Time-varying return predictability and equity market fragmentation.*

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Abstract

In the wake of the Markets in Financial Instruments Directive (MiFID), in 2007, the establishment of a number of new stock trading venues, so called MTFs, have lead to an increased fragmentation in trading of European stocks. In this paper we study the effect of this increased fragmentation on the level of weak-form market efficiency, i.e. on the level of stock return predictability, using data for Swedish stocks traded on the regular NASDAQ OMX Nordic stock exchange, as well as on the recently established MTF venues, Chi-X, Bates, Turqouis, and Burgundy. By use of different variance ratio tests, on moving sub-sample windows over the period 2008-2011, a panel of time-varying measures of return predictability on the regular NASDAQ OMX Nordic stock exchange is used in the analysis of fragmentation effects. The results indicate, among other, that the relative level of return predictability has decreased, i.e. the level of weak-form information efficiency has increased, with the increasing level of stock fragmentation.

Keywords: Market fragmentation, time-varying weak form market efficiency, variance ratio test.

JEL: G12; G14; G15.

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1 Introduction

The recognition that the level of information efficiency varies over time has renewed the interest in financial market efficiency studies during recent years (e.g. Gu and Finnerty, 2002; Lagoarde-Segot, 2009; Kim, Shamsuddin and Lim, 2011; Chuluun, Eun and Kilic, 2011). This literature acknowledges that different financial markets may be weak-form efficient to varying degrees, rather than weak-form efficient or not, and that this level may change over time.[1] A central issue within this research concern the underlying factors that lead markets to become efficient. As noted by Lim et al. (2011), potential factors leading to departures from market efficiency include the characteristics of the market microstructure, limitations to arbitrage, psychological biases among investors, noise trading, and market imperfections. The degree of market efficiency is also likely to evolve over time due to changes in market conditions, macro institutions, market regulations, and information technologies. Studies linking events to periods of lower market efficiency include among other Hoque et al. (2007), Kim and Shamsuddin (2008), and Kim, Shamsuddin and Lim, 2011, who relate market conditions (mainly financial crises) to market efficiency, Lagoarde-Segot, 2009, Kim and Singal (2000a, b), Antoniou (1997), and Groenewold et al. (2004), linking financial reforms and changes in regulatory framework to market efficiency, and Jain (2005), Naidu and Rozeff (1994), Freund et al. (1997), and Ryoo and Smith (2002), testing how technology improvements (the introduction of electronic trading systems) and introduction of price limitation systems affect market efficiency.[2]

In this study we extend the evidence concerning factors affecting time-varying weak form market efficiency by testing to what extent the level of fragmentation in stock trading, i.e. whether the market structure of trading, affect the level of return predictability. The question of fragmented stock trading and market efficiency, or market quality in more general terms (O'Hara and Ye, 2011), have for long interested researchers. Arguments in favour for consolidating trading to a single trading venue resort to scale effects (lower fixed costs per share in setting up exchanges and lower trading costs associated with concentrating buyers and seller to one consolidated market, i.e. network externalities), while the main argument for fragmentation is that the increased competition between trading venues reduces trading costs. Even though the question of fragmentation and market efficiency has a relatively long history (see e.g. O'Hara and Ye, 2011), its interest has been refueled by the recent restructuring of equity markets around the world. In Europe the introduction of the Markets in Financial Instruments Directive (MiFID) in 2007 has stimulated competition between financial trading venues in Europe by allowing the creation of alternative non-regular trading facilities, Multilateral Trading Facilities (MTF). For trading in Nordic stocks, this has lead to a change in trading market structure through the introduction of the alternative trading venues, Chi-X, Bates, Turqouis, and Burgundy, in addition to the regular NASDAQ OMX Nordic stock exchange. A main

[1] The bulk of earlier empirical literature (see e.g. the survey by Lim and Brooks, 2011), testing for weak form information efficiency, builds on an assumption of a constant level of market efficiency throughout the estimation period and either seek to reject or to accept that markets are either weak form efficient or not.

[2] See e.g. Lim et al., (2011), for a more comprehensive survey.

concern with the increased level of fragmentation is, however, whether this adversely affect market quality, i.e. transaction costs and information efficiency.[3] Unfortunately, earlier empirical studies presents rather mixed results regarding this issue. Concerning market efficiency, Battalio (1997) find that it increases on the NYSE after a third market broker initiated trading, i.e. after the level of fragmentation increased. O'Hara and Ye (2011) find that fragmentation do not weaken market information efficiency. Riordan, Storkenmaier, and Wagener (2010), in a study of post MiFid competition between the London Stock Exchange and MTFs, report that despite high levels of market fragmentation, the market for FTSE 100 constituents is relativelty efficient. These results are, however, contradicted by the findings of Fioravanti and Gentile (2011) on European data, who find that market efficiency is reduced due to an increased level of fragmentation.

The main contribution of the paper in regard to earlier work is that we allow for time-varying measures of market efficiency, which in a second stage is related to the level of fragmentation using a panel data structure. In this manner variations in the level of fragmentation both over time for individual stocks, as well as cross-sectional over different stocks, are related to measures of return predictability. Since the relative level of market efficiency to a large extent depends on (for the researcher) unobservable factors, the ability to control for unobserved stock specific effects through fixed effects is a great advantage. To measure the level of return predictability the multiple variance ratio (VR) tests by Chow and Denning (1993), the multiple version of Wright's sign test (see Kim and Shamsuddin, 2008), and the wild bootstrap test of Kim (2006) on moving sub-sample windows over the considered time span are utilized. The study is performed on the sample of stocks constituting the OMX-Stockholm 30 index and cover analysis of both individual stocks and the aggregate of these (used as a proxy for the market). In addition to the main purpose additional evidence regarding market quality, i.e. the bid-ask spreads and volatility, in relation to the level of fragmentation is also provided.

