Overconfidence bias in stock trading

Empirical results from the Nasdaq Stockholm market

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Abstract

Excessive trading patterns refers to a tendency of trading more than what is usually seen as rational, due to accompanied transaction costs, reducing the profits. It is one of the most well-documented anomalies in classical finance theory. Researchers within behavioral finance suggest that overconfidence bias and self-attribution are the primary drivers of this outlier. Moreover, research proposes to measure overconfidence on the basis of a correlation between trading frequency and lagged market returns. Utilizing this information, and controlling for other variables eliciting increased trading, this paper empirically analyzes the correlation between market return and subsequent market turnover - where a positive result is interpreted as proof of overconfidence. This paper is limited to the Nasdaq Stockholm market, with a sample period from 1st of January 2010 until 31st of December 2019. I use the OMX Stockholm 30 index, which consists of the thirty most traded stocks from the past year, as a proxy for the entire Swedish market. The raw data is extracted from Thomson Datastream, which is an internationally recognised financial historical database. Moreover, I follow the methodology of Statman et al. (2006) by employing vector autoregression, optimal lag length, and impulse response analysis. My findings are two-sided with conflicting evidence. The initial result is a negative correlation suggesting that stock traders in Nasdaq Stockholm are not overconfident. However, there is a non-statistically significant positive correlation in lag two, three, and four, indicating that a weak form of overconfidence bias may exist in the market.

Keywords: overconfidence bias, self-attribution, behavioral finance, VAR, Impulse response.

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1. Introduction

A crucial part of the process of investing is to comprehend the underlying factors that may affect decision making. Recent theory within the finance discipline has recognized behavioral finance as a legitimate subfield, and subsequently how it alters the theoretical approach from the traditional framework. The deviation originates from incorporating human factors, such as cognitive biases, with the pre-existing paradigm consisting of rationality and logical decision-making (Ritter, 2003). Therefore, making behavioral finance a particularly relevant phenomenon to further analyze. One of the most well-known cognitive biases in behavioral finance, is the overconfidence bias - which is derived from an overestimation of an individual's own abilities. If not accounted for, the bias can ultimately elicit overtrading, excessive risk-taking, and failure to diversify (Ritter, 2003). This becomes problematic since it can adversely affect investor performance. In terms of excessive trading, increased commissions and fees accompanied by the execution of trades will transpire, ultimately reducing the profits.

There is a comprehensive strand of literature on the topic of behavioral finance. In particular, overconfidence bias and its relationship with the stock exchange. My paper is based on the work of Statman et al. (2006), who studied the existence of overconfidence bias in the New York Stock exchange. They approached the problem by applying a vector autoregressive model to analyze the relationship between market turnover and lagged market return. Urooj et al. (2019) replicated this work and applied it to Pakistani investors. Ismaliia (2019) conducted a similar study on the Tunisian stock exchange. Glaser and Weber (2007) tested overconfidence bias, using a survey questionnaire approach instead, and finally Zaiane (2009) tested the existence of the bias on emergent markets. The common denominator among these papers, is reported evidence of overconfidence bias in the stock market.

This finding, consequently, form the basis of my hypothesis: that overconfidence bias likewise will be found in the Nasdaq Stockholm market. Nasdaq Stockholm is a well-established market, the largest in the Nordics, which indicates that the results will be similar to other markets with resembling characteristics. For instance, NYSE. However, there may be cultural differences between the traders of the two markets caused by geographic divergence. This potential disparity between the markets is the primary factor propelling my interest to analyze whether the Nasdaq Stockholm market also exhibits overconfidence. In addition, the available literature on overconfidence bias in the Nasdaq Stockholm market is scarce, which could result in this paper contributing to the study of behavioral finance.

1.1 Problem discussion

Behavioral finance has developed into an integral component of the traditional framework - being accepted and acknowledged in current theoretical research. It is a subfield that complements the classical finance of rational agents, with psychological factors (Ritter, 2003). However, the study of the field is limited, with uncharted territories regarding the existence of psychological biases in stock markets, and consequently, to which extent it affects investor performance. As an example, the phenomenon has not been previously studied in the Nasdaq Stockholm market, during the time period of 1st of January 2010 until 31st of December 2019. This paper specifically aims to extend the current research of the bias and reconcile this informational gap.

Gervais and Odean (2001) found that overconfident people attribute their success in the market to their own ability, even though that success is shared across the market. In addition, they report that the self-inflated view of an individual's abilities, positively correlates with past success in the market. These important findings set the basis of Statman et al's. (2006) empirical study by means of testing the correlation between market turnover and lagged market return. Since overconfident traders increase their trading frequency dependent on previous results, the correlation with market return and subsequent market turnover can be, when controlling for other variables that elicit excessive trading, used as a measurement of overconfidence bias. Following Statman et al. (2006) I employ a VAR analysis testing the correlation between market return and subsequent market turnover, using market-wide volatility and dispersion as control variables. With this, I aim to acquire a greater understanding about the underlying factors shaping how the stock market operates.

1.2 Purpose

The purpose of this paper is to obtain an extended understanding, in addition to the classical framework, of the intrinsic cogwheels shaping how Nasdaq Stockholm operates. Stated differently, to overcome the disparity between traditional finance theory and empirical findings. More specifically, to identify the potential presence and significance of overconfidence bias in the Nasdaq Stockholm market. Provided the existence is true;

subsequently, understand the foundation of the bias, in order to mitigate the negative consequences it could conceivably entail, within the Swedish stock market.

1.3 Scope and limitations

This paper investigates the Nasdaq Stockholm market, though using OMX Stockholm 30 as a proxy for the entire market. The sample period selected is from 1st of January 2010 until 31th of December 2019. By choosing this approach, I restrict the dataset to the comprising thirty components in the index. If I had instead utilized a larger dataset, with all stocks listed on the stock exchange, I would have acquired a more accurate estimation. However, the underlying reason behind this decision was to facilitate the management of the dataset. In addition, the paper does not account for the presence of macroeconomic events during the sample period that induce market-wide volatility shocks. In particular, the Eurozone Crisis which may have caused the peak trading activity during 2011 in Figure 1. Moreover, another limitation of the paper is the uncertainty whether the results are caused by the disposition effect or overconfidence. This is further explained in chapter 2.4. Finally, the findings of this paper may be constricted to other geographical markets or indexes, with corresponding characteristics, conditions, and regulations.

1.4 Layout of the paper

This paper consists of five chapters. The first chapter deals with the introduction and background material which forms my research question. The literature review, addressed in chapter two, contains a definition of overconfidence bias, followed by an explanation to the roots of its existence. Furthermore, I conduct an analysis on the possible negative effects the bias may have on investor performance. The empirical analysis, attended to in chapter three, entails a vector autoregressive analysis (VAR) on the correlation between lagged market-return and market-turnover, using market-wide volatility and dispersion as control variables. In chapter four, I demonstrate the empirical findings. To conclude the paper, chapter five contains a discussion on potential strategies, aimed to mitigate the detrimental impacts of overconfidence bias - on investor performance.

