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Can a Stock Index be Less Efficient than Underlying Shares? An Analysis Using Malta Stock Exchange Data.

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Abstract

Researchers often assume that stock market indices are the best possible yardstick in terms of market efficiency. The paper investigates this concept using data from the Malta Stock Exchange (MSE). The fact that a significant number of MSE shares do not trade everyday, may imply that the most liquid shares on this exchange are more efficient than the market index, whose value is dependent on shares of varying liquidity levels – including the less liquid ones. The paper applies various tests to compare the pricing efficiency of the MSE Index to that of the most liquid share quoted on the exchange. It is found that the MSE Index is still more efficient than the latter share.

JEL Classification: G12, G14
Keywords: Malta Stock Exchange, Non-Synchronous Trading, Stock Markets.

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1. Introduction

One recurrent objective in financial economics is to infer the degree to which stock market data reflects "fundamentals", in terms of company-specific and economy-wide information. A stock price which reflects the former factors using all currently available information is deemed "efficient".

Stock market data is at times prone to mispricings arising from various factors such as market crashes and price bubbles. When considering stock pricing on emerging market exchanges, the challenge towards efficiency is even more substantial and this is also hampered by non-synchronous trading effects. We associate the latter effects with stocks which trade infrequently, given that the last transaction price might in fact relate to a past trade which took place prior to the release of new information, and is thus outdated. Therefore whilst the transaction price might have been efficient at the time of the trade, it is now an inefficient price – yet it is still the most recent available indication!

Such non-synchronous trading effects have to be considered when analysing stock market data – not simply because they induce specific characteristics in price series, but also because they might lead to false inferences regarding market efficiency and other issues.

This paper will look at non-synchronous trading effects in the context of the Malta Stock Exchange (MSE) – an emerging market exchange which is characterised by modest liquidity levels. The underlying idea of this paper is that non-synchronous price series may make the data appear "less efficient". Our main research question is whether the MSE Index does in fact reflect the general economic fundamentals more promptly than the most liquid security traded on the exchange. Whilst it is usually assumed that stock indices perform better in terms of efficiency as compared to individual securities, this might not necessarily be the case on MSE, where the index is partly composed of securities that trade much less frequently than the most liquid security. The efficiency of the respective price series is assessed through Granger-Causality tests and Relative Return Dispersion tests.

The paper is structured as follows: Section 2 reviews the background for this research, i.e. the existing literature, the general characteristics of MSE and the possible empirical results. Section 3 describes the data set and the general limitations of this analysis. Sections 4 and 5 apply Granger-Causality tests and Relative Return Dispersion tests in order to assess the relative efficiency of the price series of interest. Section 6 discusses the results and Section 7 concludes.

2. Research Background

This section starts with a brief exposition of related literature; it then describes the empirical setting of this study and discusses the possible empirical results.

2.1 A Brief Literature Review

The concept of financial market efficiency refers to the degree to which prices reflect fundamental values and whether they adjust instantaneously to news.[1] Various methodologies have been proposed to infer whether market prices behave in the way postulated by market efficiency theories, and readers are referred to Bollerslev and Hodrick (1995: Chapter 9) and Campbell, Lo, and MacKinlay (1997: Chapter 2) for comprehensive reviews.

This study does not aim to infer whether the analysed price series can be classified as efficient or otherwise; rather it endeavours to investigate the relative efficiency of two price series. More specifically, our main hypothesis is that one of the time series analysed in this study may be "more efficient" than the other, and this emanates from the concept of non-synchronous trading effects – which occur in less liquid markets when stocks trade less frequently.

When transactions in particular securities occur infrequently, the last transaction price quotations might cease to reflect the fundamental value of the firm as new information becomes available. At face value, this gives the impression that the stock prices delay in adjusting to new information; yet the underlying cause of the apparent inefficiency is that the most recent trading prices are already outdated. Last transaction prices of infrequently traded securities might be used for calculating the value of a portfolio of stocks or the value of a market index. At times, the validity of this methodology is undermined since such calculations might be based on partly outdated data due to non-synchronous trading effects. The latter data does not imply that there still exist market participants who are willing to trade at those prices.

Non-synchronous trading induces particular characteristics in stock prices. For instance, stock price indices tend to exhibit higher levels of serial correlation than individual stocks, as discussed by Fisher (1966). Cohen, Maier, Schwartz and Whitcomb (1979) showed that non-synchronous trading induces serial correlation in market returns.

Atchison, Butler and Simonds (1987) compared the observed serial correlation of a portfolio of NYSE stocks to that predicted by a model of non-synchronous trading as proposed by Scholes and Williams (1977). They found that the actual serial correlation was higher than that predicted by the non-synchronous trading model, and they attributed this to other sources of delayed price adjustment. There might be various reasons why prices take longer to adjust to new information. For instance, market participants who submit limit orders do not necessarily monitor these orders continuously. As new information becomes available, such orders may become mispriced and some other participants might "pick off" these orders and trade profitably on the basis of superior information. A further reason why a delayed price adjustment may occur is that participants might not devote enough time in monitoring less liquid stocks, as they do with the most liquid ones. Thus, not all of the pricing delays which are evident in stock price data are the result of non-synchronous trading.

Other authors who investigated the effects of non-synchronous trading on the autocorrelation of stock returns include Lo and MacKinlay (1990), Boudoukh, Richardson and Whitelaw (1994) and Kadlec and Patterson (1999). These studies confirm that non-synchronous trading increases return serial correlation, yet they disagree as to what is the specific autocorrelation level which emanates from non-synchronous trading. Part of the discrepancy in between the studies may be attributed to different assumptions regarding non-trading intervals.

[1] A comprehensive exposition of the main notions related to market efficiency is found in Dimson and Mussavian (1998).

Given that changes in expectations may take longer to show up in share price fluctuations if the latter trade infrequently, non-synchronous trading may result in lead-lag effects in between the prices of various stocks. This induces predictability elements in the data though the latter does not necessarily translate into abnormally profitable trading opportunities, as shown by Day and Wang (2002).