The main result of the paper indicate that the increased fragmentation of trading in stocks on the NASDAQ OMX Nordic stock exchange and competing MTFs have not harmed information efficiency, but rather improved it. The result is robust over the three considered variance ratio measures of time-varying return predictability, as well as to an alternative time-varying measure of information delay (Hou and Moskowitz, 2005). A proposed explanation underlying the result is that a higher level of fragmented trading, i.e. higher levels of trading on competing MTFs, increases these new alternative trading venues attraction for both regular and arbitrage investors. This increased attention will increase the level of cross-market trading, leading to an improved information efficiency. The proposition is broadly supported by the data since stocks with a higher volatility in the level of fragmentation is found to be associated with periods of lower return predictability. This is interpreted as an indication that stocks where investors are more actively seeking best prices, i.e. have a higher volatility in the level of fragmentation in turn associated with higher levels of arbitrage trading, also have a lower level of return predictability. A second indication supporting the suggested explanation is that it is found that a higher

[3] In general, a market with relatively lower transaction costs and higher information efficiency is considered to be of higher quality.

level of fragmentation among the MTFs lowers the return predictability on the regular NASDAQ OMX Nordic stock exchange. This is taken as evidence that if there are more viable competing trading venues for a stock, i.e. more liquid MTFs, this will in general increase arbitrage trading between all markets, leading to a lower return predictability. Apart from the main result, other findings are that the increased level of fragmented trading, observed during 2008-2011, have lead to, on average, smaller bid-ask spreads, i.e. lower implicit trading costs, and decreased the volatility in stock returns on the regular NASDAQ OMX Nordic stock exchange.

The outline of the paper is as follows: In Section 2 the data is presented, while in Section 3 we discuss the utilized measures of information efficiency, liquidity and fragmentation. The empirical results are presented in Section 4, while the final section concludes.

2 Market efficiency and fragmentation

A key question in the literature concerning fragmented stock trading concerns to what extent gains from market venue competition, i.e. fragmented trading, outweights those of consolidated trading, i.e. a monopolistic market structure. Overall, the effect on market quality, e.g. direct and indirect transaction costs, and market efficiency, have been examined to provide evidence regarding this question. Early theoretical research in the area expresses a concern that increasing fragmentation would lead to a lower market quality. For example, Mendelson (1987) advances the network argument, i.e. lower trading costs associated with concentrating buyers and seller to one consolidated market, and show that fragmentation can result in less liquid and less efficient markets, while Pagano (1989) find that an equilibrium with trading in two markets is unstable as orders would naturally gravitate towards the more liquid market, i.e. a flight to liquidity. Another theoretical paper in favour towards consolidation of trading is Chowdry and Nanda (1991), arguing that adverse selection costs increases with the number of markets.

More recent theoretical literature have, however, turned and instead argue in favour towards fragmented trading. For example, Economides (1996) suggest that venue competition may improve welfare since the welfare loss due to monopoly is not offset by network externalities connected with venue competition, Harris (1993) favours fragmented trading based on the notion that investors are heterogenous regarding the types of trading problems that they confront, while Hendershott and Mendelson (2000) demonstrate that fragmentation can reduce individual dealer inventory risk. Along the same line, Biais (1993) study conditions under which fragmentation do not effect market quality, measuring quality in terms of the mean of spreads, while Stoll (2001) argue that routing can lead to greater efficiency in fragmented markets. In a more recent paper Jiang, McInish and Upson (2011) develop an alternative explanation to why fragmentation may lead to greater information efficiency. This explanation builds on Subrahmanyam (1991) and Holden and Subrahmanyam (1992), who link higher proportions of informed traders to higher levels of information efficiency. The conjecture set forth by Jiang, McInish and Upson (2011) state that as uniformed traders are able to segment their order flows to off exchange venues, here MTFs, a larger proportion of trades on the (regular) exchanges are informed, improving the price discovery and market quality of the overall market.

Given the studied context within this paper, an additional explanation for increased information efficiency due to increased fragmentation may also be proposed. The introduction of a (Swedish) stock on an alternative market (international MTF) is likely to increase the interest among international (European) investors, not previously trading the (Swedish) stock. This increased interest may be due to a higher level of awareness of the stock among international investors, but may also come from the introduction of an additional price attracting arbitrage investors seeking to profit on possible misspricing between markets (e.g. between the regular and the introduced MTF market). Both of these features, which we label as an *attraction effect* comes from the introduction of the stock on the additional market. As trading in the stock on the alternative market (MTF) increases, the attraction effect becomes stronger since larger trading volumes attract both regular, as well as arbitrage investors. Thus, a higher level of fragmentation, all else equal, is likely to increase the number of traders and analysts following and trading the individual stock. This increased investor activity will then lead to an improvement in the overall information efficiency, also on the regular stock exchange.

Turning to the empirical literature concerning market efficiency and the level of fragmentation, the results offer mixed evidence. Battalio (1997) find that market efficiency increases on the NYSE after a third market broker initiated trading, i.e. after the level of fragmentation increased. O'Hara and Ye (2011) find that fragmentation do not weaken market information efficiency. Riordan, Storkenmaier, and Wagener (2010), in a study of post MiFid competition between the London Stock Exchange and MTFs, report that despite high levels of market fragmentation, the market for FTSE 100 constituents is relatively efficient. These results are, however, contradicted by the findings of Fioravanti and Gentile (2011) (on European data), who find that market efficiency is reduced due to an increased level of fragmentation.

