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Investigating the Contemporaneous and Causal Relationships between Trading Volume and Returns in the Dutch Market

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ABSTRACT

This thesis examines the contemporaneous and causal relationships between (the change in) trading volume and returns using daily trading volume and return data for a sample of 22 Dutch firms in the period January 2013 until December 2023. I find that (the change in) trading volume does not Granger-cause stock returns in the Dutch market (with some exceptions). There does exist, however, a negative contemporaneous relationship between (the change in) trading volume and returns in the Dutch market. This paper employs a panel regression using feasible generalized least squares (GLS) and a GARCH(1,1) model to test the existence of a contemporaneous relationship, and a bivariate vector autoregressive model and Granger causality test to examine the existence of a causal relationship.

Keywords: Dutch Stock Market, Trading Volume, Granger causality

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CHAPTER 1 Introduction

One of the most extensively researched topics in finance to date revolves around the relationship between trading volume and stock returns. William J. O'Neil (1988) emphasized the significance of trading volume, stating, "Volume is the lifeblood of any stock. It's like a heartbeat, indicating the health of the market and the potential for price movement." (as cited in Baiynd, 2011). According to his perspective, understanding the dynamics of volume in stock trading is crucial for assessing market health and predicting price movements. In the literature, trading volume is commonly referred to as the total number of shares of a firm traded in a financial market over a given period of time (Harris, 2003). This metric not only offers valuable insights into market activity and investor sentiment but also complements the analysis of stock returns. Stock return, such as measured by a positive or negative change in value of the investment over time, is another key aspect of financial analysis. For instance, data from Yahoo Finance reveal a notable surge in Nvidia's trading volume by 64% from December 2023 to March 2024, concurrent with a 93% increase in its share price. This observed surge in trading activity suggests heightened investor interest and participation, potentially influencing Nvidia's stock returns during that period.

This potential relationship between stock returns and trading volume has been examined by Lee and Rui (2002). The authors employed a methodology mainly based on bivariate and multivariate vector autoregression (VAR) using a dataset comprised of daily market price index and trading volume series for the S&P500, Tokyo Stock Exchange Index (TOPIX), and the Financial Times-Stock Exchange (FT-SE). They find that, although there is a contemporaneous correlation, trading volume does not Granger-cause stock market returns on the US, Japanese and UK stock exchanges when using the whole sample period. In addition, the authors find a feedback relation in all three markets regarding trading volume and return volatility, which means that trading volume helps predict the volatility of returns but not the level of returns. This outcome seems to be in line with Clark (1973), who predicts no causal relation from trading volume to stock returns. On the other hand, this conflicts with the results obtained by Hiemstra and Jones (1994), who conducted their analysis using Dow Jones Industrial Average stock returns.

While most authors have devoted their research to data originating from the US stock market, there are some exceptions, like the research of Lee and Rui (2002), who have also included the Japanese and UK stock market in their research. As well as their study from 2000, where they conduct their research on the Chinese stock market. It is important to recognize that there are significant differences between equity markets, such as the US and Dutch stock markets. For instance, the US stock market is known for its large market size and capitalization, while the Dutch stock market is a lot smaller in size. As well as differences in the composition of listed companies across various sectors. Given these differences in market characteristics, the effectiveness of trading volume as the sole predictor of investment performance may vary between the US and Dutch stock markets. Therefore, analyzing the applicability of findings from research conducted on the US market to the Dutch market is crucial in addressing the unanswered question at hand: How effective is trading volume as the sole predictor of investment performance in the Dutch stock market?

My thesis will therefore examine how effective trading volume is as an exclusive investment indicator for the Dutch stock market. A contemporaneous and a causal analysis will be conducted using daily stock returns and trading volume for the N=22 stock components of the Amsterdam Exchange Index (AEX), starting in January 2013 up to December 2023. The goal of this research will be to analyze the contemporaneous relationship between trading volume and returns, meaning the correlation between the two series in the same time period, and the causal relationship, meaning the relationship between the two variables where one is the result of the other. The unit of analysis will be each individual stock, and the sample includes all 22 stocks included in the AEX. The primary focus of the investigation will be on trading volume and returns. Trading volume will be operationalized as the total daily number of shares of a firm traded in a financial market. Returns, on the other hand, will be operationalized as the positive or negative change in the value of the investment over a one-day period. To gather the necessary data for analysis, I will source information primarily from Yahoo Finance.

I expect to find that there will be a contemporaneous relationship, although not a causal relationship, present in the Dutch stock market. This expectation is grounded in the thought that trading volume serves as a proxy for market activity and investor sentiment. High trading volume could very well reflect increased investor participation and information flow, suggesting heightened market interest and potential price movements. Subsequently, stocks experiencing higher trading volume could very well undergo more pronounces price movements, potentially leading to returns that deviate from the expected levels. Moreover, empirical evidence from previous studies focusing on the US and other international markets like the UK, Japan and China suggest some positive association between trading volume and stock returns, indicating that trading activity likely plays a large role in price discovery and market efficiency. Furthermore, the Dutch stock market, while relatively smaller in size compared to other equity markets like the United States, is characterized by active trading and participation from both domestic and international traders. Overall, I anticipate that trading volume will serve as a valuable investment indicator and predictor of the sign of returns in the Dutch stock market.

The remainder of this paper will be arranged as follows. Chapter 2 discusses relevant literature and previous research, providing an overview of the foundational studies that inform this work. Chapter 3 reviews the data used in this paper and the methods employed for data collection. This chapter will also discuss any limitations associated with the data and the steps taken to mitigate potential biases. Chapter 4 outlines the methodology of the analysis performed in this study. This section will explain the analytical techniques used and discusses their appropriateness for addressing the research question. Chapter 5 presents the results of the analysis, offering an examination of the findings. This chapter will compare the results to those obtained from previous research and provide a critical evaluation of similarities and differences. Finally, Chapter 6 will provide a conclusion, summarizing the main points of this paper, and discussing the significance of the findings.