2.2 Empirical Setting for this Study

At this point it is sensible to give a description of the empirical setting for this study. Whilst most papers tend to relegate such descriptions till after having formulated the expected results, in this case our result expectations have to consider the particular empirical setting due to the specific characteristics of MSE.

MSE is one of the smallest European exchanges, where the number of transactions during a typical trading day does not exceed sixty. Trading activity is low primarily due to the fact that a small population of less than half a million people results in a restricted number of trading requirements. Less liquid securities on the exchange can go untraded for days. The small size implies that Malta is relatively unimportant as compared to other emerging markets, in terms of the inward financial investment flows from overseas. This impinges on liquidity and price efficiency of the market, given that larger markets thrive on the presence institutional investors.

Table 1: Number of Transactions and Average Waiting Time for Individual Securities (April-September 2004)

Security	**Number of Deals ***	**Average Waiting Time** (in trading days)
Bank of Valletta (BOV)	1107	0.1
Maltacom	798	0.2
HSBC Bank	669	0.2
Malta International Airport	326	0.4
International Hotel Investments	164	0.8
Middlesea Insurance	106	1.2
Lombard Bank	105	1.2
Simonds Farsons Cisk	86	1.5
Datatrak	50	2.5
Global Financial Services	48	2.6
FIM Bank	40	3.2
Plaza Centres	35	3.6
San Tumas Shareholdings	12	10.5
Suncrest Hotels	10	12.6

The table shows the number of deals which were realised in each security traded on MSE during the period April-September 2004 (126 trading days). Assuming that the deals were evenly spread over the period, we may compute the average waiting time in between successive transactions for each security.

* Source: Malta Stock Exchange Quarterly Report July – September 2004.

When MSE was set up in 1990, trading was manually conducted by around ten stock-broking firms and subsequently an electronic trading system was introduced in 1995. As outlined by Azzopardi and Camilleri (2003), no significant market making, short sale and derivatives activities are conducted. As at September 2004, the securities traded on MSE comprised 14 equities, 28 corporate bonds, and several government bonds. Trading turnover on MSE is heavily dependent on three equities: two major banks and a telecommunications company. In fact over 50% of the traded volume during the year 2003 consisted of order flow in these equities. The only market index compiled by MSE is the MSE Index, the value of which depends on *all* the shares trading on the exchange.

During the period January – September 2004, a total of 10,885 deals were struck on the Exchange. These consisted of 6,677 equity transactions, 1,718 transactions in corporate bonds and 2,490 transactions in government bonds.[2] Table 1 shows the number of transactions which took place during the period April-September 2004 for each of the equities traded on MSE. This study places an emphasis on the number of transactions as a liquidity measure, rather than the total transaction values or the number of shares transacted. This rests on the notion that if market participants are fully aware of the fundamental values of the securities, the only source of mispricing is non-synchronous trading, where the quoted price relating to the last trade might be an outdated one, if the final trade took place prior to the release of the last information set. In this way, the securities which trade less frequently are more prone to non-synchronous trading effects. Table 1 shows that Bank of Valletta (BOV) equity, is the most liquid security and it features around one-tenth of a trading day in terms of waiting time between transactions. In case of the least liquid security, the average waiting time in between successive transactions is around 13 trading days. This implies that the MSE index is at times computed through an information set which is partly 13 days old! This may result in the MSE Index not reflecting the fundamental value of the portfolio of securities quoted on the exchange. In this way, we may suppose that if it is indeed possible for a stock index to be less efficient than one of the underlying individual securities, MSE should be an optimal trading place from where one may glean such evidence!

2.3 Expected Results

This study aims to infer which of the analysed time series – MSE Index or BOV share – reflects new information more promptly. The latter stock was selected on the grounds that it features the highest liquidity level, as shown in Table 1. If any one of the former price series reflects new information prior to the other, we should note lead-lag effects in the data.

Such lead-lag effects are more likely to be the result of non-synchronous trading, rather than market participants taking long to adjust their judgement regarding the fundamental value of securities. In the context of a small market such as MSE, one may presume that it is fairly easy for participants to keep themselves updated with any new information issued by the respective companies. Yet, in line with the literature cited in Section 2.1, we may expect both non-synchronous trading and delayed traders' adjustments to be contributing to lead-lag effects. Irrespective of the actual source of the predictability, one may still argue that lead-lag effects imply that one time series reflects the general economic trends more promptly than the other.

It is usually assumed that market indices are better indicators of the general market trends than the underlying individual stocks, partly because of the fact that index values glean the price

[2] Malta Stock Exchange Quarterly Report July – September 2004.

fluctuations of different securities. Whilst individual stocks may be liable to mispricing and incorrect expectations, stock indices may be less prone to such errors, on the grounds that pricing errors should cancel out over a sufficiently large portfolio of stocks. Whilst such reasoning is probably justified, this may not necessarily be the case on the MSE. As outlined above, most of the stocks do not transact everyday and therefore price quotations may be subject to considerable non-synchronous trading effects. In particular, if the index value is based on a low number of stocks with sufficient liquidity in addition to a higher number of less liquid stocks, the index quotation may be subject to non-synchronous trading effects, given that the value is calculated through partly outdated information. If this limitation is severe enough, it might be the case that the most liquid MSE stocks might be more efficient than the index.

Given this, we cannot formulate any firm expectations regarding which price series will reflect new information more promptly, and therefore we investigate this issue by applying two methodologies: Granger-Causality and Relative Return Dispersion tests. We now proceed with a description of the data set.

3. Data Characteristics and General Limitations

This Section describes the characteristics of the data set and outlines the general limitations of this analysis.

3.1 Data Characteristics

The data set comprises daily closing observations of the MSE Index and BOV equity – an underlying share. The time series are both denominated in Maltese Lira and range from 18th May 1998 to 29th October 2004 – a total of 1571 observations.

