	30	60	120	240	480	960	1920	mean
EESR	upper	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	lower	0.99	0.99	0.99	0.99	0.98	0.95	0.93	0.91	0.89	0.96
GAZP	upper	1.00	1.00	1.00	0.99	0.99	0.98	0.98	0.98	0.97	0.99
	lower	0.84	0.78	0.77	0.76	0.75	0.73	0.73	0.67	0.70	0.75
GMNK	upper	1.00	1.00	1.00	1.00	0.99	0.99	0.99	0.99	0.99	1.00
	lower	1.00	1.00	1.00	1.00	1.00	0.99	0.99	0.98	0.95	0.99
LKOH	upper	0.99	0.99	0.98	0.85	0.54	0.24	0.00	0.00	0.17	0.53
	lower	0.97	0.96	0.95	0.98	0.99	0.91	0.58	0.62	0.26	0.80
RTKM	upper	1.00	1.00	1.00	1.00	0.99	0.99	0.98	0.97	0.95	0.99
	lower	1.00	1.00	1.00	0.99	0.99	0.97	0.94	0.91	0.86	0.96
SIBN	upper	0.98	0.99	0.99	0.99	0.99	0.99	0.98	0.97	0.98	0.99
	lower	1.00	1.00	1.00	1.00	0.99	0.99	0.98	0.96	0.90	0.98
SNGS	upper	1.00	1.00	1.00	1.00	0.99	0.99	0.99	0.99	0.99	0.99
	lower	0.98	0.97	0.97	0.96	0.94	0.92	0.89	0.85	0.81	0.92
TATN	upper	0.89	0.93	0.94	0.88	0.86	0.81	0.42	0.09	0.00	0.65
	lower	1.00	1.00	1.00	1.00	1.00	1.00	0.87	0.62	0.36	0.87
mean		0.98	0.98	0.97	0.96	0.94	0.90	0.83	0.78	0.74	0.90

The table summarises the upper and lower bounds of Hasbrouck information shares of MICEX vs. LSE from Equation 46, as a function of sampling frequency, for all cross-listed securities based on quotes samples.

Table 45 MICEX vs. LSE Hasbrouck Information Shares upper/lower bounds

frequency (s)	1	15	30	60	120	240	480	960	1920	mean
EESR	1.00	1.00	1.00	0.99	0.99	0.98	0.97	0.96	0.95	0.98
GAZP	0.92	0.89	0.88	0.88	0.87	0.86	0.85	0.83	0.83	0.87
GMNK	1.00	1.00	1.00	1.00	1.00	0.99	0.99	0.99	0.97	0.99
LKOH	0.98	0.97	0.96	0.92	0.77	0.57	0.29	0.31	0.22	0.67
RTKM	1.00	1.00	1.00	1.00	0.99	0.98	0.96	0.94	0.91	0.97
SIBN	0.99	1.00	1.00	1.00	0.99	0.99	0.98	0.97	0.94	0.98
SNGS	0.99	0.99	0.98	0.98	0.97	0.95	0.94	0.92	0.90	0.96
TATN	0.95	0.97	0.97	0.94	0.93	0.91	0.65	0.35	0.18	0.76
mean	0.98	0.98	0.97	0.96	0.94	0.90	0.83	0.78	0.74	0.90

The table summarises the mid-points Hasbrouck information shares of MICEX vs. LSE from Equation 46, as a function of sampling frequency, for all cross-listed securities based on quotes samples.

Table 46 MICEX vs. LSE Hasbrouck Information Share mid-points

Figure 45 and Figure 47, Table 45, Table 46, and Table 47 present a summary of HIS and GG estimates for the relationship between the MICEX market and LSE. If the presence of the microstructure effects had been ignored, then the information contribution measures of GG and HIS would have indicated that the contribution of MICEX is on average 84% and 97%, measured by GG and HIS, respectively, for all the instruments beyond the 2 minutes sampling. These findings would have potentially led to the inference that MICEX is possibly the dominant in price discovery. However, if the sampling optimum is taken into account, the findings indicate an exception for two instruments: LKOH and TATN. These instruments display a sharp decay in MICEX's share at the 480s sampling interval. According to HIS and GG measures, LSE contributes approximately 60% on average to the common component when the sampling frequency is above 480s, but within the optimum range. With the exception of LKOH and TATN, the MICEX contribution average is 80% for the GG and 95.1% for the HIS method measured at the optimum sampling range. The 80% or more contribution of MICEX suggests that even if the optimum sampling range is implemented, MICEX remains the information dominant price discovering market. With the exception of LKOH and TATN, at the optimum sampling range, LSE has a more than 50% share - it is potentially leading. The sharp decay in price discovery contributions could be attributed to the surge in contemporaneous correlation, which is the case particularly for LKOH, as indicate in the sampling frequency analysis above. The presence of higher contemporaneous correlation for LKOH and TATN suggests that the optimum sampling range for these securities has been too widely chosen. As a remedy, narrowing the range to 60-480s would perhaps improve the results. For TATN, on the other hand, moving the lower boundary of the sampling range is better avoided because of the relatively lower liquidity. Shifting the optimum range would probably be a better option.

frequency (s)	1	15	30	60	120	240	480	960	1920	mean
EESR	0.99	0.98	0.98	0.97	0.96	0.94	0.94	0.96	0.96	0.97
GAZP	0.90	0.87	0.85	0.82	0.79	0.78	0.75	0.78	0.72	0.81
GMNK	0.92	0.87	0.85	0.80	0.73	0.73	0.73	0.75	0.81	0.80
LKOH	0.81	0.77	0.75	0.65	0.56	0.51	0.45	0.45	0.37	0.59
RTKM	0.94	0.90	0.89	0.88	0.86	0.83	0.81	0.79	0.76	0.85
SIBN	0.79	0.83	0.82	0.81	0.82	0.78	0.77	0.76	0.80	0.80
SNGS	0.94	0.87	0.85	0.83	0.77	0.76	0.76	0.77	0.80	0.82
TATN	0.69	0.71	0.72	0.64	0.63	0.61	0.49	0.40	0.36	0.58
mean	0.87	0.85	0.84	0.80	0.77	0.74	0.71	0.71	0.70	0.78

The table summarises the Gonzalo and Granger measures of MICEX vs. LSE from Equation 37, as a function of sampling frequency, for all cross-listed securities based on quotes samples.

Table 47 MICEX vs. LSE Gonzalo and Granger PT measures

RTS vs. LSE

frequency (s)		1	15	30	60	120	240	480	960	1920	mean
EESR	upper	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	lower	1.00	0.99	0.99	0.98	0.97	0.94	0.92	0.90	0.87	0.95
GAZP	upper	0.98	0.95	0.95	0.97	0.98	0.98	0.98	0.99	0.99	0.98
	lower	0.95	0.95	0.93	0.83	0.76	0.72	0.69	0.60	0.57	0.78
GMNK	upper	0.99	0.98	0.95	0.89	0.74	0.79	0.82	0.90	0.97	0.89
	lower	1.00	0.99	0.97	0.91	0.83	0.89	0.94	0.99	0.99	0.95
LKOH	upper	0.01	0.01	0.00	0.03	0.08	0.13	0.24	0.27	0.32	0.12
	lower	0.06	0.06	0.06	0.03	0.02	0.03	0.03	0.05	0.07	0.05
RTKM	upper	0.88	0.86	0.84	0.81	0.57	0.47	0.38	0.37	0.21	0.60
	lower	0.91	0.92	0.91	0.90	0.74	0.70	0.66	0.70	0.66	0.79
SIBN	upper	0.61	0.53	0.42	0.22	0.15	0.03	0.05	0.01	0.00	0.22
	lower	0.63	0.54	0.43	0.24	0.17	0.05	0.08	0.03	0.03	0.24
SNGS	upper	0.99	0.96	0.95	0.90	0.74	0.52	0.67	0.77	0.89	0.82
	lower	1.00	1.00	1.00	0.99	0.93	0.82	0.94	1.00	0.97	0.96
TATN	upper	0.01	0.06	0.04	0.04	0.00	0.00	0.05	0.13	0.23	0.06
	lower	0.10	0.23	0.21	0.21	0.12	0.07	0.03	0.01	0.00	0.11
mean		0.69	0.69	0.67	0.62	0.55	0.51	0.53	0.54	0.55	0.59

The table summarises the upper and lower bounds of Hasbrouck information shares of RTS vs. LSE from Equation 46, as a function of sampling frequency, for all cross-listed securities based on quotes samples.

Table 48 RTS vs. LSE Hasbrouck Information Share upper/lower bounds

The high proportion of Moscow's contribution to common component is only partly true for RTS-LSE relationship, compared to the MICEX-LSE relationship. Table 48, Table 49 and Table 50, Figure 46 and Figure 48 present the GG and HIS contributions for the RTS market. The average RTS contribution to the common component in the sampling range between 120s and 960s is 53.3% and 47.5% for the HIS and GG methods respectively. These proportions, close to 50%, suggest that the price discovery contributions of the LSE and RTS markets are fairly well balanced overall. If the optimum sampling had been ignored, the price discovery contribution results would have pointed to a shift towards RTS in the price discovery contribution. The price discovery contributions of RTS would have been 59% and 51% for HIS and GG methods respectively. However, as in the case of MICEX-LSE, LKOH, TATN and SIBN indicate approximately an 80% share of LSE, confirming the results above, that LSE is the dominant price discoverer for LKOH and TATN securities versus cross-listings on both Moscow stock exchanges. RTKM and SNGS information shares are close to 50%. Overall, the findings suggest that LSE and RTS are balanced satellite markets relative to the central market MICEX, with the confirmed exceptions of LKOH and TATN.

frequency (s)	1	15	30	60	120	240	480	960	1920	mean
EESR	1.00	1.00	0.99	0.99	0.98	0.97	0.96	0.95	0.94	0.98
GAZP	0.97	0.95	0.94	0.90	0.87	0.85	0.84	0.80	0.78	0.88
GMNK	0.99	0.99	0.96	0.90	0.78	0.84	0.88	0.94	0.98	0.92
LKOH	0.04	0.03	0.03	0.03	0.05	0.08	0.14	0.16	0.19	0.08
RTKM	0.89	0.89	0.88	0.86	0.66	0.58	0.52	0.53	0.43	0.69
SIBN	0.62	0.53	0.43	0.23	0.16	0.04	0.07	0.02	0.01	0.23
SNGS	1.00	0.98	0.97	0.94	0.84	0.67	0.80	0.88	0.93	0.89
TATN	0.06	0.14	0.12	0.13	0.06	0.04	0.04	0.07	0.11	0.09
mean	0.69	0.69	0.67	0.62	0.55	0.51	0.53	0.54	0.55	0.59

The table summarises the mid-points Hasbrouck information shares of RTS vs. LSE from Equation 46, as a function of sampling frequency, for all cross-listed securities based on quotes samples.

Table 49 RTS vs. LSE Hasbrouck Information Share mid-points

frequency (s)	1	15	30	60	120	240	480	960	1920	mean
EESR	0.96	0.96	0.95	0.95	0.94	0.94	0.94	0.96	0.96	0.95
GAZP	0.74	0.70	0.71	0.75	0.77	0.78	0.77	0.83	0.82	0.76
GMNK	0.72	0.63	0.51	0.48	0.46	0.50	0.52	0.60	0.71	0.57
LKOH	0.27	0.26	0.26	0.24	0.22	0.24	0.23	0.28	0.29	0.25
RTKM	0.64	0.56	0.55	0.53	0.49	0.47	0.45	0.47	0.44	0.51
SIBN	0.44	0.40	0.37	0.28	0.26	0.17	0.22	0.16	0.16	0.27
SNGS	0.76	0.58	0.57	0.51	0.45	0.40	0.45	0.51	0.60	0.54
TATN	0.28	0.31	0.31	0.32	0.25	0.22	0.18	0.10	0.06	0.22
mean	0.60	0.55	0.53	0.51	0.48	0.46	0.47	0.49	0.50	0.51

The table summarises the Gonzalo and Granger measures of RTS vs. LSE from Equation 37, as a function of sampling frequency, for all cross-listed securities based on quotes samples.

Table 50 RTS vs. LSE Gonzalo and Granger PT measures

MICEX vs. RTS

In the previous chapter, the MICEX exchange indicated dominance with an average information share of 85.4%. The average contribution of MICEX to the common component resulted in 88.5% according to the GG measure, across all stocks and all given sampling frequencies. The findings were based on the average of the full spectrum of sampling intervals (1s- 1920s). The findings of the previous chapter do not differ substantially from the optimum sampling range findings of this chapter. The GG and HIS methods show 87.2% and 82.2% contribution to the common component, respectively.

Summing up, the findings point out that MICEX may be the absolute dominant price discoverer relative to the LSE and RTS markets and that the home market leads the price discovery. These results support the notion in the literature {e.g. Eun and Sabherwal (2003), Menkveld et al. (2007), Pascual et al. (2005), Grammig et al. (2005)} that the home market has a leadership in price discovery. RTS and LSE are similar markets in price discovery shares since their contributions are relatively balanced. They take a supportive role relative to the MICEX contribution, but the role of LSE may be underestimated for LKOH and TATN instruments, which is in line with the findings of Grammig and Peter (2008).

8.4.6 Analysis of the Microstructure

In the context of the Hasbrouck (1995) and Gonzalo and Granger (1995) methodologies, the nature of the high frequency analysis implies that the results of the price discovery shares are influenced by the microstructure effects and the contemporaneous correlation. Nevertheless, there is a clear finding that even at lower sampling frequencies MICEX market leads the price discovery on average. However, at the same time, the results indicate that the price discovery share of MICEX market is not a constant; the price discovery share of MICEX exhibits significant variations across the range of sampling frequencies. For example, the share of MICEX on the Moscow market ranges between 91% and 76% depending on a sampling frequency and methodology. This variation in price discovery share of MICEX is expected because of the differences in microstructure across the markets as summarised in Chapter 3 and illustrated by the statistics in Tables 13 and 14.

The variation of price discovery shares may be explained by the degree of liquidity provision of a different type of traders across the MICEX, RTS and LSE markets, which most likely varies with sampling frequencies. Given the results of price discovery shares, following tendencies are observable: a) At the highest sampling frequencies (e.g. 1-60s), the MICEX market usually indicates a higher price discovery share, above 60% - it also seems to trade mostly in a smaller size (please refer to Table 14) but in a continuous fashion as supported by the number of observed trades in Table 6. b) At a lower sampling frequency (e.g. above 10min) however, RTS and LSE markets seem to gain their price discovery shares when the trades are executed infrequently with a larger median trading size (see Table 14). For example, GAZP trading on MICEX occurs in a continuous fashion with a median size below 900 shares, whereas the trading on LSE occurs on average every 26 seconds with the median size of 2000 receipts. Yet, on RTS, the median trading size of GAZP is 50 000 shares. These differences in the median trading size can be explained by the fact that MICEX has no minimum trading size restriction unlike RTS or LSE IOB. Furthermore, MICEX facilitates the highest degree of trading liquidity in terms of market immediacy, breadth and depth. It has the lowest average bid-ask spreads which are between 60% and 80% lower than on the LSE and RTS markets. The average median trade on MICEX is about 5% of the RTS transactions. For most liquid securities on average, the MICEX market has about 80% of total securities turnover, which is partly consistent with the more than 60% market share average of an overall trading volume as illustrated by Figure 1. Given the largest overall turnover on the MICEX market, the smallest median size of these trades on MICEX are reflective of the highest trading intensity of this market relative to RTS and LSE.

One could view the contribution to price discovery at a given sampling frequency as being driven by the nature of microstructure. From this perspective, true price discovery shares should not result from a set of values based on a carefully chosen sampling frequency at which the interference of microstructure effects is minimised. According to Tables 6 and 14, for example, the nature of microstructure of MICEX tends to attract a higher number of smaller trades while the microstructure of LSE attracts a mixture of infrequent larger and smaller trades. This difference in the nature of trading activity across the markets reflects a heterogeneous microstructure constellation. Consequently, the heterogeneity of a market microstructure may cause variation in price discovery shares at a given sampling frequency. Since a single price discovery ratio across the three markets cannot exclusively represent true price discovery, all measured price discovery proportions are valid at their sampling intervals.

The higher price discovery share of MICEX at highest sampling frequencies can be attributed to the structure of the MICEX market, which enables the market to capture a higher proportion of liquidity traders and their uninformed order flow. Benveniste et al. (1992) argue that liquidity traders are sensitive to the size of a bid-ask spread and that concentrating the uninformed order flow in the central market reduces the equilibrium bid-ask spread. The resulting equilibrium spread tends to be lower on the MICEX market if liquidity traders are most likely to trade with informed traders. The pooling of informed with uninformed order flows is most likely the driver of the decreasing cost of trading because market makers are less likely to incur losses on average when the proportion of uninformed order flow is higher. The higher the proportion of the liquidity traders that MICEX market can attract, the higher is the resulting uninformed and potentially informed order flow. The combined pool of uninformed with informed order flows results in a higher overall order flow, which leads to the higher information share of the MICEX market.

Overall, the trading volume on the aggregate level of MICEX, RTS and LSE, as depicted in Figure 1, tends to be correlated with the proportions of their contribution to price discovery. Since the trading activity on MICEX occurs at high frequency, it is reasonable to assume that a large proportion of the trading volume is transacted in shorter time intervals. Contrary to this observation, RTS and LSE trading occurs less frequently but with larger trades and most of their trading volume is more likely to be transacted at lower sampling frequencies e.g. above 10min. Therefore, by implication of differences in the nature of microstructure, MICEX has managed to attract a large proportion of turnover of high frequency trades at sampling frequencies at which trading on LSE is much less active. As a result, a higher share of price discovery is attributable to the MICEX market at highest sampling frequencies, at which modest or no trading took place on RTS and LSE markets. In the end, MICEX may be seen to be an information dominant market at highest sampling frequencies (below 1min) because of the larger turnover at shorter time intervals. In contract to MICEX, RTS and LSE are alternative markets, which play a supportive role in price discovery but only at larger time intervals. The view that price discovery is determined by the microstructure of competing markets is supported by the literature. Further implications of the findings in terms of microstructure are discussed in Interpretation of the Findings section and in Chapter 10, section 10.3 in further detail.

8.4.7 MICEX Dominance Restriction LR Test

Given the predominantly high price discovery contributions of the MICEX market, could 100% price discovery be attributed to MICEX vs. LSE and RTS? In order to test the null hypothesis of MICEX being a dominant market, the common long-memory factor weight of MICEX is assumed to be 100%. This assumption implies that the error-correction coefficients alpha of MICEX, which feed into common long memory factor weight ratio of GG, must be proven to be insignificantly different from zero for all eight cross-listed securities. The greater a factor weight assigned to a market, the slower its speed of adjustment to equilibrium, thus the lower the error-correction coefficient alpha in the VECM (Equation 34). Since the common long-memory factor weights are sensitive to sampling frequency, the upper limit of optimum sampling range has been chosen as 960s for all restriction tests.

The price discovery restriction test of MICEX dominance has been carried out with the joint null hypothesis of MICEX's dominance (100%) over RTS and LSE. The error-correction coefficient alpha in the VECM for both MICEX Equations is jointly set to alpha equals zero (Equation 34). The p-values are reported in the Table 51 along with the chi-square test statistic with two degrees of freedom (Gonzalo and Granger, 1995). For all instruments, except GMNK, SIBN and SNGS, the error-correction coefficients alpha were insignificantly different from zero at 5% significance level. The restriction test inferences suggest that MICEX has a potential common long-memory factor weight of 100% for more than half the stocks in the joint relationship with LSE and RTS. Since there are exceptions to MICEX 100% dominance, MICEX is not the absolutely dominant market, but has the potential tendency to be dominant in separate cases.

In order to investigate where MICEX is relatively dominant, one must differentiate between two cases of the null hypothesis:

1. H_0: MICEX=100%, H_1: LSE=0%
2. H_0: MICEX=100%, H_1: RTS=0%

Tables 51 and 52 support the hypothesis of MICEX market price discovery dominance over LSE, but only partially. In the first case, reported in Table 51, the null of MICEX 100% price discovery dominance should be rejected in three cases. The equilibrium adjustment coefficients of MICEX are significantly different from zero at 5% level for four securities: GMNK, LKOH, SIBN and SNGS. Table 51 reports the chi-squared and p-values for the null of MICEX contribution, which is set to 100% versus RTS [please refer to case c)]. The null of MICEX price discovery 100% contribution in relationship to RTS should be rejected. EESR and GMNK display significantly far from zero error correction coefficient values. The test results indicate that MICEX is generally only dominant over LSE and RTS in separate cases. Overall, the results present a mixed picture: in separate LKOH cases, the contribution of MICEX relative to LSE and RTS is different from 100%. However, the joint hypothesis indicates that the contribution of MICEX is 100% dominant over LSE and RTS. These results are in conflict. If the null is reversed and the LSE contribution is hypothesised to be 100%, the inferences are consistent with LSE. The London market may contribute 100% for LKOH and TATN, yet for the remaining instruments the null is rejected. In other words, the restriction tests in separate cases support the notion that MICEX is dominant with the exception that LSE's contribution may be close to 100% for LKOH and TATN. The restriction test results support the notion that the satellite markets also contribute significantly to price discovery.

	a) MICEX>LSE			b) MICEX<LSE			c) MICEX>RTS		
	Chi-square(1)		**p-value**	**Chi-square(1)**		**p-value**	**Chi-square(1)**		**p-value**
EESR	2.8372		0.0921	231.9797	*	0.0000	3.8700	*	0.0492
GAZP	1.0639		0.3023	6.8408	*	0.0089	2.2277		0.1356
GMNK	12.7915	*	0.0003	32.4892	*	0.0000	7.9338	*	0.0049
LKOH	4.4143	*	0.0356	3.1817		0.0745	0.8542		0.3554
RTKM	2.2635		0.1325	22.5241	*	0.0000	0.5328		0.4654
SIBN	18.2341	*	0.0000	107.6383	*	0.0000	0.1841		0.6679
SNGS	6.3431	*	0.0118	30.6062	*	0.0000	0.4585		0.4983
TATN	3.5558		0.0593	1.2176		0.2698	0.0137		0.9068

The table reports the Chi-squared and the p-values of imposed restrictions to the adjustment coefficient alpha in VECM from Equation 34. The cases a), b) and c) represent the null hypothesis of the contribution to price discovery being 100% (alpha=0) of a) MICEX vs. LSE, b) LSE vs. MICEX and c) MICEX vs. RTS, respectively. The asterisks indicate a statistical significance at the 5% level.

Table 51 Error-Correction Coefficient LR restriction Test Summary

	a) RTS=LSE			b) RTS>LSE			c) MICEX>LSE&RTS		
	Chi-square(1)		**p-value**	**Chi-square(1)**		**p-value**	**Chi-square(2)**		**p-value**
EESR	438.0507	*	0.0000	3.7956		0.0514	5.6551		0.0592
GAZP	20.9529	*	0.0000	0.6217		0.4304	2.6945		0.2600
GMNK	74.1121	*	0.0000	28.5030	*	0.0000	17.7301	*	0.0001
LKOH	51.8551	*	0.0000	14.2341	*	0.0002	4.6224		0.0991
RTKM	78.3409	*	0.0000	32.9680	*	0.0000	4.6485		0.0979
SIBN	58.3528	*	0.0000	69.7501	*	0.0000	18.7799	*	0.0001
SNGS	75.9270	*	0.0000	34.1949	*	0.0000	7.6028	*	0.0223
TATN	26.9728	*	0.0000	22.7548	*	0.0000	4.3494		0.1136

The table reports the Chi-squared and the p-values of imposed restrictions to the adjustment coefficient alpha in VECM from Equation 34. The case a) represents the null of the adjustments coefficients alpha being equal between RTS and LSE, while cases b) and c) represent the null hypothesis of the contribution to price discovery being 100% (alpha=0) of b) RTS vs. LSE and c) MICEX vs. jointly LSE and RTS, respectively. The asterisks indicate a statistical significance at the 5% level.

