Noise Trading Approach of Capital Asset Pricing at Tehran Stock Exchange

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ABSTRACT

Noise traders as one of the key elements of the market play a significant role in determining the market volatilities, returns, and stock market mispricing. Hence, this study attempts to scrutinize the role of noise trading in capital asset pricing. Therefore, by using daily data, samples including 14105 data of 200 companies listed on stock exchange were selected and noise trading index was estimated based on Feng et al (2014). Then, using the panel method, monthly noise level of stock exchange was evaluated and the effect of noise factor on risk premium was modelled. Findings indicated that an increase in the noise level in the stock trading leads to a decrease in risk premium, however, stock fluctuations increase significantly. Moreover, the noise factor has a negative and significant effect on risk premiums. Also, market risk premium and company size have a significant positive effect on risk premium.

Keywords:

Noise Trading, Capital Asset Pricing, Risk Premium.

1. Introduction

Asset volatilities are one of the most important components of asset pricing, and an increase in market volatility can lead to a change in the distribution of risk on financial assets. Based on conventional financial theories, the Investors' behavior is considered rational and any change in assets' risk is regarded as the consequence of change in the fundamental factors, while in real conditions, the emotions and tendencies of investors may affect the asset pricing. In the framework of behavioural finance, irrational traders are defined as noise traders (Herve et al., 2019). Such traders have cognitive and emotional errors that affect the results of their activities and their preferences on stock selection (Shefrin and Statman, 1984). Compared to fundamental information-based decisions, the irrational activities of noise traders have triggered abnormal returns in financial markets (Press and Schmidt, 2017). In traditional financial field, it is often argued that the activity of noise traders is neutralized by rational traders, the institutional investors and the arbitrage process in particular (Lin et al., 2018). Meanwhile, price correction is accelerated by liquidity provided by noise traders in the market (Barrot et al., 2016). The irrational noise traders induce temporary effect. For this reason, it has not been addressed in traditional financial framework. Models of financial noise trading demonstrate investors who have not made investment decisions based on fundamental factors and can affect stock price based on unpredictable changes in their emotions. Many studies have provided a framework for the influence of investment feelings on pricing (Delong et al.,1990). The creation of models based on noise trading can lead to more studies that provided evidence for simultaneous changes in feelings of individual and institutional investors and stock exchange returns. The previous studies mainly focused on the average stock returns and less attention was paid to the effect of feelings on the formation of conditional volatility. In these studies, the impact of individual and institutional noise traders on expected returns through their effect on risk was not addressed. As a consequence, a question that arises is how investors' feelings, affect market volatility. On the other hand, this also leads to the question that if there is such an association between the investors' feelings and market volatility, whether it is caused by rational factors of risk or the noise-induced. The answer to these questions can lead to better understanding of the role of noise traders in pricing.

Black (1986) defined noise traders as investors who trade in markets for non-information-based reasons. He believed that such traders use tangible indicators including reference points in decision making. Black (1986) assumed there is no imperfect and information asymmetry, hence, there are two groups of traders, namely, information traders and noise traders. In his view, information traders have more accurate information about the true stock value compared to noise traders. Though, no one has complete information, noise traders induce mispricing in the true stock value, while the information traders use information and earn their profit indirectly from noise traders' activities. In fact, there is a close relationship between these two groups of traders: while noise traders may cause prices to deviate from fundamental values, the information traders profit from pricing errors. In fact, the market is not in a static state of equilibrium, and despite the noise traders, the market is in a dynamic equilibrium. The researchers are seeking answers to the question whether the noise traders involve in capital assets pricing or not. In the following sections, theoretical foundations and research background are discussed, the process of noise estimation and the way of making noise factor are illustrated, and finally, the results of modelling are presented.

2. Literature Review

The relationship between stock exchange volatilities and noise traders' activities was first discussed in the behavioral finance field by using developed models (Campbell and Kyle, 1993). All of these models predict the impact of noise traders on stock risk and returns. Increased noise activities in The market not only can increase return fluctuations but also can increase stock mispricing. In agent-based models, noise traders are the source of excess volatilities which, due to mispricing, can cause great changes in market sentiments and emotions and finally, when the price bubble bursts due to a fall in price, market sentiments can be modified (Hessary et al., 2016).

