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**THE RELATIONSHIP BETWEEN TRADING VOLUME,
STOCK INDEX RETURNS AND VOLATILITY:
EMPIRICAL EVIDENCE IN NORDIC COUNTRIES**

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Abstract

In this paper, several methods such as VAR and EGARCH are employed to examine the relationship between trading volume, stock index returns and volatility in Nordic countries for the period 1999 to 2009. Our results confirm a positive relationship between trading volume and absolute stock returns. More specifically, there are bidirectional causality in Denmark and Finland while Sweden and Norway are found to have unidirectional causality from returns to trading volume. This paper also points out that while trading volume may contain some information which is helpful in explaining volatility it cannot remove the persistence of volatility.

Keywords: Stock index returns, trading volume, return volatility, EGARCH, VAR, Granger causality, Nordic stock markets.

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1. Introduction

1.1. Background

Investors commonly use trading volume to predict price movements. The relationship between trading volume and price provides “an insight into structure of financial markets” since the predicted price-volume relation depends on information flow, size of the market and short selling constraints (Karpoff (1987, p. 109). It also gives “significant implications for research into futures markets” where price variability affects the trading volume and the time to delivery of future contracts affects price variability by its impact on trading volume (*ibid.* p. 110). According to Hiemstra and Jones (1994) the correlation between stock prices and trading volume may explain movements of past stock prices in relation to movements in trading volume and/or vice versa. Therefore, this relationship has received much attention from both researchers and decision-makers since the 1960s in both developed and developing markets.

Most early studies that focused on correlations between trading volume and prices report a positive contemporaneous relationship between volume and absolute returns (Crouch 1970, Clark 1973, Copland 1976, Epps and Epps 1976). However, when it comes to the causal relationship between trading volume and stock returns (Wang 1994, Chordia and Swaminathan 2000, Chen et al 2001, Pisedsalasai and Gunasekara 2007) and linear and non-linear causal relationships between trading volume and stock price (Gallant et al 1992, Llorente et al 2002), the causal relationship is still a debated issue (Pisedsalasai and Gunasekara 2007, Deo et al 2008).

Recently, the role of trading volume in explaining volatility of returns has received increased attention. According to Poon and Granger (2003), understanding the link between trading volume-volatility will improve the modeling of return distributions. However, results from previous empirical studies have often led to conflicting conclusions upon this matter. Several studies have pointed out that the arrival of information in financial markets determines the relation between volume and volatility (Lamoureux and Lastrapes, 1990) while others suggested that investors’ expectations and opinions are key to this link (Poon and Granger, 2003). Thus, “an important issue should be whether information about trading volume is

useful in improving forecasts of price changes and return volatility" (Chen et al, 2001, p.155).

1.2. Problem discussion and motivation

The background section illustrated that the relationship between price-volume is ambiguous. Second, although the relationship between trading volume and stock prices have been investigated for numerous stock markets, however no prior research has been conducted within this framework with regards to Nordic stock markets.

Third, according to the Federation of European Securities Exchanges (FESE 2009), Nordic stock markets have grown rapidly in recent years and are considered among the largest in Europe. For example, the market capitalization of the Nordic stock markets increased from US\$ 870 billion in 2004 to US\$ 1595 billion in the end of 2007. In addition, from late 2006 to 2007 the equity turnover increased by 22 percent, derivative contracts by 15 percent, and market capitalization by 33 percent. Such rapid growth, however, may increase the unpredictability and volatility in financial markets. Hence, the role of volume in forecasting volatility for Nordic markets is certainly needed.

To contribute to the above shortcomings, this study is therefore to examine the relationship between trading volume, stock return and volatility in Nordic stock markets-OMXS30 in Sweden, OMXC20 in Denmark, OBX in Norway, and OMXH25 in Finland for a ten-year period (1999-2009).

1.3. Purpose

The objective of this study is to employ different methods including Vector Autoregression (VAR)-Granger causality, Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) to examine the relationship between trading volume, stock returns and volatility in Nordic stock markets - Sweden, Denmark, Norway, and Finland during 1999-2009.

1.4. Outline

This paper is structured in the following order: The introduction is presented in section 1. Section 2 is providing an overview of the theoretical as well as empirical literature. In section

3 research hypotheses are presented for this study. The data is outlined in section 4 and a list of descriptive statistics is presented. Section 5 reviews the methodology employed and the empirical results are presented and discussed in section 6. Finally, the conclusions are explained in section 7.

2. Previous research and theory

2.1.Previous research

In early studies, trading volume was used as a proxy for information flow and the daily price change was considered as the sum of a random number of within-day price changes. For example, Clark (1973) was employing the mixture of distribution hypothesis (MDH) showing that trading volume is positively related to price changes. Epps and Epps (1976), based on the assumption of a positive relation between traders, find that greater disagreements can indicate a larger absolute price changes and thus increase the level of trading volume. Copeland (1976) introduced the sequential arrival of information hypothesis (SAIH) with asymmetrically distributed information in which information flows sequentially from one trader to another. Later, Morse (1981), Jennings, Starks and Fellingham (1981) and, Jennings and Barry (1983) have expanded on Copeland's analysis. Their SAIH suggests that price volatility can be predicted based on trading volume.

A uni-directional causality from price to volume has been found in developed markets Rogalski (1978), Smirlock and Starks (1988), Jain and Joh (1988). Gallant et al (1992) use non-linear causality to test the non-linear causal relation between New York Stock Exchange (NYSE) volume and S&P 500 stock returns and find evidence of strong nonlinear impacts from lagged stock return to trading volume but only weak evidence of a nonlinear impact from lagged volume to stock returns. Hiemstra and Jones (1994) use NYSE volume and Dow Jones return and find a uni-directional Granger causality from Dow Jones return to NYSE volume but bi-directional nonlinear causality between them. Bhagat and Bhatia (1996) show return causes volume. Moosa and Al-Loughani (1995), Saatcioglu and Starks (1998) find causality of volume on price in Asian and Latin American markets but not vice versa. Silvapulle and Choi (1999) use the linear and nonlinear Granger causality and find a significant causality between the trading volume and stock return in the Korean market. Lee and Rui (2002) find mix results of volume-price causality for four Chinese stock exchanges. Gunduz and Hatemi (2005) find bi-directional causality between price and volume in Hungary and Poland and a uni-directional from price to volume in Russia and Turkey.