Table 52 Error-Correction Coefficient LR restriction Test Summary

The close to 50% proportions, from the price discovery contribution analysis above, hint that the price discovery contributions of LSE and RTS markets may be fairly balanced overall. In order to test the null that there is a balanced 50%/50% price discovery relationship between the RTS and LSE markets, the adjustment alpha coefficients in the restriction tests were set equal. The null that RTS contribution equals the contribution of LSE could be rejected for all instruments reported in Table 52. The null that RTS is dominant over LSE should be rejected. With the exception of EESR and GAZP, the alpha adjustment coefficients for all remaining instruments are significantly different from zero at 5% level. These inferences indicate that RTS is not dominant over LSE. On the contrary, for the majority of instruments LSE's 100% contribution should be not rejected. However, the contribution of RTS tends to be superior to LSE in trading for GAZP and EESR instruments.

Summarising the results so far, price discovery is dominated almost entirely by the domestic MICEX market. However, given the optimum sampling frequency range, the dominance of MICEX is not absolute; there is evidence that LSE may have a 100% contribution to both Moscow stock markets for LKOH and TATN. RTS and LSE are similar markets in terms of liquidity, but with exception of TATN and LKOH, the home market RTS seems to contribute more than LSE for all other instruments. Overall, the results do not undermine the notion that the home market has a higher contribution to price discovery, but restriction test results support the view that the satellite markets LSE and RTS also contribute significantly to price discovery.

Interpretation of the Findings

Why is the overall cross-border price discovery relationship between MICEX/RTS and LSE is characterised by the leading role of the Moscow market and the supportive role of the London market? Any meaningful pattern across the cross-listed securities is not evident. However, the overall price discovery constellation could be explained by a number of factors, for example, home bias of investors, cross-market differences in transaction costs, cross-border information asymmetry and in the cross-market liquidity as put forward by Baruch et al. (2005). Further implications of the finding that the MICEX market is information dominant and LSE/RTS have a supportive role are discussed in Implications of the Findings section, in Chapter 10. The most plausible explanation for Moscow's leadership in price discovery can be that there is a home bias of local investors. The evidence of Moscow's market price discovery leadership is fully in line with the market segmentation hypothesis e.g. Foerster and Karolyi (1999) and could be supported by the notion that local market participants, who prefer to trade on the local market, may be better informed than foreign market participants as for example in Harris et al. (2003). Furthermore, the overall lower transaction costs on MICEX may be the major factor explaining the superior price discovery performance of the MICEX market. Tables 13 and 14 report the lowest trading costs in terms of average narrow bid-ask spread on MICEX relative to RTS and LSE. This explanation is consistent with Harris et al. (2002a), who offer evidence that the contribution to price discovery relative to satellite exchanges rises when the bid-ask spreads of the central market relative to the satellite become narrower. The rejection of the theoretical cointegrating vector of $\beta = (1, -1)'$ for half of all securities at the 0.01 significance level as reported in Table 40, can be explained by the presence of cross-border market frictions and the information asymmetry between local and foreign investors. Trading restrictions in the market microstructure can be also a confounding factor, as suggested by Park and Tavakkolb (1994). Information reflected by the order flow, which is facilitated by the trading mechanism of a market, is in the end defined by its trading rules. If the trading rules on one market are more restrictive than on the other, then the less trading rule restrictive market may attract a higher proportion of order flow. The MICEX market, for example, can be considered the least restrictive market to local investors because the trading has always been conveyed in RUB without a minimum order size. The statistical significance of informational contribution of the LSE market could be attributed to the fact that there is a short selling restriction on the Moscow market whereas in London there is not. The LSE market probably is more successful in attracting the informed order flow since short selling activity could be mostly attributed to the more informed traders, who in the end have chosen to trade without this restriction abroad. Finally, trading volume may play a major role in explaining why the MICEX market leads price discovery relative to its domestic and foreign competitors. This explanation supports the evidence found by Eun and Sabherwal (2003) and Grammig et al. (2005), that liquidity is positively related to the proportion of the price discovery contribution of a market. The hypothesis of liquidity as a factor is indirectly tested in Chapter 9, where the price discovery contributions of the Moscow market are expected to be lower when London trading activity is higher.

8.5 *Conclusion*

The price discovery relationship between MICEX, RTS and LSE for the eight most liquid cross-listed securities has been analysed in this chapter. Altogether, the average proportions of the price discovery process between MICEX, RTS and LSE correspond closely to the ratio of 60/20/20, respectively. Consequently, the home market price discovery share is on average 80%, suggesting that the home market is the dominant price discoverer. Of the three markets, MICEX trading provides the dominant contribution to price discovery at the optimum sampling range (120s– 960s) for all instruments, with the exception at lower sampling frequencies, of LKOH and TATN. The MICEX market contributes around 60% to the efficient price on average, when it is competing with RTS and LSE. By the same token, LSE and RTS provide the supportive role for price discovery on MICEX. While the quoting adjustment relationship between MICEX and RTS is unidirectional (MICEX does not adjust to RTS quoting), the relationship between LSE and MICEX is bidirectional. RTS and LSE are similar markets in terms of market immediacy, however with exception of TATN and LKOH, the home market RTS seems to contribute more, relative to LSE, for all other instruments.

The average Russian home market informational contribution accounts for 80% share relative to foreign market LSE. This finding is also true in the context of the higher microstructure effects associated with higher sampling frequencies below 60s. However, drawing inferences based on the highest sampling frequency, the relationship between MICEX and LSE may lead to findings which overstate the home market contribution. These findings are in line with the findings of the study of Grammig and Peter (2008). Overall, while the results do not undermine the notion that the home market has a higher contribution to price discovery {e.g. Menkveld et al. (2007), Eun and Sabherwal (2003) and Pascual et al. (2005)}, restriction test results support the view that the satellite markets LSE and RTS also contribute significantly to price discovery. The rejection of the theoretical cointegrating vectors between London and Moscow are indicative of the cross-border information asymmetry caused by market frictions, stemming from geographical, political and differences in market microstructure.

Taking into account the superior trading volume on MICEX, the general finding that the MICEX market is a leading price discoverer relative to RTS and LSE, is in line with the hypothesis that the more liquid market leads the lesser liquid competitor market in price discovery. This finding is in line with the findings of Eun and Sabherwal (2003), Grammig et al. (2005) and Phylaktis and Korczak (2007). Given that the trading on MICEX is the most frequent of all three stock markets, the finding that MICEX is generally the leading price discoverer is not surprising. With the exception of the two securities (LKOH and TATN), the finding is consistent with the findings in the price discovery literature e.g. Eun and Sabherwal (2003), that price discovery is lead by the relatively liquid (immediate) market. Usually the most liquid market is the central and home market as evidenced by Hasbrouck (1995), Harris et al. (2002a) and Grammig et al. (2005). However, despite that, there are exceptions such as LKOH and TANT, which indicate that there is a possibility that there might be other forms of liquidity, such as a relative trading volume or market immediacy that cause LSE to lead over MICEX and RTS. The findings of this study are indicative of the notion that liquidity is the major determinant of where the price discovery generally occurs e.g. Baruch et al. (2005). This finding is consistent with studies by Ding et al. (1999), Eun and Sabherwal (2003), Menkveld et al. (2007), Pascual et al. (2005), Grammig et al. (2004, 2005), Phylaktis and Korczak (2007) and Grammig and Peter (2008). Another important finding is that there is a form of cross-border market friction because of the presence of the equilibrium gap between MICEX/RTS and LSE. The question of relative trading volume as a determinant of the price discovery proportion, and the possible effects of information asymmetry factors are examined in the following Chapter 9. It examines the conditional price discovery between London and the leading Moscow market.

This chapter is the only study that investigated the Moscow-London cross-listed equity market relationship for the eight most liquid Russian cross-listed securities; it addresses the issue of cross-border price discovery in the context of the emerging home market (MICEX and RTS) versus the developed foreign market (LSE). The major difference between this chapter and Chapter 7 is that, this chapter deals with equity equivalent ADR securities instead of the locally traded stocks. Furthermore, together with the study of Grammig and Peter (2008), this chapter is one of the few studies that address the issue of price discovery in the context of market microstructure effects. The notion this chapter supports is that the share of foreign market contribution to price discovery may be underestimated, if the sampling frequency is chosen on the higher side of the spectrum or below the five minute sampling. It is crucial to base the inferences on the range of sampling frequencies.