CHAPTER 2 Theoretical Framework

2.1 Trading Volume

Trading volume has long been a subject of interest and analysis in financial research. According to Karpoff (1986), Trading Volume is characterized by the number of transactions between buyers and sellers of stocks who are randomly paired in the corresponding trading period. It arises in the literature in at least three settings: its relation to the bid-ask spread, its relation to price changes, and its relation to information (with some overlap). Empirical studies suggest a negative correlation between volume and the bid-ask spread, a finding consistent with the theoretical model of Copeland and Galai (1983). They characterize a dealer's position as a written straddle of put and call options available to informed investors. When dealers set bid and ask prices, they weigh the costs of offering quotes to informed traders against the potential profits from traders who prioritize liquidity. Studies such as those by Chan, Jegadeesh and Lakonishok (1996) and Easley and O'Hara (1992) have delved into the informational content of trading volume, suggesting that elevated trading volume can convey valuable information about future price movements. Nevertheless, the interpretation of trading volume as a predictor of market behavior has evolved over time, with more recent studies analyzing the nuances of the relationship of trading volume with various factors such as liquidity, volatility, and investor behavior. For instance, the works of Hasbrouck (2007) and Andersen, Bollerslev, and Diebold (2007) have highlighted the significance of distinguishing various categories of trading volume, such as institutional and retail trading. This differentiation is important for understanding how trading volume influences market efficiency and asset valuation. Several models study the relation of trading volume to price changes. Epps (1975), using individual transaction data in the form of volume and price for each transaction in all bonds and stocks on the NYSE and NASDAQ, presents a model wherein the trading volume during price upticks surpasses that during downticks. Copeland (1976) shows that volume subsequent to all investors gaining access to the information correlates positively with the extent of the price change. This model is extended by Jennings, Starks, and Fellingham (1981), who incorporate real-world margin limitations and the possibility of short sales. They further predict (similar to Epps) that volume is relatively heavy on transaction upticks. However, a notable feature of each of these models is a dependence on behavioral differentiations among various groups of market participants, such as distinguishing between "bulls" and "bears" or "optimists" and "pessimists". Karpoff (1986) developed a model that does not rely on such behavioral distinctions. His model describes two different ways informational events affect trading volume. One way is that investor disagreement leads to increased trading. However, abnormal trading volume doesn't always indicate disagreement, as volume may rise even if investors interpret information similarly, provided they had differing prior expectations. Trading volume is also important in the models of Clark (1973), Tauchen and Pitts (1983), and Harris (1983). These models forecast that trading volume correlates positively with the magnitude of the accompanying price change within set time intervals or as demonstrated by Epps and Epps (1976), within individual transactions. The model by Pfleiderer (1984) incorporates price and volume within a noisy rational expectations equilibrium. The scale of the price change is uncorrelated with trading by speculators with private information but is positively correlated to trading by investors who prioritize liquidity. Therefore, the intensity of the correlation between absolute price changes and volume is negatively correlated to the existence of private information. Empirical researchers attempt to extract insights from trading volume data, but others like Verrecchia (1981) argue that the correlation between information and volume is ambiguous. The message of their analysis is that the degree of volume reaction to new information cannot be used to infer unambiguously the extent of agreement among investors about how that information should be interpreted. Empirical evidence from Beaver (1986) and Morse (1980) suggest that trading volume tend to be lower in imperfect markets, and that information has a persistence effect on trading volume in the imperfect market. Their research also suggest that markets do not immediately fulfill all demands motivated by the information or that investors make trading mistakes and have demands to recontract in subsequent periods.

2.2 Empirical Studies

The dynamic interaction between trading volume and investment performance continues to be a central area of focus of academic inquiry in finance. Traditional finance theory suggests that increased trading volume should be associated with higher returns as new information is reflected in asset prices. However, empirical studies show varied results on this connection. While some research like that of Amihud and Mendelson (1986) and Lee and Swaminathan (2000) find correlations between trading volume and future returns, others such as Fama and French (1988) and Harris (1986) present negative associations. This inconsistency in findings highlights the need for a nuanced understanding of the mechanisms underlying the relationship between trading volume and returns. Godfrey, Granger and Morgenstern (1964) claim to have shown that there is no discernible relationship between stock price series and the series of stock sales. Similarly, they argue that no relationship could be recognized between stock price series and trading volume series. On the other hand, Crouch (1970) argues that considering economic theory is essential for gaining valuable information into stock market behavior. He holds the view that by employing economic reasoning and carefully analyzing data, stock market relationships can be understood better. In addition, research on market anomalies such as post-earnings announcement drift (PEAD) consider the complexities of stock price and trading volume movements. Martineau (2018) analyzes the occurrence of PEAD, where stock prices continue to drift after earnings announcements, which challenges the efficient market hypothesis. Even though he does not directly address trading volume, Martineau's findings show lasting trends in stock prices, emphasizing the importance of investor reactions to unique information. Studies by Chordia, Roll, and Subrahmanyam (2001) and Brennan and Subrahmanyam (1996) have highlighted the role of liquidity provision and market frictions in influencing the relationship between trading volume and returns. They propose that the informative value of trading volume might fluctuate under distinct market conditions. Several other papers have contributed to enhancing comprehension of the relation between price changes and trading volume. Granger and Morgenstern (1963) studied the relationship between price indices and aggregate exchange volume. They found that the relationship between any two series can be described in terms of the correlation and time-lag between corresponding frequency components and shown that these concepts may be applied to certain non-stationary series. Crouch (1970) investigated the simultaneous relationship between absolute price changes and trading volume, he argues that the better we reason through economic theory, apply them wisely, and carefully collect the data, the more we can understand stock market relationships. Westerfield (1977) also analyzed patterns between price changes and trading volume, as well as Tauchen and Pitts (1983), who incorporated their analysis within a rational expectations framework. Their findings suggest that traders use all available information efficiently when making trading decisions. They find that there is a positive relationship between trading volume and the variability of asset prices. They argue that the flow of information in the market drives trading activity. When new information arrives in the market, traders rebalance their beliefs and trade accordingly, resulting in changes in trading volume and price movements. Epps and Epps (1976) have analyzed how the variance of price changes relates to trading volume. Their findings suggest that there is a positive relationship between the variance of price changes and trading volume, signifying that periods with higher trading volume tend to exhibit greater variability in price changes. Harris (1983) and Clark (1973) studies the relationship between squared price changes (volatility) and trading volume. Clark's findings imply that periods of high trading volume are linked with higher volatility (variance) of price changes. These findings are consistent with earlier work that suggest larger volumes often accompany larger price movements. Smirlock and Starks (1988) analyzed the causal relationship between absolute price changes and trading volume at the firm level. Their findings suggest that on average, there exists a notable delayed correlation between trading volume and absolute price changes, and that this relationship tends to be more significant in short periods preceding and immediate after quarterly earnings announcements. Smirlock and Starks were not the first ones to use causality tests to examine the price-volume relationship. To name a few examples, Rogalski (1978) used this methodology and found that stock price changes and the level of volume contemporaneously cause each other. This study differs from Smirlock's and Starks's in the way that Rogalski utilized monthly data over a small sample and focused on examining price changes themselves rather than their absolute values. Cornell (1981) has also investigated this relationship, only in the futures markets, however, with little significant result. Moreover, the works of Barberis, Shleifer, and Vishny (1998) and Daniel, Hirshleifer, and Subrahmanyam (1998) highlight the role of investor sentiment and cognitive biases in analyzing trading volume patterns and their relation to stock market prices, exemplifying behavioral finance perspectives.

2.3 Trading Volume and Returns: the case of the Netherlands

Chen et al. (2001) have analyzed the relationship between Trading Volume and Returns for a sample of the nine largest stock exchanges, one of which is the Netherlands. In particular, they examine the contemporaneous and causal relationship. They find that there exists a positive contemporaneous relationship between trading volume and returns in the Dutch stock market. They also find that in the presence of current and past returns, trading volume adds some significant predictive power for future returns, however, their evidence indicates stronger evidence of returns causing trading volume than volume causing returns. Brida, Matesanz, and Seijas (2016) apply a multidimensional network analysis to analyze the structure of the Euro Stoxx market, including Dutch market components like ING, Phillips, Ahold Delhaize, and ASML, during the period 2002 until 2014 by including stock market returns and trading volume as the main variables to study the financial market. They argue that trading volume carries important information to the market and its inclusion is non-trivial. They find that, during times of financial crisis, the network of firms becomes a more centralized one. In addition, hierarchy becomes more country specific, suggesting that during periods of financial crisis investors seem to be most worried about country specific economic circumstances.