As far as the effect of trading volume on volatility is concerned, autoregressive conditional heteroscedasticity (ARCH) has been suggested as a good model to capture the entire time

series properties of the information (Gallant, Hsieh, and Tauchen 1988, Lamoureux and Lastrapes 1990). By using GARCH, Lamoureux and Lastrapes (1990) uncover the effect of trading volume to the market returns. Trading volume is used as an explanatory variable in the variance equation and they find that that volume has a positive effect on conditional volatility. Sharma et al. (1996) study the GARCH effect for the NYSE index from 1986 to 1989 where GARCH (1,1) with and without daily volume is used. Their results suggest that trading volume does not completely remove the GARCH effect for the market index. Wang et al (2005) use GARCH (1,1) for Chinese stock market and find that trading volume plays important role to reduce volatility of stock prices.

The comprehensive study about price-volume relationship was first used by Chen et al. (2001). They use data from nine major markets to study causal relation between stock returns, trading volume and estimate return volatility and find strong evidence that return causes volume but limited evidence to suggest that volume causes returns. By using EGARCH (1,1), they also report that the persistence in volatility is not eliminated when lagged or contemporaneous trading volume effects. By replicating Chen et al (2001), Pisedsalasai and Gunasekarage (2007) use South-East Asian data to conduct their study. They conclude that there is unidirectional causality from stock returns to trading volume for Indonesia, Thailand, and Malaysia and that trading volume information is useful in predicting volatility.

2.2.Theory

Trading volume plays a prominent role in the market information and the relationship with stock prices (Karpoff, 1987). Gallant et al (1992) postulated the notion of having a fundamental understanding of this relationship are contributing significant implications for asset pricing models as well as regulators, hedgers, speculators and other actors in the financial markets.

2.2.1.Trading volume and price changes

In general, previous studies show a positive contemporaneous correlation between trading volume and absolute returns/price volatility. This implies that these markets are liquid where traders could easily enter or exit a possible market (Clark 1973, Tauchen and Pitts 1983). According to Chen et al (2001), the explanations for this relationship are the sequential arrival of information hypothesis (SAIH) or the mixture of distributions hypothesis (MDH)

The MDH was first introduced in 1970's by Clark (1973) and further developed by Epps and Epps (1976), Tauchen and Pitts (1983), and Harris (1986). This hypothesis is based on the assumption that the variance per transaction is monotonically related to the volume of that transaction. All of whom argue that price changes and volume are jointly dependent on information because of their common distribution factor, which implies that trading volume and price changes respond at the same time to the arrival of new information.

The SAIH assumes that the dissemination of information is sequential from one person to another. It means that a single piece of information reaches one trader at the time; in other words, information is asymmetric. When the trader receives the information, s/he will react following the information arrival and thus generate a positive relationship between volume and returns/volatility (Copeland 1976, Jennings, Starks and Fellingham 1981).

2.2.2.Causality between stock price changes and trading volume

Theoretically, the current price cannot depend on past trading volume if the market is efficient and absorbs the new information quickly. Causality of price on the current volume, on the other hand, may depend on the past price trend. This is explained by that investors predict the future prices based on past price trends and take their trading decisions accordingly (Brennan and Cao, 1997). However, empirical studies of volume-price causality show mixed results.

In early research, the Granger causality test was employed to see whether trading volume lead to stock returns or vice versa. According to Granger (1969), if the past X has information which is useful to predict future Y then X cause Y. However, in more recent theoretical literature, Vector Autoregression (VAR) has replaced the Granger method. Brooks (2008) notes that VAR can estimate more than one endogenous variable and provides a framework to test Granger causality.

2.2.3.The relationship between return volatility and trading volume

The mixture of distribution hypothesis (MDH) proposes that stock returns and trading volume are positively correlated due to their joint dependence on the volume which determines the level of information flow into the market (Clark 1973, Epps and Epps 1976). Hence, the arrival of information to markets explains the variation of the security prices. The model

implies strong positive contemporaneous but response between volume and return volatility. We consider that returns over the trading day is presented as R_t , and is the sum of $i = 1, 2, \dots, n_t$ which represents intraday (security trading during trading session) equilibrium returns, δ_i .

$$R_t = \sum_{i=1}^{n_t} d_i \text{ where } d_i \sim \text{IID } N(0, \sigma^2) \quad [1]$$

The random variable n_t represents the rate of information arrival into the market on a regular trading day. The number of intraday returns is considered a random number dependent on the rate of information arrival during the day. We presume that intraday returns follow an Independent and Identical Distributed (IID) process with zero mean and variance σ^2 . In the equation above, the daily returns are generated by a stochastic process in which R_t is subordinated to δ_i and n_t is called the directing process. The daily return can thus be transformed to the following equation:

$$R_t | n_t \sim N(0, \sigma^2) \quad [2]$$

The daily returns are conditional on the number of information arrivals and normally distributed with zero mean and the variance expressing the rate of information arrival. Subsequently, the model assumes that the number of information arrival follows an autoregressive process:

$$n_t = \alpha + q(L)n_{t-1} + u_t \quad [3]$$

Where alpha sign is a constant, $\theta(L)$ is a polynomial in the lag operator L , and u_t represents the error term. The conditional variance of the daily return is expressed as follows:

$$\sigma_{R_t | n_t}^2 = E(R_t^2 | n_t) = \sigma^2 n_t \quad [4]$$

Substituting the autoregressive process into equation four yields:

$$\sigma_{R_t | n_t}^2 = \sigma^2 \alpha + q(L) \sigma_{R_{t-1} | n_{t-1}}^2 + \sigma^2 u_t \quad [5]$$

The final equation presents persistence in the conditional variance equation. Thus, the relationship between daily returns variance and the unobserved mixing variable is estimated by the application of GARCH models, inclusion of trading volume which represent a proxy measure of the information arrival.

Bollerslev (1987), Lampourey and Lastrapes (1990) assume that the trading volume (V_t) is a mixing variable and weak exogenous. The relationship between daily returns and trading volume with GARCH(1,1) follows:

$$R_t = a + bR_{t-1} + e_t \quad [6]$$

$$S_t^2 = b_0 + b_1 e_{t-1}^2 + b_2 S_{t-1}^2 + b_3 V_t \quad [7]$$

where $e_t \sim (0, S_t^2)$ is the unpredictable component of return.