Appendix

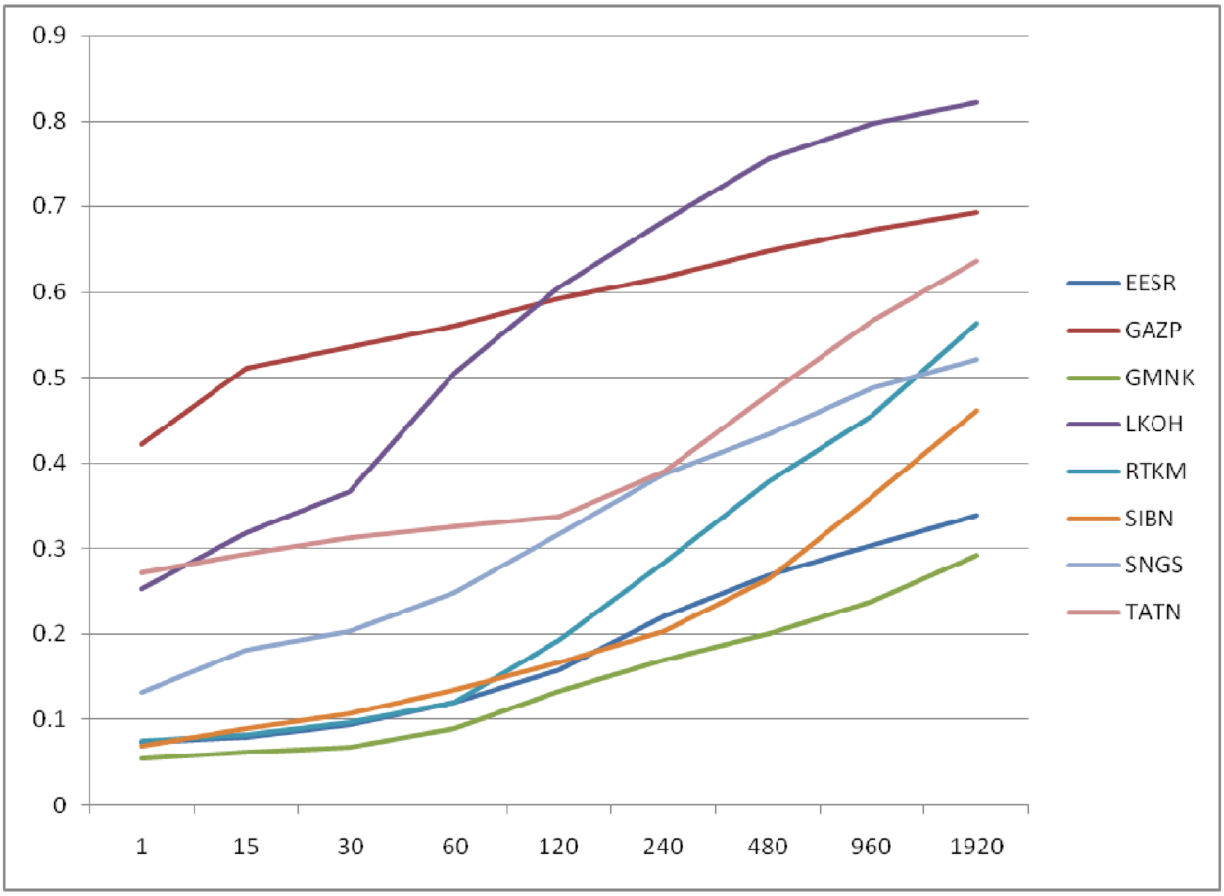

Figure 37 MICEX vs. LSE Contemporaneous Correlations

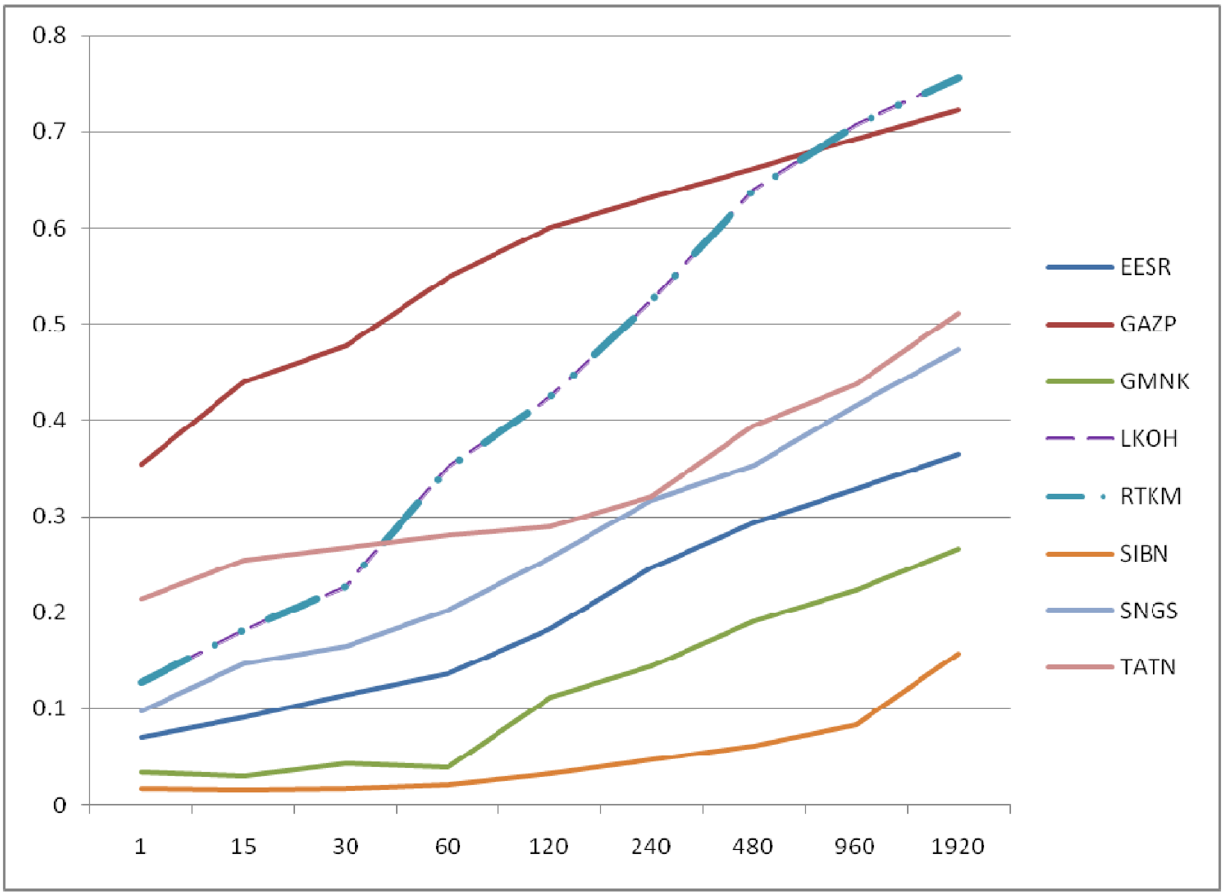

Figure 38 RTS vs. LSE Contemporaneous Correlations

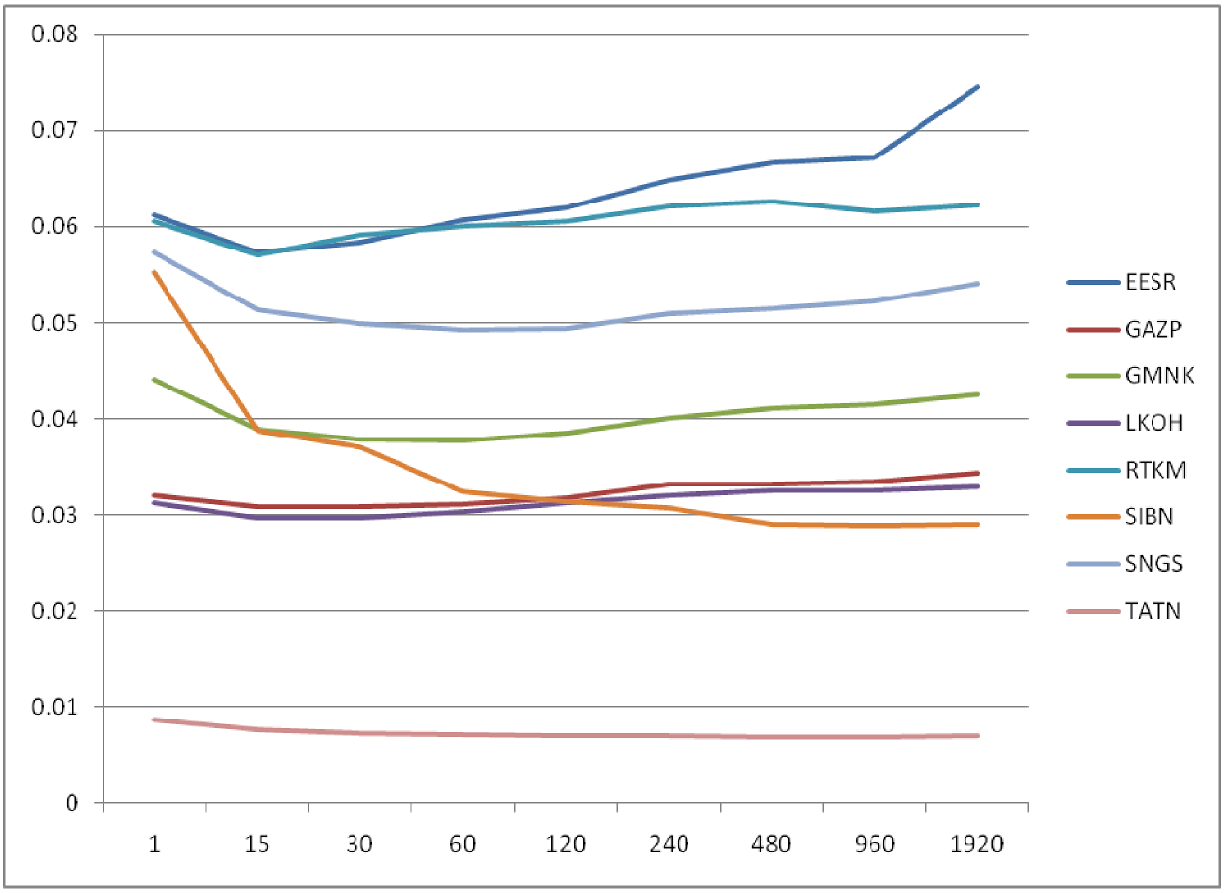

Figure 39 MICEX Realised Variance Estimators

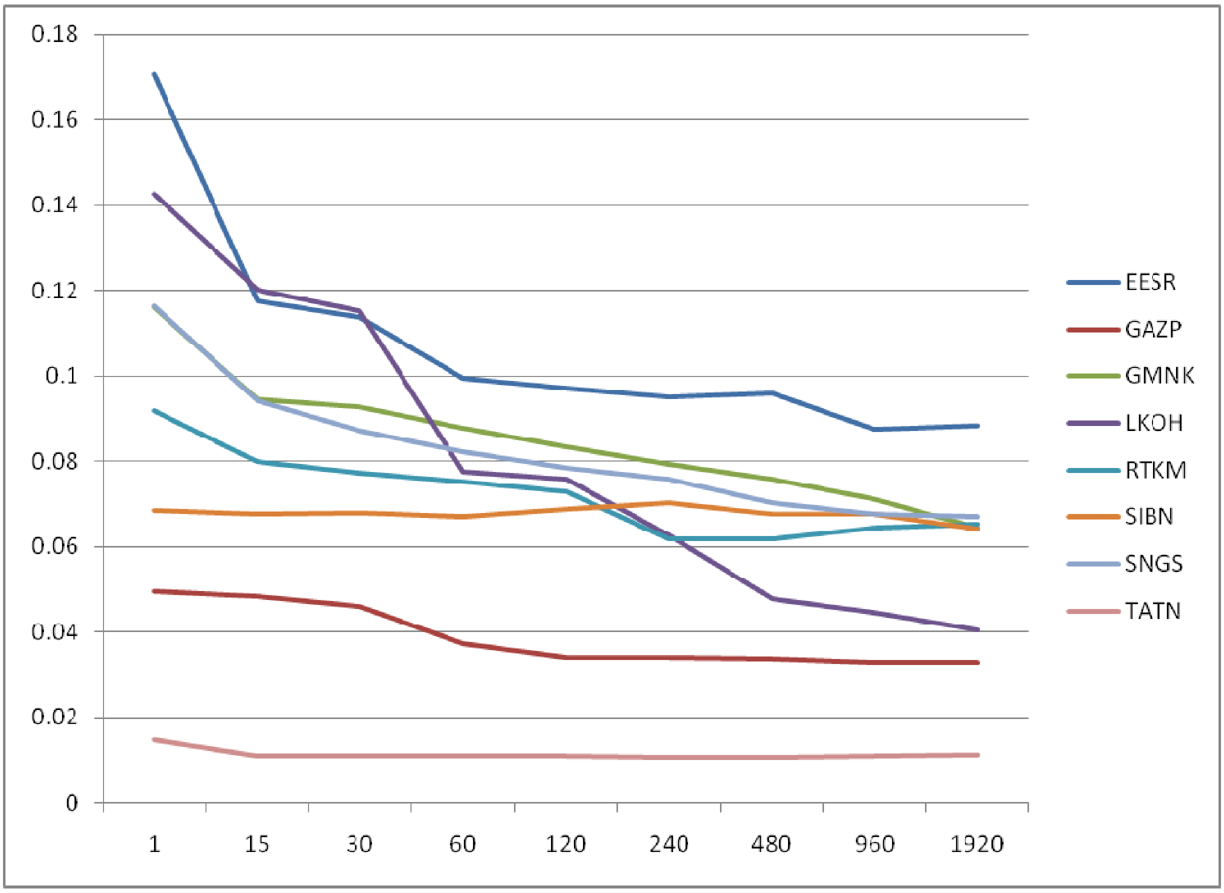

Figure 40 RTS Realised Variance Estimators

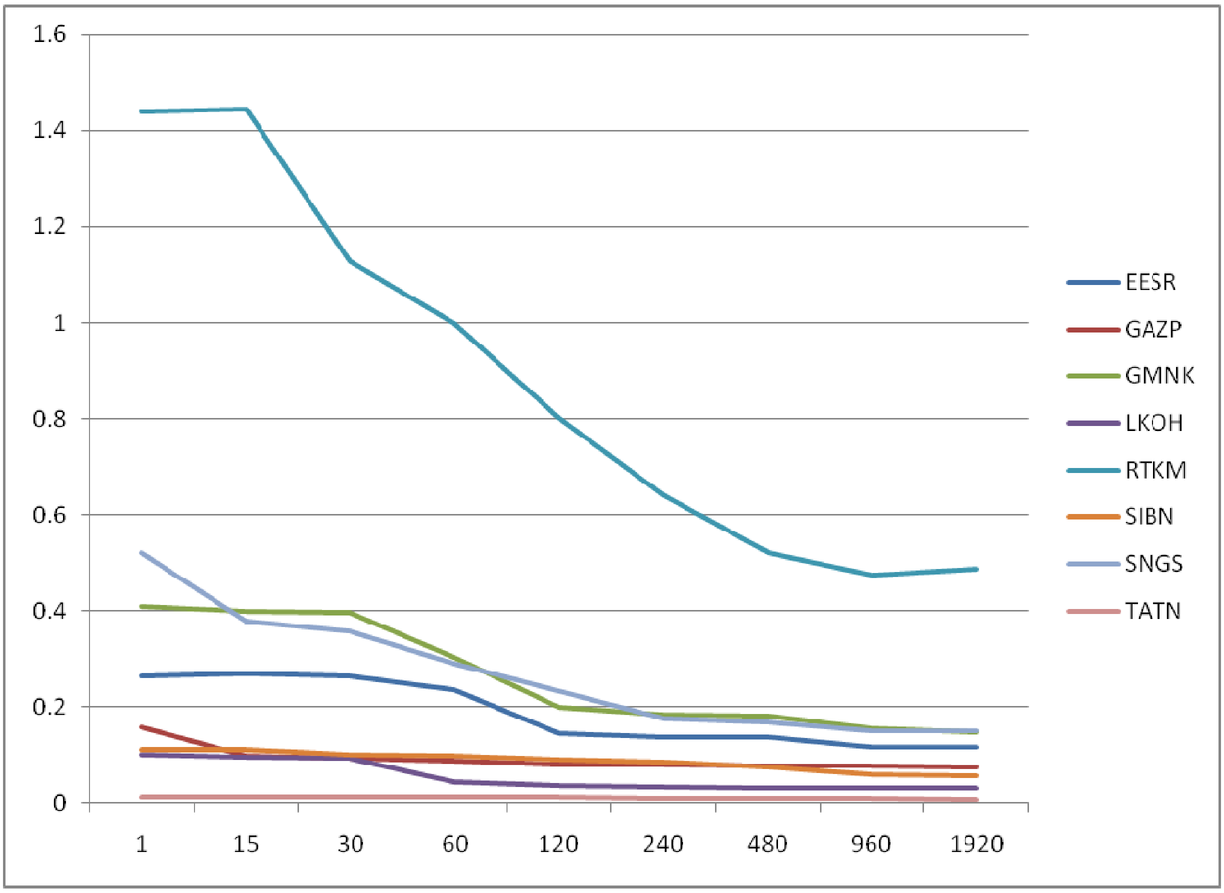

Figure 41 LSE Realised Variance Estimators

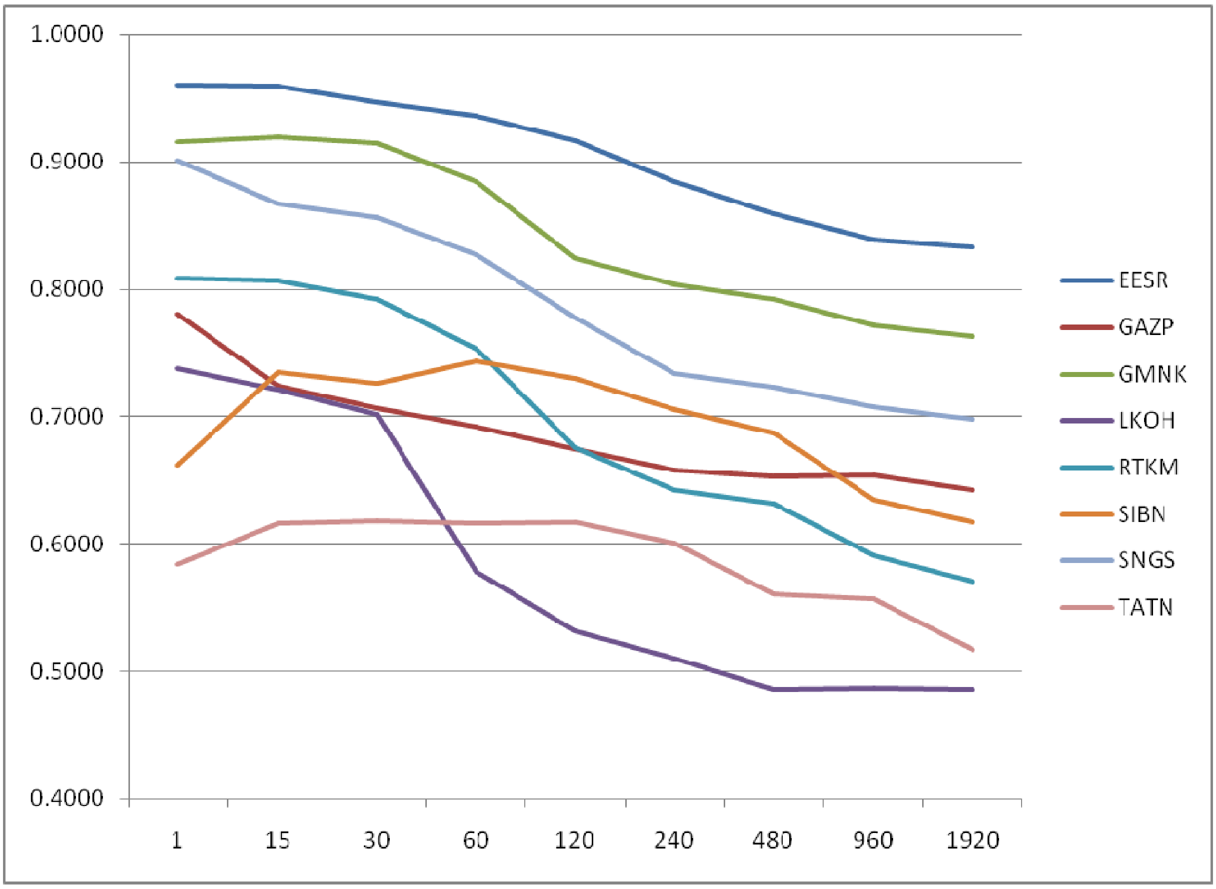

Figure 42 MICEX vs. LSE IS

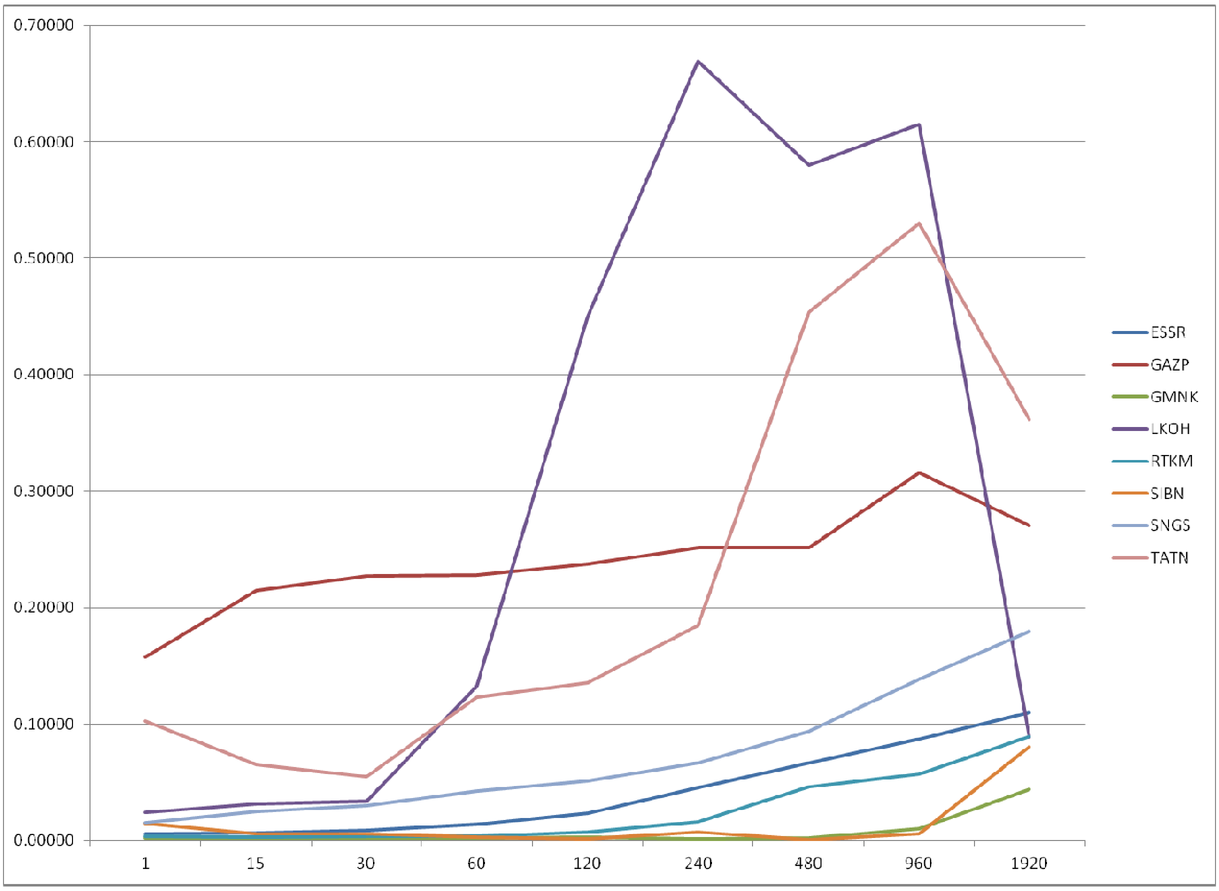

Figure 43 MICEX vs. LSE Hasbrouck Information Share absolute differences of upper-lower bounds

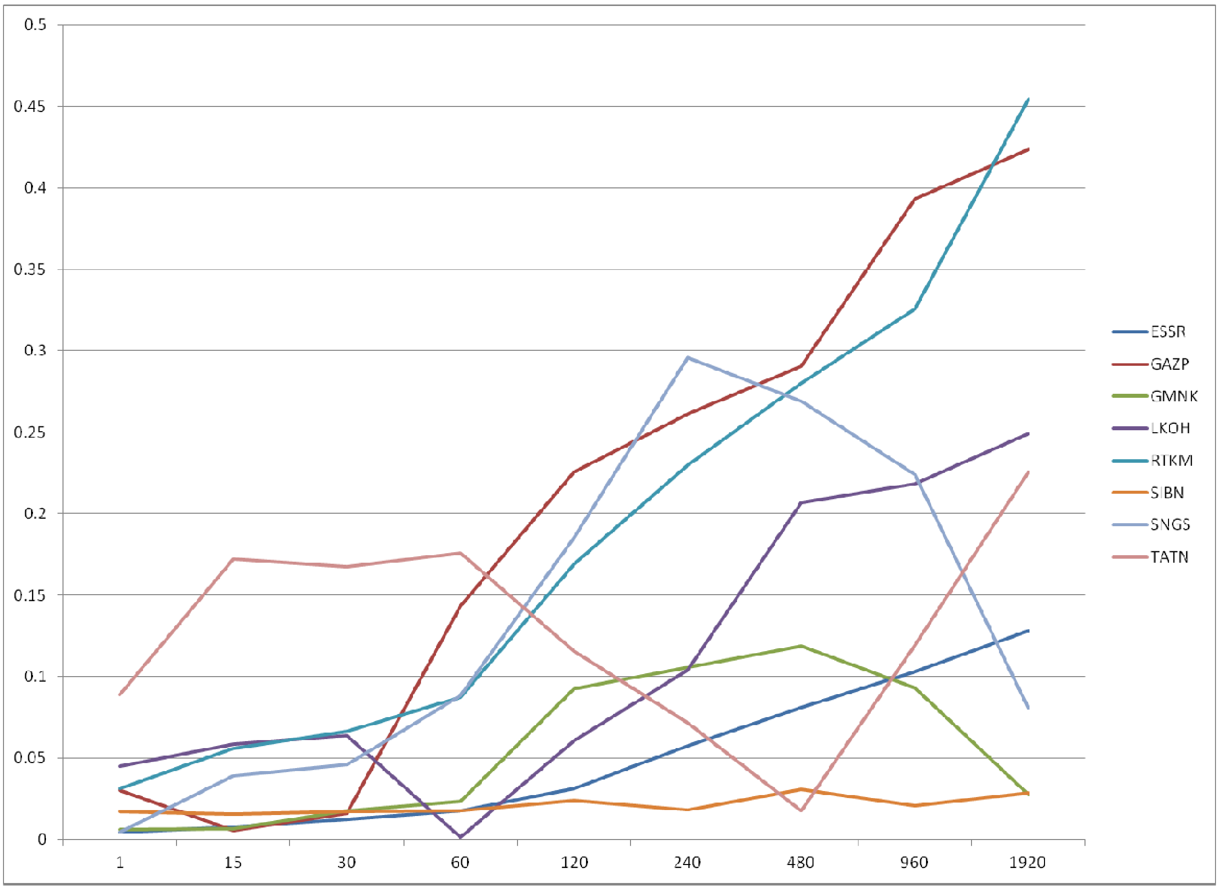

Figure 44 RTS vs. LSE Hasbrouck Information Share absolute differences of upper/lower bounds