CHAPTER 3 Data

3.1 Sample Description

The data used in this study consist of daily stock price and trading volume data for a sample of 22 Amsterdam Exchange Index (AEX) firms from January 2013 until December 2023. This data is retrieved from Yahoo Finance and gathered as a utilizable dataset using a script made with Python, initially comprising of variables *Date, Opening Price, High, Low, Closing Price, Adjusted Closing Price, Trading Volume* and, added by the help of my Python script, *Ticker*, denoting the firm's ticker symbol, initializing a usable panel dataset consisting of 22 panels (firms). In order to run the analysis, the data underwent several preprocessing steps using Stata MP to ensure its suitability for examining the effectiveness of trading volume as a predictor of investment performance in the Dutch stock market. Initially, irrelevant variables such as *Opening Price, High, Low* and *Closing Price* were dropped from the dataset, focusing the analysis on the essential variables. The *Date* variable, imported as a string variable, was converted into a Stata-recognizable date format in order to correctly run the panel regression. To capture price movements accurately, I calculated daily returns, sorted by date and ticker, using the *Adjusted Closing Price*. In addition to raw *Volume*, to take on account positive as well as negative values, daily changes in trading volume were also computed. Moreover, the lagged values for these variables were also included to allow for the analysis of both immediate and delayed effects. Furthermore, values denoted with zero in returns, trading volume and changes in trading volume were replaced with missing values and deleted from the dataset to avoid distortions in the analysis caused by non-trading days or data anomalies. In order to set up the panel regression within Stata MP, a unique identifier for each ticker was created, allowing for a more efficient analysis. This comprehensive set of transformations, including handling missing values, computing returns and volume changes, and creating lagged variables, ensures a utilizable framework for examining the predictive power of trading volume. However, given this preprocessing, the dataset is not entirely balanced, meaning some days will have more active firms than others, since not every firm has been listed on the Dutch stock exchange since the beginning of 2013. Despite this imbalance, this should not directly hinder a suitable analysis. Statistical techniques and models are well-equipped to handle such variations, ensuring that the analysis remains robust.

3.2 Variables

In order to calculate *Return*, I have opted for using the *Adjusted Closing Price*, as opposed to the regular *Closing Price*. I motivated this decision on the fact that the adjusted price incorporates actions such as dividends, stock splits and rights offerings. It reflects the true economic value of the stock, accounting for changes in the number of shares outstanding and cash distributions to shareholders. This pricing data is adjusted using appropriate split and dividend multipliers, adhering to Center for Research in Security Prices (CRSP) standards. This to provide a more consistent and accurate representation of investment performance. Given this decision, *Return* is calculated as follows:

$$Return_t = \ ln\left(\frac{Adjusted\ Closing\ Price_t}{Adjusted\ Closing\ Price_{t-1}}\right)$$

(1)

Where *Return* represents the change in the stock's *Adjusted Closing Price* from one day to the next, adjusted for any corporate actions like dividends, stock splits, or new stock offerings that might affect the stock price. *Trading Volume* denotes the total number of shares or contracts exchanged between buyers and sellers of a security during trading hours on a given day. In addition to this, I will also use the change in trading volume. Using this change in volume allows for the analysis of market dynamics and investor behavior by capturing fluctuations and trends that may indicate changes in market sentiment or investor actions. This *Change in Trading Volume* is calculated in the following way:

$$\Delta Trading\ Volume_t = \ ln\left(\frac{Trading\ Volume_t}{Trading\ Volume_{t-1}}\right)$$

(2)

Where the *Change in Trading Volume* represents the change in the stock's *Trading Volume* from one day to the next.

3.3 Summary Statistics

Table 1 and 2 represent the descriptive statistics of the *Returns* and *Trading Volume* among the stock components of the Amsterdam Exchange Index. The mean shows the average value measured across all trading days in the sample. The standard deviation captures the variability from the mean. The minimum and maximum show the range of the values in the dataset for each firm, and the frequency represents the amount of (active) trading days for each firm in the sample. Examining these statistics reveal notable variations among the different AEX firms. For example, as can be seen from table 1, ASM International exhibits a relatively high mean return of .0012 (compared to an average of .0004 across the sample) with a standard deviation of .0231, indicating a relatively high volatility. Conversely, Prosus N.V. and Just Eat Takeaway.com N.V. show negative mean returns, with standard deviations of .0274 and .0307, respectively. The range of returns also varies quite substantially across firms, with some firms like Adyen exhibiting a wider range of return (-.4940 to .3208) compared to others. Additionally, the frequency of observations ranges from 775 trading days for Unilever, to 2,787 trading days for ArcelorMittal SA, showing the differences in data availability. Table 2 shows the noteworthy disparities in *Trading Volume* among the firms. For instance, ING demonstrates a high mean trading volume of around 18 million per day (compared to an average of 3.7 million across the sample) with a wide range (1.7 million to 97.1 million), indicating substantial trading activity. Conversely, firms like Adyen have a lower mean trading volume of only 89,752, with a narrower range (2,513 to 954,082). The frequency of observations also varies quite considerably across firms, again showing the differences in data availability. Firms like Prosus NV and Unilever have a lower frequency of trading days, indicating a later listing date than other firms.

Table 1. Descriptive Statistics of Returns among AEX firms in the period 2013-2023

	Return				
Ticker	Mean	St. Dev	Min.	Max.	Frequency
ABN	.0001	.0224	-.2388	.1415	2,033
AD	.0004	.0132	-.1002	.0772	2,746
ADYEN	.0007	.0319	-.4940	.3208	1,408
AGN	.0001	.0218	-.2431	.1638	2,786
AKZA	.0003	.0151	-.1181	.1222	2,771
ASM	.0012	.0231	-.1939	.1639	2,783
ASML	.0010	.0195	-.1311	.1306	2,776
ASRNL	.0005	.0174	-.1750	.1251	1,905
GLPG	.0003	.0269	-.2790	.2012	2,464
HEIA	.0002	.0132	-.0972	.1055	2,762
IMCD	.0009	.0165	-.1640	.0995	2,344
INGA	.0004	.0211	-.2153	.1864	2,771
KPN	.0004	.0163	-.1726	.1484	2,723
MT	.0001	.0278	-.2046	.1703	2,787
NN	.0004	.0169	-.2082	.1027	2,366
PHIA	.0001	.0172	-.1679	.1290	2,776
PRX	-.0002	.0274	-.1902	.2142	1,099
RAND	.0004	.0182	-.1512	.1003	2,774
REN	.0007	.0130	-.1249	.0921	2,723
TKWY	-.0002	.0307	-.1806	.2491	1,797
UNA	.0001	.0113	-.0698	.0887	775
WKL	.0008	.0125	-.1029	.0730	2,756
Total	.0004	.0200	-.4940	.3208	52,125

Notes: The mean shows the average value measured across all trading days in the sample. The standard deviation captures the variability from the mean. The minimum and maximum show the range of the values in the dataset for each firm, and the frequency represents the amount of (active) trading days for each firm in the sample.