3. Main hypotheses

Hypothesis 1: As mentioned, from a strand of empirical research have found evidence on the existence of a positive contemporaneous relationship between trading volume and returns; we thus believe that there is a positive contemporaneous relationship between stock index return and trading volume for Sweden, Denmark, Norway and Finland.

Hypothesis 2: While the relation between stock price changes and trading volume is positive contemporaneous, the causality in the price-volume relationships is still unclear (Pisedsalasai and Gunasekarage 2007, Deo et al 2008). We study the causal relationship between stock index return and trading volume to see whether there is any causal relationship between them in Nordic markets.

Hypothesis 3: Finally, we study the ability of trading volume in predicting the volatility of stock returns.

4. Data and preliminary results

The dataset used in this study primarily comprises daily closing stock price index and corresponding trading volume series for the stock markets in Nordic countries namely Swedish Stock Exchange Composite Index (OMXS30) for Sweden, for Denmark the Copenhagen Stock Exchange Composite Index (OMXC20), the Helsinki Stock Exchange Composite Index (OMXH25) for Finland and lastly the Oslo Stock Exchange Composite Index (OBX) for Norway. Daily data is used in our study since the short horizon data are found to be more applicable to test relationships between return, volatility and trading volume. The employment of such techniques as GARCH models imposes the use of short horizon price changes.

The closing stock price index data was obtained directly from Thomson Datastream. Adjusted return was calculated as $R_t = \ln(P_t/P_{t-1})$ where P_t and P_{t-1} are stock price index on day t and day t-1, respectively. However, as corresponding trading volume series were unavailable, it was necessary to measure trading volume for these markets. According to Timothy J. Brailsford (1994), the measurement of daily trading volume is not consistent. It can be measured in three ways: the daily number of equity trades, the daily number of shares traded, or, the daily total dollar value of shares traded. We computed daily trading volume of stock market as the daily number of shares traded of all companies in the market (Timothy J. Brailsford, 1994). The trading volume for OMXS30 is measured as the daily number of shares traded by the 30 largest (in term of capitalization) and most traded companies in the market. Similarly, the trading volume series for OMXC20 and OMXH25 are calculated from the 20 and 25 largest and most traded companies in these markets respectively. For the Norwegian stock market, we calculated trading volume from the 25 companies most traded in OBX.

4.1. Summary statistics

Data on returns and trading volume for each national market are shown in table 1. Following the statistic, the OBX is the most volatile market where the standard deviation of return is highest (0,0075) compared to other markets. The returns in three out of four markets were negatively skewed, although the skewness statistics is minor. This means that the return distributions of the shares traded on these exchanges have a heavier tail of large values and

hence a higher probability of earning negative returns (Chen et al 2001). In all markets, the kurtosis values are larger than three and thus the distribution of returns have fat tails. The highest standard deviation of trading volume is reported for Norway and followed by Sweden, Finland and Denmark. Skewness of trading volume clearly shows that the distribution of trading volume is positive skewed. The correlation between trading volume and stock index return is low in all markets.

Table 1: Descriptive statistic for returns and trading volume

Country	Sweden	Denmark	Norway	Finland
Index	OMX STOCKHOLM (OMXS30)	OMX COPENHAGEN (OMXC20)	OSLO (OBX)	OMX HELSINKI (OMXH25)
Sample period	11/06/1999-27/04/2009	20/11/2000-27/04/2009	03/01/2000-27/04/2009	09/12/2002-27/04/2009
Observations (n)	2474	2111	2338	1602
<i>Return</i>				
Mean	-1.26185E-05	-4.45507E-05	1.62625E-05	3.45427E-05
SD	0.007458681	0.006100979	0.007483362	0.006238348
Skewness	0.12930681	-0.287640348	-0.623991576	-0.014434237
Kurtosis	5.888977702	9.524360434	10.056692261	8.630109156
<i>Trading volume</i>				
Mean	0.139317216	0.00853185	0.094237329	0.0616472
SD	0.06330656	0.003894111	0.073878398	0.028285533
Skewness	1.321429789	1.174078304	2.197327669	2.860501259
Kurtosis	10.473633795	5.383167118	16.41808095	17.89376616
Correlation	-0.006699426	-0.03342249	0.0100571562	-0.03590523

4.2. Stationary tests for stock return and trading volume series

Brooks (2008) states that non-stationarity can lead to unreliable estimation and spurious correlation. Hence, we verify whether the time series data for stock returns and trading volume of the hypothesis are stationary by the Augmented Dickey-Fuller (ADF) test:

$$\Delta x_t = r_0 + rx_{t-1} + \sum_{i=1}^n d_i \Delta x_{t-i} + e_t \quad [8]$$

where, x is a variable for unit root testing of stock index returns and trading volume.

Phillips and Perron (PP) can also be used to test for unit root non-stationarity. The tests are similar to ADF tests, but they incorporate an automatic correction to the DF procedure to allow for autocorrelated residuals (Brooks, 2008). However, there are criticisms of ADF and PP of their low power with a root close to the non-stationary boundary. Therefore, Kwiatkowski et al (KPSS, 1992) is employed to test stationarity. The KPSS (1992) test differs from the other unit root tests since the series y_t is assumed to be stationary under the null hypothesis. The KPSS statistic is based on the residuals from the OLS regression of y_t on the exogenous variables x_t :

$$y_t = \vec{x}_t' \hat{d} + u_t \quad [9]$$

The Lagrange Multiplier (LM) statistic is being defined as:

$$LM = \sum_t \frac{S(t)^2}{T^2 f_0} \quad [10]$$

where f_0 , is an estimator of the residual spectrum at frequency zero and where $S(t)$ is a cumulative residual function:

$$S(t) = \sum_{r=1}^t \hat{u}_r \quad [11]$$

Based on the residuals $\hat{u}_t = y_t - \vec{x}_t' \hat{d}(0)$ $[12]$

Table 2 reports stationarity tests for return and raw trading volume series. It shows that the stock index return series are clearly stationary in all markets according to ADF and PP. We also find out that the raw trading volume series are stationary with ADF and PP, statistically significant at the 1% level. So, we reject the hypothesis of a unit root.