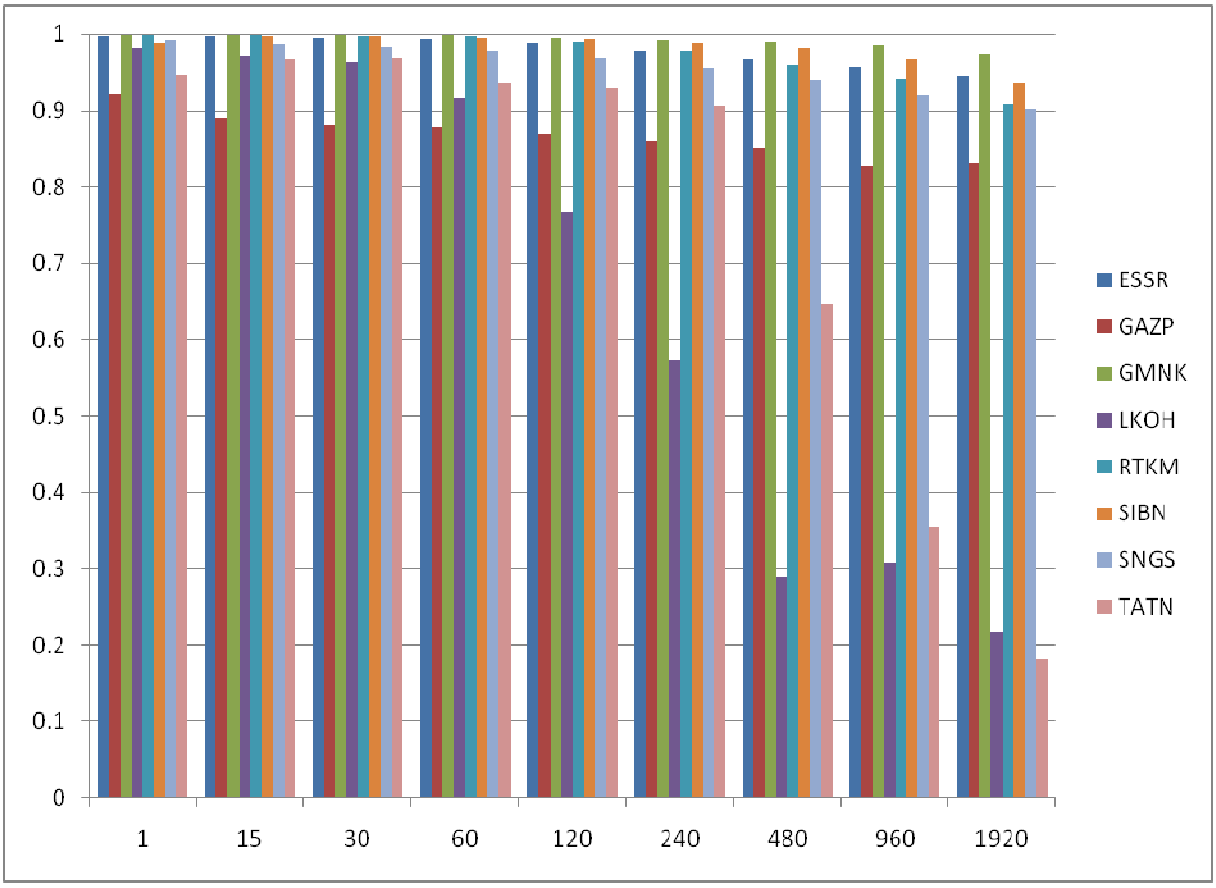

Figure 45 MICEX vs. LSE Mid-point Hasbrouck Information Shares

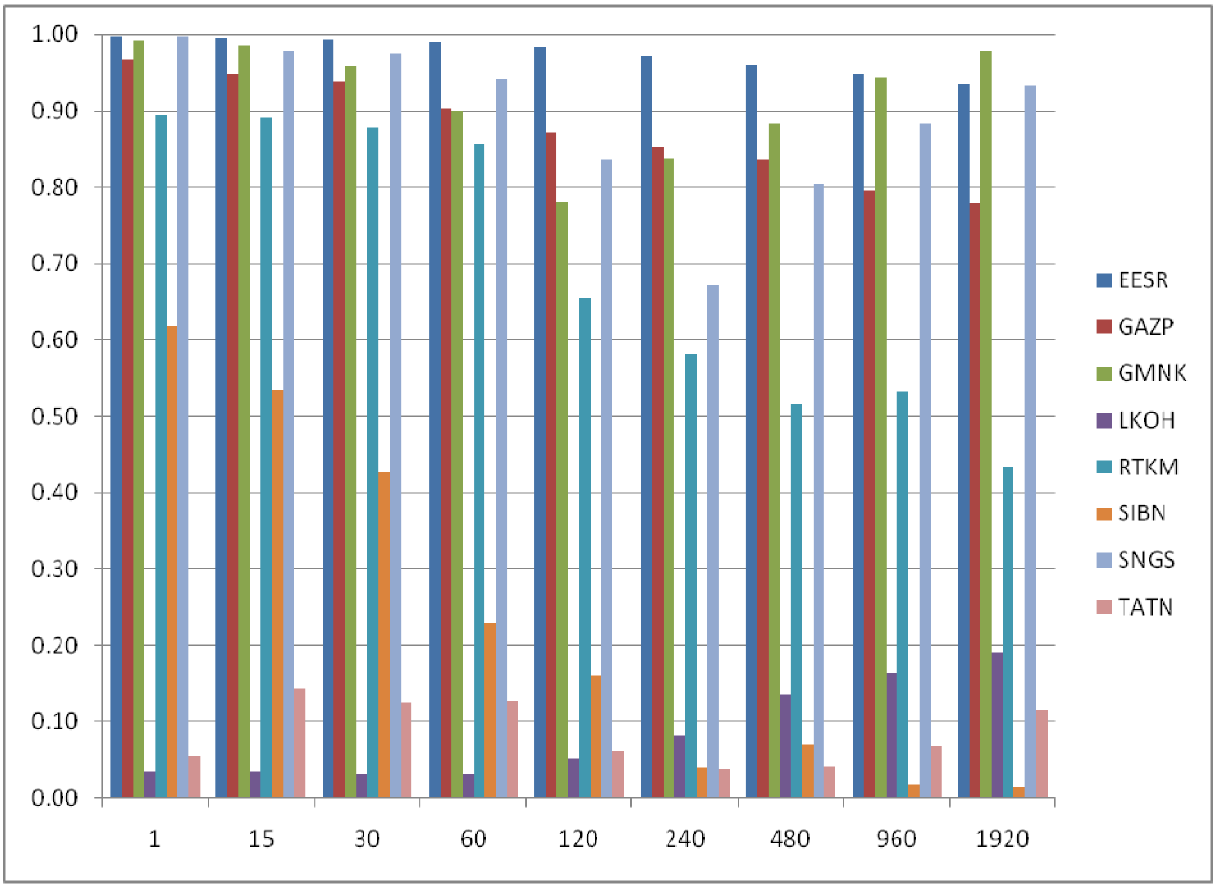

Figure 46 RTS vs. LSE Mid-point Hasbrouck Information Shares

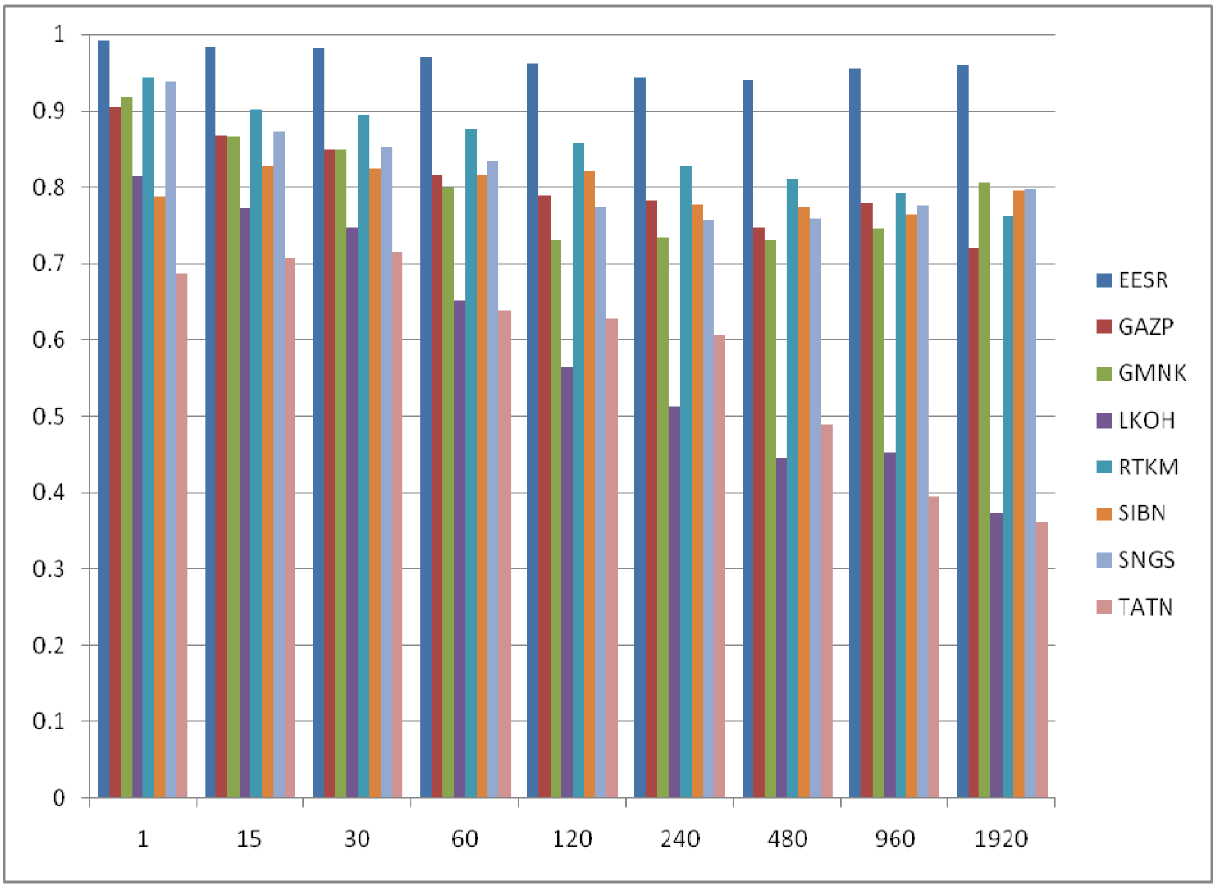

Figure 47 MICEX vs. LSE Gonzalo and Granger PT measures

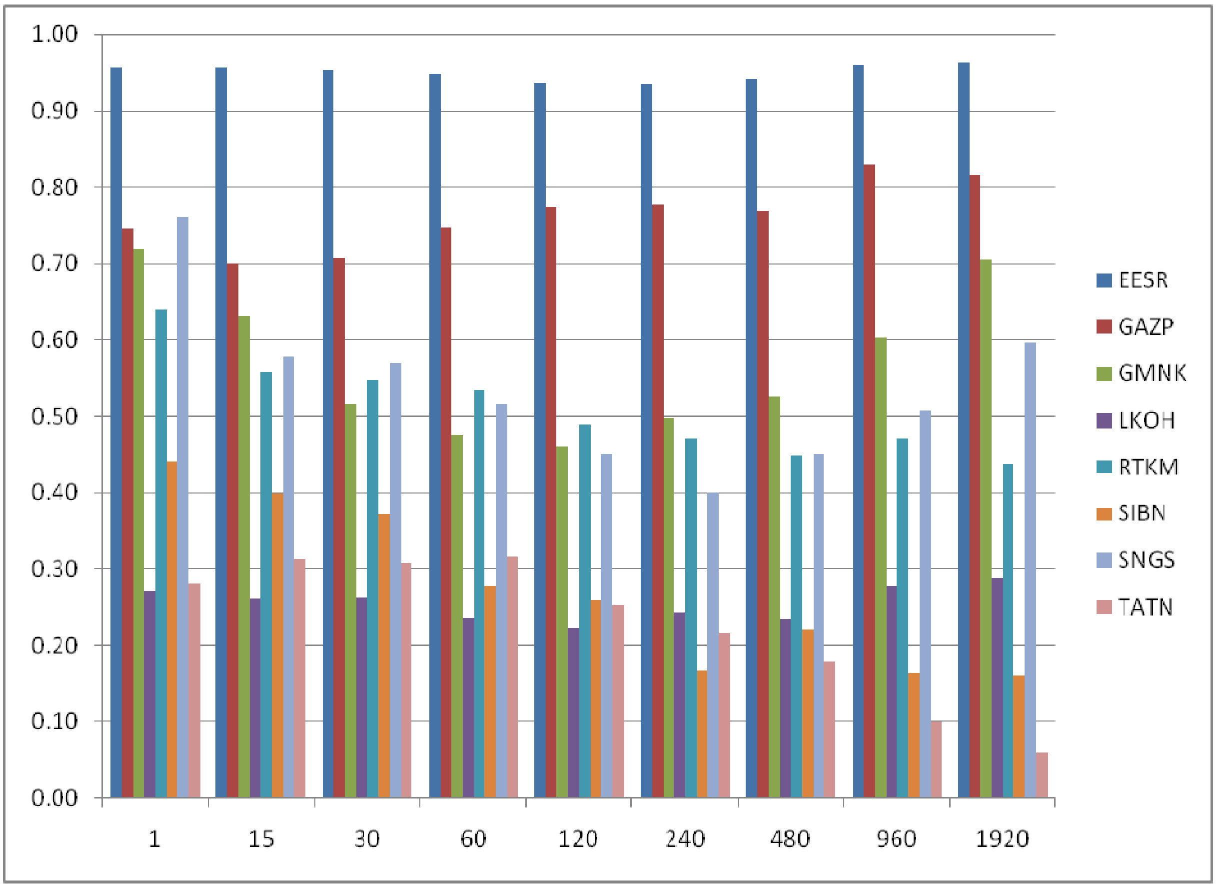

Figure 48 RTS vs. LSE Gonzalo and Granger PT measures

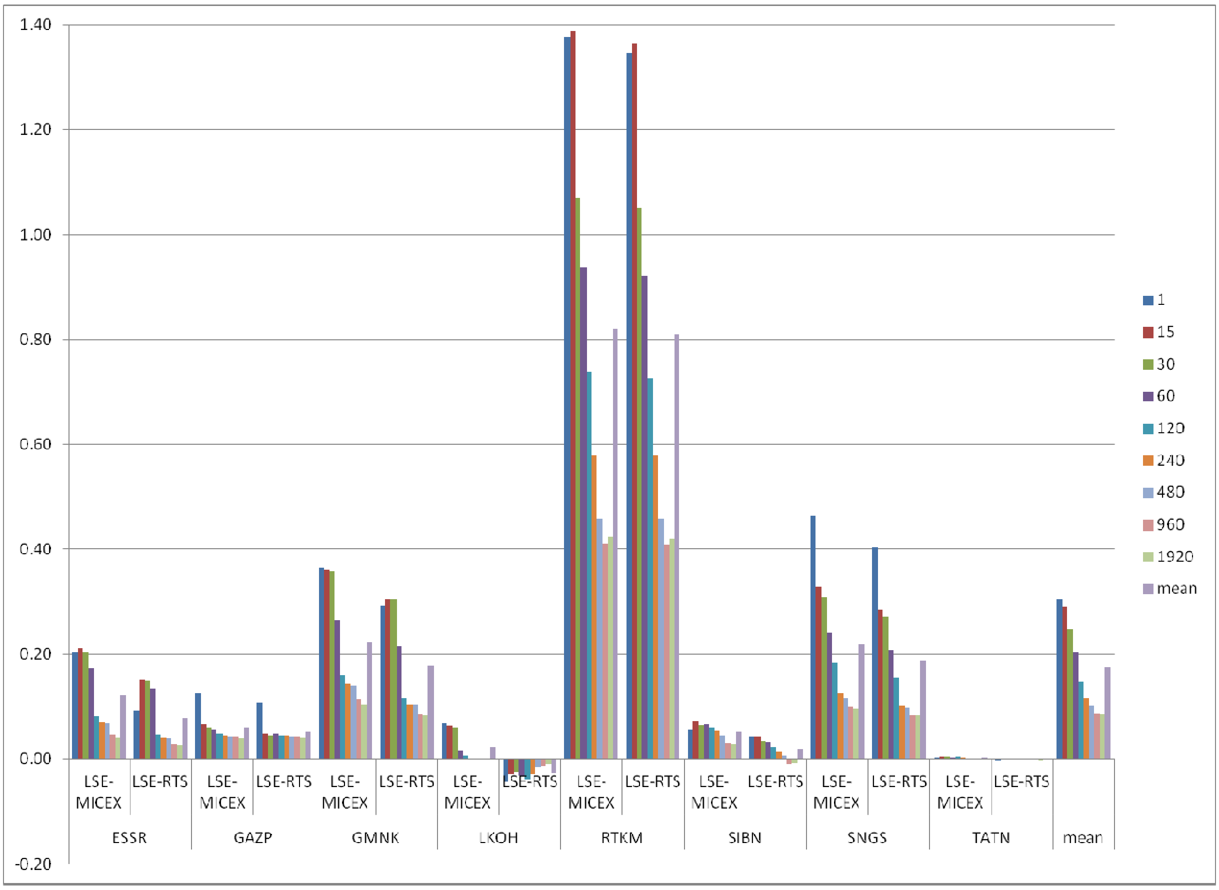

Figure 49 Absolute inter-market differences between RV estimators

Chapter Nine: Conditional Price Discovery between LSE and MICEX

9.1 *Overview*

This chapter analyses the time, trading volume and volatility aspects of international price discovery. Chapters 7 and 8 assume that the contribution of the markets to price discovery is an average constant. However, this assumption may mask more accurate price discovery measurements specifically sensitive to factors such as time, trading volume and volatility. In comparison to Chapters 7 and 8, the main objective of this chapter is to measure the conditional or factor restricted price discovery contribution, as opposed to the unrestricted aggregate average, by relaxing the assumption that the price discovery contribution is an average constant. It is assumed that trading volume and intraday volatility are reflective of the information flow between the markets. The key question addressed in this chapter is: How do time and information flow conditions affect the price discovery relationship between the London and Moscow markets?

The price discovery relationship between the London and Moscow markets is analysed by conditioning the data set upon factors determining information flow. The empirical analysis is based on modification of the data set from Chapter 8. A sample is conditioned by a factor by permuting the variables in a specific order. This is achieved by ordering the main sample by the chosen factor e.g. trading hour, and then dividing the main sample into sub samples, which contain solely the values of the temporal factor e.g. the first half hour of each trading day. The permutation can be organised according to temporal factors such as trading time and trading days, as well as the main trading indicators such as volatility and trading volume. The set of data is conditioned upon factors such as trading time, weekday and potential information asymmetry proxy, such as price volatility or the trading volume. This type of approach is an indirect way of controlling for factors, which allows the standard price discovery methodology to be applied e.g. by use of OLS estimator on Engle and Granger (1987) ECM. Therefore, this method differs from the conventional directly testable parameter based models because the condition factors are not directly controlled for. The main advantage of this approach is that it avoids model misspecifications associated with the interaction of multiple variables (such as trading volume and volatility), allowing an application of a more parsimonious methodology. Overall, the results consistency of this chapter may be regarded as an indirect way of testing the robustness of the results from the previous chapters.

Regardless of the permutation in the data set, the empirical results are in line with Chapter 8: the conditional price discovery contribution of MICEX is superior to the LSE market. The examined proxies of information asymmetry conditions, such as trading volume and intraday relative volatility as well as the sorting in respect to time, have an observable effect on the price discovery relationship between MICEX and LSE, but do not change the relationship substantially. The relative daily trading volume does not seem to affect the price discovery relationship between LSE and MICEX. The effect of trading time manifests itself in an above average unconditional contribution of MICEX for lesser liquid stocks in the first two trading hours and always below average in the consecutive two hours of the six overlapping trading hours. Further findings indicate that the dominance of MICEX increases in times of higher uncertainty or risk (higher level of volatility) and vice versa. The price discovery relationship does not display any meaningful pattern during the trading days of the week, though MICEX may have information flow advantage on Thursdays.

Based on the empirical findings of Chapter 8, there is evidence of a fair degree of cross-border information flow asymmetry between LSE and MICEX. The evidence of information asymmetry is provided by the rejection of the theoretical cointegration vector $\beta^T = (1, -1)'$ (for EESR and GMNK) as presented in Chapter 8. Unlike the inter-Moscow market case, the consequence of the rejection implies that in the cointegrating equilibrium relationship, the pricing spread between MICEX and LSE is not error-corrected on average. In other words, there is the presence of a gap in the equilibrium efficient price between these markets. Following that, there may be a condition of a pronounced presence of inter-market information flow asymmetry. This chapter attempts to address the issue of how price discovery is influenced by factors which are representative of information flow and dissipation between LSE and MICEX markets.

9.2 *Literature Review*

With the tendency of equity markets to become increasingly consolidated and globally integrated, the issue of information asymmetry in international cross-listed equity markets is becoming more important {see Stulz (1999)}. Despite the general agreement on the presence of information asymmetry between cross-border markets, especially in the context of the emerging market, the issue of how information flow is transmitted between markets and how this flow changes over time is still not clear. Harris (2003) states: "How informative prices are depends on the costs of acquiring information and on how much liquidity is available to informed traders. If information is expensive or the market is not liquid, prices will not be very informative". The market location where information is more integrated in price should have greater liquidity than the other market. Harris et al. (2003) suggest a link between liquidity, information, and home bias in international investment. They conclude that domestic investors may be better informed about and better able to monitor local firms than foreign firms.

There is a consensus in theory and in empirical findings in the price discovery literature, that the most order flow active market should have a higher proportion of price discovery. Studies such as Baruch et al. (2005), Eun and Sabherwal (2003), Grammig et al. (2005) and Phylaktis and Korczak (2005), suggest that relative market liquidity determines the price discovery proportions. According to studies of Karolyi (2002) and Harris et al. (2003), order flow intensity reflects the proportion of the information flowing on the markets. This statement could be extended to the notion that the trading activity of an order flow intensive market also results in a larger absolute aggregate trading volume relative to the less active market. When the absolute trading volume is not affected, there are, however, days with higher inter-market trading volume asymmetry. However, is the relative daily trading volume a reflection of the price discovery proportions?

The main motivation for studying the variability of price discovery proportions is the study of Harris et al. (2002a), which employ Gonzalo and Granger (1995) methodology to investigate price discovery for thirty DJIA stocks cross-listed between the NYSE, Chicago and Pacific stock exchanges. Their data set is based on transaction prices sampled at event time rather than clock time for the 1988-1995 period. Harris et al. (2002a) uncover a time-varying and statistically significant price discovery on the US market; the central market, NYSE, was information dominant at the beginning of the sample period. By 1992 the proportion of price discovery attributable to the NYSE had declined, but, by 1995 had substantially recovered. These findings indicate that price discovery proportions are not constant, but can vary substantially over time and there is a need for further research in that area.

Generally, the focus of the cross-listed equity price discovery literature is on unconditional average estimates. Despite the findings of Harris et al. (2002a) that measures of price discovery vary over time, the number of studies on cross-listed equity that specifically restrict their samples in order to evaluate the effect of the temporal restriction is limited. There is evidence that measures of information asymmetry vary over time, particularly in the course of the trading day e.g. Barclay and Hendershott (2003) and around the release of public information e.g. Lei and Wu (2005) and Ting (2006). The number of studies on cross-listed equity which specifically restrict their samples in order to evaluate the effect of the restriction is limited, but, those that do, examine the relationship between other asset types such as foreign currencies {Yan and Zivot (2006)} and futures contracts, for example Martens (1998). Overall, there are only a few studies that explicitly examine the effects of specific weekly trading days or trading hours on price discovery contributions e.g. Taylor (2008), Menkveld et al. (2007) and Barclay and Hendershott (2003).

The temporal aspect of the price discovery process in the S&P 500 and E-mini futures market is examined by Taylor (2008), utilising one minute frequency transaction data. The major findings are that market liquidity and the time around the release of key macroeconomic information are factors of relative price discovery. Price discovery appears to occur in the market for the individual stocks making up the index and in the E-mini futures market. The E-mini futures market becomes the dominant price discovery market only during periods of extreme information asymmetry and liquidity.

Menkveld et al. (2007) study price discovery behaviour continuously in twenty-four hour periods for seven Dutch securities cross-listed on NYSE. Their analysis focuses on a mix of overlapping and non overlapping trading periods. They find that the contribution of NYSE is inferior to the

Amsterdam market. One of the other findings suggests that NYSE market price discovery share under-reacts around the opening times and the Amsterdam exchange under-reacts around the closing times of the overlapping trading time period.

The other study that specifically analyses the temporal aspect of price discovery is Barclay and Hendershott (2003). They examine the effects of trading after hours on the amount and timing of price discovery over the twenty-four hour day period. A high volume of liquidity trade facilitates price discovery. Thus prices are more efficient, and more information is revealed per hour during the trading day than after hours. However, the low trading volume after hours generates significant, albeit inefficient, price discovery. Individual trades contain more information after hours than during the day. Because information asymmetry declines over the day, price changes are larger, reflect more private information, and are less noisy before the opening than after the closing.

An interesting study of temporal effect on price discovery during the eighteenth century is offered by Bell et al. (2011). From a historical perspective, they investigate how quickly news is absorbed in prices for the two English companies, the East India Company and the Bank of England. These companies were cross-listed between London and the Amsterdam stock exchange. The news between the cities was mainly transmitted by mail by boat. Bell et al. (2011) examine the historical context surrounding the defining events of the period and compute the time-varying information shares. They find that the contribution to price discovery was significant for both markets. Although the London market information share declined steadily over time, the contribution of the London market was significantly more important for both stocks.

Generally, the price discovery and information flow measuring models, reviewed in the methodology chapter, do not address the role of trading volume, volatility or time in the price formation relationship across the prices of various markets or between different securities. However, there is a strand of market microstructure literature that offers models attempting to control for trading volume and volatility factors. The size of a trade is assumed to be constant in the studies such as Glosten and Milgrom (1985) and Copeland and Galai (1983). In the Kyle

(1985) model, order size is always adjusted by the informed trader, in such a way that trade size does not affect adjustments in price in order to maintain a constant fraction of a trade. Schwert (1989) reveals that a factor explaining variability in market volatility is the variability in trading activity study. Trading volume playing a supporting role in the process of price adjustment is viewed in various theoretical works. Glosten and Milgrom (1985), extended by Easley and O'Hara (1987), consider the price formation of small versus large trades. Price discovery contribution by price and volume is analysed by Blume et al. (1994), whose model embodies an information event, with two dimensions: trade size, indicating the quality of that information and the effect of the observed price series, indicating the direction of an information effect.

However, the econometric models employed by the early empirical literature such as Schwert (1989) may suffer from model misspecification problems, as indicated for instance by Kyriacou and Sarno (1999), because the models employed contain independently or simultaneously determined variables. Furthermore, the early empirical literature, which investigates the relationship between market volatility and trading volume in the context of structural VAR, tends to fail to account for simultaneous interactions between trading activity variables. Therefore these models should be interpreted with caution because of the increased risk of model misspecification e.g. serial correlation.

There is a lack of research that explains the variation of price discovery contributions caused by conditional trading volume and volatility. The most relevant studies on the effect of trading volume and volatility is Martens (1998) and Ates and Wang (2005). The study of Martens (1998) investigates the effect of trading volume and volatility on the price discovery relationship of Bund futures contracts between the London International Financial Futures Exchange (LIFFE) and the Deutsche Terminboerse (DTB). He finds that in volatile periods, the share in trading volume of LIFFE decreases while the information share in the price discovery process increases. However, in relatively low volatility periods, DTB has the higher information share, but with a smaller share of trading volume. The findings of Martens (1998) point out that higher volatility leads to the larger trading volume market (LIFFE) having a higher share of price discovery.

Ates and Wang (2005) study the relative liquidity, price volatility and price discovery relationship between floor-based and electronic-based trading systems in the Japanese Yen, British Pound, and Euro foreign exchange futures markets traded on the Chicago Mercantile Exchange (CME). Ates and Wang (2005) employ intraday data based on transaction prices in their analysis. They find that both trading systems contribute to the price discovery process. However, for the entire sample period, automated trading dominated price discovery in the Euro foreign exchange futures market. Liquidity, which is measured by bid-ask spreads, is higher in the automated trading system, before and after controlling for variables such as price volatility and trading volume. The findings do not support the hypothesis suggested by Martens (1998), that the contribution to information shares by electronic trading systems is higher in low volatility periods and lower in high volatility periods. However, the results of their analysis support the hypothesis that relative liquidity and operational efficiency jointly influence the proportions of contribution in the price discovery process over time. Their findings are also supportive of the notion that price discovery proportions are not constant over time. At the beginning of the sample period, floor-based trading typically contributed more to price discovery in the Japanese Yen and British Pound markets. However, in the latter part of the sample period, screen trading took the dominant role and contributed more to price discovery in these same markets.

Like the studies mentioned in the literature review of Chapter 2, (Liquidity and Volatility Section 2.3), the following studies were an element in the motivation for this research even though they were supportive of, but not directly related to, conditional price discovery: The dynamic causal relationship between stock market returns, trading volume and volatility is investigated by Lee and Rui (2002). They find that there is a positive feedback effect between volatility and trading volume. At the same time, the trading volume does not help predict the level of returns. This finding suggests that information contained in returns is reflected by the trading volume indirectly, which may be predictable by volatility of returns. If this is the case, trading volume may be used as a proxy for information flow in the stochastic process generating volatility. In extended work on simultaneous volatility models, Chung and Gannon (2003) document significant trading volume and volatility transmission effects between index and index futures.

The study of Baruch et al. (2005) offers empirical support for the trading volume of cross-listed firms to be concentrated in the market with the highest correlation of cross-listed asset returns with other asset returns in that market. It could be expected that the liquidity of each market is a major factor in determining the location of price discovery as well as trading volume. Trading volume is proportionally higher on the exchange in which the cross-listed asset returns have greater correlation with returns of other assets traded on that market.

Pascual and Pascual-Fuster (2010) provide robust evidence of asymmetries in the daily contribution, made by ask and bid quotes, to the price discovery relationship between SSE and the NYSE. Asymmetric contributions are not the exception, but the rule. They are more common among small-caps, during days of relatively thin trading and higher exposure to risk, and during the overlapping trading period between the SSE and the NYSE. The ask- (bid-) quote leads price discovery in days with a substantial excess of buying (selling) initiated trading.

According to the findings in the reviewed literature in the General Literature Review Chapter 2, (Section 2.3, Liquidity and Volatility), trading volume and volatility seem to be correlated trading variables. Both variables can be connected by a mixture of distributions hypothesis (MDH), which stipulates that price volatility and trading volume are both subordinated to the same information arrival rate. The empirical price discovery literature seems to establish a link between trading volume and intraday volatility (incremental price changes or returns), but a few studies such as Martens (1998) and Taylor (2008), examine the direct effect of trading volume and volatility on the price discovery process.

Overall, there is a limited amount of literature focusing on the conditional effect of time and liquidity on price discovery. The other strand of conditional price discovery literature seems to focus on the effect of news announcements on price discovery. The use of intraday data is usually found only in recent studies. The number of studies, which adopt the indirect approach of measuring the effect of volatility and trading volume on price discovery proportions, is limited, and two of them Marten (1998) and Ates and Wang (2005) have seemingly contradictory findings on the effect of volatility. Finally, there are few conditional price discovery studies that focus on the cross-listed equity market with respect to trading volume and volatility conditions and the temporal aspect of price discovery, however, is still an under researched sub area.

The key question addressed in this chapter is:

- How does the price discovery relationship between London and Moscow behave conditioned upon time, trading volume and volatility variables?

The following null hypotheses have been established and are tested in this chapter by conditioning the data samples according to time, volume and volatility factors:

1. H_0: Daily relative trading volume conditions have an effect on the price discovery relationship between LSE and MICEX
2. H_0: Intraday relative volatility conditions have an effect on the price discovery relationship between LSE and MICEX
3. H_0: Trading hours restriction has an effect on the price discovery relationship between LSE and MICEX
4. H_0: Trading days restriction has an effect on the price discovery relationship between LSE and MICEX

9.3 *Sample Type and Sampling Frequency*

Unlike Chapter 8, the empirical analysis of this chapter is based solely on trades based samples with a fixed 300s sampling frequency. Although previous chapter findings are based on the quotes sample, the trades sample results were analysed, but not explicitly discussed because of the similarity in the findings. The rationale behind this chapter is to examine the effects of time, trading volume and volatility based on Chapter 8 trades data. However, the conditional price discovery findings are better understood when directly related to the unconditional results. So, in a way, the analysis of the conditioned and unconditioned samples is an indirect robustness test of the previous chapter, but does not deal with the sampling frequency issue in depth.

A five minute sampling frequency choice may not be ideal. It is a compromise between the maximum observation available and theoretical multi-market optimum. The other underlying compromise is a trade-off between data information censorship in lower sampling frequencies, as against the information invention caused by interpolation, which is specifically an issue in the case of trades data. The reasons 300s sampling has been chosen depend on certain factors. The optimal sampling frequency between multiple markets is ambiguous, because of the structural differences of the underlying exchanges e.g. trading frequency, trading rules, instrument liquidity etc. These factors potentially contribute to the differences in trading activity in each market. There is no guidance provided in either the conditional or unconditional price discovery literature on optimal inter-market sampling choice. At the same time, there is a need for the highest number of observations possible, the reasons for which are outlined below. The overview of observation in each sample is provided by Table 55. The only guideline is the RV estimator analysis of the previous chapter and the recommendation of five minute sampling based on RV stability found in the literature of, amongst others, Anderson et al. (2001).

