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The Effect of Google Trend as Determinant of Return and Liquidity in Indonesia Stock Exchange

(*Kesan Google Trend sebagai Penentu Pulangan dan Kecairan di Bursa Saham Indonesia*)

Ridwan Nurazi
Paulus Sulluk Kananlua
Berto Usman
(Faculty of Economics and Business, University of Bengkulu)

ABSTRACT

The impressive progress of information technology has substantially impacted economic development. Given this condition, the diffusion of information technology is related to the improvement of activities in the capital market, in which asymmetric information between investors can diminished to the lowest level. Thereby, we considered that information retrieval over the internet contributes to return and liquidity. We performed Google Trend (GT) as the surrogated indicator in attenuating the asymmetric information in Indonesia Stock Exchange. By utilizing 5976 observation data from 83 cross-sectional companies and 72 monthly time series ranging from January 2007 to December 2012, we noted that the information retrieval over the Internet has negative ($p<0.05$) contribution to return (RET). On the other hand, we confirmed that the information retrieval over the internet (GT) is positively ($p<0.01$) related to liquidity which is surrogated by trading volume (TV).

Keywords: Asymmetric information; Google trend; return; trading volume

ABSTRAK

Kemajuan teknologi informasi telah membawa impak yang cukup besar terhadap pembangunan ekonomi. Berdasarkan situasi ini, penyebaran teknologi maklumat adalah berkait dengan peningkatan aktiviti transaksi di dalam pasaran modal, di mana tahap asimetri maklumat antara pelabur boleh berkurangan ke tahap terendah. Oleh sebab itu, kita mengandaikan bahawa pencarian maklumat melalui internet memberi sumbangan kepada pulangan dan kecairan. Kami menggunakan Google Trend (GT) sebagai indikator wakil dalam mengukur asimetri maklumat di Bursa Saham Indonesia. Dengan menggunakan 5976 data pemerhatian dari 83 syarikat dan 72 siri masa dari Januari 2007 hingga Disember 2012, kami mendapati bahawa pencarian maklumat melalui Internet menunjukkan hubungan negatif ($p<0.05$) terhadap pulangan (RET). Dalam konteks lain, kajian ini juga mengesahkan bahawa pencarian maklumat melalui internet (GT) adalah berhubungan secara positif ($p<0.01$) dengan kecairan yang diwakili oleh jumlah jualbeli (TV).

Kata kunci: Asimetri maklumat; google trend; pulangan; jumlah jualbeli

INTRODUCTION

The transition of information technology from analog based system to the digital based system has brought significant impact to the economic performance of many stock exchange markets. It is observable that in the past, the order and transaction activities relating to stock exchange were manually done (Usman & Tandelilin 2014). Most stakeholders had to call their brokers directly by phone to perform their transactions, and to ask for annual reports.

However, these are no longer practiced due to the presence of internet. Henceforth, the investors can easily search for the specific information, pertinent and relevant to their interests, including the fundamental information and corporate action taken by the companies.

As pointed out by Joseph et al. (2011), there is a growing recognition about the predictive value of data collected across the various digital platforms. One rich repository of predictive data is online searches. Bank et al. (2011) and Da et al. (2011) documented that the sequential incoming information into the market has considerably influenced the investors' preference in making an investment decision. They found that the different information held by the investors leads them to two situations; i.e. whether they will experience either superior or inferior performance compared to the other investors. Thus, they assumed that the concept of asymmetric information is immensely popular in the developed markets, such as German Stock Exchange (German stocks traded on the Xetra trading system) and America Stock Exchange (The Russel 3000 index contains 3000 largest companies representing more than 90 percent of the total U.S. equity market capitalization).

There is a vast empirical literature which had tried to explore the contribution of information retrieved from the internet in the context of developed markets. For instance, Joseph et al. (2011) studied the impact of online search on the abnormal stock returns and its relation to trading volume by using investor sentiment towards S&P 500 stocks. Bank et al. (2011) examined the effect of asymmetric information measured by using Google Insight in explaining the variation of return and liquidity in German Stock Exchange. Su et al. (2012) studied asymmetric information and return-volume using a time varying model based on the imbalance of individual listed stocks in NASDAQ index. Further, Fink and Johann (2013) analyzed whether a stock's liquidity and returns are influenced by short-term fluctuation in investors' attention attached to the stock, in which they particularly used the Google Search Volume (GSV) as surrogated indicator to investors' attention.

Empirical studies indicated that the phenomenon of investors' attention is an interesting subject to be further explored. The fully integrated information technology with stock exchange is assumed to be the best alternative in attenuating asymmetric information between informed and uninformed investors. As stated by Fang and Peress (2009), internet is eminently analogized as a pool of information. Many people can utilize this facility and search for information they want. For example, it is compulsory for a company to announce its annual reports to its investors. The process of delivering annual reports usually started by printing a number of catalogs which contained financial statements and sending them directly to the stockholders. Additionally, a company may post an advertisement via newspapers, television, or other mass media inviting its stockholders to attend the company's annual meeting. In the more extreme ways, the investors may have to manually search for the documents (e.g. financial statements, annual reports, bills, and so forth) that are physically stored. This circumstance leads to the inability of stakeholders to retrieve the required information in a timely and immediate manner. Therefore, the internet truly helps the stakeholders to collect the various information of their interest.

We focused our study based on the empirical evidence from several researches conducted by Bank et al. (2011), Da et al. (2011) and Joseph et al. (2011). These researches investigated the contribution and the existence of asymmetric information between informed investors and uninformed investors in stock exchange. The concept of asymmetric information is a prevalent phenomenon which can easily be found in many capital markets. We conjecture that the performance of certain investors would considerably be influenced by the information known by them. Therefore, it is obvious that the level of asymmetric information should be reduced as to give every investor the opportunity to gain either actual or abnormal return.