We already mentioned about the drawback of ADF and PP tests, we thus use KPSS to assure our data are stationary. The null hypothesis of stationary in KPSS test and all statistics non-significant are following asymptotic critical values of KPSS (1992). Interesting, the result illustrates (table 2) that while the stock index returns series are still stationary according to KPSS test, the raw trading data volume series are totally non-stationary in all markets.

Table 2: Unit roots test for return and raw trading volumes

Country	Variables	Lag(s)	ADF	PP	KPSS
Unit roots test for full sample period					
<i>Sweden</i>	R _t	24	-8.480339**	-50.97787**	0.138919
	V _t	14	-4.675011**	-36.43245**	4.417565**
<i>Denmark</i>	R _t	5	-20.29990**	-44.55797**	0.248735
	V _t	9	-5.484966**	-28.23784**	5.041394**
<i>Norway</i>	R _t	10	-14.46739**	-48.36082**	0.229150
	V _t	13	-3.314963**	-32.29644**	4.514406**
<i>Finland</i>	R _t	4	-18.31721**	-38.98748**	0.163633
	V _t	19	-11.39996**	-30.94679**	2.092488**

** statistically significance at the 1% level.

The lag length for ADF test is chosen based on Akaike information criterion for parametric correction of serial correlation.

4.3. Detrended trading volume

Since the raw trading volume series are not stationary according to KPSS test, we need to obtain stationary series through detrending volume data. Previous studies document evidence of both linear and non-linear trends in time series of trading volume information (e.g., Gallant, Rossi, and Tauchen 1992). They estimate the linear and non-linear time trend in trading volume by the following regression equation:

$$V_t = a + b_1 t + b_2 t^2 + e_t \quad [13]$$

where V_t represents the raw trading volume in each individual stock market, while t and t^2 are linear and represent quadratic time trends.

The output of this regression is reported in table 3. The results show that the coefficients of both linear and non-linear time trend are significant at the 1% level. So, we use adjusted trading volume for linear and non-linear time trends (detrended trading volume) which is represented by the residual of equation 13 for sequence analysis.

Table 3: Test of time trend in trading volume

Country	Sweden	Denmark	Norway	Finland
<i>a</i>	0.047928 (15.91710)**	0.004745 (24.04752)**	-0.005454 (-1.582242)	0.039657 (19.50977)**
<i>b</i> ₁	0.000118 (20.95310)**	2.71E-06 (6.283192)**	0.000113 (16.57046)**	5.27E-05 (8.990478)**
<i>b</i> ₂	-2.66E-08 (-12.10235)**	6.21E-10 (3.140515)**	-1.77E-08 (-6.272021)	-2.36E-08 (-6.672222)**

** is denoted statistic significance at 1% level. t-statistics are in parenthesis

After obtaining the detrended trading volume series, we run the unit root tests again. Table 4 presents unit roots test for return index and detrended trading volume using ADF and PP. The table shows that all stock index return and detrended trading volume series follow a stationary process, statistically significant at the 1% level. Thus, we reject the hypothesis of a unit root. The KPSS test is included in table 4. According to asymptotic critical values of KPSS, we do not reject of null hypothesis of stationarity. The results from both methods hence confirm that return and detrended trading volume series are stationary. We so can continue with modeling our data without the risk of unreliable estimations and spurious correlation.

Table 4: Unit roots test for return and detrended trading volumes

Country	Variables	Lag(s)	ADF	PP	KPSS
Unit roots test for full sample period					
Sweden	R _t	24	-8.480339**	-50.97787**	0.138919
	DV _t	21	-7.374792**	-40.00857**	0.182666
Denmark	R _t	5	-20.29990**	-44.55797**	0.248735
	DV _t	14	-8.074888**	-32.43941**	0.060452
Norway	R _t	10	-14.46739**	-48.36082**	0.229150
	DV _t	13	-5.452407**	-44.80948**	0.461735
Finland	R _t	4	-18.31721**	-38.98748**	0.163633
	DV _t	19	-8.103682**	-29.75164**	0.032264

** statistically significance at the 1% level.

The lag length for ADF test is chosen based on Akaike information criterion for parametric correction of serial correlation.

4.4.Validity and reliability

4.4.1.Validity

The concept of validity includes two levels of meaning: internal and external validity. The external validity concerns the extent to which the findings are possible to generalize from the right sample (Merriam, 1998). The internal validity refers to capture the part of reality by using the right method (Yin, 1994).

For this paper, a quantitative approach for the research was chosen. Since the methods of Chen et al (2001) are recognized as robust methods in relationship between trading volume and returns, we hence believe that by replicating their methods, we can ensure the validity of our paper. To enhance the validity, we also use dummy variable to capture the global financial crisis in Nordic stock markets.

4.4.2.Reliability

The reliability of a study measures the extent to which research findings can be reproduced if the same study was conducted again under the same circumstances by another investigator (Yin, 1994). If any interpretation mistakes are conducted, the results are then less reliable. An investigation with good reliability should therefore not be affected by whom it is conducted or by the surrounding circumstances.

To enhance the reliability of our study, we explain every step how our paper is carried on in each chapter. We used data from Thomson Datastream which is considered as one of the reliable resources in finance. Trading volume is calculated based on one of the most widely used in financial market and should be considered as accurate. The statistical method in our paper is used by previous researchers in this area. By doing that, we can easily compare our result to the previous study and be compared to future studies. The length of time in our data is around 10 years which contain both a bullish market and a bearish market and hence can increase reliable.

5. Research methodology

5.1.Trading volume and stock price changes

While numerous studies confirm that there is a positive contemporaneous relationship between trading volume and absolute stock returns, the result of correlation between stock return and trading volume is still contradictory. Since we also assume that there is a positive contemporaneous relationship between trading volume and stock return in Nordic markets (hypothesis 1), we thus run the test of the following forms of stock price returns by derivation of the following regressions:

$$DV_t = a + bR_t + n_t \quad [14]$$

$$DV_t = a + b|R_t| + n_t \quad [15]$$

where, DV_t represents the detrended trading volume at time t of the dependent variable and R_t is the return at time t .