Table 2. Descriptive Statistics of Trading Volume among AEX firms in the period 2013-2023

			Trading Volume		
Ticker	Mean	St. Dev	Min.	Max.	Frequency
ABN	2,976,973	2,630,470	140,675	74,000,000	2,033
AD	3,626,451	2,436,374	184,462	67,800,000	2,746
ADYEN	89,752	71,741	2,513	954,082	1,408
AGN	9,620,745	6,011,480	736,498	133,000,000	2,786
AKZA	639,536	370,895	59,627	5,600,433	2,771
ASM	249,724	168,510	17,914	4,566,961	2,783
ASML	1,128,552	627,279	84,141	8,975,348	2,776
ASRNL	509,756	1,027,831	19,224	27,000,000	1,905
GLPG	336,351	302,187	4,968	3,764,454	2,464
HEIA	697,159	331,477	72,071	3,844,600	2,762
IMCD	102,845	110,649	1,476	3,454,108	2,344
INGA	18,000,000	8,970,959	1,661,154	97,100,000	2,771
KPN	15,600,000	11,000,000	1,153,484	218,000,000	2,723
MT	6,037,798	3,169,608	470,490	31,400,000	2,787
NN	1,007,360	667,640	23,403	10,800,000	2,366
PHIA	3,438,331	1,832,483	353,420	39,100,000	2,776
PRX	4,478,170	4,646,150	294,723	115,000,000	1,099
RAND	577,193	304,095	46,761	3,244,643	2,774
REN	2,156,831	1,275,645	145,616	13,700,000	2,723
TKWY	998,125	1,307,423	1,165	18,100,000	1,797
UNA	2,074,691	1,217,726	343,368	12,200,000	775
WKL	741,486	390,374	99,437	6,288,220	2,756
Total	3,670,684	6,363,010	1,165	218,000,000	52,125

Notes: The mean shows the average value measured across all trading days in the sample. The standard deviation captures the variability from the mean. The minimum and maximum show the range of the values in the dataset for each firm, and the frequency represents the amount of (active) trading days for each firm in the sample.

CHAPTER 4 Method

4.1 Unit Root Tests

Before applying any model to the data, I will begin by conducting unit root tests to ensure the validity and reliability of the time series data, and to ensure that every variable is stationary to avoid spurious regression results. The testing for a unit root is based on the Augmented Dickey-Fuller (ADF) (1979) test and the Phillips-Perron (PP) (1988) test. The ADF test is used to test for the presence of a unit root in a time series sample. This test helps determine whether a time series is stationary or contains a unit root, which indicates non-stationarity. The ADF test includes lagged differences of the series to account for higher-order serial correlation. The PP test is another unit root test that accounts for serial correlation and heteroskedasticity in the error terms. It improves upon the ADF test by using non-parametric statistical methods to adjust for these issues. For both of these tests, the null hypothesis states that the time series has a unit root (non-stationary), and the alternative hypothesis states that the time series is stationary. Like the ADF test, the PP test will be applied to *Return*, *Trading Volume*, and *Change in Trading Volume*. This to confirm that all series tested are stationary, and, therefore useful for further statistical analysis. The implication of these findings is that testing for causality between *Return* and *Volume* should be based on an unrestricted VAR approach.

4.2 Contemporaneous Relationship

4.2.1 Panel Regression using Feasible Generalized Least Squares (GLS)

This analysis examines the contemporaneous relation between *Return* and *Trading Volume* before testing Granger causality. With contemporaneous tests, the study examines the notion that rising market indexes are accompanied by rising volume, whereas a declining market is accompanied by falling volume. Given the panel structure of the data, I will use panel regression techniques to account for both cross-sectional (different firms) and time-series dimensions. For this I used the Generalized Least Squares (GLS) method. This approach allows estimation in the presence of autocorrelation within panels and cross-sectional correlation and heteroskedasticity across panels. Two primary models will be considered. The first model investigates the effect of *Trading Volume* on *Returns*. The second model will analyze the effect of the *Change in Trading Volume* on *Returns*. The regression equations are as follows:

$$Return_{i,t} = \alpha_i + \beta_1 Trading\ Volume_{i,t} + \upsilon_{i,t}$$

(3a)

$$Return_{i,t} = \alpha_i + \beta_2 \Delta Trading\ Volume_{i,t} + v_{i,t}$$

(3b)

Where α_i represents the individual-specific intercepts and $\epsilon_{i,t}$ is the error term that follow a first-order autoregressive process. In both models, the α_i captures unobserved heterogeneity across individual stocks, while the AR(1) structure addresses potential autocorrelation in the error terms. The heteroskedasticity option allows for different variances across panels, increasing the robustness of the estimates.

4.2.2 GARCH Model

To investigate the relationship between *Trading Volume* and the volatility of *Return*, I will employ a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. This model captures time-varying volatility:

$$Return_t = \alpha_1 + \beta_1 Return_{t-1} + b_1 Trading\ Volume_t + \varepsilon_t$$

(4a)

$$\varepsilon_t^2 | (\varepsilon_{t-1}^2, \varepsilon_{t-2}^2, \ldots) \approx N(0, h_t)$$

(5a)

$$h_t = \omega_0 + \omega_1 \varepsilon_{t-1}^2 + \omega_2 h_{t-1}$$

(6a)

And for the *Change in Trading Volume*:

$$Return_t = \alpha_2 + \beta_2 Return_{t-1} + b_2 \Delta Trading\ Volume_t + \varepsilon_t$$

(4b)

$$\varepsilon_t^2 | (\varepsilon_{t-1}^2, \varepsilon_{t-2}^2, \ldots) \approx N(0, h_t)$$

(5b)

$$h_t = \gamma_0 + \gamma_1 \varepsilon_{t-1}^2 + \gamma_2 h_{t-1}$$

(6b)

Where h_t is the variance of the error term ε_t at time t. ω_0 and γ_0 are constant and ω_1 and γ_1 are coefficients that relate to the past values of squared residuals, ε_{t-1}^2 relates to current volatility, and ω_2 and γ_2 are coefficients that relate current volatility to the volatility of the previous period.