Section 5 of this paper requires the regressing of these time series as variables depending on a wider share index in order to specify market models. Two different indices were used for this purpose. The first one was the FTSE Euro 100 Index, which is denominated in Euros and reflects the performance of 100 highly capitalised European companies. This time series ran from 22nd May 2000 to 12th February 2004 – a total of 907 observations. The second index was the FTSE European Banks Index, denominated in Euros and ranging from 18th May 1998 to 12th February 2004 – a total of 1392 observations.[3]

In compiling the data set, when an MSE Index observation was missing – in most cases due to a trading holiday – the particular date was deleted from the other time series. On those days where the BOV share did not trade, it was assumed that the security price did not change from the previous day. This is a reasonable assumption, since in most cases there were no material price changes for this security when it resumed trading on the following day. Plots of the levels and the log returns of the above price series are shown in Appendices A and B.

As shown in Table 2 the Augmented Dickey Fuller tests do not reject the null hypothesis of a unit root when considering the natural logs of the original price series. The null hypothesis of a unit root is rejected when considering the logarithmic returns. This implies that the logarithmic prices may be classified as I(1) since they are stationary in the first differences. We thus use the

[3] The author thanks MSE and FTSE International Ltd. for providing the data sets.

logarithmic returns for the purpose of the econometric models shown in Sections 4 and 5. Summary statistics for the log returns of the four price series are shown in Table 3.

Table 2: Augmented Dickey-Fuller Tests

Variable (logs)	**LM**	**LB**	**LE100**	**LEB**
ADF Test Statistics (Excluding Trend):				
ADF (1)	-1.8089	-1.7624	-1.3522	-2.2970
ADF Test Statistics (Including Trend):				
ADF (1)	-1.5811	-1.6057	-1.4364	-2.2580
Variable (log returns)	**LRM**	**LRB**	**LRE100**	**LREB**
ADF Test Statistics (Excluding Trend):				
ADF (1)	-22.191	-24.286	-22.366	-34.913
ADF Test Statistics (Including Trend):				
ADF (1)	-22.224	-24.296	-22.378	-34.901

The table shows the Augmented Dickey-Fuller test statistics for the logs and log returns of time series. (LM, LB, LE100 and LEB refer to the logarithmic series of the MSE Index, BOV share, FTSE Euro 100 Index and FTSE European Banks Index respectively. LRM, LRB, LRE100 and LREB refer to the log returns series of the MSE Index, BOV share, FTSE Euro 100 Index and FTSE European Banks Index respectively).

The ADF tests do not reject the null hypothesis of a unit root for the logarithmic series. The null hypothesis of a unit root is rejected at the 95% confidence level when considering the logarithmic returns.

The MSE Index Log Return series had a first order serial correlation of 0.39 whilst the first order serial correlation of the BOV Log Return series was 0.05. Serial correlation in financial data is usually taken as an indication of inefficiency, on the grounds that in an efficient market, prices adjust instantaneously to new information which is assumed to be serially uncorrelated. Yet, we have to caution that in this case the former serial correlation coefficients are not directly comparable, since according to Fisher (1966) stock indices typically feature higher serial correlation as compared to individual shares.

Table 3: Summary Statistics for Log Return Data Series

	MSE Index	BOV	FTSE Euro 100	FTSE European Banks Index
# of Observations	1570	1570	906	1391
Mean	0.0007	0.0008	-0.0005	-0.0001
Std. Deviation	0.009	0.015	0.017	0.018
Skewness	2.506	1.964	0.030	-0.012
Excess Kurtosis	20.944	44.252	1.454	2.554
Maximum Value	0.096	0.239	0.067	0.081
Minimum Value	-0.042	-0.138	-0.067	-0.092
Jarque-Bera Test	30,337	129,112	80	378

The table shows the summary statistics for the logarithmic returns of the data series. For all of the time series, the Jarque-Bera test rejects the null hypothesis that the data series are normally distributed at the 99% level of confidence.

3.2 Limitations

This study is subject to the general limitations inherent in analysing security price data. Firstly, when analysing stock market prices which span over long periods of time, one should be aware that the conditions which underlie the pricing process are likely to change. For instance, a long sample period might include changes in the structure of the quoted companies and changes in trading protocols. Dacorogna et. al. (2001; pp.5) described these effects as the "breakdown of the permanence hypothesis".

A further limitation emanates from the fact that stock prices are discrete prices, in the sense that each price change has to be quoted in cents or mils. Possible effects of price discreteness include price clustering i.e. a tendency for trading prices to occur at particular values.[4] Such effects might still be present to some degree in price series where trading is decimalised, given that in such cases prices have to be quoted in cents and therefore they are still not continuous.

Other limitations emanate from the respective methodologies which are being used in this study. The latter limitations are discussed following the descriptions of the methodologies in Sections 4 and 5. Such shortcomings have to be kept in mind when interpreting the empirical results obtained through the analysis of stock market data.

The paper now proceeds by investigating the relative aptitude of each time series of interest as a prompt indicator of general market movements. This is done through two different methodologies: Granger-Causality inferred through Vector Autoregression Models, and Relative Return Dispersions estimated through market models.

[4] For instance, Harris (1991) observed that on various US exchanges, stock prices tend to cluster on even-eights.

4. Granger-Causality Tests

This section applies Granger-Causality tests through the estimation of a Vector Autoregressive (VAR) Model. Granger (1969) argued that if shocks in a particular time series lead to shocks in another time series, then the former series is "Granger-causing" the latter. In this way, VARs model a time series as an autoregressive process, with the added lagged terms of another time series and an error term. If the lags of the second time series are significant, then we may argue that the latter is Granger-Causing the dependent variable. Thus, VARs offer the potential for modelling causal and feedback effects, where two or more time series Granger-cause each other.