3 Data, variable measurement and empirical model

3.1 Data

To study to what extent the return predictability on the regular NASDAQ OMX Nordic stock exchange has been affected by an increasing level of fragmentation in stock trading by the introduction of MTFs, daily stock price data has been collected from the Thomson Reuters Datastream. The sample cover the period from the introduction of Swedish stocks on the Chi-X in 2008-03-14, and include the introduction of Swedish stocks on Turquoise (2008-08-15), Bats (2008-12-05) and Burgundy (2009-06-12), up until 2011-09-23. The data concern 26 Swedish stocks included in the OMXS30 index, all introduced on at least one MTF during the considered period.[4] Data concerning trading volumes on the MTFs have been provided by Fidessa. In Figure 1, the logarithmic return for an equally weighted

[4]OMXS30 contain the 30 largest and most traded stocks on the NasdaqOMX Stockholm market. Astra Zeneca, ABB, and Nokia have been excluded since data for trading on the MTF:s were missing.

portfolio of the considered stocks is displayed over the considered period.

[Figure 1 about here.]

The return is, as expected, most volatile during the 2008 financial turmoil. To measure the level of fragmentation for each stock we use the inverse of the Herfindhal concentration index, i.e.

$$F_i = \frac{1}{\sum_{j=1}^{N} vol_{i,j}^2},$$

where $vol_{i,j}$ is the proportion of trading volume on exchange platform j for stock i. The F_i ranges from one, if all trading is concentrated to one trading venue, to N, if trading is equidistributed among all the platforms. In Figure 2 the level of fragmentation for an equally weighted portfolio of the considered stocks are displayed.

[Figure 2 about here.]

As indicted in the figure, there is a positive trend in the overall level of fragmentation over the considered period.

3.2 Measures of time-varying return predictability

To measure the relative level of stock return predictability over time we use the Chow and Denning test (1993), the multiple version of Wright's sign test (2000, see Kim and Shamsuddin, 2008), and the wild bootstrap test of Kim (2006) on moving sub-sample windows over the considered time span.[5] All these tests build on the conventional VR test, who builds on the fact that if asset return is purely random the variance of $k-$period return is k times the variance of the one-period return. The multiple VR tests considers whether the set of VR statistics for different holding periods k are jointly equal to one. Assuming r_t to be the, $t = 1, ..., T$, asset return the VR statistic can be written as

$$VR(r;k) = \frac{\frac{1}{Tk}\sum_{t=k}^{T}(r_t + r_{t-1} + ... + r_{t-k+1} - k\hat{\mu})^2}{\frac{1}{T}\sum_{t=1}^{T}(r_t - \hat{\mu})^2},$$

where $\mu = T^{-1}\sum_{t=1}^{T} r_t$. Under regularity assumptions for r_t, corresponding to r_t being serially uncorrelated with a general form of heteroscedasticity including the ARCH-type of conditional variance (see Lo and MacKinlay, 1988), it can be shown that under the null hypothesis that the unknown population VR is equal to one, i.e. $V(k) = 1$, the test statistic

$$M(r;k) = \frac{VR(r;k) - 1}{\left(\sum_{j=i}^{k-1}\left[\frac{2(k-j)}{k}\right]^2 \delta_j\right)^{1/2}},$$

where

$$\delta_j = \frac{\sum_{t=j+1}^{T}(r_t - \hat{\mu})^2(r_{t-j} - \hat{\mu})^2}{\left[\sum_{t=1}^{T}(r_t - \hat{\mu})^2\right]^2}$$

[5] We are gratful towards Professor Jae Kim for sharing the Gauss code concerning the multiple VR tests used within this paper.

is asymptotically standard normal distributed (Lo and MacKinlay, 1988). Chow and Denning (1993) suggested a multiple VR test for the joint null hypothesis $V(k_i) = 1$, for $i = 1, ..., l$ against the alternative hypothesis that $V(k_i) \neq 1$ for some holding period k_i. The test statistic is given by

$$CD = \max_{1 \leq i \leq l} |M(r; k_i)|$$

and follows the studentized maximum modulus distribution with l and T degree of freedom.[6]

A possible drawback with the C-D multiple VR test is that it may be sensitive to extreme observations (e.g. Kim and Shamsuddin, 2008). Due to this we also consider the sign based VR test of Wright (2000), which is less sensitive towards outliers. Let $s_t \in (0, 1)$, be a indicator variable with $s_t = 1$ if $r_t > 0$, and zero otherwise. The sign based test of the individual hypothesis $V(k) = 1$ against the alternative $V(k) \neq 1$ is given by

$$S_1(k) = \left(\frac{(Tk)^{-1} \sum_{t=k}^{T} (s_t + s_{t-1} + ... + s_{t-k+1})^2}{T^{-1} \sum_{t=1}^{T} s_t^2} - 1 \right) \left(\frac{2(2k-1)(k-1)}{3kT} \right)^{-1/2}.$$

Kim and Shamsuddin (2008), in spirit of Chow and Denning (1993), propose a multiple joint test of $V(k_i) = 1$ for $i = 1, ..., l$, against the alternative hypothesis that $V(k_i) \neq 1$ for some i. The test is given by

$$JS = \max_{1 \leq i \leq l} |S_1(k_i)|.$$

The exact sampling distribution of JS may be obtained through simulation, see Chow and Denning (1993) and Kim and Shamsuddin (2008).[7]

As a third measure of return predictability a test of the random walk is performed using the wild bootstrap test of Kim (2006).[8] The wild bootstrap for the Chow-Denning (CD) test is performed as follows. (i) Draw m bootstrap samples, each with T observations, according to $r_t^* = \phi_t r_t$, for $t = 1, ..., T$, where ϕ_t is a random sequence with mean zero and unit variance. (ii) For each bootstrap sample, calculate the CD^*, to form a bootstrap distribution of the test statistic, $\{CD^*(j)\}_{j=1}^{m}$.[9] The p-value of the test is estimated as the proportion of the bootstrap distribution greater than the CD statistic based on the original data. In line with Kim (2006) and Kim and Shamsuddin (2008) a standard normal distribution is used for ϕ_t.[10]

3.3 Testing for fragmentation effects

The level of market information efficiency is assumed to vary over time and depend on the characteristics of the market microstructure, limitations to arbitrage, psychological biases

[6] Critical values are given in Stoline and Ury (1979). For large T the critical value, at a confidence level of α, is given by the $[1-(\alpha^*/2)]$th percentile of the standard normal distribution, where $\alpha^* = 1-(1-\alpha)^{1/l}$.