A method that can be utilized to attenuate the risks faced by the investors is accessing as much information as possible (Lou 2014). The information can be obtained from several sources, such as annual reports, periodical balance sheets, compilation of financial statements, and the Internet. By using the search engine called Google, it is plausible for investors to collect the relevant and pertinent information in regard to their portfolio investment. Given that, a vast literature on the effect of internet on stock exchange performance is readily available from developed countries. However, very little is known about the role of internet in emerging countries. Considering that, there might be significant difference in practice and phenomenon in developed and emerging countries. Some of these emerging countries have similar characteristics which include the transition of economy, high economic growth, and bigger roles in the world economy as emerging markets. Therefore, the listed companies in an emerging country such as Indonesia might behave differently due to economics and institutional conditions.

Our study contributes to the burgeoning number of literature related to the concept of investors' attention, return, and liquidity in emerging stock markets. We primarily conjecture that asymmetric information does exist in emerging stock markets. Due to this notion, we assumed that our analysis contributes considerably to the understanding of the processes of the heterogeneous investors. In particular, the positive impact of Google's results on stock returns and liquidity. Further, as suggested by Joseph et al. (2011) and Su et al. (2012) we utilized Google Trend (GT) as surrogated indicator for information retrieval over the internet. Return (RET) as a measure of a firm's performance, and trading volume (TV) represents the liquidity in the Indonesia Stock Exchange (IDX).

LITERATURE REVIEW

This article explores the stock return, liquidity, and asymmetric information in the context of emerging market such as Indonesia. The idea relating to the use of these concepts is mainly obtained from the three aspects; namely, investors' attention which depicts the incoming information to market, the relationship of return-liquidity, and the number of incoming information related to the realized companies which provide higher return to their investors. To understand more about asymmetric information, the model of investor attention is surrogated by the use of information retrieval over internet, and reviewed to illustrate what could be its effects on stock return and liquidity. Given this consideration, we utilized the recorded data of search inquiries in Google as the proxy of investors' attention. Further, in order to investigate the return-liquidity relations, we employed the actual return as the indicator of firm performance, and trading volume as the proxy of liquidity.

As mentioned by Su et al. (2012), there are two indices derived from seminal studies in order to measure how much information contained in return and trading volume, namely order imbalance and individual stocks. In other words, they are proxies of the real asymmetric information between the investors. The previous empirical tests reported satisfying results to support the propositions. It is believed that the results of the return-volume relationship obtained in this study, as well as those discovered by previous researches are actually due to their contents of information. Nevertheless, a panel data model with time varying model was applied in our study and results are closer to reality.

GOOGLE TREND AND INFORMATION RETRIEVAL

Google Trend is a Google's feature that is basically aimed at researching keywords and searching trends in various regions in the world. At first, the previous name of Google Trend is "Google Insight", but after 2013, Google changed the term 'Google Insight' to 'Google

Trend'. This feature has become a measurement tool that can be used in many social researches. This is due to its ability that can quantify the cross-time and cross-ecological phenomenon. The data collected by Google are then compared to the data of total search inquiries which had been recorded in the Google's servers around the world (Banks et al. 2011; Da et al. 2011; Joseph et al. 2011).

According to Da et al. (2011) and Bank et al. (2011), the searches done by Google are based on the taxonomy of the words entered by internet users. Google will transform the incoming data by eliminating a number of common trends in a popular search on the internet. Thereby, we categorized the samples based on companies' names as listed in Indonesia Stock Exchange and their ticker symbols. Furthermore, Google Trend will perform the filtration of search inquiries and normalize the incoming trends. Anticipating the presence of bias, we used the data relating to the search inquiries which are limited to the categories of finance, and business industries. Further, we specifically defined the location of search inquiries within Indonesia, and observation period ranges from January 2007 to December 2012.

INVESTOR ATTENTION AND STOCK RETURN

According to the asymmetric information theory, the number of information is obviously important in supporting the process of making investments' decisions. Such information can be derived either from public or private information. Several empirical studies have examined the availability of information in attracting investors' attention towards stock returns and liquidity. As pointed by Tumarkin and Whitelaw (2001), Benbunan and Fich (2004), Fang and Peress (2009), Benzion et al. (2010), Koning et al. (2010) and Tetlock (2010), financial news are greatly considered as signals. Investors assume that good news means positive signals, and bad news are negative signals; and this can particularly influence a firm's value. This circumstance has also been highlighted by many studies, such as Bank et al. (2011), Da et al. (2011), Joseph et al. (2011), Usman et al. (2012), Usman and Tandelilin (2014). They reported that the number of information retrieval over the internet is useful in measuring the asymmetric information among the investors. The previous empirical evidence believes that the gap between informed and uninformed investor inclines to result in different levels of investment performance. The more people try to search for information from internet, the higher the probability of them selecting stocks with the best return. Given that, we conjecture that low asymmetric information increases the volume and demand of certain stocks. High demand causes the stock price climbs up and indicates higher rate of return. Thus, we formulate the first hypothesis as "High–attention stocks (in terms of monthly Google search inquiries) provide higher return".

INVESTOR ATTENTION AND LIQUIDITY

In order to describe the dynamics and channels between investors' attention and liquidity, we built our empirical work based on the notion of Fink and Johann (2013). They found that the high information retrieval over the internet clearly increases the level of liquidity. We further measured the liquidity by employing trading volume. The study by Su et al. (2012) stated that one of the basic purposes of the existence of a public trading stock market is to discover the intrinsic value of the listed stock through investors' order. They pointed out that the market mechanism that people compete to take advantage from their information is just the key to unlock the intrinsic values in a black box. Thereby, in a situation where the investors are heterogeneously informed, they can compete to earn better return for compensating their investment decisions.