Sentiments can affect the market volatilities through the influence on trading activities of noise traders. This argument is based on Liu's (2015) findings which argue that an increase in market sentiments can lead to an increase in the US stock exchange liquidity. So, the increased sentiments will also increase trading activities of noise traders, and subsequently, rational arbitrageurs enter in the financial market and attempt to profit in market from their irrational competitors. Alfano et al. (2015) argue that not only sentiments impact noise traders, but also affect information traders. Herow et al (2019) believe that first a group of traders make trade based on noise signals and then other traders make deal based on the information. Many studies have also asserted the rational investors' trends to speculative activities during high sentiment periods. (Devault at al., 2016; Jang and Kang, 2018). Other studies have indicated the herding behavior among the institutional traders. Nofsinger and Sias (1999) found that compared to individual investors, institutional investors provide more negative and positive feedbacks, while the effect of herding behavior of institutional investors on pricing is higher than herding behavior of individual investors. The investigation of behavioral process of these traders indicated that institutional investors and noise traders do not behave in contrast to each other. Therefore, fluctuations in limit occur over long periods until they move to the average behavior sensitivity. Chau et al (2016) state that emotional behaviors in the US stock market induce buying and selling. However, in some cases, emotional investors behave rationally when selling stock during high pricing. Devault et al (2019) believed that contrary to what is stated, the noise emotional traders do not behave completely irrational. Hence, if some noise traders behave rationally in some cases, they are unable to induce a stable effect since some institutional investors during the emotional periods in market, through investing in a lot of funds, irrationally behave by reinforcing herding. Other studies have indicated that irrational traders are more active during the market sentiment periods (Antoniou et al., 2015; Kim et al., 2017; Piccoli et al., 2018). In the following, an overview of conducted studies on noise trading is presented. Terasvirta (1993, 1996, 2004) modelled the process of changes in investors' behaviors against changes in payment index by using Smooth Transition Regression. Following Black studies, Macmillan (2003) in his article entitled as "Non-linear Forecast of UK Stock Exchange Return "identified noise traders as the cause of changes in stock returns. Balvers et al (1990) asserted that the optimal level of stock return illustrates the balance point between the present and future consumption of market activists. Chuang et al (2010) investigated Taiwan stock market and found that changes in the investors' emotions based on the volume of transactions, significantly impact Market volatilities so that, during high sentiments in market, high volume of transactions and volatilities indicate increased activities of noise traders. Rahman et al (2013) examined the behavior of noise traders in Bangladesh stock exchange and found that changes in market sentiments quickly affect the returns and fluctuations in the stock returns. The results are in line with those of Uygur and Tas (2014) about the intensification of conditional fluctuations in emotional periods of financial markets of the US, Japan, Hong Kong, UK, France, Germany, and Turkey. In this field, many studies have been conducted in most countries which indicate the undeniable influence of noise traders on returns and stock volatilities (Yacob, 2016; Nik, P.K, and Padhi, 2016). Other studies also argue the effect of the source of noise trading including individual investors, (Schmeling, 2007), institutional investors (Devault et al., 2019) or both groups (Verma and Soydemir, 2009) on the emotional biases in the market. Brunnermeier (2016) examined the effect of noise traders on the price trend direction and believes that noise traders survive fundamental traders and stabilize stock exchange by stabilizing fundamental orientations and liquidity orientation. During trade trends, noise traders make timing errors in selling and buying stocks since they do not make decisions based on fundamental concepts and have emotional responses to positive and negative errors. The behavioral finance studies showed that the behavioral, cognitive, and emotional biases cause irrational investment and financing decisions (Fernandes et al., 2010). Also, the financial markets are moving from fundamental space to the growth of investors' sentiments indicators, while this relationship is increasingly strengthened (Qiang and Shu-e, 2009). Sarenj et al (2018) investigated the failure in trading behaviors and risk of noise traders in Tehran Stock Exchange and found that noise traders are active in all situations of Iran's stock exchange market and cause inefficiency in stock exchange. They believed that excess reaction and mispricing are the main causes of inefficiency. Nikbakht et al (2016) examined the effect of emotional behaviours and accounting information on stock price. The results revealed that emotional behaviours increase the expected earnings and stock price. Seifoddini et al. (2015) investigated the microstructure noise in high-frequency prices found that the performance of portfolios having a high level of noise with the performance of portfolios having a lower level of noise and concluded that the risk of the high noise level presents itself as a risk premium in the future return and that asset pricing models which capture the systematic risks cannot capture the noise risk in prices. Abbasian and Farzanegan (2011) explored the existence of rational bubbles alongside arbitrage constraints and the risk of noise traders over the period of 2000 to 2008. They found that regardless of rational arbitrageurs, noise traders have played a significant role in deviation of prices from fundamental factors. In another study, Abbasian et al (2015) evaluated the effect of noise traders in formation of rational bubbles from 2004 to 2015. The findings emphasized that stock price appears vulnerable to disrupted information in market. Based on the estimated results, inflation has a significant effect on changes in stock price. The noise traders can come to dominate the market and lead to an increase in price volatilities and risk in the market. In light of what has just been stated, the main hypothesis of this study is formulated as “the noise factor is one of the determinants of capital asset pricing”.