2. **Literature review**

2.1 Overconfidence

The fundamental framework in traditional finance is based around the efficient market hypothesis (EMH), with the presumption of rational agents choosing an efficient portfolio (Sherif, 2016). The classical paradigm assumes that all information is available, and thus, incorporated in the realized stock price. However, in accordance with empirical evidence: theory and experiential learning, occasionally conflicts (Birău, 2012). When the traditional finance paradigm failed in explaining deviations in empirical research, a new subfield of finance unfolded, namely: behavioral finance (Sharma & Kumar, 2020). This discipline is a fusion of psychological- and economic theory. Conversely to the traditional approach, the possibility of irregularities among market participants is introduced, through the acknowledgement of subjective awareness among investors (Upadhyay & Shah, 2019). Consequently, influencing the reflection of prices, by deviating from pure logic and reason to including psychological factors in the framework (Singh, 2012).

This paper narrows the study of behavioral finance to focusing on the overconfidence bias. This is a cognitive phenomenon recognized by academic researchers in both the fields of economic and psychology (Merkle & Weber, 2011). Overconfidence refers to a mental state in which individuals overestimate their own intellectual ability, while concurrently neglecting the associated risks. The underlying cause being an underestimation of the significance to which external factors influence the outcome (Chuang & Lee, 2006). Merkle and Weber (2011) further explains overconfidence bias, by structuring it into three different subcategories: overestimation, overplacement, and overprecision.

According to Moore and Schatz (2017), overestimation highlights the propensity of individuals to either exaggerate the probability of desired outcomes, or to possess an exaggerated perception of their competence relative to their actual abilities. Both alternatives are derived from unfounded optimism. The first alternative is present in everyday life. For instance, it is commonly expressed in the lottery, in which individuals subjectively amplify their odds of winning. As a consequence, an excessive amount of financial resources is spent on lottery tickets (Rogers, 1998). In regard to the latter of the alternatives, a study by Feld et al. (2017) showed that the average student overestimated their examination performance. In addition, investors within the stock market actively believe they can beat the market (Stiglitz, 1989). As a result, individuals intensify the level of risk when investing capital (Ritter, 2003).

Overplacement, otherwise known as the better-than-average effect, is closely associated with overestimation. It is the universal misconception in competitive settings, that most people believe themselves to be above average. Several studies and surveys have empirical results confirming the bias including: Svenson (1981), where most drivers share the better-than-average mindset, in Cross's research (1977), 94% of college professors believed they were better instructors, in comparison to their colleagues, and Angell's study (2015), which demonstrates a majority of psychology students, ranking themselves higher than average.

The last subarea of overconfidence bias is overprecision, stating that individuals have an inflated confidence in their quality of judgment (Moore et al., 2015). Overprecision in the stock exchange can make investors overly confident in their valuation of a stock. As a result, by lowering the guard from risks they underestimate, they develop a dismissive attitude towards the individual opposite of their trade. Consequently, resulting in an excessive trading pattern (Barber & Odeon, 1999).

2.2 Overconfidence and market-wide turnover

There are several studies within economics and finance, which show the correlation between overconfidence and trading volume. Including but not exclusive to: Barber and Odeon (1999), Statman et al. (2006), and Zaiane and Abaoub (2009). The overall consensus is that overconfidence bias among investors, leads to a higher risk-taking, in the form of less diversification and increased trading patterns. The reasoning behind the conclusion is, that with a high confidence, an investor may assume his information is of higher quality than the individual on the opposite side of the trade. This feeling of superiority results in an amplification of the potential profits, and a disregard of the associated risks. Statman et al. (2006) examines this by testing the correlation between lagged market return and market turnover, which this paper carefully follows.

2.3 Overconfidence and market-wide return

Glaser and Weber (2009) analyzed the relationship between market return and overconfidence. They concluded, using panel regression models, that high lagged market returns resulted in a higher trading activity and less diversification. However, instead of attributing high market returns to these inefficiencies, they considered that self-attribution and psychological powers were at play. As previously defined, overconfidence reflects the inflation of an individual's subjective conception of themselves. This also applies to stock trading and is based on past performance. With past success in the stock exchange an individual will become more confident and consequently, amplify his chances of "beating" the market. Thus, leading to an excessive trading strategy. Conversely, previously low returns will reduce the confidence level and a less frequent trading pattern will occur (Trejos et al., 2019).

2.4 Alternative causes of high-frequency trading.

In addition to overconfidence, studies have shown that there are several other factors that stimulate a higher frequency of trading activity. Naik et al. (2018) wrote a paper on the relationship between market volatility and market volume. They concluded, which is supported by empirical findings, that market volatility is positively correlated with trading volume. This is intercorrelated with another cognitive anomaly, referred to as the disposition effect. The concept of the effect is that individuals tend to sell winners too quickly and hold on to losers for an extended period (Trejos et al., 2019). In relation to the cyclical component of the stock exchange, individuals will trade more frequently in a bull market by selling "winners", and trade less frequently in a bear market by holding on to their "losers". Consequently, a limitation of the paper is an uncertainty whether individuals trade more because they are overconfident, or because they will want to sell "winners", when testing the correlation between market return and subsequent turnover.

Furthermore, dispersion effect, otherwise known as cross-sectional volatility, is a phenomenon in which the returns of individual stocks within a portfolio, deviate from the average return of the portfolio (Menchero & Morozov, 2010). Similarly, the return of individual stocks within an index can deviate from the average return of the index. This is problematic since it can create a spurious correlation between market turnover and market return. Market turnover can be affected by high returns of individual stocks, while the market as a whole, is underperforming. According to Statman et al. (2006), return dispersion and market turnover exhibits a positive correlation, which confirms the previous statements. In order to address these issues, when conducting my vector autoregression, I employ both market volatility and dispersion as control variables.

3. Methodology

I use the OMX Stockholm 30 index as representative for the Swedish market. Because OMX Stockholm 30 contains the most traded stocks on Nasdaq Stockholm, it is appropriate to use as a benchmark for the overall performance of the market. In addition, OMXS30 is an index adjusted for the thirty most traded stocks on the Swedish market. Thus, individual stocks enter and exit the index during the sample period. The financial database does not automatically adjust to the dynamic nature of the index. Therefore, to avoid selection bias, I utilize Nasdaq semiannual reports on OMX30 from 2010-2019 to see which companies enter and exit the index (Nasdaq, 2023). I gather the raw data consisting of market value, shares traded, shares outstanding, and both daily and monthly stock price, using Thomson Datastream. This is done for each stock within OMX Stockholm 30 from 1st of January 2010 until 31st of December 2019.