Our major goal is to analyze the relationship between investors' attention measured by Google, and liquidity which is surrogated by Trading Volume (TV). Study conducted by Fink and Johann (2013) reported that daily changes in the Google Search Volume Index are related to liquidity of different dimensions. Also, they documented that the evidence with respect to attention triggers positive short-term returns. Further, Usman et al. (2012) Usman and Tandelilin (2014) have found that the higher the attention for a certain stock, the higher its short-term returns and liquidity. To the best of our knowledge, this relationship seems to be robust. Therefore, we want to verify this direct channel in hypothesis two, "High-attention stocks (in terms of monthly Google search inquiries) are more liquid".

Moreover, in revealing the correlation between the main variables, we also used several additional control variables. Martani et al. (2009) suggested to the utilization of fundamental information as proxies of microeconomic variables. Therefore, we added nine controlling variables; which are price, volume, price earnings ratio, age, dividend payout, debt-to-equity ratio, and return on investment. These controlling variables are particularly important in explaining the variation of return. As mentioned by Brigham and Ehrhardt (2005), the variation of return cannot be explained by only one factor, but it can be also explained by the other factors as revealed by arbitrage pricing theory.

METHODOLOGY

We started our research by analyzing a number of literature, journals, and annual reports from various sources which are relevant to our study. We also collected the data of internet retrieval by utilizing the search inquiries from Google feature called as Google Trend. The specific data in regard to control variables were obtained from the official website of the Indonesia Stock Exchange (www.idx.co.id) and the Indonesian Capital Market Directory (ICMD CD-ROM). Then, we selected the samples by using purposive sampling criteria. Firstly, the potential company must be listed in the Indonesia Stock Exchange during the period of observation from January 2007 to December 2012. Secondly, the company must have search inquiries which can be quantified by Google Trend. Thirdly, the company must never experience any temporary suspension or termination within the period of observation. Lastly, the company must have published its financial reports on the internet within the time period of observation. Finally, after sorting the most appropriate sample, we decided to employ 83 companies that met our sampling criteria.

After determining the criteria of purposive sampling method, we continued to compile the variable definitions. In the context of corporate finance, information regarding financial performance is essential to investors. As studied by Martani et al. (2009), we employed a number of basic information in order to strengthen the robustness of estimated output. Besides, we decided to use the fundamental information as controlling variables, and classified each sample into three groups of company size as suggested by Chan and Faff (2000). The purposes of using additional controlling variable and three groups of samples are to purify, and neutralize the effect resulted from the process of estimation. Therefore, we defined nine variables from various sources and inserted them in the form of mathematical formulas which can be seen as follows.

TABLE 1. Variable definitions

No	Variables	Measurements
1	Google Trend (GT)	Percentage (data ratio) which ranges from 0 to100 percent.
2	Return (RET)	$RET_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}}$

3	Trading Volume (TV)	$TV_{ity} = \ ln\,(VO_{ity}\ x\ P_{ity})$
4	Stock Price (LNP)	Stock price is the market value of certain stock that can be easily found on internet. Hereby, we used the logarithm natural of stock price for data testing.
5	Stock Volume(VOL)	Volume is the number of stock traded every month.
6	Price Earnings Ratio (PER)	$PER = \frac{MarketPrice}{Earnings\ Per\ Share}$
7	Age (AGE)	Age is the operational time since the first time company announced its initial public offering (IPO).
8	Dividend Payout ratio (DP)	$DP = \frac{Dividend\ Per\ Share}{Earnings\ Per\ Share}$
10	Deb-to-Equity Ratio (DER)	$DER = \frac{Total\ Debt}{Total\ Equity}$
11	Return on Investment (ROI)	$ROI = \frac{Net\ Profit\ After\ Tax}{Total\ assets}$

Description: The formulas were collected from Brigham & Erhardt (2005), Chordia et al. (2007), Usman et al. 2012, Usman and Tandelilin (2014).

From Table 1, there are nine variables used in this study, which are applied in two statistical models. The information relating to each variable is defined with its mathematical formulation. We carefully identify the appropriate measurement to confirm the influences of each independent variable towards the dependent variables. Moreover, a priori expectation with respect to the employment of those variables is based on the previous empirical research and related theories in financial management.

PREDICTIVE PANEL REGRESSION MODEL

Before running the model, we first controlled the market capitalization of each sample. The data relating to size or market capitalization are obtained by multiplying stock prices with the number of outstanding shares. It is done as to divide the sample into three categories, namely small-cap companies (S), medium-cap (M), and large-cap companies (L). We meticulously sorted the size of companies based on the pattern of portfolio formation as suggested by Chan and Faff (2002). All samples were ranked from the largest to the smallest capitalization with proportion 30: 40: 30. We finally categorized 25 companies as the small-cap samples, 33 companies as the medium-cap, 25 companies as the big-cap samples, and 83 companies as the consolidated samples. Then, we run the data by employing the statistical model as follows:

$$RET_{i,t} = \alpha + \beta_1 GT_{i,t} + \beta_2 LNVOL_{i,t} + \beta_3 PER_{i,t} + \beta_4 AGE_{i,t} + \beta_5 DP_{i,t} + \beta_6 DER_{i,t} + \beta_7 ROI_{i,t} + \beta_8 ROE_{i,t} + \varepsilon \qquad (1)$$

Statistical model 1 consists eight independent variables and a dependent variable. Hence, RET is denoted as dependent variable, which is obtained by calculating the difference between stock price at $_t$ and the stock price at $_{t-1}$. GT is the number of search inquiries conducted by internet users or potential investors which ranges from 0 to 100 percent. LNVOL is the number of logarithm natural from trading volume that occurs every month. PER refers to the price earnings ratio that describes the ratio between earnings and stock prices. AGE is the operational period of company which is calculated from the company's commencement of initial public offering (IPO) in Indonesia Stock Exchange. DP is the dividend payout ratio which describes the percentage of dividends paid to shareholders. DER is debt-to-equity ratio which reflects the comparison between debt and equity. ROI is a proxy of profitability ratio that describes the return obtained by investments, and generally made by investors. Furthermore, we also built the second statistical model to test Hypothesis two as follows:

$$TV_{i,t} = \alpha + \beta_1 GT_{i,t} + \beta_2 LNP_{i,t} + \beta_3 PER_{i,t} + \beta_4 AGE_{i,t} + \beta_5 DP_{i,t} + \beta_6 DER_{i,t} + \beta_7 ROI_{i,t} + \beta_8 ROE_{i,t} + \varepsilon \quad (2)$$