3. Methodology

In this study which is an objective data-based retrospective study, the role of noise trading in capital asset pricing is investigated. The statistical population of the study included all companies listed on Tehran Stock Exchange, excluding investment companies, banks, insurance institutions, and financial intermediaries to avoid double counting. Meanwhile, companies with more than three months of trading halt have been excluded from the statistical sample. Finally, statistic samples including the required data were collected using *RAHAVARD NOVIN* software and referring to the statistics of the listed companies on Tehran stock exchange.

Steps of the research process

1) Based on the daily data, the noise evaluation was modelled for each company in each individual year (Equation 1).

$$V_t = \beta_0 + \beta_1 V_{t-n} + \beta_2 r_{dt} + \gamma_t \quad (1)$$

Where V_t is the relative trading volume.

$V_{t=}$ The value of trading(Rial)/the total value of company. (2)

Where, r_{dt} is the daily return for each company.

In order to evaluate the equation 1, time-series based models were used for each company in each year. According to the investigation of classical assumptions, an appropriate model has been applied and, considering the heterogeneity of variance, most estimation models are GARCH models of the following general form. When the square of error sentences P during t-1 to t-p is able to illustrate the error variance in the period t, GARCH $_{(P)}$ is modelled as follows:

$$Y_t = \alpha + \beta_1 X_{1t} + \beta_2 X_{2t} + \cdots. + \beta_n X_{nt} + \varepsilon_t$$

$$\sigma_{\varepsilon t}^2 = \rho_1 \sigma_{\varepsilon t-1}^2 + \cdots + \rho_p \sigma_{\varepsilon t-p}^2 = \sum_{j=1}^{p} \rho_j \sigma_{\varepsilon t-j}^2$$

Considering equation 1, (mean equation), Y indicates a dependent variable, while, Xi_s are independent variables.

Considering equation 2 (conditional variance equation), the variance of error is a function of error variance q of the earlier period. Equation 2 is identified as GARCH sentence. When the GARCH pattern is applicable for error sentence of the mean equation, GARCH sentence (with optimal intervals) should be included in mean equation. The number of equations is an estimation performed by conducting classical assumption tests for each company each year and performing diagnostic tests to determine the appropriate interval by adopting different methods including conditional heterogeneity based models (Garch and Arch). Models were estimated for 200 companies over 9 different years from 2009 to 2017. In total, 1800 models were estimated and 900 models were estimated by using GARSCH methods, 830 models were estimated by using ARCH method and the other models were estimated based on a simple regression.

2) γt is the error of each created model used to estimate the noise level.
3) noise (ψt) is estimated as follows.

$$\psi_t = \frac{\gamma_t - \bar{\gamma}_t}{V_t} \quad (3)$$

γ_t is the daily mean of γ_t in each month.

4) The total noise is calculated daily for each month
$Noise_{IM}$=$\sum_{t=}^{t=n}\psi_{It}$ (4)

5) Noise factor (HNL) is defined as the difference between the average return on a portfolio of stocks with the low and high noise level.