[7] The 5 and 10 percent critical values used in this paper, correponding to $k_i = \{2, 5, 10, 20, 40\}$ with $T = 500$, are 2.40 and 2.10, respectively.

[8] The bootstrap is a resampling method to approximate the sampling distribution of the test statistic.

[9] The bootstrap distribution is used to approximate the sampling distribution of the CD statistic.

[10] Kim (2006) find that other choices for ϕ_t gives qualitatively similar results.

among investors, noise trading, market imperfections and to be affected by changes in market conditions, macro institutions, market regulations, and information technologies. Since the level of information efficiency is not directly observed we model the probability of deviations from a random walk with a binary indicator variable.[11] The indicator is based on the VR-tests and indicate whether the null hypothesis of a random walk, for a given sub-sample, is rejected or not. The binary indicator variable is constructed as $W \in (0, 1)$, where one indicates a period with a significant deviation from a random walk, zero otherwise. In the empirical analysis the binary indicator is linked to the level of fragmentation through a binary model. A challenge in isolating the effect of fragmentation on the level of information efficiency concern endogeneity. Since the level of fragmentation is the aggregated result of the investors stock trading venue choice, most likely affected by the level of return predictability on the regular market, this creates an endogeneity problem.[12] To handle this an instrumental variable approach is utilized in the empirical analysis. In spirit of O'Hara and Ye (2011) the market capitalization and the sub-sample period average total trading volume in the stock (on the NASDAQ OMX Nordic plus on the MTFs) are used as instruments for the level of fragmentation and sub-sample period variance in fragmentation.

To study the effect of the level of fragmentation on return predictability a linear probability model (LPM) is considered.[13] The LPM has the advantage that endogenous variables are more easy to handled than in the logit or probit panel framework and that marginal effects are more straightforwardly interpreted. The drawback with the LPM is, however, that it is can predict probabilities outside the 0-1 interval, unless restrictions are placed on the parameters of the model, and that it will by definition produce heteroscedasticity in the residual variance (see e.g. Wooldridge, 2003, p243-244).

As control variates in the study, the volume of trade in a stock on the regular NASDAQ OMX Nordic market is used both as a control for changes in trading activity over time for the individual stock, as well as a control for size differences between stocks.[14] Earlier research, e.g. Hoque et al. (2007), Kim and Shamsuddin (2008), and Kim, Shamsuddin and Lim, 2011, have shown a link between the market situation and weak-form market efficiency. Due to this the volume of trade on the aggregated market is included to capture changes in the market situation. In all regressions stock specific fix effects are included as controls for all other unobserved factors possibly affecting a stocks market information efficiency.

[11] An alternative strategy would be to interpret the value of the VR-test statistic for the different sub-periods as a measure of the relative return predictability. Although one could be sceptic about using this approach we have also tried this in the empirical analysis. We do, however, conceptually prefer the results based on the binary indicator approach.

[12] The selction problem discussed and dealt with in e.g. O'Hara and Ye (2011), is not present in the current paper since the sample only consist of stocks introduced on multiple trading venues, i.e. all stock are to some degree fragmented.

[13] A more appropriate binary choice model, i.e. a probit model with endogenous regressors, including fix effects, is used in the robustness testing of the results.

[14] The correlation between a stocks volume of trade on the regular NasdaqOMX stock exchange and the stocks market capitalization is about 0.6.

4 Empirical analysis

4.1 Return predictability

To obtain time-varying measures of return predictability the Chow and Denning test (CD), the multiple version of Wright's sign test (JS), and the wild bootstrap test of Kim (WB) is performed on moving sub-sample windows of two years (500 trading days), moving the window forward one day at a time. In Table 1 summary statistics for the repeated test statistics over the considered period is reported for all firms.

[Table 1 about here.]

From the table we can see that for the CD test 15 out of the 26 stocks have at least one period with a value of the test statistic greater than the critical value, implying a deviation from the random walk hypothesis. The corresponding number for the JS and WB tests are 7 and 15, respectively. Thus, the JS statistic indicate a significantly lower number of deviations from the random walk hypothesis than the other tests. Studying maximum values for the CD and the JS test statistics also indicate that the CD statistic is more sensitive to extreme return observations, compare, for example, the maximum values for the Ericsson stock. In Table 1, summary statistics for the level of fragmentation, market capitalization and the stock trading volume on the NASDAQ OMX Nordic stock market for each stock are also provided. These statistics are based on the mean values over each of the two year moving sub-sample windows. From the table it can be seen that during the studied period the average level of fragmentation is the highest in the Eniro, TeliaSonera, Swedish Match, and the Volvo stocks, respectively, while the Atlas Copco B, Hennes & Mauritz, and the SEB stocks, have the lowest average level of fragmentation. In Figure 3a,b-5a,b the evolution of the CD, JS and the WB test statistics over the considered period for the Volvo, Skanska and the Nordea stocks are displayed along with the 5 percent critical value for the tests.

[Figure 3-5 about here.]

In Figure 3a, it is evident that the CD and JS statistics capture quite different stories regarding periods of deviations from the random walk hypothesis. In comparison with the WB statistic in Figure 3b, the CD is visually closer. The same pattern is even more clear when inspecting Figure 4a,b and 5a,b. In these figures the CD and the WB statistics seem to visually indicate the same periods of return predictability. In these later figures there is an overall stronger correspondence between the CD and the JS statistics, but with the JS statistic at a, in general, lower level.