To calculate trading activity there are typically two ways to proceed. Both market volume and market turnover are appropriate measurements for this task. However, I choose to follow Statman et al. (2006) by computing market turnover instead of market volume. The paper argues that market turnover is more accurate in its estimation, since it accounts for a growing trend that naturally occurs during an extended time series. Market volume, on the other hand, easily becomes inflated with share-splits and consequently results in a suboptimal metric.

I calculate market turnover through a value-weighted average based on market capitalization, instead of an equal-weighted process. The difference is that the value-weighted approach is based on market capitalization and the value of a constituent to its index, while the equal-weighted technique assigns equal weight to each constituent. Since stocks with lower market capitalization often trades more frequently, it is appropriate to assign different weights when conducting market turnover - in order to accurately represent the market.

To calculate the weights of each stock, I divide the respective market value with the total market capitalization. Furthermore, I need to calculate the individual turnover for each stock. I execute this by dividing shares traded by volume with total outstanding shares in the company. I subsequently multiply the weight with the individual turnover. Finally, I take the sum of all constituents to create the market turnover series. The formula is provided in Equation 1:

$$Mturn = \sum_{i=1}^{n} W_i t_i | \tag{1}$$

W_i = individual weight, (Market cap_i / Market cap_{tot}) t_i = individual turnover (Market cap_i / Market cap_{tot}), subscript (i) stands for individual, and (tot) for total. N is the total amount of stocks in the index (i.e., 30).

The time series is represented in Figure 1 in the appendix. As demonstrated in Figure 1, a slight downward trend during the period with a peak trading activity during late 2011 with ≈ 15% market turnover, is observable. More importantly, a trend seems to be present - indicating a non-stationary process. Before additional analysis can be conducted, I need to assure a stationary process. This is done using GretL software and the Augmented Dickey-Fuller test (ADF). ADF test is specified using the following regression:

$$\Delta y_t = \mu_t + \varphi\, y_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta y_{t-i} + \epsilon_t \tag{2}$$

Δy_t represents the first difference in Mturn. μ_t is a constant signifying the mean of Mturn. φ y_{t-1} represents the impact the previous value has on the current one - depicting the autoregressive structure of Mturn. p is the number of lags; in this paper I use AIC criterion which provides me with the optimal choice of 4 lags. ϵ_t is the error term in the model. The regression is a unit root test, which tests the null hypothesis of $\varphi = 0$ (unit root), indicating a non-stationary process, alternatively $\varphi < 0$, indicating stationarity - making it a one-sided test. The P value is .335, thus, failing to reject the null hypothesis of a unit root, indicating that the time series is non-stationary.

This is problematic as it can cause inaccurate and spurious estimations in subsequent analysis. VAR analysis requires stationary processes in each variable since it otherwise becomes difficult to identify reliable correlations between the variables, which makes it difficult to draw accurate conclusions from the analysis. However, before I detrend the series, I decide to take the natural logarithm of it, with the objective to reduce the skewness (see Table 1), to make the data follow a normal distribution. Given that a high level of skewness can elicit a misrepresentation in the shape of the distribution; consequently, affect the accuracy of the statistical analysis, it is ideal to keep it minimized. After this, I detrend the series by applying Hodrick-Prescott (HP) filter with default settings (lambda 14400). This is illustrated in Figure 2. Henceforth, I utilize the cyclical component of the graph, which is referred to as Mturn1.

However, Lo and Wang (2000) proposes that one should not detrend the series. An important finding in their paper, is the theoretical idea that the relationship between lagged market returns and market turnover anticipates a nonstationary process - with secular trends in turnover. As a result, by detrending the series, additional biases may be introduced when using trading activity as proxy for overconfidence bias (Lo & Wang, 2000). Although, all things considered, verifiable estimations in my VAR model are of greater importance, which is why I ultimately choose to detrend the series.

To calculate the other endogenous variable - market return, I once again calculate a value-weighted average. I take the monthly stock return difference between two months of each constituent and divide it by the earliest. Then I multiply the outcome with its respective weight towards the index. This procedure is executed on a monthly process of each stock, and subsequently extended, by totaling the sum to get the market-wide return series. Equation 3 represents the formula I used:

$$\text{Mret} = \sum_{i=1}^{N} \left(W_i\right)\left(\frac{\left(Mret_i - Mret_{i-1}\right)}{Mret_{i-1}}\right) \tag{3}$$

The result is illustrated in Figure 3. The figure shows the monthly market return during the sample period. On visual inspection, no secular trends are noticeable, indicating a stationary process. However, to ensure my hypothesis I, once again, utilize the Augmented Dickey-Fuller test (ADF). The reported P value is $< .001$ so the null hypothesis can be rejected, indicating a stationary series. Thus, no additional steps are needed.

When I calculate monthly volatility, I first remove default data on non-trading days. I later calculate monthly standard deviations for the entire series - using daily returns. For accuracy and consistency, I employ a value-weighted average, in which I multiply the monthly standard deviation of each stock with its respective weight to the index. To obtain monthly volatility instead of daily volatility I multiply with the square root of 21, since this is the average number of trading days in a month. Finally, I sum up the constituents to get an aggregated monthly volatility. The formula is provided in Equation 4:

$$\mathrm{MVol}_t = \sum_{i=1}^{N}((\sqrt{\frac{\Sigma(x-\bar{x})^2}{(n-1)}}_i * \mathrm{W}_i) * \sqrt{21}) \tag{4}$$

N is the number of constituents within the index. X represents daily returns; W is the individual weight to the index. The results are shown in Figure 4. As we can see the market volatility is generally consistent, but with two outliers of high volatility. One during late 2011 and the other during early 2016.

In addition to market volatility, dispersion is my second control variable. The reason behind using this as a control variable is to catch the idiocentric risks of individual stocks within the market. Dispersion in simple terms, is the risk of individual stocks, which complements the control for market-wide volatility. To calculate this variable, I use the methodology derived from Ankrim and Dings (2002), by squaring the subtraction of the individual monthly stock return with the average return across all constitutions, and then multiplying with its individual weight relative to the index. Equation 5 is the formula:

$$\mathrm{Disp} = \sqrt{\sum_{i=1}^{N} W_i} \left(r_i - \bar{r}\right)^2 \tag{5}$$

The graph of the time series is shown in Figure 5. As illustrated, the dispersion is consistent on a monthly basis and gives no signs of a non-stationary process. Thus, we have four calculated variables, which are summarized in Table 1. To analyze the relationships between multiple time series variables, I need to employ a multivariate time series. A vector autoregression model has the appropriate properties to supply this framework. The following formula lay the foundation for generalized VAR analysis:

$$Y_t = a + \sum_{i=1}^{P} A_i Y_{t-i} + \sum_{j=0}^{Q} B_j X_{t-j} + e_t \quad (6)$$

Moreover, I conduct the vector autoregression model by using market turnover and market return as endogenous variables, which is represented by Y_t as a nx1 vector. I employ dispersion and volatility as exogenous variables, which is represented by X. The small a, A_i, and B_j are the regressions coefficients, which analyzes the dynamic relationships between the variables. P and Q represent the number of lags for endogenous and exogenous variables respectively. Finally, the variable e_t represents a nx1 vector of error terms.