Noise factor is estimated as follows:
To estimate the noise factor, considering the noise, data was monthly classified into ten categories from the smallest to largest. The first two deciles were classified as categories with low level of noise, while the last two deciles were classified as categories with high noise levels; the low and high noise categories were classified into three categories in terms of the ratio of book-to-the market value.

$$HNL = \left(\frac{HN}{L} + \frac{HN}{M} + \frac{HN}{H}\Big/3\right) - \left(\frac{LN}{L} + \frac{LN}{M} + \frac{LN}{H}\Big/3\right)$$

LN/N is the value-weighted portfolio of companies with small noise and a low ratio of the book-to-the market value.
LN/M is the value-weighted portfolio of companies with small noise and the average ratio of the book-to-the market value.
LN/H is the value-weighted portfolio of companies with small noise and a high ratio of the book-to-the market value.
HN/L is the value-weighted portfolio of companies with a big noise and low ratio of the book-to-the market value.
HN/M is the value-weighted portfolio of companies with big noise and average ratio of the book-to-the market value.
HN/H is the value-weighted portfolio of companies with big noise and low high ratio of the book-to-the market value.

6) Other required variables are as follows:
r_{imt} is the monthly returns of each company.
r_{mt} is monthly market returns.
r_{mft} is monthly risk free returns.
7) The analytical estimation of the main model
$r_{i,mt} - r_{mft} = \alpha_0 + \alpha_1(r_{mt} - r_{mft}) + \alpha_2 HNL_{imt} + \varepsilon_{i,t}$

The panel regression was used in estimating this model.

4. Results

Descriptive statistics

The Descriptive statistics of the research major variables are totally presented in table 1. The results of the descriptive statistics indicated that the noise variable with a mean of 0.05 and a relatively high standard deviation of 0.085 indicates positive skewness and is consistent with most of the variables of extended distribution toward high kurtosis. The stock risk premium with a monthly mean of 0.011 and a relatively high standard deviation of 0.262 indicates significant measure of excess positive skewness which could be indicative of relatively high stock performance toward free rate of return. The average of market risk premium is 0.007 which is an evidence of a relative good performance of market than free rate of return.

The descriptive statistics of related variables of companies with high and low noise levels are presented in table 2. As shown above, the portfolio noise means, companies with high and low noise levels are significantly different. The average risk premium of companies with low noise is 0.038 and the average returns of companies with high noise are 0.012 indicating a significant difference. In other words, companies with low noise levels earn more return compared to companies with high noise levels.

Table 1: The descriptive statistics of research variables

variables	Stock risk premium	Noise factor	market risk premium	Company size	market value
mean	0.011	0.050	0.007	8.294	0.299
Standard deviation	0.262	0.085	0.053	1.287	0.269
skewness	20.070	0.144	0.603	-0.568	1.029
kurtosis	80.755	13.731	2.818	3.558	2.963

On the other hand, return distribution in companies with high noise levels is far greater than the companies with low noise levels. In fact, it can be argued that high noise intensifies the risk phenomenon. There is not a significant difference among other portfolio variables of companies with high and low noise levels.

Table 2: The descriptive statistics results of the first two deciles

The descriptive statistics of companies listed on two low noise deciles					
variables	**Stock risk premium**	**Risk premium mean**	**Company size**	**The ratio of book-to-the market value**	**Noise factor**
Mean	0.038	0.007	8.181	0.280	0.000022
Standard deviation	0.272	0.026	1.636	0.273	0.00024
Skewness	2.404	7.379	-0.311	1.144	14.400
Kurtosis	13.78	11.182	-0.275	0.164	27.169
The descriptive statistics of companies listed on two high noise deciles					
Mean	0.012	0.0011	8.295	0.299	0.196
Standard deviation	2.861	0.262	1.287	0.269	9.173
Skewness	10.551	20.078	-0.568	1.029	10.742
Kurtosis	13.083	86.27	0.559	-0.037	10.896

Stationarity test

Before estimating the model, a stationarity test of variables used in research estimation is required as stationarity will result in a spurious regression.

Considering Levin –Lin –Chu Test (LLC), the following hypotheses are suggested:

H0: The examined variable is nonstationary.

H1: The data are stationary.

The results of Levin –Lin –Chu Test are presented in Tables 3 and 4. Levin –Lin –Chu Test suggests the following hypotheses:

H0: A time series variable is non-stationary and possesses a unit root.

H1: A time series variable is stationary and has no unit roots.