5.2.Causal relation between trading volume and stock price changes

In order to see whether there is any causal relationship between stock return and trading volume in Nordic markets (hypothesis 2), we apply Granger test for discovering causal relations. As mentioned in theory part, VAR method can estimate more than one endogenous variable and provides a framework to test Granger causality. Therefore, we also employ bi-VAR to test for causality of stock return and trading volume. By incorporating the bivariate auto regressions we test the causality between trading volumes and stock returns. Consider the following regressions as proposed below:

$$R_t = a_0 + \sum_{i=1}^p g_i R_{t-i} + \sum_{j=1}^p d_j DV_{t-j} + mDUM + e_t \quad [16]$$

$$DV_t = a_0 + \sum_{i=1}^p a_i R_{t-i} + \sum_{j=1}^p b_{t-j} DV_{t-j} + mDUM + e_t \quad [17]$$

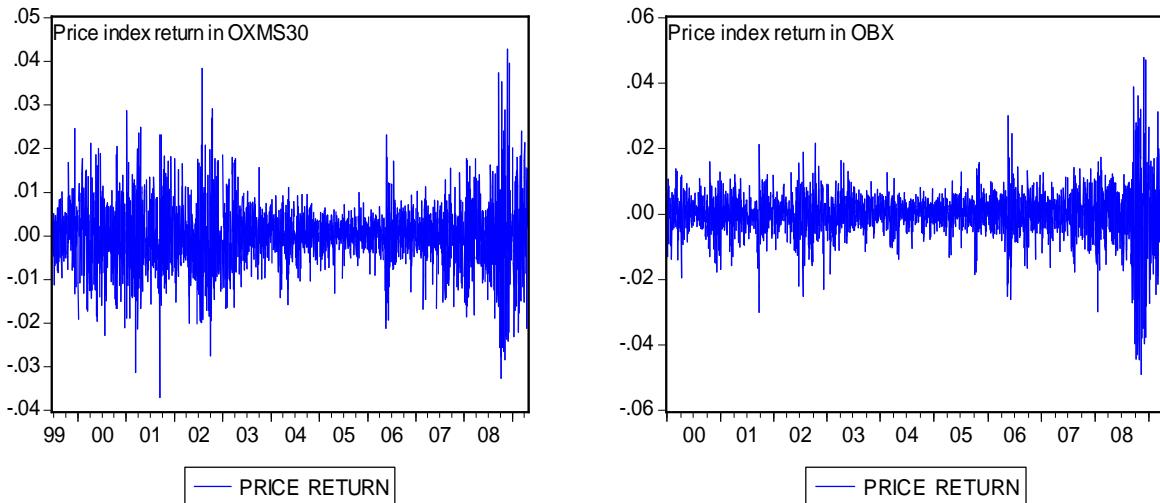
where V_t represents the detrended trading volume at time t and R_t is the return at time t and DUM is dummy variable for the global financial crisis. While estimating the VAR approach we intend to utilize lags accordingly to the Akaike Information Criterion (AIC).

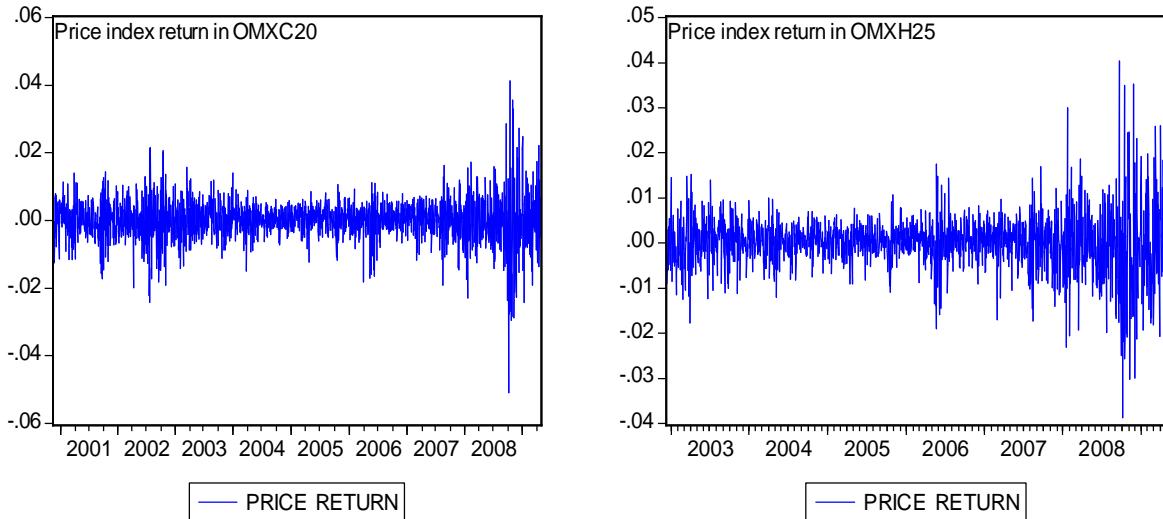
In equation 16, if volume (DV) causes return (R), lags of DV should be significant in the equation. If this is the case and not vice versa, there exists unidirectional causality from volume to return. On other hand, if return (R) causes volume (DV), lags of R should be

significant in the equation 17. If this is the case and not vice versa, there exists unidirectional causality from return to volume. If both sets of lags are significant, there is bi-directional causality. In order to test for causality, F-statistic is employed. If F-test rejects the null hypothesis of $\delta_j = \mathbf{0}$ for all j in equation 16, then volume causes return. In equation 17, if F-stats rejects the null hypothesis of $\alpha_i = \mathbf{0}$ for all i , then return cause volume. If both δ_j and α_i are different from zero, there exists bi-directional causality between return and volume.

According to World Crisis (2009), the global financial crisis became prominently visible on the global markets in September, 2008 with the collapse of several large United States-based financial firms. Figure 1 shows that the stock index returns are becoming extremely volatile by the end of 2008, which shows that the Nordic markets are also affected by the global financial crisis. Lee and Rui (2002) notice a financial crisis may lead to a strong dynamic relationship. Furthermore, there is some evidence demonstrating that the extreme market movements during the crisis can have significant impact on stock returns/volatility (Wang et al 2002, Maroney et al 2004). Hence, in order to make sure the results are strong, we decide to use a dummy variable equal to one for observations from 15/09/2008 to 27/04/2009 to the capture financial crisis, and zero otherwise.