The objective is to estimate a correlation between lagged market return and turnover, when controlling for volatility and dispersion. A vector autoregression model is a multivariable analysis which makes it possible to estimate the relationship between multiple variables, where all variables are treated as endogenous. Thus, the model provides me with suitable properties to achieve the objective. To select the optimal lag, I utilize the inbuilt analysis in GretL software called "Var lag selection", using *AIC, BIC, HQC* criterion. The criterions are mathematically expressed as:

$$AIC = -2\ell(\hat{\theta}) + 2k \quad | \quad BIC = -2\ell(\hat{\theta}) + k \log n \quad | \quad HQC = -2\ell(\hat{\theta}) + 2k \log \log n$$ [1]

One lag came to be the ideal option (see Table 2). Therefore, the new VAR model become:

$$\begin{pmatrix} Mturn1_t \\ Mret_t \end{pmatrix} = \begin{pmatrix} a_{1,t} \\ a_{2,t} \end{pmatrix} + \sum_{i=1}^{1} A_i \begin{pmatrix} Mturn1_{t-i} \\ Mret_{t-i} \end{pmatrix} + \sum_{i=0}^{1} B_j \begin{pmatrix} Mvol_{t-j} \\ Disp_{t-j} \end{pmatrix} + \begin{pmatrix} e_{1,t} \\ e_{2,t} \end{pmatrix} \quad (7)$$

Y_t develops into a 2x1 matrix with the endogenous variables, Mturn and Mret. X_t transforms into a similar 2x1 matrix with the exogenous variables. The small coefficient (a) and the error vector have extended themselves to a 2x1 matrix. The results are illustrated in Table 3. In addition to the VAR analysis, I also employ impulse response analysis, to obtain a more comprehensive understanding on the relationship between the endogenous variables. The general idea of the statistical mechanism is to understand the dynamic relationship between

[1] There are several mathematical versions of the criterions. These expressions are the ones GretL software uses and thus, the ones I use.

multiple variables when there is a shock in one of them. The impulse response analysis in this paper demonstrates how market turnover and market return respond to a shock in the other variable, holding all other variables constant. I utilized the method using 1 lag-length. The four different outcomes are illustrated in Figure 6. In the top-right panel of Figure 6, a negative correlation in the first lag is being portrayed, which is inconsistent with the theory of overconfidence bias (Statman et al., 2006). However, in lag two and beyond the correlation smoothest out to zero. To see if the inconsistency extends over a longer period of time, I run an additional VAR- and impulse response analysis using four lags. The former is illustrated in Table 4 and the latter in Figure 7. The new VAR model then specifies as:

$$\left(\frac{Mturn1_t}{Mret_t}\right) = \left(\frac{a_{1,t}}{a_{2,t}}\right) + \sum_{i=1}^{4} A_i \left(\frac{Mturn1_{t-i}}{Mret_{t-i}}\right) + \sum_{i=0}^{1} B_j \left(\frac{Mvol_{t-j}}{Disp_{t-j}}\right) + \left(\frac{e_{1,t}}{e_{2,t}}\right) \tag{8}$$

Although, it is important to keep in mind that with every lag introduced a loss of degrees of freedom occurs simultaneously.

4. Empirical results

The results obtained from the VAR analysis are shown in Table 3 and 4. Table 3 displays four variables named Mturn1, Mret, Mvol, and Disp. Mturn1 stands for the logged and detrended market turnover. Mret denotes the market-wide return, while Mvol and Disp represents the market-wide volatility and dispersion. The table demonstrates both the correlation between Mturn1 as the dependent variable, with each of the four observed variables, and Mret as the dependent variable, with the equivalent variables. The tables consist of coefficients, std errors, and P values, for each of the variables demonstrated in the separate rows. Table 4 is built in an identical manner, with the only exception of including 4 lags of the endogenous variables instead of 1.

Table 3 illustrates a small autocorrelation in market turnover in lag 1, with a coefficient value of approximately .016, but with a statistically non-significant P value of .867. This means that past turnover may affect the current one, but we cannot rule out that it may be caused by chance. To eliminate any doubt, I utilize the Durbin Watson test statistic, which is a measurement in statistics that can identify if the time series is autocorrelated. The test provides a range between values zero and four, with the baseline of two indicating no autocorrelation. Given a value of 1.98, meaning little to no autocorrelation, I ultimately do not account for it. The autocorrelation later becomes negative in lag 2, 3, and 4, but only with a statistically significant P value in lag 2 of .0052.

Contrary to my hypothesis, I cannot detect a positive correlation between Mturn1 and lagged market return, using one lag-length. Observably in Table 3 we obtain a negative coefficient of −0.23, which does not support the existence of overconfidence bias (Statman et al., 2006). The reasons why I obtain this result is discussed in chapter 5 of this paper. When I utilize a larger number of lags and thus deviate from the optimal amount "Var lag selection" proposes, the results alter moderately. The initial negative coefficient in lag one turns positive in lag two, three and four. However, while a positive correlation is present, it fails to be statistically significant with respective P values of .1116, .8492, and .7052. In conclusion, indicating mixed evidence, but nonetheless supporting a potentially weak existence of overconfidence during the second, third and fourth month.

Furthermore, the results indicate a substantial correlation between market turnover and market volatility. In Table 3 the correlation has a coefficient of 3.04 and is highly significant, with a P value of < 1%. In lag 1 the coefficient declines but still remains high at 1.02, however, it is no longer statistically significant. Observably in Table 4 the relationship alters when including more lags, but still remains high, with statistically significant coefficients of 3.18 and 2.24, for contemporaneous correlation and lag 1 respectively. As for the correlation between market dispersion and turnover we notice a negative relationship with a coefficient of -0.88, which turns positive in lag 1 to 1.16972. The relationship remains the same when adjusting to 4 lags, although with slightly different values.

The key finding of this paper can be observed in the top-right panel of Figure 6. A negative response of market turnover to a shock in market return can be observed. This means that turnover decreases with a shock in market return, disputing the presence of overconfidence. However, as shown in Figure 7, when I include more lags and take the perspective of a more long-term relationship, the findings differentiate between respective months. Where a positive correlation is found in lag two, three, and four, and a reversed sign in lag one and five - providing a two-sided finding. The result provides both evidence supporting the presence of a weak form of overconfidence, while simultaneously casting uncertainty about its existence in the Nasdaq Stockholm market.