Similar to statistical model 1, we utilized eight independent variables in order to estimate the variation of dependent variable in statistical model 2. We replaced the dependent variable from RET to TV with the objective to investigate the variation of TV as surrogated indicator of liquidity. As such, we used TV as surrogated indicator of liquidity as suggested by Chordia et al. (2007). It is necessary to explore whether return (RET) and trading volume (TV) correlate with each other. The increase of return is particularly related to the increase of trading volume. Besides, we also have seven controlling variables as predictors, which are specifically intended for neutralizing the effect of exogenous variables towards the endogenous variables.

MODEL SELECTION

The process of model selection will influence the estimation of statistical output. This indicates that selecting appropriate model will greatly affect the interaction of each independent variable towards the dependent variable. In panel data regression, there are three techniques or approaches that can be used in testing the statistical model, such as Pooled Least Squares model (PLS), Fixed Effect Model (FEM), and Random Effect Model (REM). In order to determine which model will be used in the process of estimation on each hypothesis, the Chow test was performed. Chow test itself is used to compare between pooled least squares and fixed effects model. Moreover, in order to compare the fixed effect model and random effects, the Hausman test is needed (Gujarati 1995; Baltagi 2005). The first step of comparing between fixed effect model and pooled least square model was performed and the Chow test results are as follows:

TABLE 2. Chow Test result

Redundant Fixed Effects Tests
Pool: POOLED
Test cross-section fixed effects

	RET			TV		
Effects Test	Statistic	d.f.	Prob.	Statistic	d.f.	Prob.
Cross-section F	0.628587	(82,5881)	0.4683	1.346269	(82,5882)	0.1547

*** : Statistically significant at 1% alpha.
** : Statistically significant at 5% alpha.
* : Statistically significant at 10% alpha.

Description: Chow test was performed by first conducting the fixed effect model as the base of comparison between pooled least square and fixed effect model. After discovering the outputs, justification in regard to Chow test result is based on the value of cross section F probability. Hereby, we found that even though the regression are conducted either by using model 1: $RET_{i,t} = \alpha + \beta_1 GT_{i,t} + \beta_3 LNVOL_{i,t} + \beta_3 PER_{i,t} + \beta_4 AGE_{i,t} + \beta_5 DP_{i,t} + \beta_6 DER_{i,t} + \beta_7 ROI_{i,t} + \varepsilon$ or model 2; $TV_{i,t} = \alpha + \beta_1 GT_{i,t} + \beta_2 LNP_{i,t} + \beta_3 PER_{i,t} + \beta_4 AGE_{i,t} + \beta_5 DP_{i,t} + \beta_6 DER_{i,t} + \beta_7 ROI_{i,t} + \varepsilon$, the Chow test output recommends to the use of Pooled least square model as the best model which can produce the most efficient output in hypotheses testing. Therefore, we did not have to continue with the process of model selection to the Hausman test.

Statistical output as shown in Table 2 contains of Chow test results from two models. We conducted the preliminary study by employing model 1 and model 2. Firstly, we show that the information regarding to cross section F Prob in model 1 and 2 have insignificant result at 5 % level of alpha. Therefore, we noted that the null hypothesis is supported and the alternative hypothesis, which supposes to use the fixed effect model, is unsupported. According to Baltagi (2005), the recommended model obtained from Chow test is obviously important, in which the developed model has accommodated the BLUE criteria, and the problems of classical assumption can be minimized. Thus, the output result which supports the corresponding null hypothesis must be stopped at this stage without continuing to the Hausman test. Despite having the recommended model, we might probably have heteroskedasticity problem. Given this circumstance, we decided to employ the pooled least square with EGLS model (Estimated Generalized Least Squared) and cross sectional weight in every hypothesis testing, either in using the controlling samples (small-cap, medium-cap, and large-cap) or consolidated samples with total number of observations as many as 5976.

EMPIRICAL RESULTS

We first processed the data in summary statistics by showing the mean value, maximum, minimum, standard deviation, and the number of observations from cross-sectional and time series data. Then, the samples were classified into three categories. It is necessary for neutralizing and cleaning the effects arising from the exogenous variables towards endogenous variables. As pointed out by Baltagi (2005), several groups are needed as to minimize the existence of bias when performing the statistical analysis. The summary statistics relating to the specific characteristics of samples are presented in Table 3, and are as follows.

TABLE 3. Summary statistics of Small-cap, Medium-cap, Large-cap and consolidated samples

PANEL A. Small-cap

	Variables								
	RET	GT	LNP	TV	PER	AGE	DP	DER	ROI
Mean	0.07	13.30	6.12	43.95	15.51	10.18	13.24	2.22	1.36
Max	0.39	100	10.84	123.77	344.16	21	944.99	38.79	18.62
Min	-1	0	0	-26.150	-445.79	0	0	0	-30.35
Stdv	1.16	25.31	1.42	25.96	67.43	5.55	80.65	3.89	7.20
Observation	1800	1800	1800	1800	1800	1800	1800	1800	1800
Cross sections	25	25	25	25	25	25	25	25	25

PANEL B. Medium-cap

	Variables								
	RET	GT	LNP	TV	PER	AGE	DP	DER	ROI
Mean	0.04	11.80	6.87	68.41	29.13	14.47	16.45	1.70	6.20
Max	0.11	100	11.96	142.884	1193.89	31	500.03	14.29	50.95
Min	-0.92	0	0	-15.905	-34.62	1	0	0	-66.73
Stdv	0.505	24.904	1.40	27.307	105.19	5.63	51.307	1.692	12.035
Observations	2375	2375	2375	2375	2375	2375	2375	2375	2375
Cross sections	33	33	33	33	33	33	33	33	33