A bivariate VAR may be formulated as follows:

$$x_t = \sum_{i=1}^{n} \alpha_{1i} x_{t-i} + \sum_{i=1}^{n} \beta_{1i} y_{t-i} + u_{1t} \quad (1)$$

and

$$y_t = \sum_{i=1}^{n} \alpha_{2i} x_{t-i} + \sum_{i=1}^{n} \beta_{2i} y_{t-i} + u_{2t} \quad (2)$$

where x_t and y_t are the variables that are assumed to Granger-cause each other, n is the number of lags, αs and βs are estimated coefficients, whilst u_t is an error term.

Various authors such as Niarchos and Alexakis (1998) argue that Granger-Causality from one stock price series to the other may be taken as evidence against market efficiency. This rests on the notion that in an efficient market, all stocks adjust instantaneously to new information, ruling out the presence of lead-lag effects. Yet, the latter effects may also be caused by non-synchronous trading rather than market inefficiency *per se*, as shown by Camilleri and Green (2004).

VAR and Granger-Causality are subject to a number of limitations. Granger-Causality does not necessarily imply actual causality, since the time series may be influenced by an exogenous variable, and therefore the actual causality runs from the latter variable to the time series being studied. This is implicitly the case with this analysis, which is based on the notion that fluctuations in the two price series of interest are in fact caused by a third variable – general economic news. A further limitation as outlined by Baek and Brock (1992) is that linear Granger-Causality tests may fail to detect non-linear causal relations. Non-linearity implies that the extent of the dependency between the time series varies during the sample period.

We now turn to the empirical results. A preliminary 24 order VAR was estimated (using the log returns series) in order to select the optimal lag length of the VAR. The Akaike Information Criterion selected a VAR(3) model, and the Schwarz Bayesian Criterion selected a VAR(1) model, yet the log-likelihood ratio statistics rejected all orders less than 6. In view of this, three VAR models were estimated: a VAR(1), a VAR(3) and a VAR(6) model. The former two models were deemed superior on the basis of higher System Log Likelihood Ratio, higher Log Likelihood Ratios for the individual equations, higher F-statistics, and higher Akaike Information Criterion and Schwarz Bayesian Criterion, and therefore the VAR(6) model was ruled out.[5] The decision between a VAR(1) and a VAR(3) model was less clear cut. The VAR(3) model may be deemed as superior in terms of the System Log-Likelihood Ratio and the explanatory power of the individual

[5] Appendix C shows a summary of these statistics.

regressions in terms of the Adjusted-R-squared. Yet most of the other statistics favoured the VAR(1) model. It was thus decided to estimate both models – and in effect they do not lead to differing qualitative results. The VAR(1) model is discussed here for the sake of working with a simpler model, yet the statistics for *both* models are reported in Appendices D and E respectively.

The LM statistic for the MSE Index regression of the VAR(1) (as shown in Appendix D) indicates that error term is heteroskedastic. This may be attributed to exogenous factors which are not being captured by the model. Given that our main interest is the relationship between the time series, this might not be particularly problematic as long as the omitted variables do not lead to spurious results.

Summary statistics of the VAR(1) model are presented in Table 4. In both equations, the relationship between the dependent variable and the lags are significant. The "ideal" results through which one may deduce a clear lead-lag relationship would show that, for instance the MSE Index log return is significant in explaining the BOV log return, but the latter return is not significant in explaining the former. In such a case, there would be a clear Granger-Causality running from the MSE Index to the BOV share.

The results in Table 4 reveal that both lagged variables are relevant in explaining the current return, for both the MSE Index and the BOV share. Thus, Granger-Causality tends to run in both directions. Judging by the t-ratios, it seems that for both regressions, the MSE Index lag is more significant in explaining the current return, as compared to the BOV index. This may be partly expected in case of the MSE Index regression since in most cases a variable may be better explained through its own lag, rather than through the lag of an external variable. Yet, the MSE Index lag is still more significant in explaining the BOV return, as compared to the lag of the latter share, and this may indicate that the larger impact runs from the MSE Index to BOV, rather than the other way round. This may be taken as an indication that the MSE Index time series is more efficient than the BOV time series.

Table 4: VAR(1) Model Coefficients

	MSE Index Regression			**BOV Regression**		
Regressor	Coefficient	Standard Error	T-Ratio	Coefficient	Standard Error	T-Ratio
LRM(-1)	0.3350	0.0259	12.93	0.4079	0.0473	8.63
LRB(-1)	0.0746	0.0152	4.91	-0.0603	0.0277	-2.18
CONST	0.0004	0.0002	1.85	0.0005	0.0004	1.43
F-Statistic	F(2, 1566): 157.22			F(2, 1566): 39.19		

The first column shows the regressor, where LRM and LRB stand for MSE Index and BOV Log Return, whilst Const is the intercept of the regression. The first lag of a variable is denoted as (-1). For both the MSE Index and BOV equations, the table shows the regression coefficients, standard errors and T-ratios. The F-statistics reject the null hypothesis that the estimated coefficients are equal to zero.

In order to investigate further, Granger non-causality tests were conducted on the MSE Index and BOV Log Return series in the system of equations. This methodology tests the null hypothesis of no causality for each of the variables. The test is χ^2 distributed with one degree of freedom, and test statistics of 72.92 for the index and 23.95 for the share permitted the rejection of the null hypothesis of no-causality for both variables at the 99% level of confidence. We now turn to an alternative methodology in order to infer whether we obtain similar indications.

5. Relative Return Dispersion Tests

This section applies Relative Return Dispersion (RRD) tests as indicators of the relative efficiency of the MSE Index and the BOV time series. RRD as described by Amihud, Mendelson and Lauterbach (1997), is calculated by averaging the squared residuals of the market model. The latter model hypothesises a linear relationship between the return on the dependent variable (usually an individual security but in this case we also use MSE Index) and the general market return approximated through an index. Thus:

$$r_{i,t} = \alpha_i + \beta_i r_{m,t} + \varepsilon_{i,t} \qquad (3)$$

where $r_{i,t}$ is the log return of stock *i* on day *t*, $r_{m,t}$ is the market log return, α_i and β_i are estimated coefficients, and $\varepsilon_{i,t}$ is a residual term. This approach is advantageous not only due to the inherent simplicity, but also due to technical reasons. For instance Brown and Warner (1980) and MacKinlay (1997) argued that more elaborate models do not usually present significant gains. Similarly, Cable and Holland (1999) empirically showed that the market model tends to outperform the other principal return-generating models.