4.2 Return predictability and fragmented trading

In Table 2, panel A, we report the results from LPM:s including fixed effects, instrumenting for the level of fragmentation with the stocks market capitalization.[15]

[Table 2 about here.]

[15] The first stage estimation instrumenting for fragmentation can be obtained from the authors upon request.

The results indicate that for the models using the CD and the WB time-varying measures of return predictability as the dependent variable there is a negative significant effect (at the 5 percent level) from increasing levels of fragmentation. This indicates that the probability of observing deviations from a random walk is lower for stocks associated with higher levels of fragmentation. The results is, however, contradicted from the model with the dependent variable from the JS test. In this model the effect from increasing levels of fragmentation is instead positive, significant at the 5 percent level. The results collaborate the above story from Figures 3-5, that the association between the CD and the WB statistics are closer than with the JS statistic. The effect from the trading volume of the stock on the regular NASDAQ OMX Nordic exchange, used to control for stock size effects, is only significant (at the 5 percent level) in the model with WB as the dependent variable. In this case it has negative effect on the probability of observing a deviation from the random walk hypothesis. Thus, a higher level of trading in stock i on the NASDAQ OMX Nordic exchange increases the information efficiency. The effect of the aggregated market trading volume on the NASDAQ OMX Nordic stock exchange, used as a control for the prevailing market condition[16], indicate for two of the models (CD and WB) a negative significant (at the 5 percent level) relationship with the probability of a deviation from the random walk hypothesis. This indicates that periods of higher trading activity at the aggregated market level is associated with a higher information efficiency at the individual stock level. In line with the fragmentation variable, this later result is contradicted by the model using the JS statistic as the dependent variable.

To find possible evidence regarding whether the proposed explanation - that the introduction of a stock on an alternative trading venue attracts new investors that combined with increasing levels of fragmentation may increase arbitrage trading - leading to higher levels of information efficiency, find support in the data, the volatility of the level of fragmentation during the sub-sample windows is also included in the analysis. The hypothesis is that stocks experiencing higher levels of arbitrage trading, also experience a higher level of volatility in the level of fragmentation. Thus, the level of fragmentation is assumed to vary more as investors seek to take advantage of the best available price. That price competition is important for investors and that investors often execute at the best available price is supported in the study by Riordan, Storkenmaier, and Wagener (2010). Following this, we expect an increased level of information efficiency for stocks with a higher volatility in the level of fragmentation. Results pertaining to models including the volatility in the level of fragmentation are reported in Table 2, panel B. The results, that are similar for all three dependent variables (CD, JS and WB), indicate that both the level of fragmentation, as well as the volatility of fragmentation, lowers the probability of observing periods with significant deviations from a random walk. This is taken as weak evidence that the positive effect of fragmentation upon information efficiency may, at least partly, be driven by a higher level of arbitrage trading between markets.

To elaborate even further, we also calculate a fragmentation measure only accounting for trading on the MTFs, i.e. measuring the concentration of trading only on the MTFs.

[16] Models using a dummy for periods with relatively higher return volatility at the market level, measured as the variance in the return of the OMXS30 stock market index, give similar results as using the aggregated volume of trade at the market level as an indicator of the prevailing market condition.

The hypothesis for this variable is that, all else equal, a higher level of MTF fragmentation for a stock increases the number of attractive markets (prices) for arbitrage investors.[17] Thus, for a stock with a high level of MTF fragmentation, arbitrage trading is more active, leading to decreased levels of return predictability, i.e. higher information efficiency. The expectation is then that relatively higher levels of MTF fragmentation decreases the probability of observing periods with deviations from a random walk. Results for models including measures of the MTF fragmentation level is reported in Table 2, panel C. As can be seen, a significant (at the 5 percent level) negative association between MTF fragmentation and the probability of observing periods with significant deviations from a random walk is obtained for all three dependent variables (CD, JS and WB). This further strengthen the argument that the positive effect of fragmentation upon information efficiency may, at least partly, be driven by a higher level of arbitrage trading between markets.

4.3 Alternative measure of information efficiency

To test the robustness of our results we also consider an alternative measure of time-varying information efficiency. Following Hou and Moskowitz (2005) we use a parsimonious measure of the average delay at which prices respond to information. The market return is utilized as the relevant news to which stock returns respond. The delay measure, thought to capture possible market frictions is specified as

$$D = 1 - \frac{R^2_{\delta_i^{(-n)}=0,\text{ for all } n\in[1,4]}}{R^2},$$

where R^2 is the fit of the regression

$$r_{it} = \alpha_i + \beta_i R_{mt} + \sum_{n=1}^{4} \delta_i^{(-n)} R_{mt-n} + \varepsilon_{it}.$$

In the equation r_{it} is the return on stock i and R_{mt} is the return on a broad stock market index.[18] The simple idea captured by the delay measure is that if stocks respond immediately to market news then β_i will be significantly different from zero, but none of the δ's will differ from zero. If stock i's price respond with a delay, then some of the $\delta_i^{(-n)}$'s will differ significantly from zero. Thus, a comparison of the R^2 from the restricted model with the R^2 from the unrestricted model then gives a measure of the delay at which stock prices respond to information. In line with the previous analysis a moving sub-sample window of two years (500 days) is used to obtain a time-varying delay measure.[19]

[17] The fragmentation measure increases either if the proportion of trading on each MTF market becomes more similar in size, or if the number of MTFs the stock is trading on increases.

[18] In the regressions both the OMXS30, as well as the Affärsvärldens generalindex, a broader index, have been used as a measure of broad market movements. Results based on these indeces gives qualitatively similar results.