PANEL C. Large-cap

	Variables								
	RET	GT	LNP	TV	PER	AGE	DP	DER	ROI
Mean	0.06	15.85	8.70	86.03	18.81	15.38	21.64	1.038	16.41
Max	0.11	100	13.51	196.636	204.32	30	213.02	8.44	62.16
Min	-0.92	0	5.85	-24.913	2.37	4	0	0.15	1.25
Stdv	0.63	25.67	1.38	28.898	20.89	5.15	33.04	0.93	11.13
Observations	1800	1800	1800	1800	1800	1800	1800	1800	1800
Cross sections	25	25	25	25	25	25	25	25	25

PANEL D. Consolidation Samples

	Variables								
	RET	GT	LNP	TV	PER	AGE	DP	DER	ROI
Mean	0.05	13.67	8.96	66.19	22.11	13.57	17.18	1.66	8.14
Maximum	0.39	100	13.51	196.6365	1193.89	31	944.99	38.79	62.16
Minimum	-1	0	0	-26.1504	-445.79	0	0	0	-66.73
Std. Dev.	0.80	25.34	1.60	31.73	77.02	6.06	57.99	2.48	12.55
Observations	5976	5976	5976	5976	5976	5976	5976	5976	5976
Cross sections	83	83	83	83	83	83	83	83	83

Table 3 illustrates the output of data processing in regard to the three controlling groups of samples. Panel A is the group of companies which are incorporated in small-cap with the number of cross-sectional samples as many as 25 companies. Panel B consists 33 medium-cap companies, and Panel C is the group of large-cap companies with 25 cross-sectional samples. We also present the additional information in Panel D, i.e. the total number of samples used in our study, 83 companies.

The three factors, Google Trend (GT), return (RET), and trading volume (TV), are proposed as proxies for investors' attention, firm performance, and liquidity, respectively. In this paper, we used several additional control variables as an effort to reduce the effects and purify the effect of main independent variable towards dependent variable. Specifically, every Panel of Table 3 presents the statistics of collected data in different basic information. We divided the samples into three categories based on their market capitalization as the firms' characteristics. As shown in Panel A, B, C and D, we performed the test by calculating the basic data related to mean, maximum, minimum, standard deviation, and data observation of variables. We also categorized the samples of 83 objects into small-cap, medium-cap, large-cap companies, and lastly reconsolidated the samples into pooled data.

As presented in Table 3, we noted that virtually all the firms' performance, measured by RET, showed positive trends, in which the small, medium and large-cap companies reported positive RET. It is clearly shown that all samples generated positive return for their investors. However, it is interesting when we specifically compared the average RET of three groups of sample. Our results reported that the small-cap has the highest return. This indicates that the small-cap companies tried to attract investors by promising the best return. It is believed that by investing a number of funds into small-cap companies will result in a high risk, but it is comparable in view that those companies can offer an equal return for the risks perceived by the investors. This finding is confirmed by the data relating to internet information retrieval. We found that the small-cap companies have been searched and realized by the investors, in which the GT of small-cap has high search inquiries (13.30) over the medium-cap companies (11.80) on average.

Moreover, we are focused on elaborating the descriptive results relating to trading volume (TV). The information with respect to TV in Panel C shows that large-cap companies dominate the TV (86.03) on average. The data are then followed by medium-cap (68.41); and subsequently, small-cap (43.59). Meanwhile, we also employed the controlling variables such as price, price earnings ratio, age, dividend payout ratio, dividend yield, debt-to-equity ratio, return on investment, and return on equity. The utilization of all these variables are to neutralize and purify the effects resulted by the interaction of main variables as proposed in the hypotheses development.

THE SENSITIVITY OF GOOGLE TREND TOWARDS RETURN (CASE OF SML SIZE)

We have previously presented three controlling samples. These samples are important in identifying and determining the preliminary results related to the proposed hypotheses. As can be observed in Table 4, we performed the panel data regression by employing three groups of samples. The specific results of preliminary samples in regard to return variation are presented as follows:

TABLE 4. Executive regression of panel data with Pooled Least Square model towards return (RET) in SML case

Variables	Small-cap (n=25) Observation (1800)		Medium-cap (n=33) Observation (2375)		Big-cap (n=25) Observation (1800)	
	B	t-Stat	B	t-Stat	β	t-Stat
C	-1.2068***	-12.9443	-0.3982***	-7.5952	-0.7622***	-9.1887
GT	-0.0001	-0.7059	-0.0004***	-2.9577	-0.0007***	-6.0120
LNVOL	0.0025*	1.6942	0.0126***	6.6492	0.0179***	8.0275
PER	-0.0002***	-5.1718	1.7009	0.0395	9.6699	0.0326
AGE	0.0081**	2.2148	0.0030	1.3352	-0.0210***	-5.3727
DP	4.2678	0.9703	0.0001**	1.9929	-4.3805	-0.1701
DER	-0.0014	-0.7770	-0.0111**	-2.4811	-0.0374***	-3.6704
ROI	-0.0058***	-3.8205	0.0016***	3.9946	-0.0036***	-4.0512
R-squared		0.1268		0.0635		0.1304
Adjusted R-squared		0.1100		0.0466		0.1136
F-statistic		7.5423		3.7651		7.7858
Prob(F-statistic)		0.0000		0.0000		0.0000
Durbin-Watson stat		2.0248		1.8481		2.0823

*** : Statistically significant at 1% alpha.
** : Statistically significant at 5% alpha.
* : Statistically significant at 10% alpha.

Description: The empirical examination was conducted by employing panel data analysis. We run the pooled least square EGLS model with cross sectional weight in the process of investigation the influences of every variable used. Our output indicates that the goodness of fit model in the proposed model, which is measured by using coefficient of determination (R^2), has relatively small value. The investigation on the small-cap companies shows R^2 number as 0.1268 or equal as 12.68 %. Meanwhile, medium-cap and big-cap show 0.0635 (6.35%) and 0.1304 (13.04 %), respectively.