Table 3: The stationarity test of research variable

Variables	The statistic value of Levin –Lin –Chu	The level of significance
return	-15.61	00.0
size	-13.09	00.0
The book- to-the market value	-26.77	00.0
Noise factor	-14.28	00.0

The regression and Levin –Lin –Chu Test results

F-Limer test is used to determine whether the appropriate regression model is integrated regression or panel regression. The results of F-Limer test for the first model are illustrated in the following table

Table 4: The results of F-limer test and Hausman test

Hausman Test			**F-Limer Test**			
The results of Hausman Test	The level of significance	Chi-square test results	Model	F-statistics	Level of significance	The result of F-Limer Test
$r_{i,t} - r_f = \alpha_0 + \alpha_1(r_m - r_f) + \alpha_2 HNL + \varepsilon_{i,t}$						
Model of fixed effects	0,00	16,32	Model 1	2.99	00,0	Panel data
$r_{i,t} - r_f = \alpha_0 + \alpha_1(r_m - r_f) + \alpha_2 HNL + \alpha_3 size + \varepsilon_{i,t}$						
Model of fixed effects	00,0	18,23	Model 2	2.07	00.0	Panel data
$r_{i,t} - r_f = \alpha_0 + \alpha_1(r_m - r_f) + \alpha_2 \mathrm{HNL}_{i,t} + \alpha_3 bbm + \alpha_4 bsize + \varepsilon_{i,t}$						
Model of fixed effects	0.0007	17,12	Model 3	2.48		Panel data

Wooldridge Test for autocorrelation

One of the important assumptions in linear regression is the hypothesis that the residuals are not linearly auto-correlated. The results are reflected in Table 5.

Since, the P- value for model 1, 2, and 3 is less than 0.05, there is evidence of the correlation structure in the model.

Table 5: The results of no autocorrelation test

Research models	F-statistics	P-value	Results
$r_{i,t} - r_f = \alpha_0 + \alpha_1(r_m - r_f) + \alpha_2 HNL + \varepsilon_{i,t}$			
Model1	5.788	0.0065	Auto-correlation
$r_{i,t} - r_f = \alpha_0 + \alpha_1(r_m - r_f) + \alpha_2 HNL + \alpha_3 size + \varepsilon_{i,t}$			
Model 2	5,71	0.0183	Auto-correlation
$r_{i,t} - r_f = \alpha_0 + \alpha_1(r_m - r_f) + \alpha_2 \mathrm{HNL}_{i,t} + \alpha_3 bbm + \alpha_4 bsize + \varepsilon_{i,t}$			
Model 3	4,623	0,0123	Auto-correlation

Source: Research findings

The results of heterogeneity of variance test

The maximum likelihood statistic test was used for estimating the heterogeneity of variance tests. The results of the likelihood ratio test are presented in table 6.

Since the P-value for models 1 and 3 is greater than 0.05, there is evidence of lack of heterogeneity of variance in these models, while, p-value for model 2 is less than 0.05, which is an indication of heterogeneity of variance for model 2

Table 6: The results of the likelihood ratio test(LR)

Model	LR chi2	P-value	Results
$r_{i,t} - r_f = \alpha_0 + \alpha_1(r_m - r_f) + \alpha_2 HNL + \varepsilon_{i,t}$			
Model 1	0,9123	0,23564	Lack of heterogeneity of variance
$r_{i,t} - r_f = \alpha_0 + \alpha_1(r_m - r_f) + \alpha_2 HNL + \alpha_3 size + \varepsilon_{i,t}$			
Model 2	32523,05	0,0000	heterogeneity of variance
$r_{i,t} - r_f = \alpha_0 + \alpha_1(r_m - r_f) + \alpha_2 \mathrm{HNL}_{i,t} + \alpha_3 bbm + \alpha_4 bsize + \varepsilon_{i,t}$			
Model 3	0,1223	0,5231	Lack of heterogeneity of variance

The results of the fitness of model 1

Considering Tables 5 and 6, the auto-correlation test indicates autocorrelation and the results of heterogeneity of variance test indicate the lack of heterogeneity of variance. Hence, in order to improve serial auto-correlation, Price-Vincent regression was used and the results are presented in Table 7.