RRD is then defined as:

$$RRD_i = \frac{1}{n}\sum_{t=1}^{n} \varepsilon^2{}_{i,t} \qquad (4)$$

where RRD_i is the Relative Return Dispersion for the sampled index or security *i*, $\varepsilon_{i,t}$ is the market model residual for index or security *i* at time *t*, and *n* is the number of observations.

This measure may be taken as an indicator of market efficiency on the grounds that efficient price series should reflect general market conditions. Yet, one limitation of this measure is that it tends to abstract from the fact that price series – especially individual securities – also reflect company specific news, and therefore price fluctuations which run counter to the general market movements are not necessarily an indicator of inefficiency. Another limitation of RRD is that the simple market model does not account for the fact that the sensitivity of the independent variable to the dependent variable (commonly called *beta*) can change over time.

When applying this indicator in the context of the Maltese market, some prior considerations are warranted. Firstly, the MSE index is the only index available for the Maltese economy, and therefore the "general market yardstick" which has to be selected for the market model estimation has to be a foreign one. The natural choice is a European index. It makes sense to estimate the market model for the BOV share through a European bank index and to estimate the market model for the MSE Index through a European general company index. The FTSE European Banks Index was chosen as a European bank index, whilst the FTSE Euro 100 Index was selected as the general European index.

Four market models were estimated: two for each of the BOV share and the MSE index. In each case, the first market model specified the FTSE European Banks Index as an independent variable, whilst the independent variable of the second market model was the FTSE Euro 100 Index.

A second factor which has to be considered is the difference in currencies – where the Maltese price series are quoted in Maltese Lira, whilst the European index values are quoted in Euro. In this respect, one should start by noting that the Maltese Lira is a fixed exchange rate, the value of which is mainly determined by the Euro. Therefore this exchange rate problem is not as troublesome. It was decided not to convert the price series to a common currency. This rests on the grounds that under this efficiency criterion, the price series should broadly move in the same direction. Thus, frequent price changes in a common direction are an indicator of efficiency – irrespective of the currency in which these changes are denominated. If the price series are converted to a common currency, the conversion may change the direction of the movement. For instance, on some particular day the returns on both the Maltese as well as the European price series might be negative indicating that the Maltese price series are reflecting general European expectations. Yet, an appreciation of the Euro on the same day might yield a positive return when converting the European index value to Maltese Lira that offsets the former negative return. In such an instance, we would infer that the price series are moving in *opposite* directions, when this is not the case!

Table 5: Market Model and RRD Estimations

		FTSE European Banks Index	**FTSE Euro 100 Index**
Number of Observations		1391	906
MSE Index Regression			
Market Model Coefficients:	α	0.0006	-0.0005
	β	0.0280	0.0229
RRD		0.000085	0.000044
BOV Regression			
Market Model Coefficients:	α	0.0005	-0.0005
	β	0.0505	0.0640
RRD		0.000251	0.000250

The table shows the coefficients (alpha and beta) for the four market models. The results for the market models with the MSE index as the dependent variable are shown on top, whilst the bottom panel shows the market models for the regressions with BOV as dependent variable. Two market models were estimated for each of the MSE Index and BOV: the independent variable of the first model was the FTSE European Banks Index, whilst the independent variable of the second model was the FTSE Euro 100 Index. RRD statistics indicate that the MSE index tends to move more congruently with the European indices.

The empirical results are shown in Table 5. The RRDs for the MSE index are lower than those for the BOV share. Two t-tests on the paired means for the squared residual series of the MSE index regressions and the BOV regression were conducted – the first test compared the market model residuals when the FTSE European Banks Index was used as an independent variable, whilst the second test compared the residuals when the FTSE Euro 100 Index was specified as an independent variable. Both tests rejected the hypothesis of equal means at the 99% confidence level.

In addition, following the notion that the MSE index may move more in line with the Euro 100 Index (since both are general market indices) and that the BOV share may move more congruently with the FTSE European Banks Index (since both price series relate specifically to banks), we still observe that the MSE Index series has a lower RRD when we compare the respective market model statistics.

Thus the MSE Index price series features a lower RRD as compared to the BOV price series, and therefore the former can be classified as more efficient than the latter. The higher RRD for BOV share may be partly due to the fact that some relatively large fluctuations may be expected as the share goes ex-dividend. This does not happen in the case of market indices since these are typically adjusted for dividend payments. [6] In addition, the lower RRD for the MSE index may be due to the fact that it is a measure taken from a number of underlying securities and therefore is less sensitive to company specific news. Yet, these arguments still imply that the MSE Index performs better as a general market indicator than the BOV share value, irrespective of the sources which make the former index a better indicator.

Overall, this confirms the results obtained in the previous section.

6. Discussion

This analysis compared the efficiency of the MSE Index to that of the BOV equity. The latter share was chosen on the grounds that it is one of the most frequently traded securities on MSE. The two methodologies which were used to infer which of the price series is more efficient in terms of promptly reflecting general economic trends yield similar indications. The VAR model indicates that the MSE Index returns are more relevant in predicting BOV returns, rather than the other way round. In addition, the MSE Index tends to move more contemporaneously with the selected European indices, as inferred from the RRDs.

Although this research did not specifically investigate the price series of other securities traded on MSE, we may assume that the remaining shares tend to be less efficient given that they trade less frequently, and therefore they are more prone to non-synchronous trading effects. Overall, it seems that the MSE Index is the best indicator from the Maltese securities markets in terms of reflecting general economic trends. In addition, the index features a further advantage since it still yields an indication on those days when the BOV share does not trade.