Table 4 illustrates the estimation output related to the variation of return of indifferent groups of samples. Based on the output, we particularly concentrated to elaborate on the effect of Google Trend (GT) on return (RET). We noted that there are negative influences (p<0.01), as indicated by the coefficient regression of GT towards RET. Firstly, we found negative contribution collected from small-cap, medium-cap, and large-cap samples. Our results exhibited that the influence of GT towards RET in medium-cap and large-cap have negative and significant impact at 1 % level of alpha. On the other hand, even though the small-cap showed similar result, the output depicts that it does not significantly contribute to RET at the levels 1, 5, and 10 % of alpha.

The other contribution comes from controlling variables. We meticulously used seven additional independent variables to neutralize the compounding effect from each exogenous variable towards the endogenous variable. Firstly, we noted that the controlling variable is logarithm natural of shares traded every month (LNVOL). The LNVOL positively and significantly (p<0.01) contributes to RET. PER shows inconsistent and insignificant result within the groups of samples. Further, we noted that PER negatively (p<0.01) contributes to RET of small-cap companies. However, the coefficients of PER on medium-cap and large-cap are different from small-cap with positive signs. It is clearly seen that the increasing PER, in general, encourages the investors to put their money into medium and large-cap companies. AGE consistently exhibits a positive relationship with RET, in which the value of AGE is significant at 5 % alpha. However, we noted that it negatively (p<0.01) contributes to the large-cap companies. We also performed dividend payout ratio (DP) as the indicators of return gained by the investors. It was discovered that the influence of DP is insignificant towards small-cap and big-cap companies. Given this condition, this variable significantly contributes (p<0.05) to medium-cap companies. We further used DER as the indicator of risk faced by the investor. Here, we conjecture that high DER will result in low RET. Our finding is noticeably consistent with the concept of high risk high return, in which the signs of DER towards RET on the three groups of samples are clearly negative and significant (p<0.05). Lastly, we considered return on investment (ROI) as determinants of RET. We found that ROI as the representation of profitability ratios have inconsistent results. ROI negatively (p<0.01) contributes to RET in small-cap and large-cap companies. Otherwise, it is found that ROI is positively (p<0.01) related to RET in medium-cap companies. We presumed that this condition appears due to the motive of investment from investors. ROI is explicitly important basic information if investors are willing to invest their funds long-term. Reciprocally, this information is trivial for investors who want short-term profit.

THE SENSITIVITY OF GOOGLE TREND TOWARDS TRADING VOLUME (CASE OF SML SIZE)

After elaborating on the estimation results from statistical model 1 which are tested by employing pooled least square (EGLS model) with cross section weight, we continued with the second model which tested the similar pattern of independent variables. However, we focused on the relationship between GT and TV as can be seen in Table 5 as follows:

TABLE 5. Executive regression of panel data with Pooled Least Square model towards trading volume (TV) in SML case

Variables	Small Size (n=25) Observation (1800)		Medium Size (n=33) Observation (2375)		Big Size (n=25) Observation (1800)	
	B	t-Stat	B	t-Stat	B	t-Stat
C	27.9301***	14.2935	40.8832***	13.9071	8.7702***	3.4718
GT	0.0972***	5.4827	0.0534**	2.5199	0.0056	0.7657
LNP	4.4823***	14.2288	5.9552***	12.1573	8.2829***	30.01546
PER	-0.0029	-0.3972	0.0032	0.6393	0.0079	0.5486
AGE	-0.9000***	-14.3499	-1.3436***	-12.5831	0.3630***	3.0883
DP	-0.0386***	-8.3165	0.0148	1.1064	0.0343***	3.3967
DER	-2.1085***	-10.3577	3.2908***	9.9293	-1.7244***	-2.7124
ROI	1.0408***	7.0287	-0.1858***	-3.4482	-0.2024***	-2.9284
R-squared		0.2197		0.1323		0.8875
Adjusted R-squared		0.2157		0.1290		0.8854
F-statistic		56.000		40.0914		422.5022
Prob(F-statistic)		0.0000		0.0000		0.0000
Durbin-Watson stat		0.3597		0.2166		0.9372

*** : Statistically significant at 1% alpha.
** : Statistically significant at 5% alpha.
* : Statistically significant at 10% alpha.

Description: The above result was obtained by conducting the panel data regression with EGLS model. We note that the goodness of fit model, measured by using R^2 value, shows a high value. The coefficient of determination is 0.2197 or equal as 21.97 % for small-cap samples, 0.1323 or equal as 13.23 % for medium-cap, and 0.8875 or equal as 88.75 % for big-cap samples.

We further analyzed the estimation output relating to the examination of statistical model 2 of trading volume (TV) on small-cap, medium-cap, and large-cap companies. Our research reports that GT has positive ($p<0.01$) influence on TV. This is observable by identifying the value of GT towards TV on each group of samples. We strongly argued that high information retrieval by the internet users through Google affect the intensity of trading volume (TV). This finding is in line with the previous studies, which noted that the sequential incoming information into the market has an influence on the investors' preference in the process of making investment decision (Bank et al. 2011; Usman & Tandelilin 2014).