[19] In the regressions lags of 1, 2, 3, 5 (one week) and 10 (two weeks), have been used in the estimation of the delay measure. Estimation results for the calculation of the delay measure for each sub-sample may be provided by the authors upon request.

In Table 2, panel D, the results from fixed effects linear regression models[20], relating the information delay measure to the (instrumented) level of fragmentation, are displayed. For all specifications these results confirm the positive effect of fragmentation upon weak-form market efficiency obtained from the variance ratio based models. The results indicate that as the level of fragmentation in stock trading increases, the delay measure decreases, i.e. the information efficiency increases. The results also further strengthen the evidence that this positive effect of fragmentation may, at least partly, be driven by a higher level of arbitrage trading between markets.

4.4 Other market quality measures and fragmentation

The interest in effects from fragmented trading is in general broader than the information efficiency dimension. For example, Lagoarde-Segot (2009), O'Hara and Ye (2011), Fioravanti and Gentile (2011), and Jiang, McInish and Upson (2011) also study the effect upon implicit trading costs, in terms of bid-ask spreads, and risks, in terms of stock volatility. In line with this earlier literature some evidence regarding these issues are also provided in this paper. Since we lack detailed data concerning bid-ask spreads, the bid-ask estimator of Corwin and Schults (2012), based on observing the daily high and low prices, is used in order to estimate both the daily average bid-ask spreads, as well as volatilities for each stock. In Table 3, estimation results for fixed effects regression models, instrumenting for the level of fragmentation, analyzing the effect from fragmentation upon bid-ask spreads and volatilities are reported.

[Table 3 about here.]

The results indicate that higher levels of fragmentation significantly (at the 5 percent level) have lowered bid-ask spreads, i.e. implicit trading costs, as well as return volatility for stocks.

5 Conclusions

The main objective in this paper has been to study the effect of increasing levels of fragmentation upon return predictability, i.e. weak-form information efficiency. The main result indicate that the increased fragmentation of trading in stocks on the NASDAQ OMX Nordic stock exchange and competing MTFs have not harmed information efficiency, but rather improved it. The result is robust over three different variance ratio measures of time-varying return predictability, as well as to an alternative time-varying measure of information delay (Hou and Moskowitz, 2005). A proposed explanation underlying the result is that a higher level of fragmented trading, i.e. higher levels of trading on competing MTFs, increases these new alternative trading venues attraction for both regular and arbitrage investors. This increased attention will increase the level of cross-market trading, leading to an improved information efficiency. The proposition is broadly supported by the data since stocks with a higher volatility in the level of fragmentation is found to be

[20] Since the delay measure is a proportion between 0 and 1, making linear regression less appropriate, it has been transformed to a continious variable by an inverse logistic transformation.

associated with periods of higher information efficiency, i.e. lower return predictability. This is interpreted as an indication that stocks where investors are more actively seeking best prices, i.e. have a higher volatility in the level of fragmentation in turn associated with higher levels of arbitrage trading, also have a lower level of return predictability. A second indication supporting the suggested explanation is that it is found that a higher level of fragmentation among the MTFs lowers the return predictability on the regular NASDAQ OMX Nordic stock exchange. This is taken as evidence that if there are more viable competing trading venues for a stock, i.e. more liquid MTFs, this will in general increase arbitrage trading between all markets, leading to a lower return predictability, i.e. a higher information efficiency. Apart from the main result, other findings are that the increased level of fragmented trading, observed during 2008-2011, have lead to, on average, smaller bid-ask spreads, i.e. lower implicit trading costs, and decreased the volatility in stock returns on the regular NASDAQ OMX Nordic stock exchange. Overall the results are in line with those found by e.g. O'Hara and Ye (2011) and Lagoarde-Segot (2009), but contradicts those found by Fioravanti and Gentile (2011) for the fragmentation - information efficiency relationship.

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6 Tables and figures

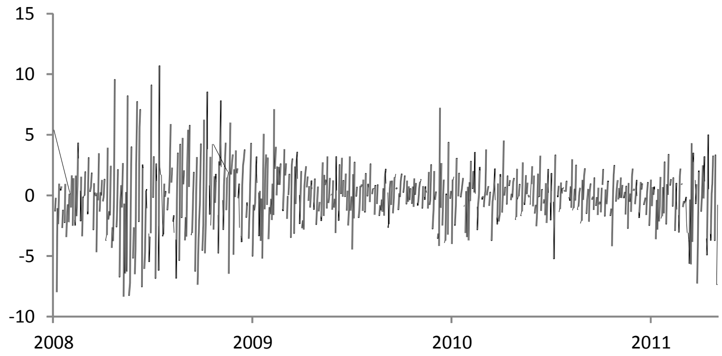

Figure 1: Return for equally weighted stock portfolio.

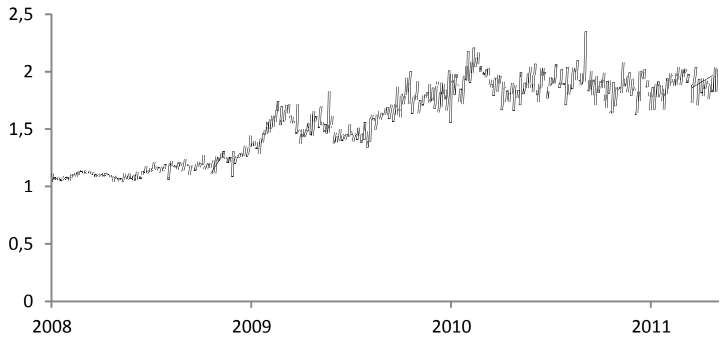

Figure 2: Level of fragmentation for equally weighted portfolio.