Despite this, researchers should still avoid putting unwarranted reliance on the MSE Index. As discussed in Section 2.2, the index value is also dependent on the less liquid stocks trading on MSE, and therefore it is calculated using partly outdated information. This may be inferred

[6] In order to account for the ex-dividend days of the BOV share, the RRDs for the security were re-estimated as follows. In case of the BOV-FTSE European Banks Index regression, the share was assumed to go ex-dividend for 10 times (2 times each year), whilst in case of the BOV-FTSE Euro 100 regression the share was assumed to go ex-dividend for 8 times. It was assumed that the largest positive residuals of the market model were related to the share going ex-dividend. Thus, the 10 largest positive residuals were not considered for calculating the RRD in case of the BOV-FTSE European Banks Index market model, and similarly the 8 largest positive residuals were not considered in calculating the other RRD statistic. In this case the BOV RRDs drop to 0.00019 in case of the FTSE European Banks Index market model and to 0.00017 in case of the FTSE Euro 100 market model. This does not qualitatively change the above inferences since the statistics are still larger than those of the MSE Index.

through the relatively high level of serial correlation of the MSE Index as compared to the BOV share.

Overall, it might be optimal to infer general market movements relating to the Maltese economy by utilising the MSE Index in the context of other economic indicators, for instance GDP. Yet, since the latter type of time series are usually available at quarterly frequency, they might be relatively unattractive as compared to the higher-frequency series which may be easily obtained through securities markets.

7. Conclusion

One of the main research branches in financial economics relates to the area of market efficiency. This analysis investigated the issue of whether a share index might be less efficient than a frequently traded underlying share, in the context of MSE. One may assume that the latter exchange provides an optimal empirical setting where such an (unusual) characteristic may occur, on the grounds that the MSE Index reflects the value of a collection of shares, where half of the latter do not on average trade everyday.

The chosen market efficiency tests – VARs and RRDs – tend to favour the MSE Index as a better indicator of general market movements and in this sense the index may be classified as more efficient than the BOV share. In addition, the MSE Index still provides an indication of market occurrences on those days when the BOV share does not trade and the usefulness of the index is thus confirmed.

Yet, one should still note that the index is subject to a high degree of non-synchronous trading effects, since other infrequently traded shares are included in its value. It may be useful to inquire the net gains or losses of dropping infrequently traded shares from the index composition. Such an action may result in a price series which is less prone to non-synchronous trading effects; yet it may also imply that the index might not represent particular industries of the Maltese economy.

One possible "middle of the road" course of action would be to compute the values of two different indices: a wide-composition index such as the current one, and a further index composed of the most liquid shares. The latter index would be less prone to non-synchronous trading effects. Whilst the compilation of a new index should be welcome by researchers and market practitioners, the advantages of such a policy might not be immediately appreciated by general market participants who might even consider a second index as unnecessary. These issues are left for future research.

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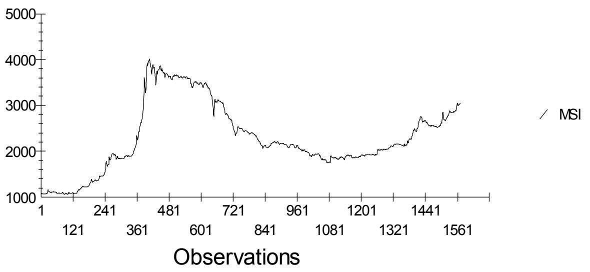
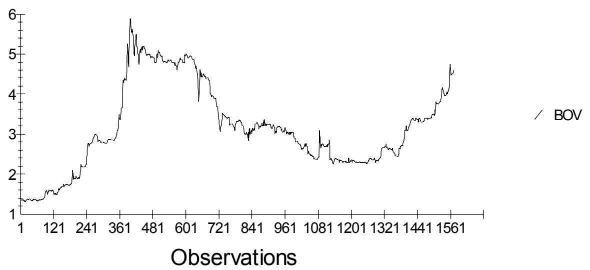
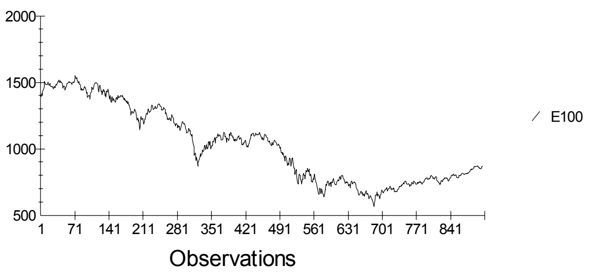
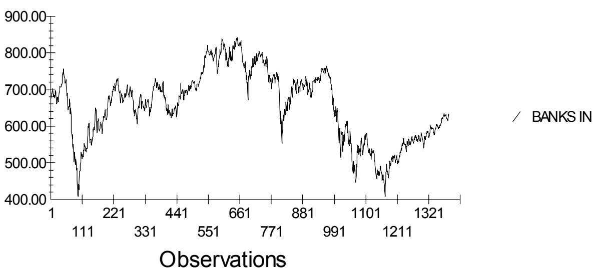
Appendix A:
Plots of the Original Time Series