Moreover, the other variables were employed for the same reason as in statistical model 1. Thus, we used seven additional variables as the controlling variables in testing model 2. We also discovered various results from the output in Table 5. Specifically, logarithm natural of price (LNP) is primarily related to trading volume (TV). We found that LNP has positive and significant ($p<0.01$) contribution to TV. Price Earnings Ratio (PER) supports the result exhibited by LNP. We noted that PER is positively related to TV, but insignificant at 1, 5, or 10 %. The length establishment period of companies (AGE) in Indonesia stock exchange show a contrary result, in which we noted that AGE negatively ($p<0.01$) influences the TV of small-cap and medium-cap. Moreover, as expected DP also has an inconsistent contribution to TV. We noted that the variation of DP towards TV is presumably caused by the motive and several factors relating to investors' preference or investors' irrationality. Almost all investors want the highest dividend as compensation to their investments. However, in this case, we assumed that the investors incline to seek short-term profit. Therefore, they consciously ignore the fundamental information relating to dividend payout. Moreover, we discovered that the affect of DER on TV is negative ($p<0.01$) for small-cap companies and large-cap companies. The last controlling variable (ROI) also exhibits various signs, in which ROI negatively ($p<0.01$) affects the medium-cap and large-cap companies.

Further, we examined the effects of every independent variable in statistical model 1 by employing the consolidated samples, which comprises 5976 observations from 83 companies. The test with pooled data as can be seen in Table 6.

TABLE 6. Executive regression of panel data with pooled sample towards RET (consolidated samples)

Variables	Predicted signs	Coefficient	t-Statistic	Prob.
C		-0.2920***	-9.7442	0.0000
GT	+	-0.0002**	-1.9852	0.0472
LNVOL	+	0.0100***	9.0814	0.0000
PER	+	-2.1905	-0.7802	0.4353
AGE	+	-0.0008	-0.6540	0.5131
DP	+	2.6705	0.6457	0.5185
DER	-	-9.7606	-0.0103	0.9918
ROI	+	0.0008**	2.3755	0.0176
R-squared	0.0452			
Adjusted R-squared	0.0303			
S.E. of regression	10.7493			
F-statistic	3.0322			
Prob(F-statistic)	0.0000			
Durbin-Watson stat	1.9554			

*** : Statistically significant at 1% alpha.
** : Statistically significant at 5% alpha.

* : Statistically significant at 10% alpha.

Description: We run the Pooled least square with EGLS model and attached the cross sectional weight in order to anticipate the existence of bias in our estimation output. The number of exogenous variables used here consist ten variables. We focused on the interaction between the main independent, namely GT towards RET. In particular, we noted that the goodness of fit model in the statistical model 1 shows a slightly small value of R^2 as 0.0452 or equal as 4.52 %. It denotes that after pooling all data (5976 observations in which encompassed the combination from 83 companies and 72 monthly series data) into panel model regression, the ability of independent variables in explaining the variation happens in dependent variable is only 4.52 %. Meanwhile, the other contribution comes up from the error term, in which 95.48 % of variation is explained by the other factors which are not included in our statistical model.

Table 6 presents the output relating to the results of the first hypothesis testing. We noted that the output shows negative ($p<0.05$) relationships from GT to RET. Hence, this result is not in line with a priori expectation. We presumed that the sequential incoming information within the market is not evenly spread. Besides, the probability of time varying attention is highly suspected. With the long term period of observation from January 2007 to December 2010, there are many factors that could distort the investors' preference in making investment decisions. We already have identified several numbers of events ranging from the time period between 2007 and 2012. One of them is the Global financial crisis, triggered by the failure of America in managing its debt. Therefore, at that time, America proposed a number of action plans in anticipating the negative impact of nonperforming loan of subprime mortgages. Nonetheless, we conjecture that as an impact of global financial crisis, virtually all stock indices of Indonesia stock exchange have negative abnormal return. This problem is also sparked by a number of investors who presumably have a strong sentiment towards crisis. Given that, investors can collect either the news or information related to recent condition in Indonesian capital market sector easily. If we compare the output in Table 6, it is reasonable to say that the more information investors get, the more careful their decisions relating to portfolio investment will be.

The following finding further proves the argument relating to the negative effect of GT on RET. In particular, Table 7 contains the continuity of hypothesis testing in regard to the contribution of GT towards TV. We would like to investigate the cross relationship of return-volume relations. In the literature review, we previously conjectured that high investor attention will result in higher RET and TV. In order to confirm the first hypothesis, we had also tested the second hypothesis in which the output is depicted in Table 7 as follows:

TABLE 7. Executive regression of panel data with pooled sample towards TV (consolidated samples)

Variables	Predicted signs	Coefficient	t-Statistic	Prob.
C		3.2284***	2.7970	0.0052
GT	+	0.0395***	4.3727	0.0000
LNP	+	9.6843***	50.129	0.0000
PER	+	0.0105***	2.9234	0.0035
AGE	+	-0.2417***	-5.6048	0.0000
DP	+	0.0007	0.1003	0.9200
DER	-	-0.7978***	-5.1875	0.0000
ROI	+	0.1498***	5.4343	0.0000
R-squared	0.4726			
Adjusted R-squared	0.4718			
S.E. of regression	26.9285			
F-statistic	593.9166			
Prob(F-statistic)	0.0000			
Durbin-Watson stat	0.3380			

*** : Statistically significant at 1% alpha.
** : Statistically significant at 5% alpha.
* : Statistically significant at 10% alpha.

Description: The output in Table 7 presents a number of samples collected from 83 companies and 72 monthly time series data ranging from January 2007 to December 2012. We periodically identified the behavior of trading volume relating to firms performance in this time period of observation. Hence, we decided to use TV as the dependent variables in which suspected to be influenced by GT (p<0.01). Our result also indicates that the proposed model in the second hypothesis testing experiences better goodness of fit model than the first hypothesis in model 1. We noted that the ability of the second model in explaining the variation happens in dependent variable (TV) is around 0.4727 or equal as 47.26 %. Meanwhile, the remaining variation is explained by the other factors which are not included into the proposed model.

