Google Search Volume And Investors' Decision On Return And Liquidity In Indonesia

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Abstract

This research investigates whether investors' attention measured by Google Search Volume, has any impact over the stock 's return and liquidity. The Fama French three factor model is used to test the relationship between investors'attention and the stock 's return. This research found that Google Search Volume primarily captures the attention of investors, resulting in a short-term buying pressure that creates a higher return. In conclusion, an increase in Google Search Volume fails to reduce information asymmetry that leads to an increase in liquidity.

Keywords: Google, Search, Volume, Stock, Return.

El volumen de búsquedas de Google y la decisión de los inversores sobre el retorno y la liquidez en Indonesia

Resumen

Esta investigación si la atención de los inversores medida por el volumen de búsqueda de Google tiene algún impacto sobre el rendimiento y la liquidez de las acciones. El modelo de tres factores de Fama French se utiliza para probar la relación entre la atención de los inversores y el rendimiento de las acciones. Esta investigación descubrió que el volumen de búsqueda de Google capta principalmente la atención de los inversores, lo que genera una presión de compra a corto plazo que genera un mayor rendimiento. En conclusión, un aumento en el volumen de búsqueda de Google no logra reducir la asimetría de la información que conduce a un aumento de la liquidez.

Palabras clave: volumen de búsquedas de Google, retorno de acciones.

1. INTRODUCTION

Investors' attention has been extensively studied in hope of predicting the stock market movement despite the absence of direct measures. To compensate for the missing variable of measurement, the researcher had come up with several indirect proxies. Such as; price limits, media or news coverage (Fang and Peress, 2009), extreme returns (Barber and Odean, 2007), and many more. I hope to find the most accurate representation of investors' attention, the researcher keeps coming out with new proxies. And one of the most novel attempts is by using the aggregate search frequency in Google. The attempt is possible with the advancement of technology that drives us toward the digital era and changes the way investors behave. Internet nowadays has become an essential research tool, and it is particularly evident in Indonesia, which based on the Internet World Stats survey, placed 5th on Top 20 Countries with the Highest Number of Internet Users, with a total of 50.04% users across the country.

The Internet provides us a way to obtain desired information from various sources, and the most common one is through the search engine. Search is a revealed attention measure: if you search for a stock in a search engine, you are undoubtedly paying attention to it. Therefore, aggregate search frequency in that search engine is a direct and unambiguous measure of attention. There is a lot of evidence that investors exhibit a home bias, a behavior when an investor is tending to favor investments in firms that are familiar to them either because of geographic proximity or some other feature (Grullon et al., 2004). And in order to get familiar with a firm, investors need to acquire relevant information about the firms, which means, individual investors who are unable to access professional information vendors or applications might rely solely on public search engines. There are several available search engines in Indonesia, but a survey from the GlobalStats Counter shows that Google holds the main market share with 97.81%, which means that Google Trend, a public Search Volume Index (SVI) data provider, is the most reliable source to measure Indonesian investors' attention.

Fama & French three-factor model is selected because it has the ability to provide a better explanation of the variation in the stocks rate of return over CAPM, and also has a superior power to predict the portfolio rates of return over the single factor model (Almwalla et al., 2011). The model usage in Indonesia is supported by a research on the firms listed in Indonesia Stock Exchange 2000-2004 period Hardianto et al. (2009) and Jakarta Islamic Index 2007-2009 period (Dewi et al., 2011); with both results show that Fama & French three-factor model is applicable in the Indonesian stock market along with syariah market. While the relation between investors' attention and liquidity will be examined using Dynamic Panel and Generalized Method of Moments approach. In order to ensure the certainty of the phenomenon appears in the result, research will be conducted in two frequencies: the weekly and monthly frequency data. All the data for the firms being used in the research will be taken from The Indonesia Capital Market Institute (TICMI), while the Google Search Volume data will be obtained from the official Google Trends website, and the risk-free rate will be taken from Bank Indonesia official website.