Firgure 1: Daily index returns of markets





5.3.Trading volume and conditional volatility

To explore the role of trading volume in explaining return volatility (hypothesis 3), ARCH models are appropriate to capture the entire time series properties of the information (Gallant, Hsieh, and Tauchen 1988, Lamoureux and Lastrapes 1990). Lamoureux and Lastrapes (1990) used GRACH (1,1) to find the role of trading volume to the market returns. However, a drawback of the GARCH model is that it assumes asymmetric response of volatility for both positive and negative shocks. Conversely, financial data series has proved that a negative shock cause volatility more often than a positive shock of the same magnitude (Brooks, 2008). In order to capture the negative asymmetry problem, Nelson (1991) proposed using Exponential GARCH, which has several advantages. First, EGARCH use logarithm of s_t^2 , hence s_t^2 is always positive even if the parameters are negative. This removes the necessity to impose non-negativity constraints on the model parameters. Second, EGARCH can capture negative asymmetry (Brooks, 2008) which is useful for the relationship between volatility and return when it comes to negative. For the purpose of this study EGARCH suitable to examine the relationship between trading volume and stock volatility.

The following EGARCH(1,1) model is intended to be utilized to estimate stock return volatility

$$R_t = a + bR_{t-1} + cDUM + e_t \quad [18]$$

$$e | I_{t-1} \sim N(0, s_t^2) \quad [19]$$

$$\ln(s_t^2) = w + I \left| \frac{e_{t-1}}{\sqrt{s_{t-1}^2}} \right| + q \frac{e_{t-1}}{\sqrt{s_{t-1}^2}} + b \ln(s_{t-1}^2) + j DUM \quad [20]$$

where R_t and s_t^2 are the stock returns and conditional volatility. The dummy variable is included to capture the impact of financial crisis on volatility.

We are concerned that the information flow into the markets would be problematic to observe, therefore using trading volume to determine for the information flow. Consequently, we evaluate the arrival of information flow by daily trading volume:

$$R_t = a + bR_{t-1} + cDUM + e_t \quad [21]$$

$$e_t | I_{t-1} \sim N(0, s_t^2) \quad [22]$$

$$\ln(s_t^2) = w + I \left| \frac{e_{t-1}}{\sqrt{s_{t-1}^2}} \right| + q \frac{e_{t-1}}{\sqrt{s_{t-1}^2}} + b \ln(s_{t-1}^2) + xDV_t + j DUM \quad [23]$$

According to Lampourey and Lastrapes (1990), if volume of trade is serial correlation, and works as a proxy for information, then it can be expected that $x > 0$. For $x > 0$, the λ , θ and β will become small and statistically insignificant. In this equation, β is used to measure the persistence of volatility.

6. Results

6.1. Contemporaneous returns-volume relationships

The table 5 panel A shows regression results (equation 14), which are not significant for any of the markets. Therefore, there is no evidence of contemporaneous correlation between returns and volume of these markets.

Table 5: Regression for detrended trading volume on stock index returns

Country	Sweden	Denmark	Norway	Finland
Panel A: Regression for daily trading volume and stock returns (equation 14)				
a	-0.000333 (-0.332609)	1.23E-06 (0.018728)	-0.000193 (-0.167942)	-3.60E-05 (-0.053262)
b	-0.048962 (-0.364143)	-0.016761 (-1.557099)	0.129664 (0.845279)	-0.141411 (-1.304311)
R ²	0.000054	0.001148	0.000306	0.001062
Panel B: Regression for daily trading volume and absolute stock return (equation 15)				
a	-0.013576 (-9.714376)**	-0.000804 (-9.182813)**	-0.003054 (-1.950641)	-0.005014 (-5.528449)**
b	2.465348 (13.15492)**	0.190633 (13.27756)**	0.561754 (2.684085)**	1.169108 (8.038999)**
R ²	0.065425	0.077143	0.003075	0.038823

** statistically significance at the 1% level. t-statistics are in parenthesis

In panel B table 5, all coefficients are positive and significant at the 1% level. It means that in all Nordic markets, the variance of changing price is positively related to trading volume. This confirms, with respect to MDH and SAIH, that there is a positive correlation between trading volume and absolute stock return. It also consistent with previous research where were found a positive contemporaneous between trading volume and stock returns (Clark 1973, Chen et al 2001). Thus, we can conclude that Nordic markets are well liquidity where traders can easily enter or exit the markets.

6.2. VAR model estimation and Granger tests

To determine the lag order of the unrestricted VAR, which explains the relationship between trading volume and stock index returns, estimations of 20 lag orders of the model were performed. For presentation purposes only the first 7 lags are shown. The results of the estimated VAR models were then compared using the Akaike and (or) Schwarz information criteria to determine the optimum model. Table 6 presents our selection for optimal choice of

the lag order. From table, Sweden, Norway and Finland have 5 lags as optimal choice according to AIC. Denmark shows its best choice as 5 lags following SC and 6 lags following AIC. As Brooks (2008, p233) commented “there is no criterion is definitely superior to others”, we hence choose 5 lags as the best choice for our VAR model.

Table 6: The optimal choice of lag order for VAR estimation

Sweden								
Lag(s)	0	1	2	3	4	5	6	7
AIC	-10.121	-10.354	-10.364	-10.377	-10.395	-10.408*	-10.407	-10.407
SC	-10.111	-10.335	-10.335	-10.340	-10.347	-10.350*	-10.342	-10.332
Denmark								
Lag(s)	0	1	2	3	4	5	6	7
AIC	-16.146	-16.4179	-16.4238	-16.4301	-16.4488	-16.465	-16.468*	-16.466
SC	-16.1357	-16.3941	-16.3918	-16.3879	-16.3950	-16.401*	-16.393	-16.380
Norway								
Lag(s)	0	1	2	3	4	5	6	7
AIC	-9.91797	-10.2335	-10.3058	-10.3431	-10.3525	-10.396*	-10.367	-10.369
SC	-9.90808	-10.2134	-10.2761	-10.3035	-10.3035	-10.308*	-10.298	-10.299
Finland								
Lag(s)	0	1	2	3	4	5	6	7
AIC	-11.6944	-11.8358	-11.8358	-11.8348	-11.8394	-11.851*	-11.847	-11.846
SC	-11.6806	-11.808*	-11.795	-11.7805	-11.7720	-11.770	-11.753	-11.738

* indicates the best choice for VAR estimation

Table 7 below shows the causality test using VAR model (from equation 16 and 17) with 5 lags. Panel A presents the result of equation 16 where stock return is the dependent variable. Panel B shows the result from equation 17 where trading volume is the dependent variable.