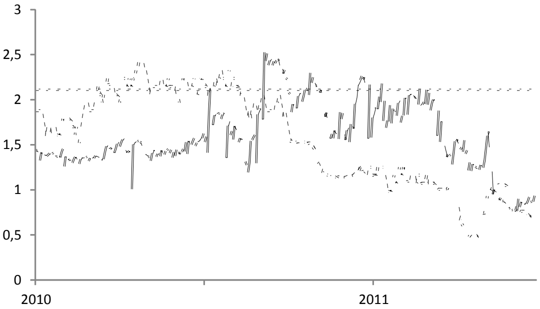

Figure 3a: CD (solid) and JS statistics for Skanska.

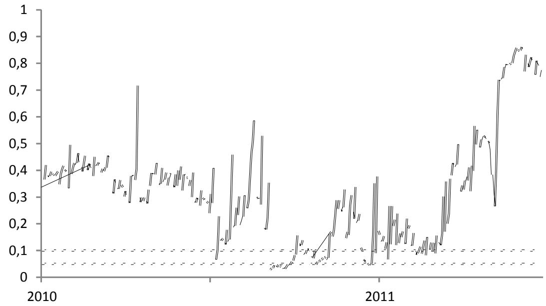

Figure 3b: The Wild bootstrap statistic for Skanska.

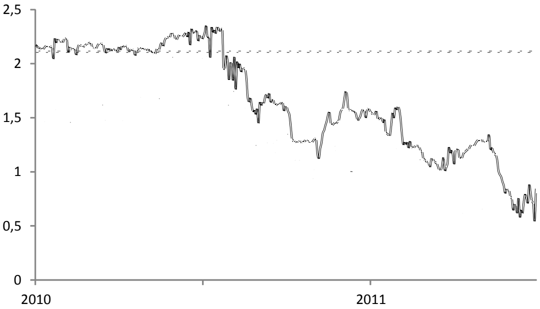

Figure 4a: CD (solid) and JS statistics for Volvo.

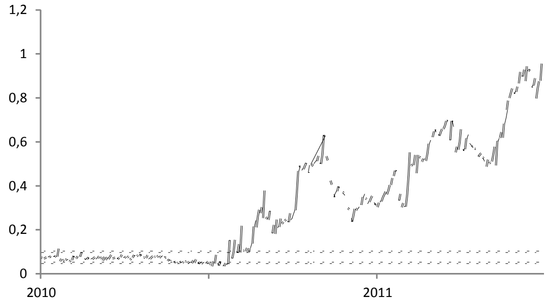

Figure 4b: The Wild bootstrap statistic for Volvo.

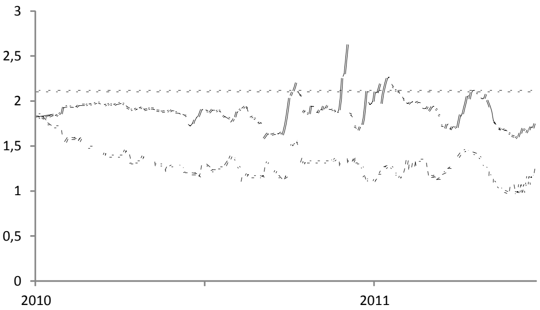

Figure 5a: CD (solid) and JS statistics for Nordea.

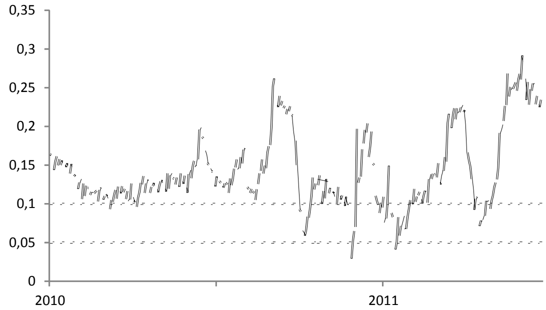

Figure 5b: The Wild bootstrap statistic for Nordea.

Table 1: Summary statistics for random walk tests.