Considering the optimum sampling results from Chapter 8, one would be tempted to use these sampling frequency optima in this chapter. Firstly, however, these optimum sampling range results were based on non interpolated quotes based data and secondly, there is a large asymmetry in the trading frequency and liquidity structure between LSE and MICEX. The trading on LSE is far less immediate (frequent) and has less breadth than on MICEX, partly resulting in rather larger than fifteen minute differences in the sampling frequency optimum in some cases. Finally, given MICEX is the most active market and LSE at times the most inactive, it is inconclusive which sampling frequency is jointly optimal.

The differences in inter-market liquidity expressed in total shares exchanged between MICEX and LSE are substantial. In order to eliminate the price factor effect of trading volume product, only the traded volume (size) is chosen as the conditioning factor. Table 53 depicts the relative total daily trading size ratios between MICEX and LSE. For instance, in the case of lesser liquid SNGS security, the total daily ratio of securities exchanged between MICEX and LSE is over two hundred times. This implies that, on a daily average, MICEX market liquidity based on SNGS shares is over two hundred times larger, relative to LSE. The statement is true, even for the most liquid stock such as LKOH, but total MICEX daily trading is just over twice the size on average, because of two days which can be classified as outliers. Overall, as presented in Chapter 3, by Table 4, the total trading volume of MICEX is unsurpassed, if all eight Russian securities traded on LSE IOB are taken into account.

	Average Size Ratio	ADR Ratio	Total Ratio	Size Correlation
EESR	530.2	100	5.3	0.79
GAZP	120.8	4	30.2	0.65
GMNK	10.0	1	10.0	0.61
LKOH	2.4	1	2.4	0.43
RTKM	260.3	6	43.4	0.41
SIBN	6.3	5	1.3	0.40
SNGS	250.9	50	5.0	0.34
TATN	125.7	20	6.3	0.30
mean	163.3		13.0	0.49

The table presents the average daily trading size ratio and the correlation of average trading sizes between MICEX and LSE for all securities.

Table 53 Trading Quantity (Size) Ratio of LSE to MICEX

The data set sorting procedure is described in detail in the following sample partitioning methodology section. Generally, the data sample is partitioned by truncating the data set into smaller sub-samples. Sample partitioning implies that individual sub-samples only contain a fraction of total sample observations. The sample size is crucial, because the number of observations in some restricted sub-samples becomes increasingly limited by the research sorting criteria and the factor availability in the data. Choosing sampling above 960s for example, would have left the total sub-sample size below an acceptable minimum. For instance, in Table 55, this issue is illustrated for HL regime sub-samples for the 33/66 percentile threshold for EESR, LKOH, RTKM and SNGS, where the number of effective day observations is already below five.

9.4 *Sample Partitioning Methodology*

Trading Volume

The analysis is performed based on selective sorting of the data sample according to a chosen factor. Once the sample is sorted, or in other words conditioned, upon a chosen factor, standard econometric methodology is applied. In order to test the hypothesis of trading volume and its effect on the price discovery relationship, the original 300 second sample is grouped into four truncated sub-samples which contain inter-market relative low and high trading volume sorted price-time series. Each sub-sample then directly represents a factor based condition. By applying a model on that conditioned sub-sample, one can observe the effect of the given factor. The differentiation between high and low trading volume is based on the aggregate trading size of the day. The trading regime has been defined as high, if the daily trading size is above the threshold point, and as low if below. The difference between the low and high trading volume day is dependent on the threshold point between high and low, which is defined in the next paragraph.

Analysis of the trading volume distribution suggests a median as the initial threshold point, because it offers maximum observations for each trading regime sub-sample. Trading size distribution has the tendency to be normal, but the skewness is mostly positive for all securities. Mean, median and 33th/66th percentile threshold options were considered, but each of them is merely a compromise because the number of observations is traded off for a better sub-sample representation. Given that there are two trading venues in question, the partitioning results were grouped into four trading regime permutations: information symmetrical MICEXhi/LSEhi (HH), MICEXlo/LSElo (LL) and asymmetrical MICEXhi/LSElo (HL), MICEXlo/LSEhi (LH).

The trading regimes have been defined as:

$$
\begin{aligned}
&HH \Leftrightarrow S_{LSE} \wedge S_{MICEX} \geq T_M \\
&HL \Leftrightarrow S_{MICEX} \geq T_M \wedge S_{LSE} \leq T_M \\
&LH \Leftrightarrow S_{MICEX} \leq T_M \wedge S_{LSE} \geq T_M \\
&LL \Leftrightarrow S_{LSE} \wedge S_{MICEX} \leq T_M
\end{aligned}
$$

Where S stands for the daily quantity of securities exchanged (size) and T is the threshold point.

The trading size correlation proved to be a decisive factor in determining the number of trading days contained in each regime, reported in Table 54. If the trading size correlation is relatively high, then the number of days in the symmetrical regimes would outweigh the asymmetric ones. The average cross market trading size correlation is 0.49, meaning that there is a substantial information asymmetry between MICEX and LSE. The correlation of the GAZP, RTKM and SNGS trading volume is above the average, where GAZP has 0.79, the highest correlation. Consequently, there is a minimum number of days available in the sub-samples for the asymmetry HL/LH regimes. On the other hand, SIBN and GMNK, are better examples of asymmetry regimes, because their correlations are 0.29 and 0.33 respectively.

GAZP	RTKM	SNGS	EESR	LKOH	TATN	GMNK	SIBN	mean
0.79	0.65	0.61	0.43	0.41	0.40	0.34	0.30	0.49

The table shows the average daily trading volume correlations between MICEX and LSE

Table 54 Daily Trading Volume Correlations between MICEX and LSE

	threshold	HH	HL	LH	LL	Total
EESR	median	29	8	9	29	75
	33/66	16	1	4	15	36
GAZP	median	23	10	9	23	65
	33/66	15	5	3	12	35
GMNK	median	23	15	15	23	76
	33/66	12	6	6	16	40
LKOH	median	25	12	12	26	75
	33/66	15	3	4	15	37
RTKM	median	29	9	9	29	76
	33/66	17	3	3	13	36
SIBN	median	24	13	14	24	75
	33/66	12	5	4	12	33
SNGS	median	25	13	13	25	76
	33/66	16	2	3	14	35
TATN	median	7	7	7	8	29
	33/66	15	6	6	4	31

The table presents the number of trading days contained in each trading regime group (MICEXhi/LSEhi (HH), MICEXlo/LSElo (LL) and MICEXhi/LSElo (HL), MICEXlo/LSEhi (LH)) depending on the chosen threshold point.

Table 55 Trading volume samples of available trading days

In the proposed research method, it is assumed that the cumulative daily trading volume of a market reflects the relative informational contribution captured by that market. However, the reverse of this causality relationship, if any, may also be true. In that the measured daily price discovery contribution of a market reflects the amount of daily trading volume that this market facilitated. The day's cumulative trading result at the end of that trading day is not necessarily pre-determined. Following that, the results of daily trading volume and the measured price discovery contributions can be considered as endogenous variables. If this is the case, then the issue of endogeneity arises in this particular relationship. The endogeneity issue between the daily trading size groups and their contribution to price discovery measures arises because of the contemporaneous feedback between these variables. Contemporaneous feedback causes problems associated with serial correlation when estimating parameters for example via the OLS estimation method. Since the methodology utilised in this chapter does not explicitly control for the variable of daily trading volume, the problem of serial correlation may implicitly bias the choice of trading days, and may, therefore, bias the inferences and may contribute to the inconsistency of estimated parameters. In order to prevent this contemporaneous feedback between the endogenous variables from occurring, the daily trading size group variable could be instrumented to be a group of days with the trading sizes of previous trading days. This approach has been adopted in the analysis.

Relative Volatility

Another objective of this chapter is to measure price discovery conditioned upon a different degree of estimated intraday volatility conditions relative to MICEX market pricing activity. Proxy for volatility for each intraday period has been defined as a log return squared over each sampling interval n of the MICEX market, similar to the realised variance (RV) estimator without the summation.

$$V_n^{MICEX} = \left[\log(r_n^{MICEX})\right]^2 \qquad (56)$$

Since cross-market daily volatility estimates are highly correlated, it would make no sense to condition the samples accordingly. The intraday period variations are, however, almost uncorrelated. Therefore, each subsequent intraday squared return was calculated in order to measure the degree of pricing variation. Then, all sample periods were grouped according to the magnitude of each period return squared into four inter quartile ranges Hi, MedHi, MedLo and Lo, relative to the volatility of the MICEX market. In order to avoid the permuted sub-samples resulting in complete alienation from the original, each group was chronologically reordered in the final stage. Finally, each grouped sub-sample contains isolated observations according to the intraday MICEX return variance criterion, but follows the original time series evolution.

There are alternative proxies for volatility estimation, such as the high-low estimator and standard deviation. However, both High/Low and standard deviation volatility estimators rely on the assumption that the returns are normally distributed with conditional volatility σt. That assumption may hold with daily return, but does not hold with intraday returns. Anderson et al. (2001) stipulate that the distributions of the realised daily variances are highly non-normal, but the logarithms of the realised variances are approximately normal. The proposed methodology is similar to that of Martens (1998), who employs standard deviation as a proxy of intraday return volatility. However, this chapter uses a RV estimator derived definition of volatility.

Trading Time

In order to measure the effects of trading hours and trading days, the trades sample has been restricted into sub-samples according to certain criteria. Initially, the total six overlapping trading hours of each day, were truncated into three two hour sub-samples on a day by day basis. Since the first two trading hour results appeared to be the most promising, they were additionally first subdivided into one hour periods, and later into half hour periods, in order to examine the robustness of the results.

The sample conditioning procedure for trading days was performed in a similar fashion. However instead of truncating the total sample on an hourly basis, the sample was split into weekday sub-samples consisting only of Mondays, Tuesdays, Wednesdays Thursdays and

Fridays. Trading hours and days were simply isolated from the unconditioned sample by deleting the values that were not required. In the sample period, London had more trading days than Moscow, because the latter had more public holidays. The samples contain all trading days except the public holidays. They were excluded from all samples.

9.5 *Empirical Results*

Regardless of how the data is restricted, conditioned or permuted, the results are stable and consistent with the findings of Chapters 7 and 8 that the MICEX market is the leading price discoverer. Surprisingly, the relative daily trading volume seems to have no significant impact on the price discovery relationship relative to the unconditional relationship. In contrast to trading volume results, relative volatility has a positive correlation with the price discovery contribution of MICEX, relative to the unconditional relationship. Besides the trading process itself, time has a varying effect on price discovery proportions. There seems to be a price discovery pattern during the overlapping trading hours; the first and the last two trading hours are more pronounced on the MICEX market than the intermediate two trading hours; the first two trading hours are positively associated with the MICEX contribution for relatively lesser liquid securities. The effect of weekdays revealed a mixed result, but Thursdays may have an above average effect on the MICEX price discovery contribution. Yet, overall, none of the above findings undermine the leading price discovery position of MICEX.

9.5.1 **Unconditional Price Discovery based on Trades**

Unlike the underlying VECM models in Chapter 8, the GG PT contribution measures of this chapter are based on simplified unconditional ECM Engle and Granger (1987) models (Equations 31 and 32). However, the price discovery proportions between LSE and MICEX based on ECM models remain stable with a presence of negligible differences compared to VECM models. The comparison of GG price discovery contribution measures between these two model types is shown in Table 57. The mean GG contribution of ECM based models is 91%, which is close to 92% of the VECM based models in Chapter 8. The findings based on unconditioned data of this chapter are in line with the overall average results of Chapter 8.

frequency (s)	1	15	30	60	120	240	300	480	960	1920	mean
EESR	0.97	0.98	0.98	0.98	0.98	0.99	0.97	0.93	0.93	0.88	0.96
GAZP	0.98	0.95	0.94	0.94	0.90	0.81	0.80	0.75	0.70	0.58	0.84
GMNK	0.97	0.97	0.98	0.98	0.98	0.99	0.99	1.00	1.00	1.00	0.98
LKOH	0.99	0.99	1.00	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00
RTKM	0.84	0.86	0.87	0.87	0.88	0.88	0.87	0.89	0.85	0.87	0.87
SIBN	0.97	0.97	0.98	0.98	0.98	0.73	0.77	0.76	0.85	0.82	0.88
SNGS	0.95	0.95	0.95	0.95	0.95	0.96	0.93	0.97	0.97	0.96	0.96
TATN	0.75	0.75	0.75	0.75	0.75	0.93	0.94	0.96	0.99	1.01	0.86
mean	0.93	0.93	0.93	0.93	0.93	0.91	0.91	0.91	0.91	0.89	0.92

The table summarises the unconditional Gonzalo and Granger measures of MICEX market from Equation 37, as a function of sampling frequency, for all cross-listed securities based on trades samples.

Table 56 MICEX Gonzalo and Granger method for Unconditional Price Discovery based on Trades

The GG permanent-transitory measures from Chapter 8 of unconditional five minute interval sampled transaction time series indicate a GG 92% average contribution to price discovery on the MICEX exchange. The results are presented in Table 56. There is far less cross-sectional and contemporal variation across the GG contribution estimates compared to the quotes based data examined in Chapter 8. The MICEX price discovery contribution average constitutes close to 100% for three stocks EESR, GMNK and LKOH. GAZP, RTKM, SNGS and TATN display a close to or above 90% share, measured by GG. Only SIBN has a slightly below 80% MICEX share.

	EESR	GAZP	GMNK	LKOH	RTKM	SIBN	SNGS	TATN	mean
VECM 300	0.97	0.80	0.99	1.00	0.87	0.77	0.93	0.94	0.91
ECM 300	0.99	0.81	0.99	1.00	0.87	0.77	0.97	0.94	0.92

The table presents a comparison of unconditional the Gonzalo and Granger measures of MICEX market from VECM (Equation 37) and ECM (Equation 25), sampled at 300s sampling frequency, for all cross-listed securities based on trades samples.

Table 57 Comparison between Gonzalo-Granger methods based on Unconditional VECM vs. ECM models

9.5.2 Price Discovery by Trading Volume (Size)

Contrary to expectations, the relative daily trading volume results are rather inconclusive. On the one hand, the daily trading size does not seem to affect the price discovery relationship between LSE and MICEX. This finding is different from Taylor's (2008) finding that one market becomes dominant only in extreme liquidity and information asymmetry. The potentially conflicting finding can be explained by the absolute trading volume of MICEX, which for almost all securities is usually mostly above LSE trading volume, thus the major contribution MICEX to price discovery is never undermined. Consequently, the relationship between these exchanges is relatively similar to the one in the findings of the previous chapter, which points out that MICEX is the undisputed leader in price discovery for all Russian cross-listed securities. That finding is consistent with the findings of Gagnon and Karolyi (2005) and Baruch et al. (2005). On the other hand, the alternative explanation is that price discovery contributions cannot be attributed to the daily trading volume. For securities such as LKOH and GMNK, the market immediacy associated with trading durations may be the major factor determining the price discovery contribution, rather than the depth of a market.

The issue of endogeneity between the daily trading volume variable and the permanent-transitory measure has been addressed by breaking up the contemporaneous feedback loop i.e. by transforming the day's daily trading volume to be the daily trading volume of the previous day. The results of instrumented daily trading volume groups indicate that the price discovery leadership of MICEX conditioned upon the daily trading volume of the previous trading day generally remains unchanged. Table 58 reports the Gonzalo-Granger price discovery shares for MICEX. The average informational contribution of the MICEX market is distinctly found to be around 80% irrespective of the trading volume group. The relationship does not change even at the highest asymmetry groups of HL and LH.

Trading size group	HH	HL	LH	LL	uncond	mean
EESR	0.88	0.99	0.93	0.75	0.99	0.89
GAZP	0.62	0.57	0.55	0.63	0.81	0.59
GMNK	0.77	0.65	0.75	0.99	0.99	0.79
LKOH	1.00	0.59	0.66	0.90	1.00	0.79
RTKM	0.83	0.88	0.83	0.89	0.87	0.86
SIBN	0.93	0.89	0.83	0.81	0.77	0.86
SNGS	0.95	0.76	0.73	0.96	0.97	0.85
TATN	0.99	0.99	0.94	0.96	0.94	0.97
mean	0.87	0.79	0.78	0.86	0.92	0.83

The table presents and compares the conditional and Gonzalo and Granger measures of MICEX market from Equation 37 conditioned upon trading volume 50%centile thresholds of the daily trading volume with the unconditional measures at 300s sampling frequency, for all cross-listed securities based on trades samples. The trading regime groups are MICEXhi/LSEhi (HH), MICEXlo/LSElo (LL) and MICEXhi/LSElo (HL), MICEXlo/LSEhi (LH).

Table 58 MICEX Gonzalo and Granger measures conditioned upon trading volume 50%centile thresholds

The price discovery contribution of MICEX dominates in all trading regimes. Overall, the MICEX GG share is 83% on average for all stocks in all trading regimes within relatively narrow range of 87% and 78%, as reported in Table 58. The notion of MICEX informational dominance is additionally supported by the average contribution of around 80% in HL and LH regimes, which deviate below the unconditional average. The conditioned price discovery relationship shifts slightly in favour of LSE in those regimes when the trading volume is mostly asymmetrically distributed between MICEX and LSE. In this case, GAZP, GMNK and LKOH securities on MICEX display below average GG values. However, taking into account that the liquidity of MICEX is unsurpassed, the GG permanent-transitory measures clearly support the notion that MICEX is information dominant regardless of the trading regime. The evidence is consistent with the notion that liquidity plays an important role in LSE and MICEX price discovery for internationally cross-listed securities. This finding is consistent with the findings of Ates and Wang (2005), Grammig et al. (2004, 2005), Phylaktis and Korczak (2004, 2005) and Eun and Sabherwal (2003), which show that trading volume is positively related to the share of price discovery. Further implications of the overall findings are discussed in section 10.3, Implications of the Findings, in Conclusions, Chapter 10.

MICEX is the market, where major trading volume takes place, as illustrated in Chapter 3, Table 4 and Chapter 5, Table 13. In contrast to MICEX, LSE is a relatively minor market for Russian cross listed securities. Table 53 shows that LKOH, GAZP and SIBN security quantities are traded on a daily basis in relatively close ratios. At the same time only the LKOH absolute trading volume on LSE is larger than on MICEX. Yet, the average MICEX daily trading size is not overtaken by LSE. For instance, despite a higher overall LKOH turnover on LSE, the average trading size on LSE reaches approximately half the trading size of MICEX. This is particularly true for securities such as LKOH and GMNK - the trading volumes for both securities are larger on LSE than on MICEX. The relative average trading sizes and frequency of trading (duration) differences between LSE and MICEX may explain the findings. However, it may be the relative market immediacy that explains where the majority of price discovery takes place. In Chapter 4, MICEX is shown to be a more immediate market. This notion is in line with the findings of Ting (2006) that trading duration has a larger effect on information asymmetry than trading volume. The issue of which type of liquidity explains the proportions of price discovery remains a subject for further research.

The error-correction coefficients explaining the LSE pricing adjustment are statistically significant at 5% level from zero for all trading regimes, but do not explain MICEX adjustments for the majority of securities. This finding is consistent with the findings in Chapter 8 on uni-directional causality relationship. The results are in line with the one-way price discovery hypothesis; MICEX pricing mostly does not adjust, while LSE pricing reacts mainly to MICEX pricing. With exception of GAZP and LL regime, all error-correction coefficients explaining MICEX pricing adjustments are insignificant. At times there are also exceptions on the MICEX side: EESR and TATN indicate both-way price discovery for the LL and GMNK but also SIBN for LH trading regimes. It is interesting to see that there is a unidirectional relationship in symmetrical as well as asymmetrical information regimes. However, the direction of information flow also seems to change in exceptional cases, indicating that LSE also has information dominance at times.

9.5.3 **Price Discovery by Volatility**

Daily volatility, as measured by a realised variance estimator between markets, is highly cross correlated, as advocated by e.g. Anderson et al. (2001), but intraday squared returns are not. The cross correlation of each squared return is typically below 0.01, meaning that the intraday variations across markets are almost not cross-correlated. Since MICEX proved to be the dominant price discoverer, one would expect that rising noisiness on MICEX could affect its price discovery relationship with LSE. The point of interest has been to test whether, for instance, the moments of high intraday volatility of the MICEX market lead to it having a higher proportion of price discovery.

The null that the price discovery relationship is constant relative to MICEX intraday volatility should be rejected. The average GG results for each relative volatility group indicate a directly proportional rise or decay of the MICEX price discovery contribution displayed by Table 59. The overall group measured by the GG average of MICEX is 0.81 which is close to the 0.92 unconditional sample results. The MICEX share rises from 0.71 for the low volatility group to 0.79 (medium low) to 0.86 (medium high) and to 0.89 for the high volatility group. The price discovery proportion of the MICEX high volatility group is the closest to the unconditional sample average. With the exception of TATN, all the other stocks display a substantial variation of GG measures across the quartiles. In the case of GAZP for instance, when the Moscow market intraday volatility is low the MICEX share is close to 0.3, but when volatility is higher the MICEX share is higher, rising to 0.7 when MICEX volatility is highest. EESR, LKOH and SNGS share a similar rising pattern compared to GAZP.

Volatility regime	LO	ML	MH	HI	uncond	mean
EESR	0.62	0.97	0.83	0.93	0.99	0.84
GAZP	0.28	0.37	0.65	0.70	0.81	0.50
GMNK	0.99	0.80	0.81	0.81	0.99	0.85
LKOH	0.48	0.53	0.97	1.00	1.00	0.75
RTKM	0.77	1.03	0.90	0.93	0.87	0.91
SIBN	0.81	0.90	1.02	0.84	0.77	0.89
SNGS	0.67	0.66	0.77	0.98	0.97	0.77
TATN	1.04	1.02	0.94	0.95	0.94	0.99
mean	0.71	0.79	0.86	0.89	0.92	0.81

The table shows a comparison between the conditional Gonzalo and Granger measures of MICEX market from Equation 37 conditioned upon inter-daily price volatility and the unconditional measures sampled at 300s sampling frequency, for all cross-listed securities based on trades samples. The sample periods were grouped according to the magnitude of each period return squared into four inter quartile ranges Hi, MedHi, MedLo and Lo, relative to the volatility of the MICEX market.

Table 59 MICEX Gonzalo and Granger measures conditioned on intraday volatility

If one compares the GG group values of each security relative to the all group average, the relationship between MICEX relative volatility and its price discovery dominance becomes more evident. Almost all stocks traded on MICEX display a below average GG proportion in the low volatility groups, and above average proportion for the higher volatility groups, with the exception of GMNK and TANT. For some unidentified reason, these two stocks behave in the opposite way - they indicate a higher contribution of price discovery in the low and a lower price discovery contribution in the high volatility groups. TATN is a relatively low liquidity stock, while GMNK belongs to the category of higher liquidity stocks. The findings indicating MICEX information dominance increase in times of higher uncertainty or risk (higher level of volatility) and vice versa, with a lower level of uncertainty or risk (lower level of volatility), the dominance of MICEX diminishes. Trading abroad watches the pricing of MICEX rather than initiating its own. Overall, there is evidence that volatility seems to have a positive (negative) correlation with the common component contribution of the MICEX (LSE) market. This finding is consistent with Martens (1998), where higher volatility leads to a higher price discovery share of the larger trading volume market.