4.3 Granger Causality Test

My analysis covers not only the contemporaneous but also the causal relationship. I will employ the Granger (1969) Causality test to examine the causal relationship between *Trading Volume* and *Return*. In detail, I will examine if the *Change in Trading Volume* causes *Return* to change even when controlled for past changes in *Return*, and vice versa. The unit root test will show whether I can test for Granger causality without making error correction models. If so, I will analyze causality between the two variables in both directions following bivariate Vector Autoregressive (VAR) models:

$$Return_t = \alpha + \sum_{i=1}^{n} \alpha_i Return_{t-i} + \sum_{i=1}^{n} \beta_i Trading\ Volume_{t-i} + \varepsilon_t$$

(7a)

$$Trading\ Volume_t = \alpha + \sum_{i=1}^{n} \alpha_i Trading\ Volume_{t-i} + \sum_{i=1}^{n} \beta_i Return_{t-i} + \varepsilon_t$$

(8a)

Where the null hypothesis is that *Trading* Volume does not Granger-cause *Returns*, and vice versa. And the alternative hypothesis is that *Trading Volume* Granger-causes *Returns*, and vice versa. And for the *Change in Trading Volume*:

$$Return_t = \alpha + \sum_{i=1}^{n} \alpha_i Return_{t-i} + \sum_{i=1}^{n} \beta_i \Delta Trading\ Volume_{t-i} + \varepsilon_t$$

(7b)

$$\Delta Trading\ Volume_t = \alpha + \sum_{i=1}^{n} \alpha_i \Delta Trading\ Volume_{t-i} + \sum_{i=1}^{n} \beta_i Return_{t-i} + \varepsilon_t$$

(8b)

Where the null hypothesis is that the *Change in Trading Volume* does not Granger-cause *Returns*, and vice versa. And the alternative hypothesis is that the *Change in Trading Volume* Granger-causes *Returns*, and vice versa.

CHAPTER 5 Results & Discussion

5.1 Unit Root Tests

The Bivariate Vector Autoregressions I will employ for causality test assumes the variables are stationary, so I will test for stationarity of Volume, Change in Volume and Returns by means of a unit root test. To test for a unit root (or the difference stationary process), I will employ both the Augmented Dickey-Fuller (ADF) test (1979) and the Phillips-Perron (PP) test (1988). The difference between these tests lies in the adjustment for serial correlation. The ADF test adjusts for serial correlation by including the lagged differences of the dependent variable. The PP test uses non-parametric methods to adjust for serial correlation and heteroskedasticity. Table 3 shows the results of the ADF and PP tests for Unit Root. The results show that all P-values are equal to 0.000 and therefore that the null hypotheses that Trading Volume, Change in Trading Volume and Returns are non-stationary (i.e. have a Unit Root) are rejected for all series. This confirms that all series tested are stationary and therefore are useful for further statistical analysis. The main implication of these findings is that testing for causality between Trading Volume and Returns should be based on an unrestricted VAR approach.

Table 3. Unit Root Tests for Return, Volume and Change in Volume

Variable	*P*	*Z*	*L**	P_m
Return_{ADF}	1585.92*	-38.11*	-93.62*	164.36*
Volume_{ADF}	1285.98*	-33.20*	-75.92*	132.40*
$\Delta\text{Volume}_{ADF}$	1585.92*	-38.11*	-93.62*	164.37*
Return_{PP}	1585.92*	-38.11*	-93.62*	164.36*
Volume_{PP}	1585.92*	-38.11*	-93.62*	164.37*
ΔVolume_{PP}	1585.92*	-38.11*	-93.62*	164.37*

Notes: ADF = Augmented Dickey Fuller. PP = Phillips Perron.
** Significant at the 1 percent level.*
*** Significant at the 5 percent level.*
**** Significant at the 10 percent level.*

5.2 Contemporaneous Relationship

Before testing for a causal relationship by means of a Granger Causality test, this study examines the contemporaneous relationship between Trading Volume and Returns, and between the Change in Trading Volume and Returns. Prior to running the contemporaneous relationship test, a Woolridge test for autocorrelation in panel data is employed for (the Change in) Volume and Returns, where in all cases the null hypothesis of no first-order autocorrelation cannot be rejected. This means all series exhibit first-order autocorrelation. In addition, I tested for multicollinearity by means of Variance Inflation Factor (VIF). The VIF is tested 1 for all series, hence they do not exhibit multicollinearity. Lastly, after inspecting the residuals, the error distributions of all series do not seem to exhibit a constant variance, which could be an indicator for Heteroskedasticity.

Given the structure of my sample, I will employ a panel regression using Feasible Generalized Least Squares (GLS) to account for both cross-sectional and time-series dimensions. This approach allows estimation in the presence of autocorrelation within panels and cross-sectional correlation and heteroskedasticity across panels. However, the total sum of squares cannot be broken down in the same way as with Ordinary Least Squares (OLS) when estimating the model's parameters, which reduces the usefulness of the R-squared statistic as a diagnostic tool for GLS regressions, which is the main reason why it is not displayed. The results reported in Table 4 indicate that the coefficient of regressing Returns on Trading Volume is $-4.36*10^{-11}$ and is significant at the 1 percent level, which indicates a negative contemporaneous relationship between Returns and Trading Volume. While statistically significant, the impact of such a small coefficient is minimal. In practical terms, changes in trading volume would need to be extremely large to have a noticeable effect on log-returns.

Table 4. Panel Regression Results for Daily Trading Volume and Returns

Panel A:	$Return_{it} = \alpha_1 +$	$\beta_1\ Trading\ Volume_{it}$	$+ \upsilon_{it}$
Variable	Coefficient	*Z*-Statistic	95% Conf. Interval
α_1	.0006 (.0001)	7.02*	[.0004, .0008]
β_1	$-4.36*10^{-11}$ ($1.29*10^{-11}$)	-3.38*	[$-6.89*10^{-11}$, $-1.83*10^{-11}$]

Notes: The values in parentheses are the standard errors of the measurement.
** Significant at the 1 percent level.*
*** Significant at the 5 percent level.*
**** Significant at the 10 percent level.*

Table 5 shows that the coefficient of regressing Returns on the Change in Trading Volume is -.0017 and significant at the 1 percent level, which also indicates that there is a negative contemporaneous relationship between Returns and the Change in Trading Volume. Same as for raw volume, while statistically significant, the impact of such a small coefficient is minimal.

Table 5. Panel Regression Results for Daily Change in Trading Volume and Returns

Panel B:	$Return_{it} = \alpha_2 +$	$\beta_2\, \Delta Trading\ Volume_{it}$	$+ \upsilon_{it}$
Variable	Coefficient	*Z*-Statistic	95% Conf. Interval
α_2	.0005 (.0001)	6.17*	[.0003, .0006]
β_2	-.0017 (.0002)	-9.69*	[-.0020, -.0013]

Notes: The values in parentheses are the standard errors of the measurement.
** Significant at the 1 percent level.*
*** Significant at the 5 percent level.*
**** Significant at the 10 percent level.*

Since the error distributions of all series do not exhibit a constant variance, I will use a GARCH model to further investigate the relationship between (the Change in) Trading Volume and Returns, following Lee and Rui (2002). The GARCH model encompasses an autocorrelation correction and incorporates heteroskedasticity in a sensible way and can be extended to include other effects on conditional variances. Thus, the model offers considerable flexibility in robust modelling of Returns. To test whether the negative contemporaneous relationship between (the Change in) Trading Volume and Returns preserves after taking heteroskedasticity into account, GARCH (1,1) models are estimated for all stocks in the sample. Table 6 shows the GARCH robust test of contemporaneous relationship between Trading Volume and Returns. As can be seen from the table, the coefficients of ASRNL, GLPG, TKWY, UNA and WKL do not seem to be significant. For all other stocks, they are significant. Also, the $Wald\ \chi^2$ statistic seems to be significant for a lot of stocks, which implies that the GARCH model is an attractive representation of daily stock behavior for those specific stocks, successfully capturing the temporal dependence of return volatility. For most of these stocks, the negative contemporaneous relationship between Trading Volume and Returns preserves after taking heteroskedasticity into account, except for AKZA and KPN, since their coefficients are positive, and not negative.