	Chow-Denning				Joint Sign test				Wild bootstrap				Fragmentation		Market cap.		Trad. vol.$_{Omx}$	
	Mean	s.d.	min	max	Mean	s.d	min	max	Mean	s.d.	min	max	Mean	s.d.	Mean	s.d.	Mean	s.d.
Atlas Copco A	1.850	0.340	1.323	2.505	1.380	0.344	0.441	1.923	0.194	0.136	0.041	0.455	1.559	0.145	8948	1661	6.045	1.017
Electrolux	1.383	0.209	0.935	1.835	1.039	0.241	0.537	1.520	0.435	0.143	0.153	0.747	1.606	0.163	4349	656	2.942	0.282
Hennes & Mauritz	1.885	0.778	1.248	13.940	1.557	0.603	0.539	2.773	0.211	0.125	0.053	0.539	1.451	0.176	30307	2823	4.811	0.727
Investor	1.591	0.187	1.181	2.359	1.468	0.143	1.049	1.715	0.288	0.093	0.037	0.592	1.509	0.108	5983	406	1.971	0.141
SKF	1.740	0.375	1.138	2.536	2.347	0.611	1.208	3.179	0.249	0.168	0.031	0.624	1.533	0.144	5134	921	3.879	0.625
Ericsson	2.235	1.727	1.084	26.043	2.082	0.366	1.263	2.596	0.187	0.131	0.028	0.662	1.610	0.179	22277	1519	16.991	2.729
SCA	0.921	0.168	0.439	1.311	0.987	0.211	0.626	1.520	0.746	0.109	0.472	0.984	1.638	0.144	5596	541	2.707	0.175
Skanska	1.597	0.384	0.754	2.526	1.543	0.533	0.466	2.415	0.318	0.204	0.028	0.861	1.513	0.128	4334	515	2.138	0.219
Volvo	1.659	0.482	0.545	2.352	1.247	0.425	0.447	2.147	0.317	0.257	0.033	0.956	1.660	0.185	10697	1931	10.061	0.685
Atlas Copco B	2.114	0.382	1.443	2.850	0.860	0.398	0.179	1.519	0.118	0.106	0.015	0.360	1.364	0.078	3769	695	1.345	0.138
SEB	1.135	0.256	0.680	1.925	1.034	0.371	0.407	2.114	0.594	0.173	0.157	0.896	1.493	0.157	9328	1425	11.635	1.290
Securitas	1.492	0.400	0.793	2.301	1.204	0.222	0.715	1.699	0.385	0.213	0.047	0.831	1.609	0.148	2480	93	1.993	0.249
SSAB	1.354	0.289	0.396	2.394	1.106	0.287	0.447	1.599	0.440	0.183	0.027	0.988	1.514	0.149	2586	132	2.749	0.237
SHB	1.411	0.254	0.934	2.108	1.266	0.156	0.931	1.617	0.404	0.147	0.096	0.744	1.628	0.160	11313	1239	2.347	0.384
Swedbank	0.986	0.399	0.271	2.449	1.204	0.422	0.506	1.827	0.688	0.233	0.147	0.998	1.522	0.184	6128	1482	9.841	1.515
Assa Abloy	1.582	0.296	1.071	2.597	1.605	0.185	1.073	1.968	0.318	0.145	0.053	0.637	1.503	0.140	4695	768	2.096	0.298
Scania	1.591	0.313	0.892	2.106	1.585	0.626	0.500	2.647	0.307	0.181	0.078	0.787	1.593	0.165	4296	682	1.378	0.176
Swedish Match	2.218	0.173	1.877	2.692	2.013	0.392	1.177	2.564	0.068	0.032	0.014	0.161	1.671	0.147	3809	411	1.235	0.207
Tele2	1.406	0.309	0.926	3.148	1.466	0.314	0.930	1.864	0.423	0.174	0.145	0.726	1.639	0.173	4570	679	2.126	0.249
Nordea	1.889	0.147	1.583	2.629	1.306	0.170	0.965	1.845	0.142	0.049	0.029	0.291	1.660	0.202	26561	2675	11.375	1.257
Sandvik	1.627	0.269	0.877	2.475	1.149	0.333	0.588	1.968	0.288	0.169	0.022	0.788	1.572	0.152	10128	1616	6.897	0.861
Teliasonera	1.947	0.195	1.479	2.594	1.308	0.276	0.864	1.943	0.132	0.061	0.031	0.337	1.695	0.187	21467	1678	10.797	1.448
Alfa Laval	2.183	1.933	1.297	32.373	0.929	0.399	0.100	1.789	0.203	0.140	0.034	0.554	1.590	0.169	4143	610	2.525	0.475
Eniro	1.994	1.812	0.389	28.394	2.804	0.927	1.453	4.455	0.411	0.359	0.008	0.997	2.329	0.085	343	22	0.367	0.143
Lundin petrolium	1.006	0.308	0.314	1.680	1.101	0.329	0.447	1.682	0.685	0.197	0.239	0.995	1.507	0.160	1838	204	2.255	0.230
Boliden	1.056	0.288	0.559	1.786	0.914	0.391	0.376	1.845	0.662	0.188	0.174	0.946	1.534	0.156	2311	535	5.457	0.907

Table 2: Estimation results for linear probability model.

	Panel A			Panel B			Panel C			Panel D		
	CD	JS	WB	CD	JS	WB	CD	JS	WB	D	D	D
Constant	2.057**	-1.809**	4.431**	7.929**	3.797**	23.514**	2.111**	-1.580**	4.479**	6.115**	14.434**	6.439**
	(0.283)	(0.245)	(0.334)	(0.938)	(0.959)	(2.159)	(0.267)	(0.237)	(0.315)	(0.604)	(2.126)	(0.581)
Stock trading volume$_{NasdaqOmx}$	-0.004	-0.005	-0.063**	0.044**	0.042**	0.095**	-0.000	0.014**	-0.059**	0.116**	0.185**	0.143**
	(0.006)	(0.005)	(0.007)	(0.010)	(0.011)	(0.023)	(0.007)	(0.007)	(0.009)	(0.013)	(0.023)	(0.016)
Market trading volume$_{NasdaqOmx}$	-0.001**	0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	0.000**	-0.001**	-0.001**	-0.001**	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fragmentation	-0.329**	0.323**	-0.643**	-0.919**	-0.240**	-2.561**	-0.104	1.274**	-0.445**	-1.000**	-1.836**	0.343
	(0.059)	(0.051)	(0.070)	(0.111)	(0.114)	(0.256)	(0.146)	(0.131)	(0.173)	(0.126)	(0.252)	(0.319)
Volatility of fragmentation	-	-	-	-8.629**	-8.238**	-28.042**	-	-	-	-	-12.225**	-
				(1.299)	(1.329)	(2.991)					(2.946)	
Fragmentation$_{MTF}$	-	-	-	-	-	-	-0.151**	-0.638**	-0.133*	-	-	-0.902**
							(0.066)	(0.059)	(0.077)			(0.144)

** Significant at the 5 percent level; * Significant at the 10 percent level. Robust standard errors in paranthesis.

Dependent variable based on: CD = Chow-Denning test; JS = Joint sign test; WB = Wild bootstrap test; D = Delay measure.

Table 3: Estimation results for other market quality measuresl.

	Bid-ask spread	Stock variance
Constant	0.008**	0.060**
	(0.001)	(0.002)
Stock trading volume$_{NasdaqOmx}$	0.001**	0.001**
	(0.000)	(0.000)
Market trading volume$_{NasdaqOmx}$	0.001**	0.001*
	(0.000)	(0.000)
Fragmentation	-0.005**	-0.027**
	(0.000)	(0.001)

** Significant at the 5 percent level; * Significant at the 10 percent level.