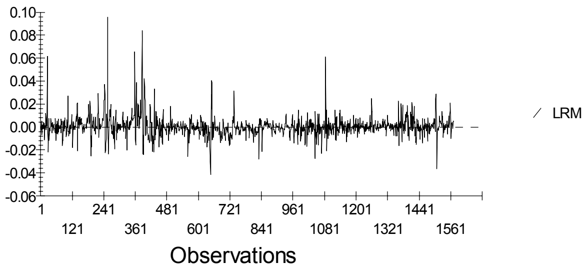


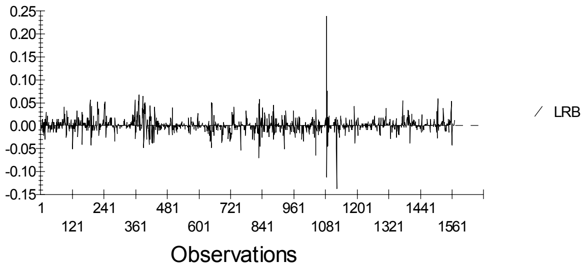


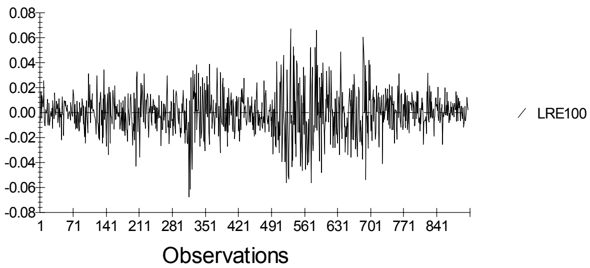


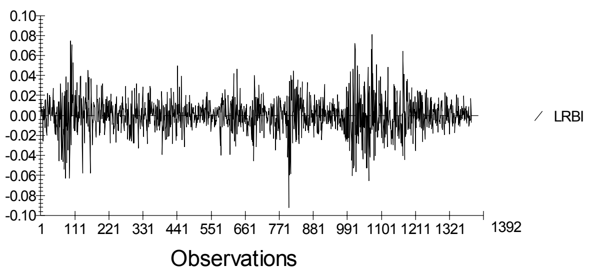
MSI - Malta Stock Exchange Index
BOV - Bank of Valletta
E100 - FTSE Euro 100 Index
BANKS IN - FTSE European Banks Index

Appendix B:
Plots of the Logarithmic Return Time Series









LRM - Malta Stock Exchange Index log returns
LRB - Bank of Valletta log returns
LRE100 - FTSE Euro 100 Index log returns
LRBI - FTSE European Banks Index log returns

Appendix C: Selecting the Order of the VAR

The table shows various explanatory power statistics for the VAR(1), VAR(3) and the VAR(6) models. Although the individual statistics tend to select different "optimal" models, they tend to indicate that the VAR(1) and the VAR (3) models perform better than the VAR (6).

VAR (1)	**MSI Regression**	**BOV Regression**
System Log-likelihood	9805.1	9805.1
Equation Log-likelihood	5295.6	4352.7
F-Statistic F(2,1566)	157.22	39.197
R-Bar-Squared	0.16616	.046458
Akaike Info. Criterion	5292.6	4349.7
Schwarz Bayesian Criterion	5284.6	4341.7
VAR (3)	**MSI Regression**	**BOV Regression**
System Log-likelihood	9807.2	9807.2
Equation Log-likelihood	5292.3	4354.2
F-Statistic F(6,1560)	53.983	15.785
R-Bar-Squared	0.1688	0.0536
Akaike Info. Criterion	5285.3	4347.2
Schwarz Bayesian Criterion	5266.6	4328.5
VAR (6)	**MSI Regression**	**BOV Regression**
System Log-likelihood	9797.4	9797.4
Equation Log-likelihood	5287.6	4350.3
F-Statistic F(12,1551)	28.110	8.8662
R-Bar-Squared	0.1723	0.0570
Akaike Info. Criterion	5274.6	4337.3
Schwarz Bayesian Criterion	5239.8	4302.5

A revised version of this paper may be referred to:

Camilleri, Silvio John, 2005, Can a Stock Index Be Less Efficient Than Underlying Shares? An Analysis Using Malta Stock Exchange Data, *The FEMA Research Bulletin,* 1(1), 29-41.

Appendix D: VAR(1) Model Results

```
          OLS estimation of a single equation in the Unrestricted VAR
                                  Dependent variable is LRM
                     1569 observations used for estimation from 3 to 1571
*******************************************************************************
 Regressor              Coefficient       Standard Error         T-Ratio[Prob]
 LRM(-1)                    .33498             .025909            12.9295[.000]
 LRB(-1)                   .074564             .015192             4.9081[.000]
 C                        .3875E-3            .2098E-3             1.8470[.065]
*******************************************************************************
 R-Squared                     .16722   R-Bar-Squared                    .16616
 S.E. of Regression          .0082864   F-stat.    F(  2,1566)  157.2231[.000]
 Mean of Dependent Variable  .6666E-3   S.D. of Dependent Variable    .0090745
 Residual Sum of Squares       .10753   Equation Log-likelihood         5295.6
 Akaike Info. Criterion        5292.6   Schwarz Bayesian Criterion      5284.6
 DW-statistic                  1.9855   System Log-likelihood           9805.1
*******************************************************************************

                               Diagnostic Tests
*******************************************************************************
*    Test Statistics  *        LM Version        *         F Version          *
*******************************************************************************
* A:Serial Correlation*CHSQ(   1)=   .49141[.483]*F(   1,1565)=   .49031[.484]*
* B:Functional Form   *CHSQ(   1)=   7.1346[.008]*F(   1,1565)=   7.1489[.008]*
* C:Normality         *CHSQ(   2)=  32169.5[.000]*       Not applicable       *
* D:Heteroscedasticity*CHSQ(   1)= 149.7525[.000]*F(   1,1567)= 165.3427[.000]*
*******************************************************************************
   A:Lagrange multiplier test of residual serial correlation
   B:Ramsey's RESET test using the square of the fitted values
   C:Based on a test of skewness and kurtosis of residuals
   D:Based on the regression of squared residuals on squared fitted values
```

```
          OLS estimation of a single equation in the Unrestricted VAR
                                  Dependent variable is LRB
                     1569 observations used for estimation from 3 to 1571
*******************************************************************************
 Regressor              Coefficient       Standard Error         T-Ratio[Prob]
 LRM(-1)                    .40785             .047254             8.6310[.000]
 LRB(-1)                  -.060303             .027708            -2.1764[.030]
 C                        .5485E-3            .3826E-3             1.4335[.152]
*******************************************************************************
 R-Squared                    .047674   R-Bar-Squared                  .046458
 S.E. of Regression           .015113   F-stat.    F(  2,1566)   39.1973[.000]
 Mean of Dependent Variable  .7720E-3   S.D. of Dependent Variable     .015477
 Residual Sum of Squares       .35769   Equation Log-likelihood         4352.7
 Akaike Info. Criterion        4349.7   Schwarz Bayesian Criterion      4341.7
 DW-statistic                  2.0268   System Log-likelihood           9805.1
*******************************************************************************

                               Diagnostic Tests
*******************************************************************************
*    Test Statistics  *        LM Version        *         F Version          *
*******************************************************************************
* A:Serial Correlation*CHSQ(   1)=   6.5879[.010]*F(   1,1565)=   6.5989[.010]*
* B:Functional Form   *CHSQ(   1)=   2.0387[.153]*F(   1,1565)=   2.0362[.154]*
* C:Normality         *CHSQ(   2)= 154910.6[.000]*       Not applicable       *
* D:Heteroscedasticity*CHSQ(   1)=   4.9822[.026]*F(   1,1567)=   4.9917[.026]*
*******************************************************************************
   A:Lagrange multiplier test of residual serial correlation
   B:Ramsey's RESET test using the square of the fitted values
   C:Based on a test of skewness and kurtosis of residuals
   D:Based on the regression of squared residuals on squared fitted values
```