Table 6. GARCH Robust Test of Contemporaneous Relationship between Trading Volume and Returns among AEX Firms

Panel A:	$Return_t = \alpha_1 +$	$\beta_1\ Return_{t-1} +$	$b_1\ Trading\ Volume$	$+\ \varepsilon_t$
	$h_t = \omega_0 + \omega_1 \varepsilon_{t-1}^2$	$+\ \omega_2 h_{t-1}$		
Ticker	α_1	β_1	b_1	$Wald\ \chi^2$
ABN	.0024*	.0800*	$-7.37*10^{-11}$*	18.25*
AD	.0017*	-.0073	$-2.69*10^{-10}$**	0.11
ADYEN	.0052*	.0298	$-2.94*10^{-8}$*	52.60*
AGN	.0045*	.0687*	$-4.87*10^{-10}$*	10.23*
AKZA	.0001	.0042	$7.22*10^{-10}$***	3.37
ASM	.0022*	-.0090	$-3.67*10^{-9}$*	19.30*
ASML	.0019*	-.0002	$-6.01*10^{-10}$***	3.61
ASRNL	.0007***	.0108	$-4.71*10^{-11}$	0.30
GLPG	.0004	.0491*	$-6.58*10^{-11}$	10.27*
HEIA	.0027*	-.0308	$-3.48*10^{-9}$*	71.58*
IMCD	.0018*	.0287	$-6.06*10^{-9}$*	9.24*
INGA	.0015**	.0906*	$-5.07*10^{-11}$**	59.68*
KPN	-.0015*	-.0334	$1.27*10^{-10}$*	1.85
MT	.0018***	.0349	$-3.72*10^{-10}$**	2.69
NN	.0039*	.0033	$-3.46*10^{-9}$*	46.13*
PHIA	.0052*	-.0116	$-1.53*10^{-9}$*	0.25
PRX	.0014	.0096	$-3.61*10^{-10}$**	0.10
RAND	.0038*	.0167	$-5.97*10^{-9}$*	111.99*
REN	.0023*	-.0347***	$-6.64*10^{-10}$*	3.05***
TKWY	.0001	.0246	$-4.12*10^{-10}$	3.16
UNA	-.0001	-.1174*	$8.92*10^{-11}$	8.31*
WKL	.0014*	.0271	$-4.50*10^{-10}$	3.06

*Notes: * Significant at the 1 percent level.*
*** Significant at the 5 percent level.*
**** Significant at the 10 percent level.*

Table 7 presents the GARCH robust test of contemporaneous relationship between the Change in Trading Volume and Returns. Like before, as can be seen from the table, the coefficients of ADYEN, AKZA, ASM, ASRNL, GLPG, KPN, TKWY and UNA do not seem to be significant. For all other stocks, they are significant. Also, the $Wald\ \chi^2$ statistic seems to be significant for a lot of stocks, which implies that the GARCH model is an attractive representation of daily stock behavior for those specific stocks, successfully capturing the temporal dependence of return volatility. For most of these stocks, the negative contemporaneous relationship between Trading Volume and Returns preserves after taking heteroskedasticity into account, except for IMCD, since their coefficients is positive, and not negative.

Table 7. GARCH Robust Test of Contemporaneous Relationship between the Change in Trading Volume and Returns among AEX Firms

Panel B:	$Return_t = \alpha_2 +$	$\beta_2\ Return_{t-1} +$	$b_2\ \Delta\ Trading\ Volume$	$+ \varepsilon_t$
	$h_t = \gamma_0 + \gamma_1 \varepsilon_{t-1}^2$	$+ \gamma_2 h_{t-1}$		
Ticker	α_2	β_2	b_2	$Wald\ \chi^2$
ABN	.0005	.0836*	-.0027*	34.51*
AD	.0008*	-.0043	-.0012*	6.61**
ADYEN	.0029*	.0231	.0022	2.93
AGN	.0001	.0632*	-.0054*	91.26*
AKZA	.0006***	.0027	-.0007	1.32
ASM	.0013*	-.0083	.0005	0.92
ASML	.0012*	.0015	-.0028*	13.07*
ASRNL	.0007***	.0109	$3.42*10^6$	0.33
GLPG	.0004	.0480*	-.0006	12.33*
HEIA	.0004	-.0261	-.0024*	25.69*
IMCD	.0013*	.0320	.0011**	6.78**
INGA	.0007***	.0866*	-.0029*	78.52*
KPN	.0003	-.0297	.0003	2.17
MT	-.0002	.0342***	-.0040*	18.77*
NN	-.0001	.0351***	-.0037*	95.21*
PHIA	.0002	.0024	-.0043*	54.12*
PRX	-.0001	.0119	-.0036**	6.40**
RAND	.0005	.0278**	-.0028*	18.95*
REN	.0010*	-.0279	-.0028*	31.20*
TKWY	-.0002	.0255	.0007	2.28
UNA	.0001	-.1173*	.0005	8.18**
WKL	.0010*	.0274	-.0014*	8.70**

*Notes: * Significant at the 1 percent level.*
*** Significant at the 5 percent level.*
**** Significant at the 10 percent level.*

5.3 Causal Relationship

This sections tests whether Trading Volume or the Change in Trading Volume precedes Returns, and vice versa, based on the premise that the future cannot cause the present or the past. If an event x occurs before an event y, then we can say that x causes y. The unit root test has shown that it is possible to test for Granger causality between Trading Volume and Returns without making error correction models, so this analysis will examine the causal relationship between the two variables in both directions using bivariate Vector Autoregressive VAR models. The null hypothesis in a Granger causality test states that Return (Trading Volume) does not cause Trading Volume (Return) for equations 7a and 8a, and that Return (Change in Trading Volume) does not cause the Change in Trading Volume (Return) for equations 7b and 8b. Given the importance of the predictability of Stock Returns, I am primarily interested in the causal relationship from Trading Volume to Returns. For the estimation of Granger causality, I use the model with the lowest AIC for every stock. The choice of the number of lags is therefore not constant for every stock. Table 8 presents the results of the causal relationship test between Trading Volume and Returns for all stocks in the sample, along with the F-statistics and corresponding significance levels. As can be seen from the table, at the 5 percent significance level, Trading Volume does not Granger-cause stock market Returns on each of the firms in the sample. This implies that, although there is a contemporaneous relationship between Trading Volume and Returns, Trading Volume does not add significant predictive power for future returns in the presence of current and past returns. This finding is consistent with that of Clark (1973), who predicts no causal relation from Trading Volume to Returns. However, inconsistent with the findings of Hiemstra and Jones (1994) who, using Dow Jones stock returns, find some evidence supporting linear Granger causality from trading volume to stock returns for some securities and time periods, suggesting that past trading volume can predict future returns after accounting for past stock returns. At the 10 percent significance level, Trading Volume seems to Granger-cause Returns for Prosus N.V. This implies that Trading Volume does add predictive power, although at the 10 percent significance level, for future returns of Prosus N.V.