Panel A reports our test for the null hypothesis that trading volume does not Granger-cause stock returns. The F-statistics are shown in panel A and are significant at the 1% level for Denmark and the 5% level for Finland. There are no significant F-statistic for Sweden and Norway. Thus, we reject the null hypothesis that trading volume does not cause stock returns in Denmark and Finland. The dummy variable (D) which we use to capture the financial crisis

is significantly negatively related with the stock returns in Denmark at the 1% level, Norway and Finland at the 5% level. This implies that the financial crisis had a negative impact on stock returns in these countries. The causality relationship from trading volume to returns in Denmark and Finland

Panel B shows the result of testing the null hypothesis that returns do not Granger-cause trading volume. F-statistic is significant at 1% level for all of the markets. The hypothesis that returns do not Granger-cause trading volume is rejected, hence, the stock return lead to trading volumes in the Nordic markets. For Sweden in particular, a_1 and a_2 are negative and significant at the 5% level. This indicates a negative impact of stock return on trading volume in Sweden at the first and second lag. There is also a small negative impact on trading volume in Denmark where the coefficient is significant at the 5% level at the fourth lag. The dummy variable for the financial crisis is positively significant at the 5% level in Sweden and Denmark.

In general, our tests show that there are bi-directional causality in Denmark and Finland while Sweden and Norway have uni-directional causality from returns to trading volume. The dependence of trading volume on lagged stock return in Sweden and Norway is consistent with many previous studies in developed markets such as Hiemstra and Jones (1994), Chen et al (2001), and Lee and Rui (2002). This can be explained by that investors predict the future prices based on feedback from past price trends and take their trading decisions accordingly (Brennan and Cao, 1997). In Swedish and Norwegian markets, we therefore suggest that traders diversify their portfolios to optimize their returns, while managers of registered companies use the historical price to measure the performance of market so that new shares are not issued when markets underperform. On other hand, the bi-directional causality in Denmark and Finland entail that the forecast in current stock return can be developed by knowledge of past trading volume and vice versa. According to Gunduz and Hatemi (2005), bi-directional causality occurs in markets with low trading volume and legal restriction. It also implies that these markets are not efficient since the stock return depends on past trading volume which is public information and known to all (Badhani, K.N, 2006). Thus, in Denmark and Finland, we suggest that investors use both past price and trading volume when predicting future price in order to get optimal returns. In order to increase the stock market efficiency relevant policymakers may consider reducing trading restrictions.

Table 7: VAR analysis for the relation between return and volume

Country	Sweden	Denmark	Norway	Finland
Panel A: coefficient estimates of equation 16 for returns				
a_0	6.77E-06 (0.04359)	5.97E-05 (0.43413)	0.000111 (0.69551)	0.000178 (1.08703)
g_1	-0.023953 (-1.18741)	0.031614 (1.44829)	-0.001225 (-0.05914)	0.026590 (1.05943)
g_2	-0.047855 (-2.36919)*	-0.022621 (-1.03711)	-0.040642 (-1.96217)*	-0.051793 (-2.06170)*
g_3	-0.041663 (-2.06037)*	-0.026913 (-1.23631)	-0.013935 (-0.67225)	-0.013935 (-0.55374)
g_4	0.012672 (0.62640)	0.064247 (2.94670)**	0.020526 (0.99121)	0.048265 (1.91496)
g_5	-0.015228 (-0.75300)	-0.063389 (-2.90558)**	-0.059764 (-2.88448)**	-0.051486 (-2.04384)*
d_1	-0.000720 (-0.20652)	0.011481 (0.22952)	0.000609 (0.17293)	0.007046 (1.13219)
d_2	0.001215 (0.32866)	-0.030037 (-0.54041)	0.002559 (0.69810)	-0.003539 (-0.53929)
d_3	0.000336 (0.09092)	0.087358 (1.57052)	-0.005468 (-1.49074)	0.001606 (0.24471)
d_4	-0.000164 (-0.04425)	0.060606 (1.08978)	-8.22E-05 (-0.02244)	0.007274 (1.10957)
d_5	0.001994 (0.57252)	-0.018511 (-0.35895)	0.004301 (1.22295)	-0.003720 (-0.59907)
m	-0.000310 (-0.49178)	-0.001345 (-2.57620)**	-0.001355 (-2.12477)*	-0.001348 (-2.52271)*
F - stats	1.135657	2.942835**	1.926567	2.024085*
R ²	0.005059	0.015224	0.009048	0.013853
Panel B: coefficient estimates of equation 17 for detrended trading volume				
a_0	-0.000564 (-0.63235)	-3.44E-05 (-0.59444)	0.000360 (0.38422)	-5.68E-05 (-0.08636)
a_1	-0.264553 (-2.28264)*	-0.016895 (-1.83890)	0.017625 (0.14531)	-0.185084 (-1.83834)
a_2	-0.245298 (-2.11377)*	-0.014991 (-1.63287)	-0.230739 (-1.90212)	-0.127191 (-1.26215)
a_3	-0.093230 (-0.80249)	-0.013408 (-1.46329)	0.099012 (0.81556)	-0.142784 (-1.41445)
a_4	-0.015880 (-0.13663)	-0.021283 (-2.31921)*	-0.170830 (-1.4081)	-0.162343 (-1.60568)
a_5	0.026075 (0.22442)	-0.002775 (-0.30216)	-0.034412 (-0.28359)	-0.151444 (-1.49869)
b_1	0.364121 (18.1801)**	0.406165 (18.7055)**	0.297759 (14.4412)**	0.331686 (13.2855)**
b_2	0.031832 (1.49823)	0.045490 (1.94444)	0.147920 (6.89066)**	0.012329 (0.46835)
b_3	0.061209 (2.88446)*	0.017491 (0.76632)	0.139780 (6.50666)**	0.017954 (0.68218)
b_4	0.094989 (4.47179)**	0.072524 (3.09829)*	0.071570 (3.33693)**	0.035294 (1.34210)
b_5	0.121501 (6.07095)**	0.126102 (5.80962)**	0.122841 (5.96468)**	0.112258 (4.50684)**
m	0.007562 (2.09042)*	0.000435 (1.98143)*	-0.007213 (-1.93114)	0.000281 (0.13112)
F-stats	80.61915**	77.57175**	130.6322**	26.91512**
R ²	0.265210	0.289517	0.382377	0.157393