In addition, we also have three other panels which provide great insights. In these, we can observe a positive autoregression in market turnover and market return in the top-left and bottom-right panel respectively. In figure 7 this, however, quickly turns negative when introducing more lags. Finally, the bottom-left panel describes how market returns respond to a shock in market turnover, indicating that returns follow when a more frequent trading pattern occurs. When more lags are introduced, the response is positive in lag 1 and 2, then turns negative in lag 3 but reverses back to positive in lag 4.

5. Discussion

The first interesting finding of this paper is the negative correlation between market dispersion and market turnover. More specifically, a coefficient of −0.88 is found when using 1 lag length. According to previous academia, a positive relationship should be expected. A potential explanation for this is the autocorrelated nature of the variable. Statman et al. (2006) faced a similar situation with market volatility, which they interpreted as a consequence of autocorrelation in the variable, causing a multicollinearity problem between the lagged and subsequent output. Following Statman et al. (2006) I tested for autocorrelation in the exogenous variables and a statistically significant autocorrelation was found in both market volatility and dispersion, which can explain the finding. Statman et al. (2006) subsequently suggests that news or fresh information in the market induces this occurrence.

The second and most important finding of this paper, is weak evidence of overconfidence in Nasdaq Stockholm - during the selected sample period. When utilizing 1 lag, a negative correlation is found, indicating that traders on the Nasdaq Stockholm market do not have overconfidence. However, when more lags are introduced, the results differ, and the initial negative response turns positive in further lags. Nevertheless, the positive relationship does not achieve statistically significant results, having very high P values. Therefore, indicating that there may be overconfidence in the Nasdaq Stockholm market but we cannot draw any conclusions. This result differs from many other papers on the subject, specifically Statman et al. (2006), which found a much stronger presence of the bias. A potential reason behind this deviation is that I used a different sample period, in particular, a much shorter one. The relatively short time series may not have been adequate for this particular investigation. To improve the paper, a longer one may be required in order to capture a statistically significant effect on the relationship between market turnover and lagged market return. Another potential reason that could have restrained the results is that OMX Stockholm 30 is not suitable as a representative index for the Nasdaq Stockholm market. As a consequence of these shortcomings, the results are not as accurate and valid as they could have been.

However, the findings are that there is non-statistically weak evidence supporting overconfidence among traders in the Nasdaq Stockholm market. Consequently, individuals who are actively trading in Nasdaq Stockholm need to be aware of the potential existence of the cognitive bias and the adverse effects it has on investor performance. The main concern of overconfidence bias is its tendency to elicit excessive trading. Trading in itself is accompanied by transaction costs, in terms of fees and commissions. Excessive trading then becomes problematic since it increases the transaction costs and consequently, reduces the realized profits. In addition, it also contributes to the negligence of potential risks, and when combining these two side effects, it ultimately results in irrational decision-making.

Furthermore, the findings highlight an important implication for financial institutions. As previously discussed, overconfidence bias elicits excessive trading and reduces realized returns. For financial institutions this may entail issues within the risk-department that needs to be addressed and considered. Individual traders representing financial institutions may need to get extended training, or other interventions may need to be implemented to mitigate the negative consequences of overconfidence.

The findings of a positive correlation between market turnover and market return are also in line with the disposition effect. Excessive trading can thus be a consequence of either overconfidence bias, or that traders trade more frequently to sell realized gain in a bull market. Contrarily, individuals may trade less frequently in a bear market because of diminished overconfidence, or because they tend to hold on to losers. In an attempt to extend the paper, a distinction between disposition effect and overconfidence bias could be conducted through analyzing the return of an individual security model in contrast to the whole market. By following Statman et al. (2006) one could extend the VAR analysis to a trivariate one with Market return, individual security return, and security turnover as endogenous variables, controlling with individual security volatility. By repeating this analysis on all stocks in the sample, and then aggregating it into a single model, using either bootstrap procedure (Statman et al., 2006), or panel data approach (Cheng & Zhang, 2011), one could distinguish whether the correlation is founded on overconfidence bias in the market, or an aggregation of individual disposition effects. If individual security return could significantly explain individual security turnover - the disposition effect may be present. While, if market return could significantly explain individual stock turnover, overconfidence bias is present. However, it is important to mention that both biases could coexist.

6 Conclusion

The influential philanthropist Bill Gates once voiced “Success is a lousy teacher. It seduces smart people into thinking they can’t lose” (BrainyQuote, n.d.). In the development of modernized finance theory, empirical findings about the positive correlation between trading activity and trading return, validate the true significance of this statement. This prior research establishes the foundation for this paper. Following Statman et al. (2006) I executed a VAR analysis, testing the correlation between market turnover and lagged market return. To account for alternative variables that elicit an increased trading activity, I used the employment of market volatility and dispersion as control variables. I restricted my study to Nasdaq Stockholm, using OMX Stockholm 30 as a proxy for the entire market. The findings demonstrate mixed evidence, but a weak positive correlation is found in lag 2, 3, and 4 - potentially supporting the existence of overconfidence bias during 1st of January 2010 until 31st of December 2019. To substantiate this relationship, I further utilized Impulse response analysis in order to test how market turnover responds to a shock in market return. Once again, the outcome displays a weak positive correspondence. However, it is important to note that the findings are not statistically significant so further analysis needs to be conducted, to draw accurate conclusions.

Thus, the evidence is not as strong as in other similar studies, such as the one performed by Statman et al. (2006). A possible explanation could be that Swedish stock traders are not as overconfident as American ones. Alternatively, OMX Stockholm 30 cannot accurately operate as a proxy, when capturing the behavior of investors engaged in the collective market.

Appendix

Figure 1: Monthly market turnover based on OMX Stockholm 30 (2010-2020)