Based on the proposed hypothesis raised about the role of noise factor in capital assets pricing, the effects of noise factor on the excess revenue is significantly negative.

Table 7: The examination results of model 1

$r_{i,t} - r_f = \alpha_0 + \alpha_1(r_m - r_f) + \alpha_2 HNL + \varepsilon_{i,t}$					
Variables	**Symbol**	**Coefficients**	**Standard error**	**Z-statistics**	**Level of significance**
Intercept	α 0	0.01325	0.00328	4.04	00.0
Risk premium(rm-r_m)	α 1	0.88	0.0397	22.17	00.0
Noise factor	α 2	-0.2023	0.0247	-8.19	00.0
The adjusted coefficient of determination 0.14					

The results of the fitness of model 2

Considering Tables 5 and 6, the results of autocorrelation test indicate autocorrelation, while the results of heterogeneity of variance test indicate the heterogeneity of variance. Hence, in order to remove serial autocorrelation and heterogeneity of variance simultaneously, Newey-West was used.

Results are presented in table 8. Based on the proposed hypothesis raise about the effect of noise factor on capital assets pricing, noise factor has a negative and significant effect on excess revenue.

Table 8: The estimation result of model 2

$r_{i,t} - r_f = \alpha_0 + \alpha_1(r_m - r_f) + \alpha_2 HNL + \alpha_3 size + \varepsilon_{i,t}$					
Variables	**Symbol**	**Coefficient**	**Standard error**	**Z-statistics**	**Level of significance**
Intercept	α 0	-0.1541	0.0257	-5.99	00.0
Risk premium(r_m–r_f)	α 1	0.9276	0.0640	14,48	00.0
Noise factor(HNL)	α 2	-.22444	0.0397	-5.65	00.0
Company size	α 3	0.205	0.00322	6.34	00.0

The results of the fitness of model 3

Considering table (6 and 5), the estimation result of the autocorrelation test indicates autocorrelation and the results of heterogeneity of variance test indicate the lack of heterogeneity of variance. Therefore, Price-Vincent regression was used to remove serial autocorrelation. The results are presented in table 9. Based on the proposed hypothesis raised about the role of noise factor on capital asset pricing, the effect of noise factor on excess revenue is negative and significant.

Table 9: the estimation results of model 3

$r_{i,t} - r_f = \alpha_0 + \alpha_1(r_m - r_f) + \alpha_2 \mathrm{HNL}_{i,t} + \alpha_3 bbm + \alpha_4 bsize + \varepsilon_{i,t}$					
Variables	**Symbol**	**coefficient**	**Standard error**	**z-statistics**	**Level of significance**
intercept	α 0	0.4991	0.0047	10.46	00.0
Risk premium(r_m–r_f)	α 1	0.9340	0.0420	22.21	00.0
Noise factor(HNL)	α 2	0.2090	0.026	7.92	00.0
Company size	α 3	0.215	0.0214	10.04	00.0
The ratio of the book- to-the market value	α 4	0.1159	0.01339	8.66	00.0

5. Discussion and Conclusions

Since the market nature is influenced by investors' tendencies, noise phenomenon is an integral part of capital market in each country. Hence, this study examined the role of noise traders and noise factors in capital asset pricing. The results of descriptive statistics revealed that portfolio companies with high noise levels earn fewer returns compared to companies with low noise levels. Also, at high noise level, there is high dispersion at the returns level which indicates the role of noise traders in inducing intensified volatilities and risk which is in line with findings of Chuang et al (2010) claiming that intensified emotional behaviors are the cause of an increase in market volatilities. Uygur and Tas (2014) identified emotional behaviors as the cause of increased market volatilities in the financial markets of the US, Japan, Hong Kong, UK, France, Germany, and Turkey. The results of estimating pricing model showed that in addition to market risk premium factor and company size, the noise factor also has a significant and positive effect on capital asset pricing. However, the effect of noise factor on capital asset pricing is less than market factor. The results confirm the undeniable role of noise trading in capital asset pricing. These findings are in line with Rahman et al (2013), Uygur and Tas (2014), Yacob (2016), and Nik and Padhi (2016). Sarenj et al (2018) referred to noise traders as the cause of excess reaction and mispricing. Abbasian et al (2015) asserted the vulnerability of stock prices to disruptive information.

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