** statistically significance at 1% level. * statistically significance at 5% level. t-statistics are in parenthesis

6.3. EGARCH volatility models

We use equation 20 to test the properties of the volatilities without the effect of trading volume on return. The result results are reported in table 8, where b values for all market are significant at the 1 % level. This implies that the volatility is stationary but persistent to volatility shocks (Lamoureux and Lastrapes 1990, Chen et al 2001). The coefficient of asymmetric q is negatively significant in all markets, which suggests that the volatility of market decrease when information arrives that signals to the stock markets to increase the return or trading volume.

Unsurprisingly, the financial crisis had a positive significant influence on all markets, resulting in a higher return volatility. This is confirmed by studies in the United Kingdom (Harris and Pisedtasalasai, 2006), Malaysia and Singapore (Pisedsalasai and Gunasekharage, 2007).

Table 8: EGARCH (1,1) without trading volume

Country	Sweden	Denmark	Norway	Finland
a	7.81E-05 (0.739755)	0.000106 (1.089739)	0.000253 (2.325358)*	0.000185 (1.662854)
b	-0.024852 (-1.188842)	0.024132 (1.078663)	0.010540 (0.470395)	0.030386 (1.115731)
c	-0.000295 (-0.311709)	-0.000708 (-0.777268)	-0.001783 (-1.402921)	-0.001104 (-1.280840)
w	-0.345431 (-8.034808)**	-0.495291 (-7.066615)**	-0.806942 (-7.708980)**	-0.387031 (-5.989842)**
I	0.158922 (10.05282)**	0.140115 (8.946100)**	0.186599 (8.281885)**	0.116235 (5.373188)**
q	-0.085292 (-9.801179)**	-0.086656 (-7.964261)**	-0.119604 (-8.582321)**	-0.094412 (-7.797592)**
b	0.978399 (278.0153)**	0.964089 (161.3977)**	0.936949 (99.35942)**	0.972458 (182.3975)**
j	0.033032 (2.279779)*	0.069446 (4.085792)**	0.145710 (4.555003)**	0.054849 (3.099455)**
Ljung Box (36)	45.393 [0.136]	34.281 [0.551]	25.039 [0.915]	33.305 [0.597]

** statistically significance at the 1% level. * statistically significance at 5% level. t-statistics are in parenthesis

Table 9: EGARCH (1,1) with trading volume

Country	Sweden	Denmark	Norway	Finland
a	8.09E-05 (0.775699)	0.000104 (1.080230)	0.000240 (2.200357)	0.000182 (1.650672)
b	-0.023742 (-1.145010)	0.024722 (1.111008)	0.012880 (0.574603)	0.035605 (1.296726)
c	-0.000418 (-0.441416)	-0.000623 (-0.685673)	-0.001761 (-1.390255)	-0.001228 (-1.396613)
w	-0.381687 (-8.203875)**	-0.519858 (-7.173251)**	-0.851633 (-7.835669)**	-0.370435 (-5.986379)**
I	0.154047 (9.343619)**	0.139051 (8.733174)**	0.178482 (7.846658)**	0.106505 (5.482393)**
q	-0.087794 (-9.726420)**	-0.089645 (-8.066286)**	-0.124951 (-8.852878)**	-0.091770 (-7.942814)**
b	0.974474 (255.6234)**	0.961729 (154.6751)	0.932171 (95.31650)**	0.973306 (188.2595)**
x	0.336853 (3.441683)**	6.261259 (4.192102)**	0.346364 (3.147495)**	0.769754 (3.175020)**
j	0.034752 (2.337122)*	0.067272 (3.809609)**	0.169866 (5.042360)**	0.053624 (3.156288)**
Ljung Box(36)	46.557 [0.112]	35.909 [0.473]	25.280 [0.90]	34.921 [0.520]

** statistically significant at the 1% level. * statistically significant at the 5% level t-statistics are in parenthesis

Equation 23 is used to analyze the effect of trading volume on return volatilities. Table 9 gives the *b* values and *I* values which are significant at the 1% level in all markets. This means that the high persistence of past volatility explains the current price volatility. Thus, trading volume as a proxy of information does not reduce the persistence in return volatility. This agrees with Chen et al (2001) and differs with Lampourey and Lastrapes (1990) and Wang et al (2005). However, the *x* values for trading volume are significant for all of markets. It is explained that trading volume may contain some information which is helpful in forecasting volatility. Consequently, traders should include trading volume in their predicting return volatility.

7. Conclusions

In this paper, we examined the relationship between trading volume, stock index returns and volatility in Nordic countries - Sweden, Denmark, Norway, and Finland. Our results confirm the variance of changing price is positively related to trading volume, or a positive correlation between trading volume and absolute stock returns in other words. This finding shows that the Nordic markets are liquidity where traders can enter and exit easily.

The bi-VAR tests of causal relationship between stock returns and trading volume, show that there are bidirectional causality in Denmark and Finland while Sweden and Norway have a unidirectional causality from returns to trading volume. The dependence of trading volume on lagged stock return in Sweden and Norway suggest that traders should base the past return to predict the future price. It also implies that managers should keep track of the historical return for planning when to issue new shares to the market. On other hand, the bi-directional causality in Denmark and Finland mean that investors can predict stock returns from past trading volume and past returns. Our findings point out that, in these cases there is a need to reduce restrictions on traders and trading activities so as to improve the market efficiency.

Furthermore, EGARCH (1, 1) is employed to find the role of trading volume in explaining volatility of stock prices. Our study points out that trading volume may contain an element of information that is helpful for investors in forecasting volatility. Consequently, traders should include trading volume in their predicting volatility.

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