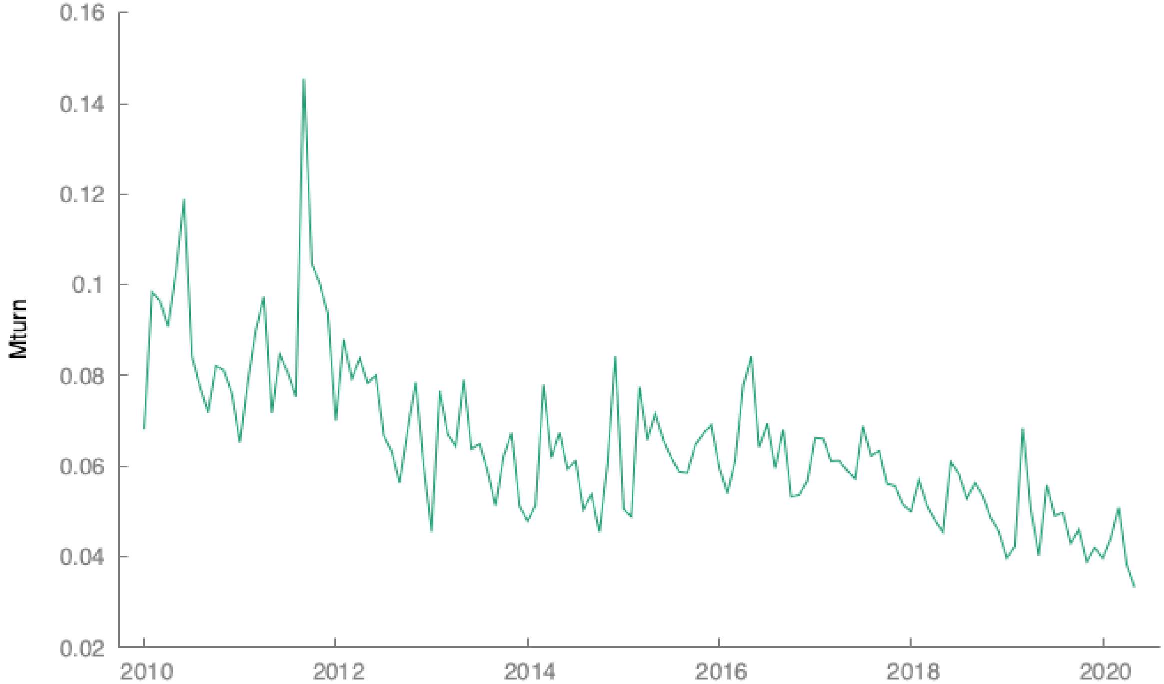


Figure 2: Logged and detrended Mturn | HP Filter: Lambda = 14440

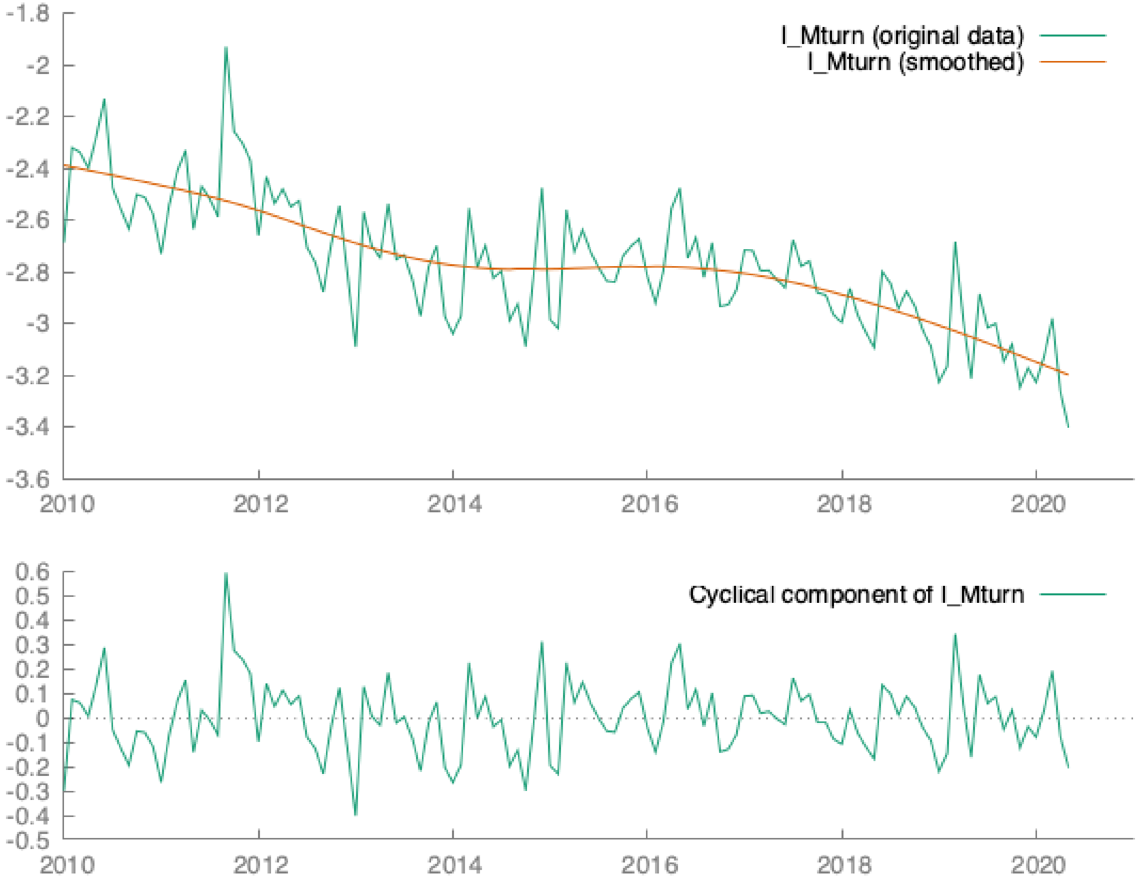


Figure 3: Monthly market return based on OMX Stockholm 30 (2010-2020)

Figure 4: Monthly market volatility based on OMX Stockholm 30 (2010-2020)

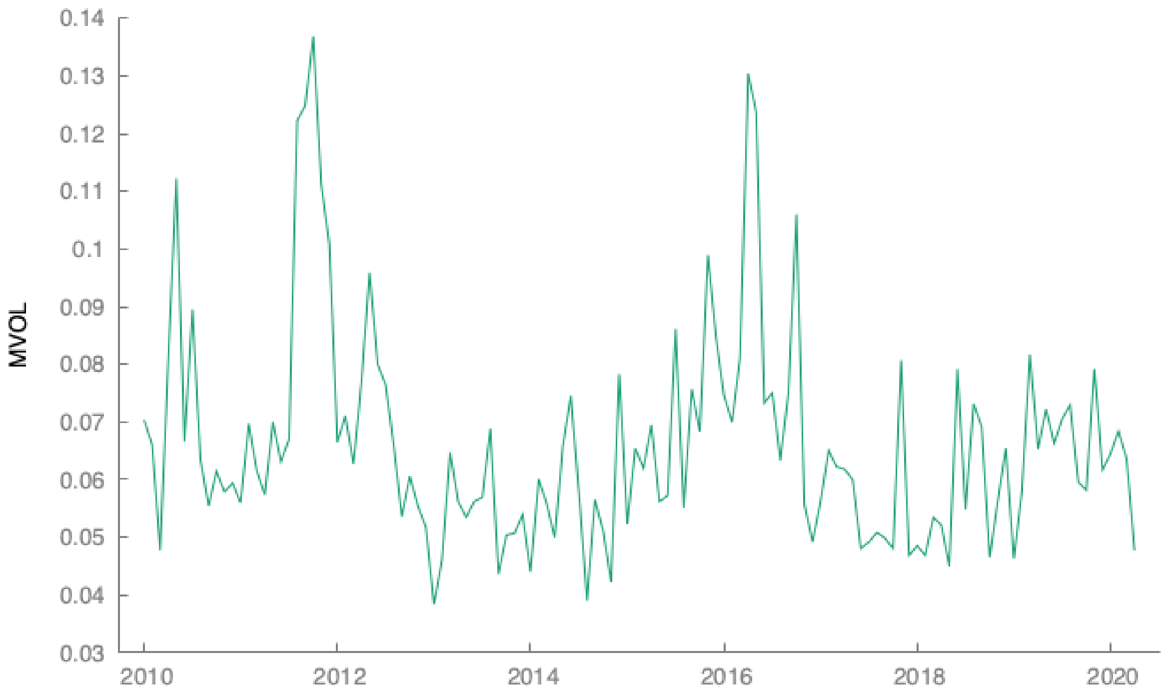


Figure 5: Monthly market dispersion based on OMX Stockholm 30 (2010-2020)