Table 8. Test of Causal Relationship among Trading Volume and Returns per Firm based on bivariate VAR

Panel A				
Ticker	Hypothesis	F-Statistic	Probability	Granger-causal Relationship
ABN	$V \overset{GC}{\rightarrow} R$	F(1, 751) = 0.931	0.760	No
	$R \overset{GC}{\rightarrow} V$	F(2, 750) = 0.164	0.848	No
AD	$V \overset{GC}{\rightarrow} R$	F(2, 488) = 0.865	0.421	No
	$R \overset{GC}{\rightarrow} V$	F(4, 486) = 0.907	0.459	No
ADYEN	$V \overset{GC}{\rightarrow} R$	F(2, 538) = 0.263	0.769	No
	$R \overset{GC}{\rightarrow} V$	F(2, 538) = 2.480	0.084	Yes*
AGN	$V \overset{GC}{\rightarrow} R$	F(1, 510) = 1.370	0.242	No
	$R \overset{GC}{\rightarrow} V$	F(4, 507) = 5.965	0.000	Yes
AKZA	$V \overset{GC}{\rightarrow} R$	F(2, 1600) = 0.070	0.933	No
	$R \overset{GC}{\rightarrow} V$	F(2, 1600) = 2.408	0.090	Yes*
ASM	$V \overset{GC}{\rightarrow} R$	F(2, 1052) = 1.206	0.299	No
	$R \overset{GC}{\rightarrow} V$	F(2, 1052) = 2.4724	0.084	Yes*
ASML	$V \overset{GC}{\rightarrow} R$	F(2, 1603) = 0.577	0.561	No
	$R \overset{GC}{\rightarrow} V$	F(2, 1603) = 0.586	0.556	No
ASRNL	$V \overset{GC}{\rightarrow} R$	F(2, 1100) = 0.381	0.683	No
	$R \overset{GC}{\rightarrow} V$	F(2, 1100) = 1.147	0.318	No
GLPG	$V \overset{GC}{\rightarrow} R$	F(2, 935) = 0.051	0.950	No
	$R \overset{GC}{\rightarrow} V$	F(2, 935) = 1.048	0.351	No
HEIA	$V \overset{GC}{\rightarrow} R$	F(4, 497) = 0.563	0.689	No
	$R \overset{GC}{\rightarrow} V$	F(4, 497) = 0.534	0.711	No
IMCD	$V \overset{GC}{\rightarrow} R$	F(2, 1329) = 1.422	0.241	No
	$R \overset{GC}{\rightarrow} V$	F(2, 1329) = 2.898	0.055	Yes*

Notes: V = Trading Volume. R = Returns. The numbers in parentheses in the F-statistic are the degrees of freedom for the numerator and denominator, respectively. Yes denotes the causal relationship being significant at the 5 percent level. Yes denotes the causal relationship being significant at the 10 percent level.*

Table 8. Continued

Panel A				
Ticker	Hypothesis	F-Statistic	Probability	Granger-causal Relationship
INGA	$V \overset{GC}{\rightarrow} R$	F(3, 1041) = 1.608	0.179	No
	$R \overset{GC}{\rightarrow} V$	F(3, 1041) = 1.904	0.127	No
KPN	$V \overset{GC}{\rightarrow} R$	F(2, 1001) = 1.491	0.268	No
	$R \overset{GC}{\rightarrow} V$	F(2, 1001) = 4.145	0.016	Yes
MT	$V \overset{GC}{\rightarrow} R$	F(3, 512) = 1.253	0.289	No
	$R \overset{GC}{\rightarrow} V$	F(2, 1619) = 3.570	0.028	Yes
NN	$V \overset{GC}{\rightarrow} R$	F(4, 414) = 0.682	0.604	No
	$R \overset{GC}{\rightarrow} V$	F(4, 414) = 7.514	0.000	Yes
PHIA	$V \overset{GC}{\rightarrow} R$	F(2, 1049) = 1.657	0.191	No
	$R \overset{GC}{\rightarrow} V$	F(3, 1048) = 1.343	0.258	No
PRX	$V \overset{GC}{\rightarrow} R$	F(1, 423) = 3.416	0.065	Yes*
	$R \overset{GC}{\rightarrow} V$	F(3, 421) = 0.796	0.496	No
RAND	$V \overset{GC}{\rightarrow} R$	F(3, 1043) = 1.412	0.237	No
	$R \overset{GC}{\rightarrow} V$	F(3, 1043) = 1.381	0.246	No
REN	$V \overset{GC}{\rightarrow} R$	F(2, 1006) = 2.045	0.129	No
	$R \overset{GC}{\rightarrow} V$	F(1, 2125) = 1.381	0.240	No
TWKY	$V \overset{GC}{\rightarrow} R$	F(3, 660) = 0.864	0.459	No
	$R \overset{GC}{\rightarrow} V$	F(3, 660) = 1.786	0.147	No
UNA	$V \overset{GC}{\rightarrow} R$	F(1, 610) = 0.257	0.612	No
	$R \overset{GC}{\rightarrow} V$	F(1, 610) = 1.433	0.231	No
WKL	$V \overset{GC}{\rightarrow} R$	F(2, 1032) = 0.664	0.515	No
	$R \overset{GC}{\rightarrow} V$	F(2, 1032) = 0.101	0.904	No

Notes: V = Trading Volume. R = Returns. The numbers in parentheses in the F-statistic are the degrees of freedom for the numerator and denominator, respectively. Yes denotes the causal relationship being significant at the 5 percent level. Yes denotes the causal relationship being significant at the 10 percent level.*

Table 9 presents the results of the causal relationship test between the Change in Trading Volume and Returns for all stocks in the sample, along with the *F*-statistics and corresponding significance levels. At the 5 percent level, the Change in Trading Volume does not Granger-cause Returns, implying that although there is a contemporaneous relationship, the Change in Trading Volume does not add predictive power for future Returns. At the 10 percent level however, there seems to be Granger causality from the Change in Trading Volume to Returns, indicating that the Change in Trading Volume does add predictive power for future Returns in the presence of current and past Returns of Wolters Kluwer.