A revised version of this paper may be referred to:

Camilleri, Silvio John, 2005, Can a Stock Index Be Less Efficient Than Underlying Shares? An Analysis Using Malta Stock Exchange Data, *The FEMA Research Bulletin,* 1(1), 29-41.

Appendix E: VAR(3) Model Results

```
OLS estimation of a single equation in the Unrestricted VAR
Dependent variable is LRM: 1567 observations used for estimation from 5 to 1571
*******************************************************************************
 Regressor              Coefficient       Standard Error         T-Ratio[Prob]
 LRM(-1)                    .33716            .027953            12.0616[.000]
 LRM(-2)                  -.016668            .029225            -.57034[.569]
 LRM(-3)                  -.073256            .027418            -2.6718[.008]
 LRB(-1)                   .078617            .015374             5.1137[.000]
 LRB(-2)                   .014195            .015528             .91418[.361]
 LRB(-3)                   .026365            .015409             1.7110[.087]
 C                        .4115E-3           .2102E-3             1.9576[.050]
*******************************************************************************
 R-Squared                     .17193   R-Bar-Squared                   .16875
 S.E. of Regression          .0082787   F-stat.    F(  6,1560)   53.9834[.000]
 Mean of Dependent Variable  .6675E-3   S.D. of Dependent Variable    .0090801
 Residual Sum of Squares       .10692   Equation Log-likelihood         5292.3
 Akaike Info. Criterion        5285.3   Schwarz Bayesian Criterion      5266.6
 DW-statistic                  2.0009   System Log-likelihood           9807.2
*******************************************************************************

                               Diagnostic Tests
*******************************************************************************
*    Test Statistics  *        LM Version        *         F Version          *
*******************************************************************************
* A:Serial Correlation*CHSQ(   1)=   .10897[.741]*F(   1,1559)=   .10843[.742]*
* B:Functional Form   *CHSQ(   1)=   6.9176[.009]*F(   1,1559)=   6.9128[.009]*
* C:Normality         *CHSQ(   2)=  33100.6[.000]*       Not applicable       *
* D:Heteroscedasticity*CHSQ(   1)= 125.9450[.000]*F(   1,1565)= 136.7776[.000]*
*******************************************************************************
   A:Lagrange multiplier test of residual serial correlation
   B:Ramsey's RESET test using the square of the fitted values
   C:Based on a test of skewness and kurtosis of residuals
   D:Based on the regression of squared residuals on squared fitted values
```

```
OLS estimation of a single equation in the Unrestricted VAR
Dependent variable is LRB: 1567 observations used for estimation from 5 to 1571
*******************************************************************************
 Regressor              Coefficient       Standard Error         T-Ratio[Prob]
 LRM(-1)                    .34249            .050866             6.7332[.000]
 LRM(-2)                    .15225            .053181             2.8629[.004]
 LRM(-3)                  -.025623            .049893            -.51356[.608]
 LRB(-1)                  -.054541            .027976            -1.9496[.051]
 LRB(-2)                   .029092            .028256             1.0296[.303]
 LRB(-3)                  -.053141            .028040            -1.8952[.058]
 C                        .5270E-3           .3826E-3             1.3777[.168]
*******************************************************************************
 R-Squared                   .057235   R-Bar-Squared                   .053609
 S.E. of Regression          .015065   F-stat.    F(  6,1560)   15.7847[.000]
 Mean of Dependent Variable  .7776E-3   S.D. of Dependent Variable     .015485
 Residual Sum of Squares       .35403   Equation Log-likelihood         4354.2
 Akaike Info. Criterion        4347.2   Schwarz Bayesian Criterion      4328.5
 DW-statistic                  2.0037   System Log-likelihood           9807.2
*******************************************************************************

                               Diagnostic Tests
*******************************************************************************
*    Test Statistics  *        LM Version        *         F Version          *
*******************************************************************************
* A:Serial Correlation*CHSQ(   1)=   1.8341[.176]*F(   1,1559)=   1.8269[.177]*
* B:Functional Form   *CHSQ(   1)= .0061584[.937]*F(   1,1559)= .0061270[.938]*
* C:Normality         *CHSQ(   2)= 152945.3[.000]*       Not applicable       *
* D:Heteroscedasticity*CHSQ(   1)=   5.0799[.024]*F(   1,1565)=   5.0900[.024]*
*******************************************************************************
   A:Lagrange multiplier test of residual serial correlation
   B:Ramsey's RESET test using the square of the fitted values
   C:Based on a test of skewness and kurtosis of residuals
   D:Based on the regression of squared residuals on squared fitted values
```