Table 1: Summary Statistics, using the 120 observations 2010:01 - 2020:01.
(Missing values were skipped)

Variable	***Observations***	***Mean***	***Median***	***Minimum***	***Maximum***
MVOL	*119*	*0.066*	*0.062*	*0.038*	*0.137*
Disp	*115*	*0.053*	*0.053*	*0.022*	*0.093*
MRet	*115*	*0.006*	*0.011*	*-0.093*	*0.088*
Mturn	*120*	*0.065*	*0.062*	*0.033*	*0.145*
Mturn1	*120*	*-4.2988e-15*	*-0.007*	*-0.401*	*0.596*
Variable	***Observations***	***Std. Dev.***	***C.V.***	***Skewness***	***Ex. kurtosis***
MVOL	*119*	*0.019*	*0.287*	*1.623*	*2.925*
Disp	*115*	*0.015*	*0.291*	*0.277*	*-0.295*
MRet	*115*	*0.038*	*6.119*	*-0.447*	*-0.004*
Mturn	*120*	*0.018*	*0.269*	*1.222*	*2.894*
Mturn1	*120*	*0.150*	*3.5002e+13*	*0.432*	*1.290*
Variable	***Observations***	***5% Perc.***	***95% Perc.***	***IQ range***	***Missing obs.***
MVOL	*119*	*0.045*	*0.112*	*0.019*	*1*
Disp	*115*	*0.027*	*0.082*	*0.022*	*5*
MRet	*115*	*-0.068*	*0.067*	*0.046*	*5*
Mturn	*120*	*0.041*	*0.098*	*0.024*	*0*
Mturn1	*120*	*-0.230*	*0.266*	*0.184*	*0*

Mturn = Market turnover | Mturn1 = Logged and detrended market turnover | MVOL = Market volatility | Disp = Dispersion

Table 2: Lag structure, maximum lag order 12 | * represents optimal lag-length for respective criterion (Log and detrended Mturn)

lags	loglik	p(LR)	AIC	BIC	HQC
1	271.01355		-4.833584*	-4.585239*	-4.732889*
2	273.45164	0.30024	-4.804660	-4.456976	-4.663687
3	275.04272	0.52782	-4.760050	-4.313029	-4.578799
4	277.83294	0.23275	-4.737647	-4.191287	-4.516118
5	278.56815	0.83187	-4.677188	-4.031490	-4.415381
6	279.76847	0.66251	-4.625342	-3.880306	-4.323257
7	282.49396	0.24407	-4.601740	-3.757365	-4.259377
8	283.29385	0.80883	-4.542479	-3.598766	-4.159837
9	285.66591	0.31457	-4.512332	-3.469281	-4.089412
10	286.70387	0.72180	-4.457479	-3.315090	-3.994282
11	287.93791	0.65036	-4.406258	-3.164530	-3.902782
12	296.84731	0.00134	-4.497172	-3.156107	-3.953419

AIC = Akaike criterion, BIC = Schwarz Bayesian criterion and HQC = Hannan-Quinn criterion.

Table 3: VAR estimation 1 lag-length

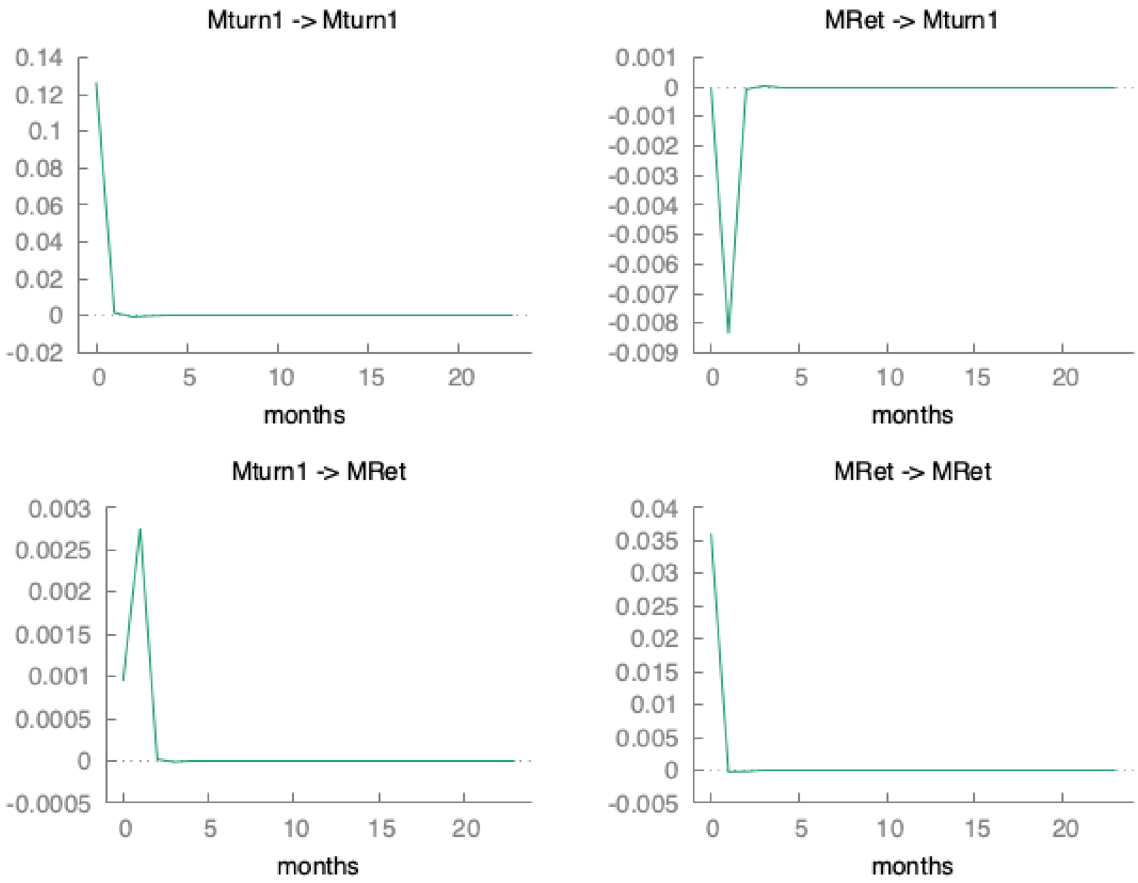
		MRet	Mturn1
Const	Coefficient	0.0123146	−0.297612
	Std. Error	0.0227	0.0794
	P Value	0.5878	0.0003
Mturn1_1	Coefficient	0.0218018	0.0156767
	Std. Error	0.0265	0.0930
	P Value	0.4131	0.8666
MRet_1	Coefficient	−0.00677984	−0.231265
	Std. Error	0.0949	0.3329
	P Value	0.9432	0.4887
Disp	Coefficient	0.456059	−0.880992
	Std. Error	0.2273	0.7974
	P Value	0.0473	0.2717
Disp_1	Coefficient	−0.0454252	1.16972
	Std. Error	0.2364	0.8293
	P Value	0.8480	0.1612
MVOL	Coefficient	−0.627687	3.03821
	Std. Error	0.2230	0.7820
	P Value	0.0058	0.0002
MVOL_1	Coefficient	0.243062	1.01703
	Std. Error	0.2350	0.8242
	P Value	0.3032	0.2198