However, the finding that volatility is positively related to price discovery does not comply with the finding of Ates and Wang (2005). The differences to their findings may be explained by the fact that different volatility measures were employed. Ates and Wang (2005) employed daily High/Low price volatility measures, while Martens (1998) on the other hand employed an intraday period standard deviation volatility measure. Assuming that price discovery proportions are characterised by the level of a market activity e.g. trading volume, and given that MICEX is the most active market in terms of trading volume, there is indirect evidence that a higher level of volatility is associated with higher market activity. This finding would lie within the MDH assumptions and would therefore be consistent with the findings of Chatrath et al. (1995) and Kim et al. (2004).

9.5.4 Price discovery by Trading Hours

In the unconditional price discovery literature, the contribution to price discovery as measured by HIS or GG is usually presented as an aggregate constant, but these information measures are not only a function of observation (sampling) frequency but also a function of the trading time of the day. The null that the GG measure is constant during the days of the week or trading hours during the day is rejected. This chapter shows how the GG information measure itself varies throughout the overlapping trading hours.

If six overlapping trading hours are split into 3 equal parts, an intraday GG information measure pattern is clearly observable. Figure 51 and Table 60 illustrate the pattern of GG contributions of MICEX conditioned to trading time. According to the GG measure it seems that the contribution of the MICEX exchange relative to LSE is at its lowest from 2pm until 4pm Moscow time, in the middle two of the six overlapping trading hours. For all securities except EESR and RTKM, the GG measure of MICEX is at its highest for the first 2 overlapping hours compared to the remaining hours. The second 2 hours of overlapping trading are always below the first 2 hours for all stocks. The last 2 trading hours are either below the second for 4 stocks (GAZP, GMNK, SNGS and SIBN) or above for the rest, while for EESR and RTKM, the last 2 hours indicate an even higher MICEX share than the first 2 hours.

Trading hour	EESR	GAZP	GMNK	LKOH	RTKM	SIBN	SNGS	TATN
1st2	0.92	0.83	1.00	0.83	0.97	0.88	0.92	1.00
2nd2	0.89	0.72	0.93	0.82	0.45	0.74	0.80	0.92
3rd2	1.00	1.28	0.89	1.00	1.72	0.64	0.77	0.82
uncond	1.00	0.92	1.00	0.99	0.92	0.79	0.86	0.92

The table displays a comparison between the conditional Gonzalo and Granger measures of MICEX market from Equation 37 conditioned upon overlapping daily trading hours and the unconditional measures sampled at 300s sampling frequency, for all cross-listed securities based on trades samples. The sample periods were grouped according to the first, second and third two trading hours.

Table 60 MICEX Gonzalo and Granger measures conditioned on trading hours

Is there a Moscow lunchtime or London morning effect? If the conditional GG results are compared with the aggregate unconditional results, it becomes apparent that in the first two trading hours, 12- 2pm Moscow time, when LSE is just starting to trade, MICEX has above the unconditional GG level information share. This is true for five out of eight stocks: GMNK, RTKM, SIBN, SNGS and TATN. Interestingly, these stocks are relatively less often traded than EESR, GAZP and LKOH. The summary of price discovery results is reported in Table 57. Even, if the first hour or first half hour is considered, the relationship still holds - the London pricing contribution seems to be informationally inferior in the beginning, but superior in the intermediate part of the trading day. For the second 2 hours of the trading day, almost all securities on MICEX, except one on par, indicate lower than average GG measures. This means that the MICEX price discovery contribution slows down after lunch time. This anomaly could be called a Moscow after lunch effect.

On the other hand, half of all securities: GMNK, SIBN, SNGS and TATN, are below the average GG measure in the last two trading hours. Again, these stocks are from the relatively less liquid category as stated above. However, this time price discovery performance on MICEX is below the average - the opposite of the first 2 trading hours. Consequently, for the more liquid stocks, EESR, GAZP and LKOH, MICEX performs even better than average towards the end of the trading day.

Trading hour	EESR	GAZP	GMNK	LKOH	RTKM	SIBN	SNGS	TATN
1st/2	0.94	0.99	0.90	0.91	0.90	0.84	0.94	1.01
1st	0.93	0.43	0.94	0.87	0.92	0.83	0.92	1.12
1st2	0.92	0.83	1.00	0.83	0.97	0.88	0.92	1.00
2nd2	0.89	0.72	0.93	0.82	0.45	0.74	0.80	0.92
3rd2	1.00	1.28	0.89	1.00	1.72	0.64	0.77	0.82
uncond	1.00	0.92	1.00	0.99	0.92	0.79	0.86	0.92

The table displays a comparison between the conditional Gonzalo and Granger measures of MICEX market from Equation 37 conditioned upon overlapping daily trading hours and the unconditional measures sampled at 300s sampling frequency, for all cross-listed securities based on trades samples. The sample periods were grouped according to the first, second and third two trading hours with an additional split of the first two trading hour into first hour and first half an hour.

Table 61 Summary of MICEX Gonzalo and Granger measures conditioned on trading time

Table 61 presents the GG contributions of the MICEX market to price discovery. The results based on the first half and the first overlapping trading hour, are supportive of the finding that MICEX has an above average contribution in the first two trading hours. This finding is particularly true for the lesser liquid securities such as RTKM, SIBN, SNGS and TATN. A possible explanation for that observable pattern could be that LSE trading watches MICEX most liquid stock trading all morning, and when LSE opens to trade, a maximum information asymmetry occurs because the trading intensity is usually highest at the beginning and end of the trading session. Similar observations are documented by Menkveld et al. (2007), who uncover foreign market under-reaction around the trading session opening times. Trading volume, measured as the quantity of shares traded, tends to follow a U-shaped pattern during the trading day, as documented by Wood et al. (1985) and Wei (1992). So, when LSE trading volume is at its highest, MICEX trading is at its normal, relative to the 2 first trading hours after the LSE trading session opening. Conversely, the phenomenon may also be true for the less liquid stock category: the less liquid stock on MICEX is even less frequently traded on LSE, and there is a lesser degree of information asymmetry. As LSE opens, traders on LSE seem to have more informational advantage again than later in the 2nd two trading hours, because of the relatively higher trading intensity.

9.5.5 Price discovery by Weekdays

If the weekday conditional average results are compared to the aggregate GG, Thursday seems to be the day of the week when almost all stocks show that the conditional GG of MICEX are on or above the average information levels, as presented by Table 62 and Figure 52. Three stocks (GAZP, SNGS and TATN) on MICEX have, additionally, above the average price discovery contributions on Wednesday. Otherwise, for the remaining weekdays (Monday, Tuesday and Friday), the results present a mixed variation of GG shares above and below the average levels for all stocks.

Trading day	EESR	GAZP	GMNK	LKOH	RTKM	SIBN	SNGS	TATN
Mon	0.85	1.02	0.95	0.99	0.80	0.76	0.58	0.65
Tue	1.00	0.56	0.91	0.79	0.88	0.90	0.84	0.90
Wed	0.87	0.95	0.57	0.93	0.89	0.77	0.90	0.99
Thu	1.07	1.17	1.00	1.00	1.00	0.90	0.88	1.00
Fri	0.89	0.88	0.73	0.85	1.12	0.67	0.92	0.86
uncond	1.00	0.92	1.00	0.99	0.92	0.79	0.86	0.92

The table displays a comparison between the conditional Gonzalo and Granger measures of MICEX market from Equation 37 conditioned upon overlapping weekly trading days and the unconditional measures sampled at 300s sampling frequency, for all cross-listed securities based on trades samples. The sample periods were grouped according to the trading days that occurred on Mondays, Tuesdays, Wednesdays, Thursdays and Fridays.

Table 62 MICEX Gonzalo and Granger measures conditioned on trading days

When looking at the weekday results generally on Tuesdays and Wednesdays, MICEX seems to be the less dominant price discoverer. For LKOH and RTKM, on Tuesdays in particular, there is a substantial reduction of information shares on the MICEX side. In the case of GMNK, for instance, the London market displays a significant increase in contribution on Wednesdays. The contribution is around 30% during the rest of the week, while Wednesday indicates a contribution of over 60%, which is double the contribution of the other weekdays. These variations may be attributed to company related announcements, made usually at the beginning or the end of the week on the Russian side, or the growing information availability abroad towards the middle and the end of the week.

9.6 *Robustness of the Findings*

Summarising the findings so far, the hypothesis that relative trading volume is indicative of the conditional price discovery, has been rejected. In order to minimise a selection bias when partitioning data samples, the samples have been re-portioned according a stricter threshold criterion. Different threshold points in the distribution of quantity traded across markets may affect the relative price discovery proportions. Instead of a median, a stricter threshold of 33th and 66thcentile has been chosen in the robustness test (reported in Table 63). However, the results when the more restrictive percentile thresholds are applied are in line with the initial findings that the relative trading volume does not change the price discovery relationship. The test results indicate a variation averaging 20% across the trading regimes for all stocks relative to the median threshold results (Table 64). Most of the deviation is caused by the GG outliers in the HL trading regime, where the average difference is 36%. The main reason for the larger discrepancies is the relatively low number of observations in HL/LH asymmetry regimes, due to the trading volume correlation across markets with stricter threshold points and an even more finite sample size. This may have resulted in statistically insignificant error correction parameters on both sides of the ECM and therefore a blurred price discovery relationship.

Trading size group	HH	HL	LH	LL	uncond	mean
EESR	1.07	0.56	1.04	0.95	0.99	0.91
GAZP	0.56	0.60	1.45	0.96	0.81	0.89
GMNK	0.81	1.12	0.82	0.87	0.99	0.90
LKOH	1.00	1.02	1.00	1.00	1.00	1.01
RTKM	0.99	-0.23	0.79	0.56	0.87	0.53
SIBN	0.74	0.85	0.77	1.36	0.77	0.93
SNGS	0.96	0.86	1.29	0.80	0.97	0.98
TATN	0.89	1.00	0.83	0.75	0.94	0.87
mean	0.88	0.72	1.00	0.91	0.92	0.88

The table presents and compares the conditional and Gonzalo and Granger measures of MICEX market from Equation 37 conditioned upon trading volume 33/66%centile thresholds of the daily trading volume with the unconditional measures at 300s sampling frequency, for all cross-listed securities based on trades samples. The trading regime groups are MICEXhi/LSEhi (HH), MICEXlo/LSElo (LL) and MICEXhi/LSElo (HL), MICEXlo/LSEhi (LH).

Table 63 Gonzalo and Granger measures conditioned on trading volume 33/66%centile thresholds

However, if the robustness test results based on the trading regimes are compared with the initial results, similarities to the initial results are observable: the number of stocks having an above the average price discovery contribution is equal in each regime, though not for all securities. HH and LL regimes offer, however, an almost identical outcome because the stocks that are above and below the average are identical. Only HL and LH regimes differ more profoundly because the stricter threshold points cause a lower number of trading days that fall in the HL and LH categories.

Trading size group	HH	HL	LH	LL	mean
EESR	0.04	0.44	0.08	0.18	0.18
GAZP	0.18	0.40	0.71	0.01	0.32
GMNK	0.01	0.23	0.04	0.09	0.09
LKOH	0.01	0.13	0.00	0.01	0.04
RTKM	0.04	1.49	0.14	0.35	0.51
SIBN	0.05	0.10	0.20	0.67	0.26
SNGS	0.05	0.07	0.44	0.06	0.16
TATN	0.01	0.03	0.03	0.03	0.03
mean	0.05	0.36	0.21	0.17	0.20

The table shows the variation of conditional Gonzalo and Granger measures of MICEX market from Equation 37 conditioned upon trading volume 50%centile and 33/66%centile thresholds of the daily trading volume at 300s sampling frequency, for all cross-listed securities based on trades samples. The trading regime groups are MICEXhi/LSEhi (HH), MICEXlo/LSElo (LL) and MICEXhi/LSElo (HL), MICEXlo/LSEhi (LH).

Table 64 Variation between 50%centile and 33/66%centile threshold

There are almost negligible variations below 5% in the GG measure, relative to the initial GG results across the HH trading regime for LKOH SIBN and TATN. LKOH, for instance, does not vary significantly from the average relative to the initial result. The proportion of MICEX information is close to 100% across all regimes. Only GAZP and RTKM display larger differences in the HL asymmetry regimes because of the given percentile threshold, which lead to low number of observations ranging below two trading days. Otherwise, the GG measures vary below 10% in the HH/LL symmetry regimes for most stocks except RTKM and SIBN, where LL regimes vary within 20%

Cointegration Restriction Robustness Test

The findings in Chapter 8 exhibit evidence of the potential presence of a more pronounced information flow asymmetry relative to the inter-Moscow market. The evidence constitutes a rejection of the cointegration LR restriction test with the cointegrating vector restricted to $\beta^T = (1, -1)'$. This finding is based on the unconditioned sample average. In the case of the conditioned samples, would the cointegrating restrictions still hold in symmetric and asymmetric trading volume regimes? Tables 65 and 66 present a summary of LR tests for median and 33/66/33 percentile thresholds, respectively. Generally, if the conditional restriction test results are compared to the aggregate of Chapter 8, all restriction rejections of the unconditional restriction test are in line with the conditional symmetrical regimes. GMNK is the only firm that, for an unidentified reason, consistently rejects the null of the cointegrating vector being a theoretical ideal of $\beta^T = (1, -1)'$. Otherwise, the relationship between the asymmetry regimes and the LR test results seems to be contrary to expectations: the asymmetry regimes (HL and LH) are less null rejecting than the symmetrical ones (HH and LL). This is true for six out of eight firms for the median threshold, but not entirely confirmed by the stricter 33/66/33 percentile threshold samples. The conditional, sample based restriction test results imply that there may be a negative correlation between the trading volume and the information flow asymmetry. In other words, when there are larger differences between the trading activity between London and Moscow, there is less information flow asymmetry. That may either mean that rejection of the cointegrating vector is not indicative of information flow asymmetry or that asymmetries in relative trading volume do not influence the asymmetry in information flow, as initially assumed. Given the finding that trading volume regimes do not display a substantial effect on the Moscow/London price discovery relationship, it may be the latter case: the relative trading volume does not affect the estimated information flow.

		HH	HL	LH	LL	uncond
EESR	Chi-square(1)	1.9350	1.0075	0.4950	7.4818 *	6.6014 *
	Probability	0.1642	0.3155	0.4817	0.0062	0.0102
GAZP	Chi-square(1)	4.7262 *	2.2206	0.4817	20.7502 *	3.5389
	Probability	0.0297	0.1362	0.4877	0.0000	0.0599
GMNK	Chi-square(1)	53.2749 *	32.2133 *	36.6290 *	26.5553 *	60.0099 *
	Probability	0.0000	0.0000	0.0000	0.0000	0.0000
LKOH	Chi-square(1)	0.0797	4.1415 *	0.0396	1.8896	1.5786
	Probability	0.7777	0.0418	0.8422	0.1692	0.2090
RTKM	Chi-square(1)	11.8305 *	0.0528	1.5434	3.7090	4.4494 *
	Probability	0.0006	0.8183	0.2141	0.0541	0.0349
SIBN	Chi-square(1)	0.3885	2.7611	0.1933	0.0955	0.7562
	Probability	0.5331	0.0966	0.6602	0.7573	0.3845
SNGS	Chi-square(1)	2.7948	1.3516	0.0079	1.6893	3.2906
	Probability	0.0946	0.2450	0.9292	0.1937	0.0697
TATN	Chi-square(1)	42.8644 *	0.4765	0.0149	1.3834	0.1945
	Probability	0.0000	0.4900	0.9028	0.2395	0.6592

The table reports and compares the trading volume regime conditioned Chi-squared test statistics and their p-values for the imposed restriction of cointegration vector β^T = (1, –1)’ from Equation 34 of the 50%centile threshold assumption with unconditional measures for all cross-listed securities based on trades samples, sampled at 300s frequency. The trading regime groups are MICEXhi/LSEhi (HH), MICEXlo/LSElo (LL) and MICEXhi/LSElo (HL), MICEXlo/LSEhi (LH). The asterisks indicate a statistical significance at the 5% level.

Table 65 Cointegration Restriction LR Test with 50th percentile threshold assumption

		HH	HL	LH	LL	uncond
EESR	Chi-square(1)	0.0195	4.8746 *	3.3367	0.4141	6.6014 *
	Probability	0.8889	0.0273	0.0678	0.5199	0.0102
GAZP	Chi-square(1)	1.5621	1.4135	9.6230 *	33.9575 *	3.5389
	Probability	0.2114	0.2345	0.0019	0.0000	0.0599
GMNK	Chi-square(1)	31.4062 *	36.9391 *	22.4402 *	13.3884 *	60.0099 *
	Probability	0.0000	0.0000	0.0000	0.0003	0.0000
LKOH	Chi-square(1)	0.2434	0.3038	2.2942	5.2563 *	1.5786
	Probability	0.6218	0.5815	0.1299	0.0219	0.2090
RTKM	Chi-square(1)	18.4454 *	2.5414	0.0003	0.1472	4.4494 *
	Probability	0.0000	0.1109	0.9864	0.7012	0.0349
SIBN	Chi-square(1)	1.4928	0.0701	0.4763	0.0955	0.7562
	Probability	0.2218	0.7912	0.4901	0.7573	0.3845
SNGS	Chi-square(1)	5.9450 *	9.4851 *	13.7057 *	4.5118 *	3.2906
	Probability	0.0148	0.0021	0.0002	0.0337	0.0697
TATN	Chi-square(1)	21.5722 *	0.3078	0.0012	6.8147 *	0.1945
	Probability	0.0000	0.5790	0.9728	0.0090	0.6592

The table shows and compares the trading volume regime conditioned Chi-squared test statistics and their p-values for the imposed restriction of cointegration vector β^T = (1, –1)’ from Equation 34 of the 33/66%centile threshold assumption with unconditional measures for all cross-listed securities based on trades samples, sampled at 300s frequency. The trading regime groups are MICEXhi/LSEhi (HH), MICEXlo/LSElo (LL) and MICEXhi/LSElo (HL), MICEXlo/LSEhi (LH). The asterisks indicate a statistical significance at the 5% level.

Table 66 Cointegration Restriction LR Test with 33rd/66th-percentile threshold assumption

9.7 *Conclusion*

This chapter addresses the question of the effect of trading activity (volume and volatility) and temporal aspects on the price discovery relationship between London and Moscow markets. The price discovery relationship is not only sensitive to sampling frequency, but also dependent on factors of absolute trading volume, MICEX relative volatility state and time. Given these factors, the MICEX exchange remains to a high degree the leading price discoverer even if the trades samples are permuted and conditioned upon these factors. As the conditional price discovery measures are significantly dependent upon the conditioned data samples of the underlying data via a set of conditioning factors, then the price discovery measures themselves are also dependent upon these factors.

The results for trading size effect on price discovery proportions are inconclusive. Relative daily trading size may not affect the price discovery relationship between the markets. However, the relationship does not change, partly because, with the exception of LKOH and GMNK, the absolute trading volume on LSE, in the given sample, never supersedes the trading volume on MICEX. On the other hand, that may imply that (ceteris paribus) only the absolute trading volume is the determinant factor for the London-Moscow price discovery relationship. Despite the fact that overall trading volume for LKOH and GMNK is higher on LSE, the daily trading size variation seems to have no effect on the price discovery contributions. This finding points to a possibility that it is not only absolute trading volume that matters, but that aggregate trading volume or perhaps market immediacy is the key to determining the price discovery relationship. The inconclusive finding on daily trading volume may contrast with the notion that the fraction of trading volume is the major determinant of the price discovery relationship found by studies such as Grammig et al. (2005), Phylaktis and Korczak (2007).

In the findings of this study, the link between the relative daily trading volume and price discovery contributions seems to be inconclusive. However, a link may still exist on the intraday level, where the trading sizes of the LSE market may be larger at some periods. In further research, the assumption of relative daily trading volume could be changed to intraday trading size. The changed assumption may reveal an association between the relative trading size and the price discovery relationship.

In contrast to daily trading size results, intraday volatility has a direct effect on the degree of MICEX leadership. Though the dominance of MICEX is never undermined, higher intraday volatility on the more trading intensive MICEX market implies a higher GG contribution of MICEX and vice versa. This finding suggests that volatility is positively correlated with a higher price discovery contribution of the higher trading volume market. This finding is consistent with Martens (1998) and the studies that support the notion of the MDH such as Lamoureux and Lastrapes (1990), Chatrath et al. (1995), Kyriacou and Sarno (1999) and Kim et al. (2004). This finding, however, is only partly in line with the finding of Ates and Wang (2005) that the most liquid market remains information dominant regardless of the relative state of volatility. What remains to be examined is the MDH hypothesis i.e. the intraday trading volume and intraday volatility joint effect on price discovery. A positive correlation in both cases is expected. Furthermore, it would also be interesting to apply the proposed research methodology to the quotes based sample. The quotes based sample would allow an analysis to be carried out similar to that of Pascual and Pascual-Fuster (2010), in order to examine the asymmetry of the contributions of the effects of trading volume, volatility and time on the bid and ask quotes.

Overall, regardless of the trading conditions: liquidity (defined as daily total market transaction size), volatility (defined by partial RV estimator, i.e. intraday return squared) asymmetries, the information dominant MICEX market remains the leading price discovery market. This finding is still consistent with the theoretical arguments and empirical findings proposed by Ates and Wang (2005). Further findings are that time in overlapping trading hours can be associated with varying price discovery proportions between the London and Moscow markets. This finding is consistent with the finding of Harris et al. (2002a) that price discovery proportions are not constant over time. Similar to the findings of Menkveld et al. (2007), the foreign market has a lower information share at the main trading session opening. Mid day trading has the lowest Moscow price discovery contribution. Days of the week affect the information flow intensity. Thursdays seem to be the most informative MICEX days, but this finding may not be robust in the longer sample period.

This chapter contributes to the literature of conditional price discovery by examining trading volume, volatility and time in the context of conditional cross-border price discovery. The amount of literature in the conditional price discovery is limited e.g. Martens (1998), Ates and Wang (2005) and Taylor (2008). Apart from this chapter, Martens (1998) is the only study, which deals with the cross-border conditional price discovery relationship, in terms of the conditional trading volume and volatility effect on proportions of price discovery. This study is also important in that, rather than modifying a conventional parametric model, it applies a standard methodology on a factor conditioned data set. This approach differs from conventional parametric methodologies, which are modified to control for the desired factors. This study therefore avoids the risk of additional model misspecification caused by controlling for highly correlated variables such as trading volume and volatility. An additional benefit of the conditioning method used in this study, is that it makes the isolation and analysis of the trading volume and volatility variables possible.