In pooled data testing, we found an interesting result in which the contribution of GT towards TV shows positive (p<0.01) and significant relationship. As previously explained in the literature review, GT is appropriate in explaining the variation happens in trading volume. The high frequencies of buying and selling certain stocks indicate that the stocks are favored by the investors. However, the basic purpose of the high trading volume is not only about the good performance of firms' liquidity, but it is also influenced by the sequential incoming information which directs the investors to take specific action. If we compare to the result between GT towards RET, we reciprocally confirmed that GT positively contribute to TV. We assumed that there is a relation between return and trading volume. Even though GT is unable to enhance the value of RET, the high frequency is supposedly boosted by the selling action. Therefore, the more investors selling their shares as the results of incoming information will not instantaneously lead to higher return. Otherwise, the investors will sell their shares at lower prices. It can be inferred that this situation is triggered by investors' irrationality and the incoming noise in stock market which distorts the investors' preference. Henceforth, TV increases as GT gets higher, as 0.0395 (p<0.01).

We particularly searched for several empirical results which report the negative contribution of GT to RET. Generally, the relationship between these two variables is positive. Nevertheless, the research conducted by Chen (2011) reported that from the 21 listed firms in Dutch Stock Exchange, 7 companies had consistently showed negative output even though the information retrieval regarding the firms had high percentage from time to time. He explained that many investors preferred to hold their shares even though the stock performs negatively. The supporting reason for this action is established with an assumption that they will acquire better return in the future.

DISCUSSION

This research investigated the importance of information retrieval on the internet as the determinant of return and trading volume in the Indonesia stock exchange. Besides, we also used ten additional control variables in order to purify the compounding effect results in the estimation process by using panel data with pooled least square (EGLS model) and cross sectional weight. Our results showed different output as compared to the previous a priori expectation, in which the stock return (RET) is negatively influenced by information retrieval over the internet (GT). Further, we confirmed the seminal researches which report that the high investors' attention reflected from search inquiries in internet positively contributes to trading volume (TV).

Looking at the finance literature, there is a growing acceptance among these scholars whereby stock prices are driven by two types of investors: noise traders and arbitrageurs. Joseph et al. (2011) pointed out that arbitrageurs trade based on the fundamentals and strive to bring prices in line with "true" value, in which this term is generally known as fundamentalist. Noise traders, on the other hand, trade on pseudo-signals, noise, and other popular models in altering demand, and consequently, price abound. Sumiyana (2007) studied the noise and sequential incoming information as a specific phenomenon of price behavior in Indonesia stock exchange. He reported that the decision to sell or buy a certain stock is relatively influenced by the information held by the investors. Moreover, Setiyono et al. (2013) noted that the trend of herding behavior clearly exists in emerging markets such as Indonesia.

Similar to previous studies, we conjecture that the negative contribution of GT to RET is suspected to be caused by the presence of noise. This happens when the sequential incoming information is not evenly spread to the market. Many investors assume that the incoming information, good or even bad news will affect their portfolio; thus, the actions taken by the other investors influence their preference and lead to irrational decision.

We do believe that besides the specific problems relating to noise or sequential incoming information, the problem with respect to Indonesia's economic calibration has particular impact towards the negative value of RET. We observed a long-term period of the monthly data which ranged from January 2007 to December 2012. It is observed that in the middle of 2009, almost all stock exchanges around the world experienced the negative impact of Global financial crisis, which also resulted in bad volatility of return in the Indonesia stock exchange. Therefore, the macro factors do somewhat be blamed in explaining the variation of return in Indonesia stock exchange.

Moreover, we discovered that GT has positive and significant impact on liquidity which is surrogated by trading volume (TV). As explained by Joseph et al. (2011) while certain trading in the market resulted in noise traders with different models who cancelled each other out, a substantial fraction of trading strategies are correlated, leading to aggregated demand shifts. As cited by Joseph et al. (2012) from Shleifer and Summers (1990), the reason for this is that the judgmental biases afflicting investors in information processing tend to be the same. For instance, subjects in psychological experiments incline to make the same mistake: i.e. they do not make random mistakes. In Indonesia, this tendency is famously known as herding behavior (Setiyono et al. 2013).

The increase of trading volume as the impact of higher information retrieval has a correlation on the decrease of return. As we have already documented in the previous explanation, we see that time affects the variation of trading volume and return in our results. Likewise in the results in the output and controlling groups, the main and controlling variables somehow showed different signs than a priori expectation. Given this condition, we showed that the motive of investor will influence the firms' performances. As noted by Chordia et al. (2007) we do believe that investors who have long-term investment will not be directly distorted by the incoming information in market. Besides, the short-term traders influenced the market and result in the herding activity which is triggered by the other traders. Thus far, we admittedly note that our results cannot fully confirm and triangulate the previous study. Nevertheless, our results contribute to the burgeoning number of literature which focuses on the phenomenon of asymmetric information, return and liquidity in emerging economies.

CONCLUSION

Our study is related to the burgeoning number of similar research conducted in the area of emerging stock market. We pointed out that even though the increase in the number of information retrieval over the internet is relatively high, it does not instantaneously increase stock return. The empirical reasons for this circumstance have been reported by several studies (e.g. Joseph et al. 2011; Chen et al. 2011; Setiyono et al. 2011). Given this circumstance, we conjecture that time varying attention, Indonesia's economic calibration, the existence of noise, and asymmetric attention caused by herding behavior are presumed to be the suspected factors that distort the investor's preference in deciding to invest their funds in capital market. Further, we document that the influence of Google Trend (GT) is positively significant to Trading Volume (TV) in the Indonesia Stock Exchange (IDX).

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Ridwan Nurazi
Faculty of Economics and Business
University of Bengkulu
Jln WR Supratman, Kandang Limun
Bengkulu 38371, INDONESIA.
E-Mail: ridwan_nurazi@yahoo.co.id

Paulus Sulluk Kananlua
Faculty of Economics and Business
University of Bengkulu
Jln WR Supratman, Kandang Limun
Bengkulu 38371, INDONESIA.
E-Mail: paulus_kananlua@yahoo.com

Berto Usman (corresponding author)
Faculty of Economics and Business
University of Bengkulu
Jln WR Supratman, Kandang Limun
Bengkulu 38371, INDONESIA.
E-Mail: berto_usman@yahoo.co.id