Table 4: VAR estimation 4 lag-length

		MRet	Mturn1
Const	Coefficient	0.0312356	−0.396314
	Std. Error	0.0258236	0.0884535
	P Value	0.2292	< 0.0001
Mturn1_1	Coefficient	0.0167193	0.0243769
	Std. Error	0.0281758	0.0965104
	P Value	0.5542	0.8011
Mturn1_2	Coefficient	0.0105586	−0.259154
	Std. Error	0.0264890	0.0907327
	P Value	0.6910	0.0052
Mturn1_3	Coefficient	−0.0178600	−0.000953524
	Std. Error	0.0256048	0.0877041
	P Value	0.4871	0.9913
Mturn1_4	Coefficient	0.00890476	−0.0502163
	Std. Error	0.0243312	0.0833415
	P Value	0.7151	0.5482
MRet_1	Coefficient	−0.0429958	−0.0474695
	Std. Error	0.100329	0.343657
	P Value	0.6692	0.8904
MRet_2	Coefficient	−0.123209	0.123487
	Std. Error	0.0950394	0.325538
	P Value	0.1978	0.7052

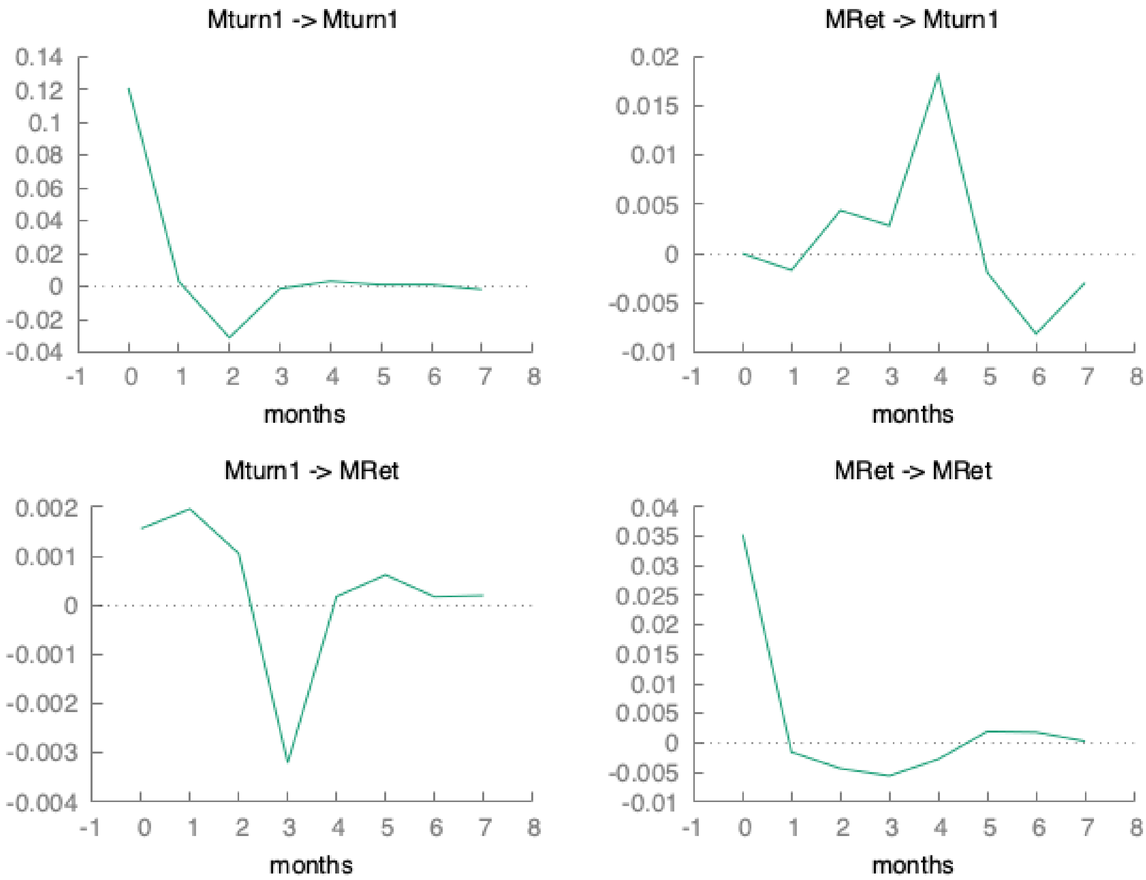
MRet_3	Coefficient	−0.168905	0.0651890
	Std. Error	0.0998462	0.342003
	P Value	0.0938	0.8492
MRet_4	Coefficient	−0.109879	0.554004
	Std. Error	0.100779	0.345198
	P Value	0.2782	0.1116
Disp	Coefficient	0.416546	−1.09531
	Std. Error	0.240058	0.822271
	P Value	0.0857	0.1858
Disp_1	Coefficient	−0.0740888	1.05307
	Std. Error	0.244799	0.838509
	P Value	0.7628	0.2120
MVOL	Coefficient	−0.731876	3.18270
	Std. Error	0.241896	0.828565
	P Value	0.0031	0.0002
MVOL_1	Coefficient	0.152454	2.24433
	Std. Error	0.267897	0.917625
	P Value	0.5706	0.0162

Figure 6: Impulse response analysis between the relationship of MTurn and MRet
1 lag-length



MTurn and MRet are abbreviations for Market Turnover and Market return.

Figure 7: Impulse response analysis between the relationship of MTurn and MRet
4 Lag-length



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