Table 9. Test of Causal Relationship among Change in Trading Volume and Returns per Firm based on bivariate VAR

Panel B				
Ticker	Hypothesis	F-Statistic	Probability	Granger-causal Relationship
ABN	$\Delta V \overset{GC}{\rightarrow} R$	$F(2, 763) = 0.233$	0.792	No
	$R \overset{GC}{\rightarrow} \Delta V$	$F(2, 763) = 0.381$	0.683	No
AD	$\Delta V \overset{GC}{\rightarrow} R$	$F(4, 486) = 0.377$	0.825	No
	$R \overset{GC}{\rightarrow} \Delta V$	$F(4, 486) = 0.119$	0.976	No
ADYEN	$\Delta V \overset{GC}{\rightarrow} R$	$F(2, 819) = 0.631$	0.532	No
	$R \overset{GC}{\rightarrow} \Delta V$	$F(2, 819) = 0.414$	0.661	No
AGN	$\Delta V \overset{GC}{\rightarrow} R$	$F(2, 1616) = 1.115$	0.328	No
	$R \overset{GC}{\rightarrow} \Delta V$	$F(2, 1616) = 0.449$	0.638	No
AKZA	$\Delta V \overset{GC}{\rightarrow} R$	$F(2, 1600) = 0.763$	0.466	No
	$R \overset{GC}{\rightarrow} \Delta V$	$F(2, 1600) = 1.737$	0.176	No
ASM	$\Delta V \overset{GC}{\rightarrow} R$	$F(2, 1615) = 2.281$	0.102	No
	$R \overset{GC}{\rightarrow} \Delta V$	$F(2, 1615) = 1.369$	0.254	No
ASML	$\Delta V \overset{GC}{\rightarrow} R$	$F(1, 2181) = 0.859$	0.354	No
	$R \overset{GC}{\rightarrow} \Delta V$	$F(1, 2181) = 0.369$	0.543	No
ASRNL	$\Delta V \overset{GC}{\rightarrow} R$	$F(3, 347) = 1.314$	0.268	No
	$R \overset{GC}{\rightarrow} \Delta V$	$F(3, 347) = 0.655$	0.580	No
GLPG	$\Delta V \overset{GC}{\rightarrow} R$	$F(2, 935) = 0.412$	0.662	No
	$R \overset{GC}{\rightarrow} \Delta V$	$F(2, 935) = 2.556$	0.078	Yes*
HEIA	$\Delta V \overset{GC}{\rightarrow} R$	$F(4, 497) = 0.959$	0.429	No
	$R \overset{GC}{\rightarrow} \Delta V$	$F(4, 497) = 0.357$	0.839	No
IMCD	$\Delta V \overset{GC}{\rightarrow} R$	$F(2, 1329) = 1.484$	0.227	No
	$R \overset{GC}{\rightarrow} \Delta V$	$F(2, 1329) = 0.959$	0.383	No

Notes: ΔV = Change in Trading Volume. R = Returns. The numbers in parentheses in the F-statistic are the degrees of freedom for the numerator and denominator, respectively. Yes denotes the causal relationship being significant at the 5 percent level. Yes denotes the causal relationship being significant at the 10 percent level.*

Table 9. Continued

Panel B				
Ticker	Hypothesis	F-Statistic	Probability	Granger-causal Relationship
INGA	$\Delta V \overset{GC}{\rightarrow} R$	$F(2, 1599) = 0.364$	0.695	No
	$R \overset{GC}{\rightarrow} \Delta V$	$F(2, 1599) = 1.419$	0.242	No
KPN	$\Delta V \overset{GC}{\rightarrow} R$	$F(2, 1001) = 0.752$	0.472	No
	$R \overset{GC}{\rightarrow} \Delta V$	$F(2, 1001) = 1.710$	0.181	No
MT	$\Delta V \overset{GC}{\rightarrow} R$	$F(3, 1056) = 0.147$	0.932	No
	$R \overset{GC}{\rightarrow} \Delta V$	$F(3, 1056) = 0.921$	0.430	No
NN	$\Delta V \overset{GC}{\rightarrow} R$	$F(4, 414) = 0.806$	0.521	No
	$R \overset{GC}{\rightarrow} \Delta V$	$F(4, 414) = 1.979$	0.095	Yes*
PHIA	$\Delta V \overset{GC}{\rightarrow} R$	$F(2, 1605) = 0.215$	0.806	No
	$R \overset{GC}{\rightarrow} \Delta V$	$F(2, 1605) = 0.479$	0.619	No
PRX	$\Delta V \overset{GC}{\rightarrow} R$	$F(3, 421) = 1.223$	0.300	No
	$R \overset{GC}{\rightarrow} \Delta V$	$F(3, 412) = 0.669$	0.571	No
RAND	$\Delta V \overset{GC}{\rightarrow} R$	$F(2, 1606) = 0.715$	0.489	No
	$R \overset{GC}{\rightarrow} \Delta V$	$F(2, 1606) = 0.380$	0.684	No
REN	$\Delta V \overset{GC}{\rightarrow} R$	$F(1, 2125) = 0.915$	0.339	No
	$R \overset{GC}{\rightarrow} \Delta V$	$F(1, 2125) = 0.105$	0.745	No
TWKY	$\Delta V \overset{GC}{\rightarrow} R$	$F(3, 317) = 0.344$	0.794	No
	$R \overset{GC}{\rightarrow} \Delta V$	$F(3, 317) = 1.115$	0.341	No
UNA	$\Delta V \overset{GC}{\rightarrow} R$	$F(2, 449) = 1.605$	0.201	No
	$R \overset{GC}{\rightarrow} \Delta V$	$F(2, 449) = 2.720$	0.066	Yes*
WKL	$\Delta V \overset{GC}{\rightarrow} R$	$F(2, 1032) = 2.528$	0.080	Yes*
	$R \overset{GC}{\rightarrow} \Delta V$	$F(2, 1032) = 0.030$	0.971	No

Notes: ΔV = Change in Trading Volume. R = Returns. The numbers in parentheses in the F-statistic are the degrees of freedom for the numerator and denominator, respectively. Yes denotes the causal relationship being significant at the 5 percent level. Yes denotes the causal relationship being significant at the 10 percent level.*

CHAPTER 6 Conclusion

The effect of trading volume on stock market returns has been a popular research topic for quite some years, but until now this topic has not really been examined for the Dutch market. In this paper, I investigated the contemporaneous and the causal relationship between Trading Volume and Returns, and the Change in Trading Volume and Returns using daily data from the AEX over the period of January 2013 until December 2023. The main motivation for this analysis has been whether Trading Volume has any explanatory or forecasting power over Returns and therefore whether information on Trading Volume is useful in improving forecasts of Returns.

To answer the questions at hand, I have analyzed the contemporaneous and (Granger) causal relationship between trading volume and returns. I find that, in contrast to some theoretical models, trading volume does not Granger-cause stock market returns in the Dutch market, except for Prosus N.V., where there does seem to be a causal relationship from trading volume to returns. I also found that the change in trading volume does not Granger-cause stock market returns in the Dutch market, except for Wolters Kluwer, where there does seem to be a causal relationship from the change in trading volume to returns.

In addition to the analysis of the causal relationship, I have also visited the contemporaneous relationship, i.e. happening at the same period of time, and found that there exists a negative contemporaneous relationship between both trading volume and stock market returns and the change in trading volume and returns. Also, after taking into account autocorrelation and heteroskedasticity by means of a GARCH model, this negative relationship seems to prevail.

This paper does have some limitations. One is that this study considers daily trading volume and stock price data. Perhaps weekly or monthly will be a better timeframe, considering factors like short term noise, such as random trading or market rumors. Also considering calendar effects like day-of-the-week effects. Another limitation could be that this paper solely focusses on the Dutch stock market. It might also be interesting to include spillover effects from other stock markets like the United States.

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