Appendix

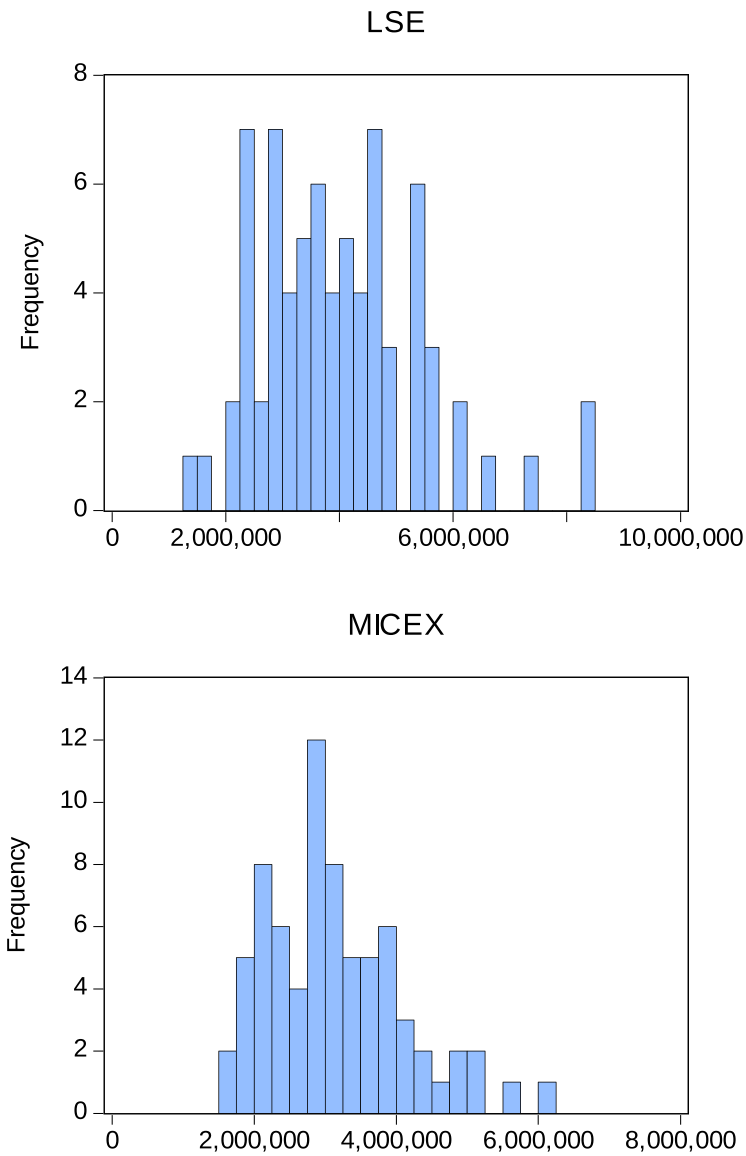

Figure 50 Daily Trading Volume Distributions MICEX and LSE in case of LKOH

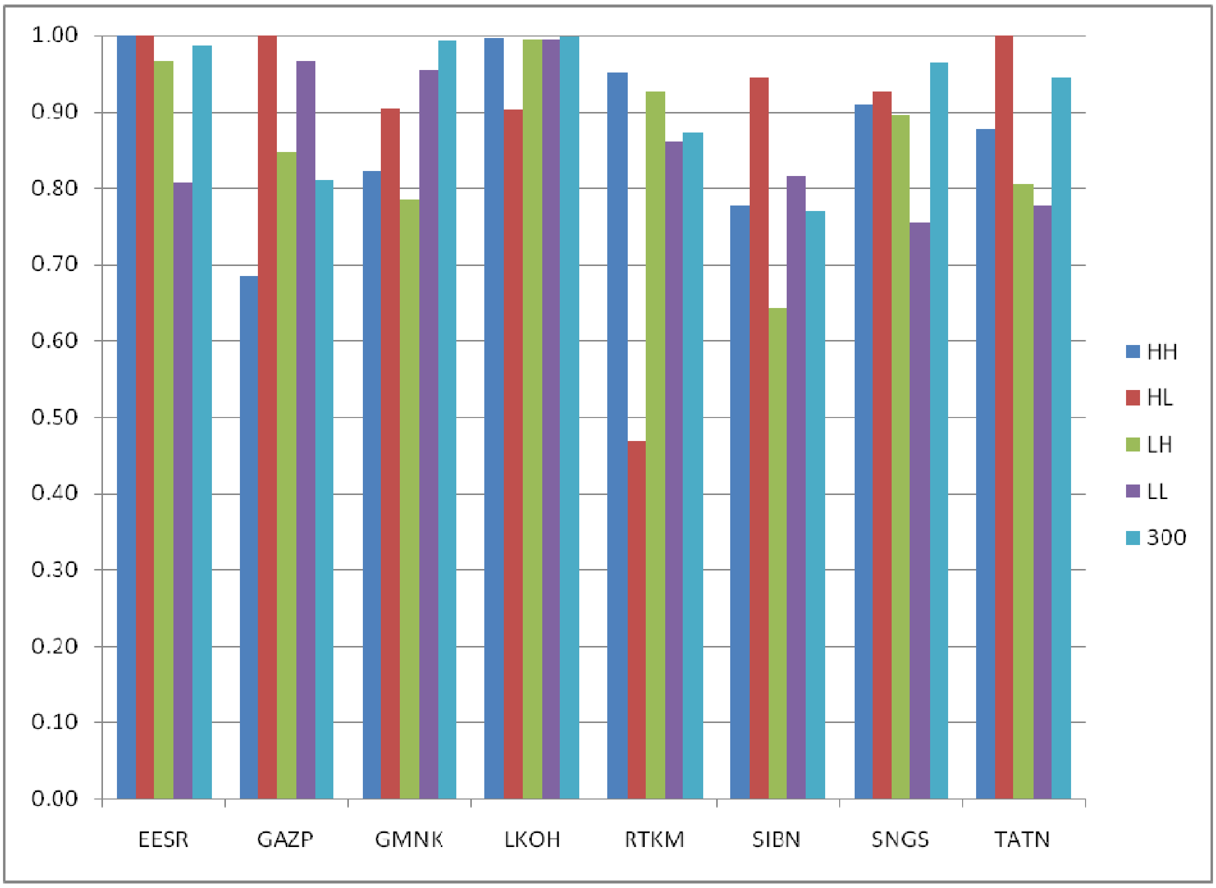

Figure 51 MICEX Gonzalo and Granger measures conditioned on trading volume 50%centile thresholds

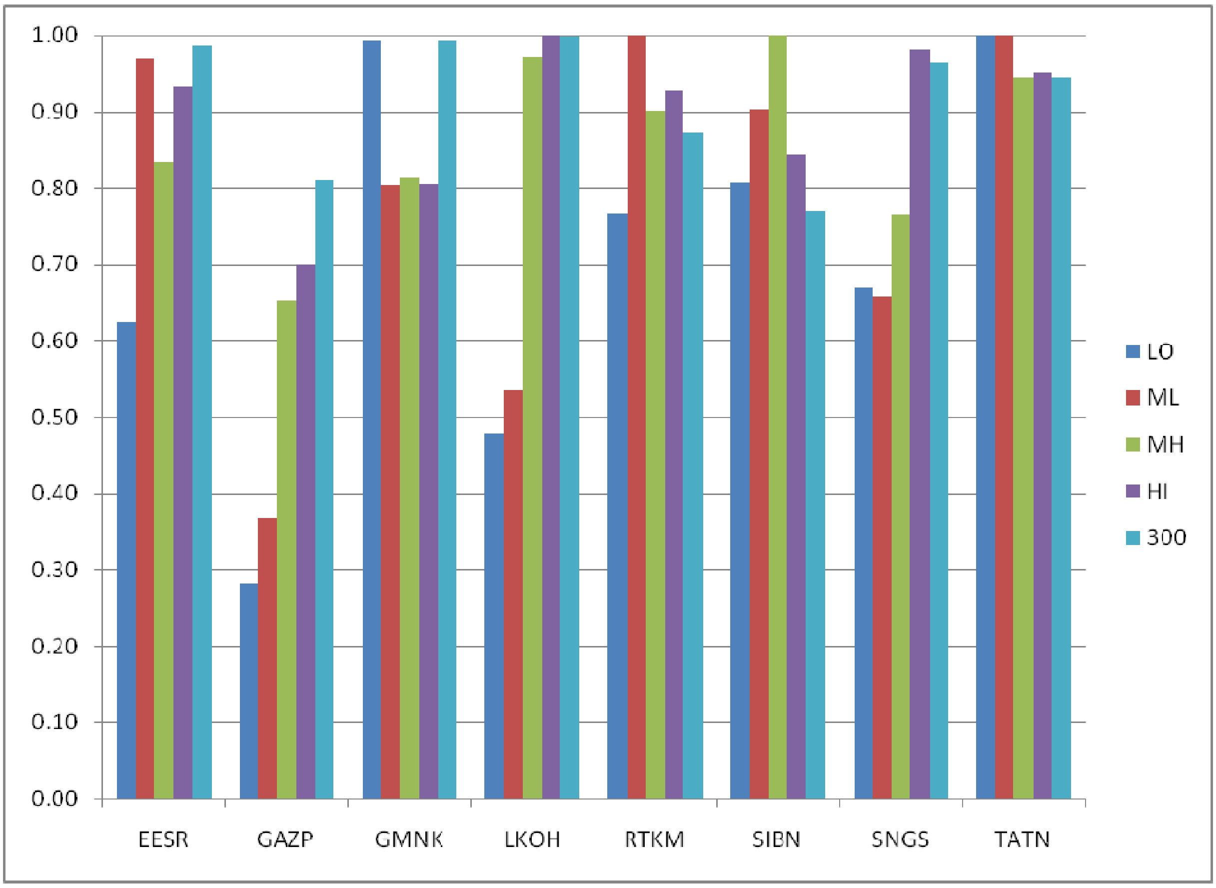

Figure 52 MICEX GG conditioned on intraday volatility

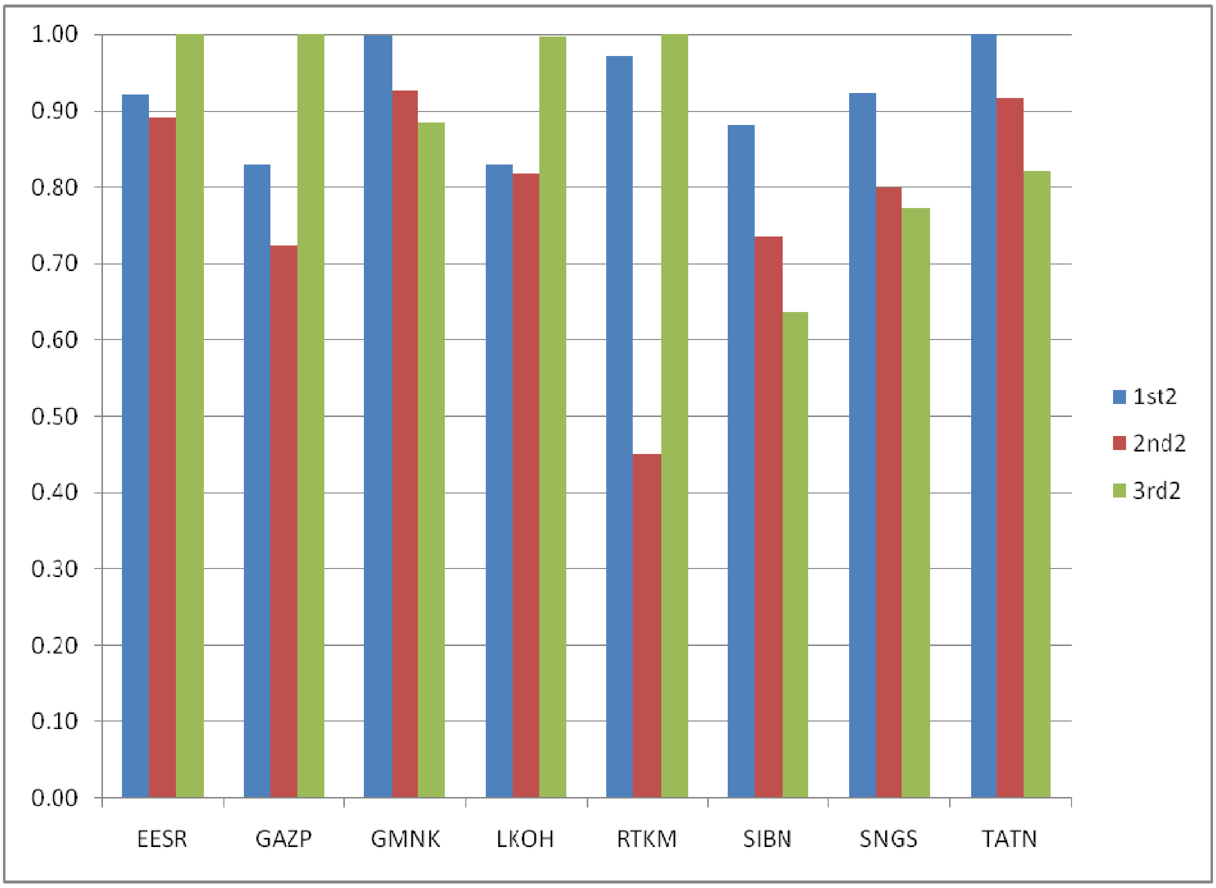

Figure 53 GG measures conditioned upon trading hours

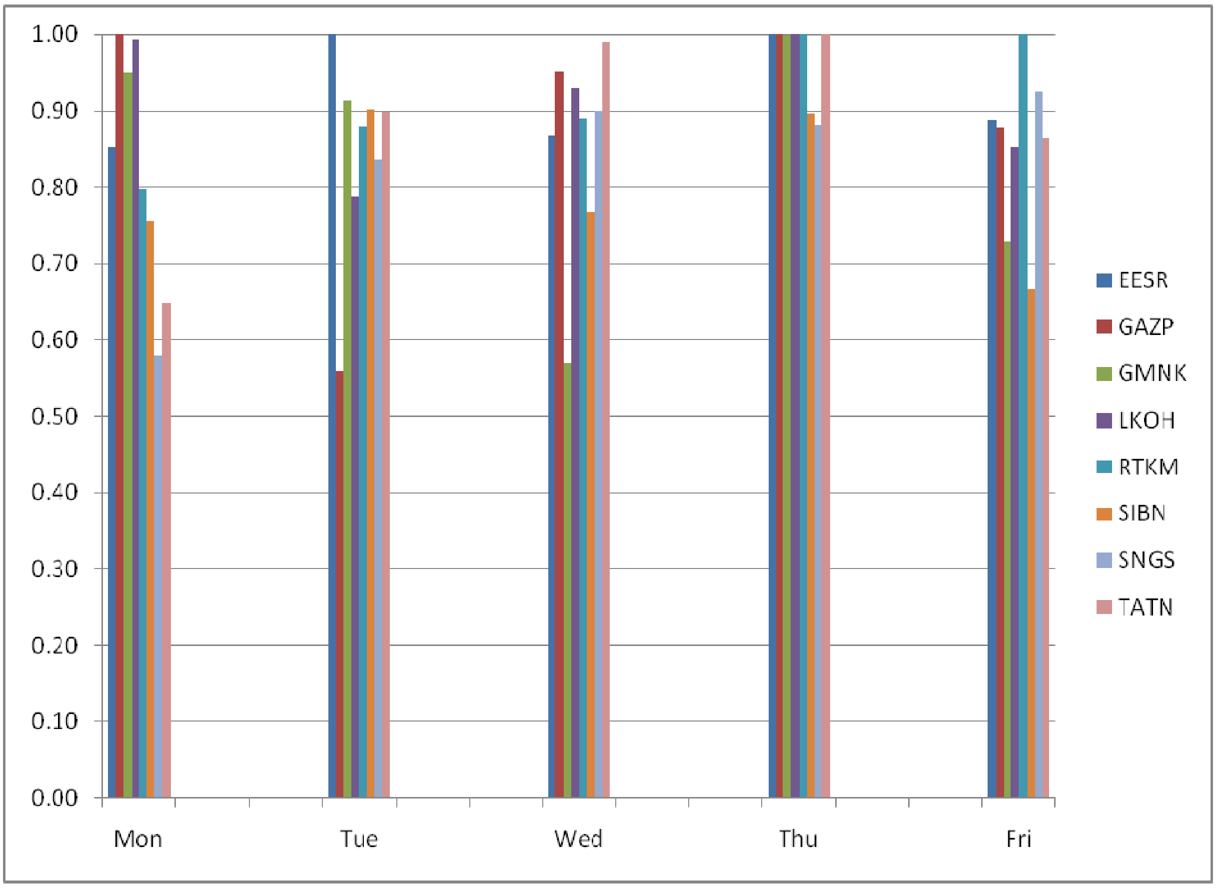

Figure 54 MICEX GG conditioned on weekly trading days

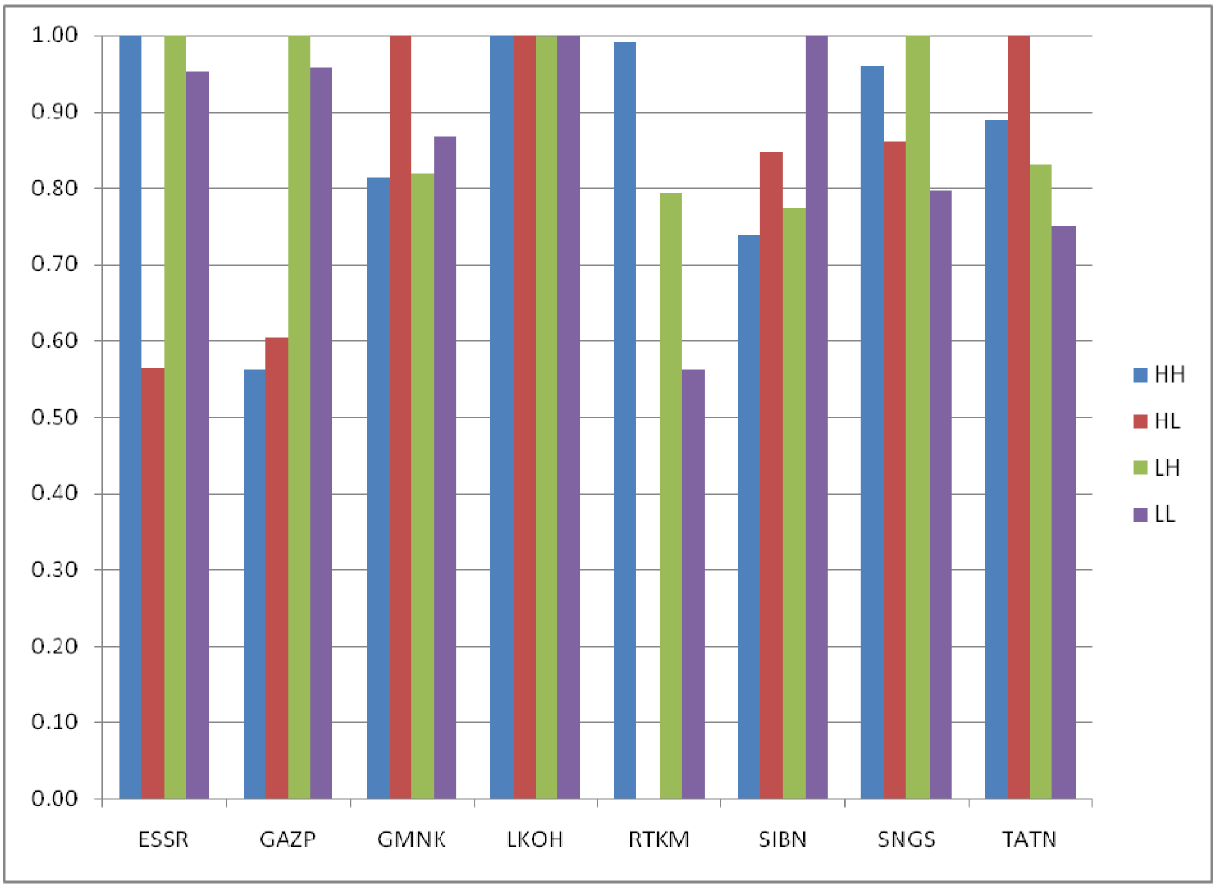

Figure 55 Gonzalo and Granger measures conditioned on trading volume 33/66%centile thresholds

Chapter Ten: Conclusions

Chapter 10: Conclusions

10.1 *Overview*

This is the first and only study which is concerned with the Moscow inter-market and cross-border price discovery for cross-listed securities and this chapter briefly summarises the key findings, discusses the implications of these findings and suggests potential areas for further research. The thesis addresses the issue of price discovery between MICEX, RTS and LSE for the eight most liquid stocks, and the investigation is carried out in the context of data type, price discovery contribution methodology, cross-section of individual security, sampling frequency, overnight returns, trading time, volatility and trading volume conditions.

The overall findings suggest that the MICEX home market is the central price discovery market for the eight cross-listed, most liquid Russian securities. RTS and LSE are mainly satellite markets, but have a supportive role. These statements are generally supported by the range of results associated with data type, price discovery contribution methodology, cross section of individual security, chosen sampling frequency (provided it is high enough and the contemporaneous correlation is not dominating), trading time, volatility and trading volume conditions. The findings can be attributed to the fact that MICEX is a more trading active market than RTS and LSE, with a larger number of trades and a gapless continuity of quotation in its LOB, as reported in Chapter 4. The RTS and LSE markets are both lacking in continuity of quotes, but more severely than on the transaction side. The findings are in line with the consensus in the price discovery literature that the competition for order flow from multiple markets determines how information is impounded into prices e.g. Baruch et al. (2005), Grammig et al. (2005) and Phylaktis and Korczak (2007).

The findings of Chapter 7 and 8 support the notion that price discovery occurs primarily in the market which attracts most order flow. The proportions of price discovery contributions in Chapter 7 are similar to the findings of Hasbrouck (1995), Harris et al. (2002a) for the NYSE price discovery contribution versus regional markets. However, despite the similarities in price discovery share proportions on the US market, the Moscow trading environment differs significantly from the US. For instance, securities traded on MICEX and RTS were denominated in different currencies, while the Russian economy operated under capital flow restrictions with limited RUB convertibility. Trading in Moscow, unlike trading on the US market, was bound by a different set of regulations such as short selling restrictions or no insider trading legislation.

A similar conclusion can be drawn for the cross-border market price discovery relationship investigated in Chapter 8. For most securities which indicate a superior order flow in the home market, the home market dominates price discovery over the foreign market. This finding can be placed in line with the findings of Eun and Sabherwal (2003), Menkveld et al. (2007), Pascual et al. (2005), Grammig et al. (2005) and Phylaktis and Korczak (2005), but contrasts with the major finding only of Hedvall et al. (1998). The major finding of Chapter 8 is true for all samples tested at an optimised sampling frequency range of 120s -960s. Sampling below the optimum sampling range, may result in overstated estimates of home market price discovery contribution. This finding is consistent with the studies of Grammig and Peter (2008, 2010), the only price discovery studies which address the issue of microstructure effects on price discovery contribution proportions.

The findings of Chapter 9 point to the fact that the price discovery process is not an average constant, but a persistently changing variable. This general finding is similar to the tidal “ebb and flow” process of price discovery proportions on the US market finding of Harris et al. (2002a). Temporal aspect has an effect on price discovery proportions. In overlapping trading hours it can be associated with different price discovery proportions between the London and Moscow markets. For instance, the finding that LSE market price discovery under-reacts at market opening is similar to the finding of Menkveld et al. (2007). Overall, the findings of this study are consistent with the finding of Harris et al. (2002a) that price discovery proportions are not constant over time. Intraday volatility has a direct effect on the degree of MICEX leadership. Higher intraday volatility seems to correlate with the higher GG contribution of MICEX and vice versa. This suggests that volatility is positively correlated with the higher price discovery contribution of the higher trading volume market. This finding is consistent with Martens (1998), and is partly in line with Ates and Wang (2005). Overall, the findings can be placed alongside the studies that support the notion of the MDH such as Lamoureux and Lastrapes (1990), Chatrath et al. (1995), Kyriacou and Sarno (1999) and Kim et al. (2004). It is possible that relative trading size does not affect the daily price discovery relationship, since the findings for trading size effect were inconclusive. However, overall this finding is still in line with Taylor (2008) and Ates and Wang (2005) because MICEX remains the dominant price discoverer even in asymmetrical trading conditions. The conditional price discovery relationship may remain unchanged, partly because the total trading volume on LSE in the given sample rarely supersedes the trading volume on MICEX.

Overall, given the findings of this thesis and all the studies that have found a link between liquidity and price discovery contributions, it can be concluded that the central (information dominant) - satellite market relationship is not exclusively applicable to the Russian emerging equity market. Despite the differences between the Russian and US trading environment, the price discovery relationship for Russian cross-listed equity is similar on average to the US market. This thesis offers firm evidence that the average price discovery relationship for the central and periphery markets is positively correlated to the proportions of relative liquidity on the competing markets. This notion supports the established stylized fact, that relative market liquidity is a factor for the magnitude of the price discovery contribution, documented in studies by amongst others, Karolyi (2002), Harris et al. (2003), Eun and Sabherwal (2003), Gagnon and Karolyi (2004), Baruch et al. (2005), Grammig et al. (2005), and Phylaktis and Korczak (2005 and 2007). The magnitude of this factor may be approximately similar or even identical for all cross-listed equity price discovery relationships. However, this hypothesis could only be tested if all studies had a homogenized data type, sampling frequency and price discovery measuring methodology.

10.2 *Key Findings*

The Moscow inter-market price discovery relationship between MICEX and RTS has been investigated in Chapter 7. The investigation was based on last-tick interpolated transaction tick prices as well on the best prevailing quotes derived from the LOB. The analysis compared the performance of two information capturing methodologies: HIS, the information shares of

Hasbrouck (1995) versus GG, Gonzalo- Granger (1995) permanent-transitory component measures.

Price discovery occurs significantly on both Moscow exchanges, while the MICEX market is the information dominant market and the RTS market has a supportive role in price discovery on a national scale. The proportions of price discovery contributions in Chapter 7 are similar to the findings of Hasbrouck (1995), Harris et al. (2002a) for the NYSE price discovery contribution versus regional markets. The findings are sensitive to the type of data utilised with the associated sampling interval rather than to the choice of the price discovery contribution methodology. The implementation of interpolated trades based data is sufficient for price discovery measuring purposes as long as transactions occur frequently enough, and the sampling frequency is not chosen at the highest level. The proportion of price discovery contributions between the two types of data is similar at a 2-5 min sampling frequency. However there are also distinct differences in the informational contributions associated with the sampling frequency. HIS appears to be larger for transactions, but smaller for orders and vice versa. The price discovery contribution is generally higher for quotes than for trades. The GG and HIS parameters, as a function of time, mostly fall monotonously for the quotes based data, while for transactions, they rise and fall because of the last-tick interpolation method.

The transaction based data is an inferior informational source for measuring the contribution of price discovery under a 120s sampling interval, otherwise, with lower sampling frequencies it is adequate for the purpose. The results are consistent with those in the Harris et al. (2002a) and Hasbrouck (1995) studies on US national stock markets. These findings are suggestive of the dependence on the type of data affecting the quality of the empirical results, sampling frequency and methodology utilised. Although RTS trading represents a relatively small portion of stock trading, it is an important contributing factor in Moscow price discovery.

In conjunction with the reflections of Chapter 4, for higher sampling frequencies, the best prevailing quotes derived from the LOB are more suitable than transaction prices compared within a security. The best prevailing quotes are arguably more informative at a higher sampling frequency, the main reason being the difference in frequency of occurrence and their nature:

quotes prevail continuously until cancelled or matched in the LOB, and are more frequently updated than the transactions can occur.

The differences in methodologies and the choice of the type of data research are over-stated in the price discovery literature. The findings indicate that the debate as to whether HIS or GG is superior, is unnecessary. Each price discovery measure should be used with the appropriate data type originally employed - trades for GG and quotes for HIS. Both measures performed similarly in the range 60s-480s for quotes and trades based data. As long as sampling frequency choice does not extend into extremes below 60s for trades and above 960s for HIS, the price discovery measurements do not deviate substantially. Given the set of data type, sampling frequency choice is more crucial than the choice of price discovery contribution methodology.

Chapter 8 addresses the issue of cross-border price discovery between the Moscow market and London Stock Exchange. The analysis focuses on sampling frequency choice associated with the presence of trade-off between the extremes of microstructure effects and the contemporaneous correlation. Incorrect choice of sampling frequency may lead to underestimation of the price discovery contribution of a market or even to misleading inferences. The analysis is based on the best prevailing quotes derived from the LOB.

The null hypothesis that the home market dominates the foreign market should not be rejected. Of the three stock markets, MICEX market trading provides the dominant contribution to price discovery at the optimum sampling (120s- 960s) for all securities other than LKOH and TATN. Higher sampling frequency results may contribute to overstatement of home market price discovery dominance - this finding is consistent with Grammig and Peter (2008, 2010). While the causality relationship between MICEX and RTS is unidirectional (MICEX is Granger-causing RTS), the relationship between LSE and MICEX is bidirectional. RTS and LSE are similar markets in terms of liquidity. However, with exception of TATN and LKOH, the home market RTS seems to contribute more than LSE for all other instruments. In line with Eun and Sabherwal (2003) and Grammig et al. (2005), the results do support the notion that the home market makes a higher contribution to price discovery, however, the restriction test results support the view that the satellite markets LSE and RTS also contribute significantly to price discovery. The rejection of the theoretical cointegrating vectors between London and Moscow are indicative of the cross-border information asymmetry caused by market frictions, stemming from geographical, political and microstructural differences.

Given that trading on MICEX is the most frequent of all three stock markets, the finding that MICEX is the mostly dominant price discoverer is not surprising. With the exception of the two instruments (LKOH and TATN), this finding is consistent with the findings in the price discovery literature e.g. Phylaktis and Korczak (2007), Grammig et al. (2005), that price discovery is lead by the most liquid market, which is usually the central, and home market. However, despite the fact that there are exceptions, such as LKOH and TANT, there is a possibility that absolute liquidity causes MICEX to dominate LSE and RTS. Another important finding is that there is a form of cross-border market friction because of the equilibrium gap in the common component between Moscow and London pricing.

It can be concluded that the sampling frequency choice may be an over-stated issue in the literature as well. Taking into account the data type employed, as long as the frequency does not extend below a minute or above 30 minutes, the trade-off between microstructure effects and contemporaneous correlation is not an issue. The more accurate price discovery contribution estimate may be achieved by optimising the choice in conjunction with other parameters such as data type and information capturing methodology. However, the accuracy of the contribution to price discovery in this study is sufficient, given the strong contrast in trading activity between MICEX and RTS/LSE. Taking this finding into account, one may question the price discovery estimates of studies which employed sampling frequencies of above 30 min or below 30s.

Chapter 9 addressed the question of the effect of trading activity (volume and volatility) and time on the price discovery relationship between the London and Moscow markets. The price discovery relationship is also dependent on factors of absolute trading volume, MICEX relative volatility state and time. Given these factors, the MICEX exchange remains the leading price discoverer even if the trades based samples are permuted and conditioned upon these factors. As the conditional price discovery contribution measures are significantly dependent upon the conditioned data samples of the underlying data via a set of conditioning factors, then the price discovery measures themselves are also dependent upon these factors.

The main finding of Chapter 9 is that the market's price discovery contribution proportions are variable depending on the conditions of time and trading activity. Regardless of these conditions, MICEX remains an information dominant market. Relative trading size may not affect the daily price discovery relationship, given that the findings for trading size effect were inconclusive. However, relative to the unconditional relationship between MICEX and LSE, the conditional relationship does not change, partly because the total trading volume on LSE in the given sample only supersedes the trading volume on MICEX in the case of the individual securities, LKOH and GMNK. On the other hand, that implies that the absolute total trading volume is the determinant factor for the London-Moscow price discovery relationship. All these findings are consistent with the findings of Ates and Wang (2005). Further findings are that intraday volatility has a direct effect on the degree of MICEX leadership. Higher intraday volatility on the more trading intensive MICEX market implies a higher GG contribution of MICEX and vice versa. This finding suggests that volatility is positively correlated with the higher price discovery contribution of the higher trading volume market, which is in line with Martens (1998). Time in overlapping trading hours can be associated with different price discovery proportions between the London and Moscow markets, which is similar to the findings of Menkveld et al. (2007). Mid day trading has the lowest Moscow price discovery contribution. Days of the week affect information flow intensity. Thursdays seem to be the most informative MICEX days. Overall, these findings are consistent with the finding of Harris et al. (2002a) that price discovery proportions are not constant over time.

This study found no direct link between the relative daily trading volume and price discovery contribution at 300s sampling frequency. This seems to contradict the findings of e.g. Eun and Sabherwal (2003) and Baruch et al. (2003), but their findings are based on the aggregate and average levels. However, a direct link may still exist on the intraday volume level, where the trading sizes of the LSE market may be larger at some periods. The trading size finding resembles the seemingly conflicting findings of Martens (1998) and Ates and Wang (2005) however, on the aspect of volatility effect on price discovery shares. In further research, the assumption of relative daily trading volume could be changed into intraday trading volume. The changed assumption may reveal an association between the relative trading size and the price discovery relationship.

In summary, regardless of which data set is manipulated or permuted, and how, the majority of the findings point to the dominance of the MICEX market for the eight most liquid Russian cross-listed securities. The role of the satellite markets is questionable in the context of Russian cross-listed securities trading. Given that MICEX has captured most of the order flow (over 80%), the role of RTS and LSE IOB trading Russian securities has been only supportive. The announcement of a merger between MICEX and RTS may support this statement.

10.3 *Implications of the Findings*

The findings of this thesis can be placed within the several previous studies that analyse the implications of a market mechanism for central and satellite securities trading. Generally, the constellation of the Russian cross-listed equity market (MICEX versus RTS and LSE) can be compared to established central-satellite market constellations in the US e.g. NYSE versus Pacific, Chicago stock exchanges and alternative trading venues such as ECNs e.g. ASX, Instinet. Fundamental to the discussion on the implications of a market structure is the notion suggested by Easley et al. (1996); the central market is characterised by a higher reliability of execution, while matching systems are characterised by a better price though for narrowly selective executions. Despite the differences in market structures across central-satellite markets between US and Russia, for example a purely order driven LOB trading mechanism on MICEX and hybrid NYSE trading, the findings of this thesis could be rationalised by three following hypothesis as discussed in Harris et al. (2002a): firstly, by the spread-sensitive-uninformed order-flow hypothesis e.g. Benveniste et al. (1992); secondly, by the institutions-of trading hypothesis (e.g. Barclay and Warner, 1993) and finally, by the trading-practices hypothesis e.g. Keim and Madhavan (1996). The spread-sensitive-uninformed order-flow hypothesis may offer the most plausible explanation as to why MICEX became an information dominant market, while the institutions-of trading hypothesis and trading-practices hypothesis offer a perspective as to why the LSE and RTS markets played a supportive role in the price discovery process of the cross-listed securities.

Given the heterogeneous nature of trading activity across MICEX, RTS and LSE as discussed in section 8.4.6., one could speculate that: Firstly, MICEX trading is predominantly characterised by retail traders because of the small and frequent transactions. These retail traders prefer to trade at home market through local brokers and in local currency. Secondly, RTS and LSE trading is predominantly made up of institutional investors because of larger trading sizes and infrequent trading. This statement is specifically true for RTS, where the average median trading size is the largest and transactions occur least frequently. Additionally, trading on LSE may be preferred by the investors who are FX risk averse and who prefer to exercise the option of short selling. Furthermore, it could be speculated that the retail traders, who are likely to be liquidity driven, entail most of the uninformed order flow and that those who exercise short selling on the LSE market are likely to be part of the informed order flow.

The spread-sensitive-uninformed order-flow hypothesis assumes that liquidity traders are sensitive to the size of a bid-ask spread and that concentrating uninformed order flow in the central market lowers the cost-covering asymmetric information component of the equilibrium spread. Following these assumptions, Benveniste et al. (1992) stipulate that for any given level of information asymmetry, the equilibrium spread can be lower on a central exchange if informed traders are most likely to trade with liquidity traders. This hypothesis implies that liquidity traders form the uninformed order flow because their trading occurs mostly inside the equilibrium spread. They are also most likely the drivers of the decreasing cost of trading because market makers on average are less likely to incur losses when the proportion of uninformed order flow is higher. In sum, the higher the proportion of liquidity traders that a market can attract, the lower is the resulting equilibrium spread. Since the causality may work in both directions. The higher uninformed order flow and the lower equilibrium spread can jointly contribute to the higher overall order flow potential and therefore to higher the information share of a market. With that hypothesis in mind, Harris et al. (2002a) seek to explain the diminished price discovery share of NYSE trading in the period of 1988-1992, given the rise of competing satellite ECN markets in the beginning of the 1990. Similarly to the US market, the spread-sensitive-uninformed order-flow hypothesis can help to explain the loss of the market share of RTS to MICEX, as depicted in Figure 1, and potentially offers a motive for their merger. The rising market share and the finding that MICEX was information dominant on the Moscow market in 2006 may be indicative of the possibility that MICEX managed to attract higher proportion of liquidity traders and therefore more uninformed order flow by outcompeting (historically central) RTS market with lower equilibrium spreads. This is consistent with the average lower bid-ask spread statistics in Table 13 and the finding that the average spreads were lower on MICEX by 60-80% in 2006. Restricted by the short sample period in this research, one only can speculate that the initial hybrid market design of RTS versus the fully electronic order driven MICEX was amongst other major factors that gave MICEX the competitive edge in capturing a larger proportion of the order flow volume and therefore higher information share relative to RTS over time.

The second hypothesis tries to explain the central-satellite market constellation from the perspective of information asymmetry. Barclay and Warner (1993) suggest that information asymmetry differs across trading venues, trade sizes or other segments within a trading venue. Trades that are based on informational advantage may concentrate in the central market, contributing to innovations in the efficient pricing process but are independent of the overall level of spreads. This scenario can result from trading practices such as “cream skimming”, tacit collusion and payment for order flow, if less informed orders suitable for selective execution at narrow spreads are rerouted to ECNs or regional specialists {Easley et al. (1996)}. The main implication of this hypothesis is that, higher share in price discovery of a market could be explained by the measure of information asymmetry such as probability of the information-based trading (PIN) method by e.g. Easley et al. (1995), regardless of the equilibrium spread. Harris et al. (2002a) employ this hypothesis in order to support their findings that NYSE price discovery rose in the period 1992-1995 in the presence of declining spreads. Despite an unknown level of information asymmetry of each market (subject of further research), this hypothesis is consistent with the findings that LSE is a competing satellite market. The presence of pronounced information asymmetry and the statistic significance of price discovery on LSE market despite higher average spread than on MICEX are indicative of the fact that trading on LSE is shaped by the informed order flow. The increasing role of LSE in price discovery could be attributed to the fact that there is a short selling restriction on the Moscow market whereas in London there is not. If short selling activity is assumed to be part of informed order flow, then LSE market is most likely be more successful in attracting the informed order flow, resulting in the trades which increasingly contributed to innovations in the common efficient price. In a long run, the possibility of short selling might have precipitated a shift in the informed order flow to LSE away from the domestic market. In the end, LSE IOB trading emerged as a stronger competitor to the Moscow exchanges. This might have been one of the main motives for the merger between the information dominant MICEX market and the statistically insignificant price discovering RTS market.

Finally, a third hypothesis which can help to explain the findings of this thesis is the hypothesis of trading-practices. It addresses any institutional traders, who look for price improvement being available on other trading venues including satellite or regional markets. The institutional trading activity is assumed to permanently move the market because of the price impact of the overall size of their trades even though their trading may be part of an uninformed order flow. Harris et al. (2002a) state that the uninformed institutional order flow re-emerged on NYSE only after hidden limit orders and some stop order practices were changed and after differential price improvement for other segments of the NYSE order flow stopped. Changes in the allowed trading practices on the central exchange are therefore consistent with the return of order flow volume and price discovery to NYSE. The trading-practices hypothesis can be used to describe the importance of institutional trading practice differences across RTS and MICEX. The trading-practices hypothesis can also be applied from the opposite perspective: instead of looking what deferred institutional traders from trading on a central exchange to what attracted this type of order flow to the satellite exchange. It could be argued that RTS managed to remain an economically significant price discovering exchange by being attractive to institutional traders due to the special quote-driven features, such as special negation orders, delayed settlement and settlement in foreign currency, which MICEX did not offer. Generally, the match making feature of RTS is the main advantage that most likely offered price improvement, which institutional trading are assumed to be seeking for. Besides that RTS also offered a much better developed derivative securities segment, in which MICEX was lagging. Overall, it could be concluded that

MICEX simply lacked the features that made RTS attractive to the institutional investors, who kept the price discovery on RTS alive.

Why, in the end, has the MICEX market attracted more order flow relative to RTS and LSE? A possible alternative explanation could be attributed to the following major factors, which interactively have caused the prevailing constellation: Firstly, changes of investor preference between the foreign currency (USD) and RUB are associated with the historic economic and political instability of Russia; Secondly, regulatory restrictions i.e. capital flow restriction associated with the capital flight problem; Thirdly, the historic choice of RTS to adopt and to remain with USD for the most liquid securities since the time of Russia's instability, while MICEX chose RUB, and RTS and LSE chose USD; Finally, as a result, these currency differences have attracted different market participants, such as domestic and foreign, with a different set of FX risk preferences and a different degree of information asymmetry. For instance, traders on MICEX are predominantly retail and domestic investors, whereas the traders on RTS and LSE are a mix of foreign and institutional investors. Given these factors, one can assume that the domestic investors are better informed than their foreign counterparts because of the language and cultural barriers, and lack of transparency of the underlying Russian firms.

RTS was the first Russian stock exchange and has increasingly attracted foreign and institutional investors in the periods of instability. MICEX started off as the second stock market trading in RUB and was relatively unattractive in the unstable periods. RTS successfully attracted those investors who preferred to avoid the risk associated with the RUB currency, especially at the times of instability and capital control restriction. However, over time, Russia's stability has improved and the preference for foreign exchange risk has changed. Though capital control restriction still remains in place, MICEX has managed increasingly to attract both domestic retail and foreign investors. In the end, the increased order flow on MICEX has been caused by differences in market participants (predominantly domestic retail), improving economic conditions and the regulatory restrictions leading to a clustering of a particular trader type for a particular market. Another equally important factor concerns currency, in that LSE and RTS were trading eight of the most liquid securities denominated in USD, whereas MICEX trading is in RUB.

Regulatory restrictions can be the key to explaining why a certain market attracts less order flow, as illustrated by Stulz and Wasserfallen (1995). The major restricting factor is a capital control restriction condition prevailing in Russia at the time of the sampling period. Capital flow restriction was established originally in order to prevent the flight of capital from Russia, and stemmed from the time of economic and political instability. However, at the same time, capital flow restriction acts as a barrier between the types of investor, because of the limited convertibility of the RUB. There is an asymmetry in the regulatory treatment of foreign and Russian investors. Russian or domestic entities cannot freely hold foreign currencies for long periods of time and are required to settle in RUB. On the other hand, foreign investors are not bound by these obligatory restrictions. As a result, trading in USD on RTS is limited predominantly to institutional and foreign investors. In contrast, the major regulatory restriction in relation to MICEX RUB trading, is that only brokers with a licence from the Central Bank of Russia (CBR) can trade on MICEX, whereas trading in USD does not require such a licence to access the RTS market. Overall, the trading on RTS and LSE is more restricted relative to MICEX, by the minimum trading size requirement. The minimum size restriction prevents retail investors trading in smaller lots and may therefore restrict the informational degree of the RTS and LSE markets. Trading on the LSE IOB is restricted by the USD currency and by the fact that the securities are traded in the form of ADRs, which is a restriction in at least two forms: the conversion ratio of ADR to underlying shares (minimum trading size) and the USD. These restrictions may also play a role in limited order flow on LSE relative to MICEX, for instance ADR convertibility, the settlement delay and cost of converting ADR to underlying shares. The above mentioned restrictions may explain why the information asymmetry is less profound on the inter-Moscow market than on the London-Moscow market. Additionally, there is a short selling restriction on the Moscow equity market, but not on LSE. The absence of such a restriction on LSE may help to explain why the share of LSE IOB trading has been growing over the years, at the expense of Moscow trading. This, in the end, may have been a motivating factor for a merger between RTS and MICEX.

In summary, this thesis contributes to the cross-listing, price discovery and multi-market trading literature by applying established methodology to the under-researched areas, focusing on the factors affecting the empirical results. The contribution is as follows: Chapter 7 addresses the price discovery issue in the context of the emerging Moscow home market. This is the first and only study that investigates both Moscow stock markets. Chapter 8 investigates the relationship between the Moscow markets and its cross-listed counterparts on LSE. This is the first study that addresses Russian securities cross-border trading on LSE. Chapter 9 focuses on the conditional aspects of price discovery. Here, the methodological approach differs from introducing modifications of an established price discovery framework. Instead of modifying established models, the data set is conditioned upon the desired factor. Furthermore, the analysis of the whole study is based on the high frequency data derived from the three underlying limit order books as described in Chapter 4.

10.4 *Further Research*

Why and how order flow gravitates between the markets is an under-researched area, according to Karolyi (2006). In the case of the Moscow market, prior to the announcement of the merger between RTS and MICEX, order flow naturally gravitated from RTS to the MICEX market over time. Why and how is still not clear, however, and is a subject for further research. One of the hypotheses would be the capital movement restriction which resulted in the limited RUB convertibility, given the USD/RUB differences between the underlying markets. That may explain why RTS later decided to change to RUB. It would be interesting to test whether the difference in currencies between RTS and MICEX has restricted the attraction of order flow to RTS. To undertake research similar to Harris et al. (2002a) on this issue, it would be necessary to obtain the data sample from RTS and MICEX for both periods, before and after RTS changed from USD to RUB, in order to test the hypothesis that currency is the factor restricting the attraction of order flow. One of the limitations is the limited number of cross-listed securities available on both stock markets over a long period of time.

In the context of capital flow restriction, Rabinovitch et al. (2003) investigate differences in the return distribution of cross-listed securities and found some arbitrage opportunities on markets in Chile and Argentina. It has been shown that the estimated arbitrage trading cost or average daily returns spreads in Argentina are significantly lower in Chile. Melvin (2004), Auguste et al. (2002) indicate that the expectation of Peso devaluation lead to significant arbitrage spreads which arose in the form of ADR premia, because of the capital control restrictions that were imposed by the government.

There is evidence of substantial inter-market spreads in some periods in the data between the Moscow traded stock and the London traded ADRs, in this thesis. There is a possibility that arbitrage opportunities could have persisted if the returns had been distributed differently. The potential sources of differences between Moscow and London traded securities could be explained by transaction costs, foreign exchange rate and lead-lag times between these markets, the markets trading hours, liquidity and any form of regulatory restriction. For instance, if transaction costs on the Moscow market are lower than those on the London market and if the exchange rate is considered, then there are sources of potential differences between the return on locally traded securities.

In contrast to daily trading volume results, intraday volatility has a direct effect on the degree of MICEX leadership. Higher intraday volatility on the more trading intensive MICEX market implies a higher GG contribution of MICEX and vice versa. This finding suggests that volatility is positively correlated with the higher price discovery contribution of the higher volume trading market. The thesis found no evidence of trading size effect on the relationship between MICEX and LSE. However, only daily trading volume has been investigated and not the intraday trading size. It may be that daily aggregate trading has no influence on the LSE-MICEX relationship, whereas intraday trading does. One could also examine the MDH hypothesis indirectly i.e. the intraday trading volume and intraday volatility joint effect on price discovery, in the expectation of a positive correlation in both cases. It would also be interesting to apply the proposed research methodology to the quotes based sample. The quotes based sample would allow an analysis similar to that of Pascual and Pascual-Fuster (2010). Further research based on quotes data, could contribute to a better understanding of the effects of trading volume and volatility variables, on the price discovery process.

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