Therefore the purpose of this research will examine the impact of investors' attention to stock return, examine the impact of investors' attention to liquidity, and it also presents an alternative direct measure to predict the stock market movement. Even the usage of wide frequency in the form of monthly trading data and Google Search Volume with 10 years timeframe, calls for inactive or delisting stocks that will be omitted from this research. The Google Trends only provides search volume data from 2004, the year the data provider was launched. It also has several limitations, with the weekly frequency only available on a maximum of 5 years. The data will be automatically served in monthly frequency upon the request of a larger range. In consideration of the data availability, the writer of this study will use several time frequencies to study the effect of investors' attention over return and liquidity.

2. LITERATURE

The operation of the human brain is described by psychologists as similar to a single-processor-computer. It deals with multiple tasks by working on one task at a time, alternating between tasks to response, to inputs in a timely fashion. The efficiency rate for each task depends on the processing time the computer allocates to the task (Peng et al., 2006). Therefore, this basic concept shows that investors' attention is limited. The relation between the vast amount of available information and limited investors' attention makes attention an important factor in the decision-making process. Barber and Odean (2007), stated that in order to manage the problem of choosing a stock to purchase from hundreds of stocks, investors limit their search to stocks that have recently caught their attention. It is true that investors do not buy all the attention-grabbing stocks, but most of the time they buy the one that does so. The link between investors' attention and stock trend prediction itself is not merely an assumption, it has been proven by several types of research. Which conclude in two sides of viewing the relationship between investors' attention and stock return.

A study by Fang and Peress (2009) about the cross-sectional relation between media coverage and stock returns show a stable negative relationship. Stocks with no media coverage earn significantly higher future returns and outperform the ones with media coverage. The return difference is particularly large among small stocks with low analyst coverage, stocks primarily owned by individuals, and stocks with high idiosyncratic volatility. The result is backed by two theories. The first one is the impediments to trade hypothesis that explains if the media effect represents an arbitrage opportunity, it can only persist if large impediments prevent rational agents from trading on it. Alternatively, the return differential may not reflect mispricing but fair compensation for risks not captured by standard factors (Fang and Peress, 2009; Goli et al., 2014). The second theory is the investor recognition hypothesis by Merton (1987) that argues, in a market with incomplete information, stocks with low investor attention provide higher returns in order to compensate investors for the unsystematic risk that cannot be diversified. Assuming that Google search volume is the proxy for investors' attention and that the stock market is characterized by incomplete information, negative interdependence in the long run between search volume and future returns is expected.

On the other side, Barber and Odean (2007) argue that investors' attention and return have a positive relationship. They propose that attention influence buying pressure of uninformed investors in the short-run. Their reasoning is that investors can choose from a large set of stocks when buying, but only have a limited choice when selling assets. Therefore, particularly for individual and mostly uninformed investors, the attention attracted by a stock should affect buying more than selling. An increase in the attention consequently may induce a positive effect on the short-term future return and price reversals in the long run.

Important news about firms also often results in significant positive or negative returns. When there is a big price move, it is likely that whatever caused the move also caught investors' attention. And even when the price is responding to private, not public information, significant returns will often attract attention (Barber and Odean, 2007). And the most novel proxy was suggested by Da in the form of Google search volume data. In the efficient market, all the available information is reflected in the price, making it impossible for investors to predict the trend. But with the help of internet search queries data from Google Trends, the prediction might be possible, because Google Trends provides investors with real-time data that varies from daily, weekly, and monthly. And the data provided is bigger and more accurate than the classic data source used by investors, the monthly government data releases. While other proxies such as the news from media, stock return, or unusual trading volume could not assure attention from investors, Google search volume able to do so. It is because, it only measures the number of search from the internet portal—Google, ensuring attention. Because investors will do the act of search only if they are having interest and want to pay attention to a particular stock.

Meanwhile, Liquidity is an elusive concept. It is not observed directly but rather has a number of aspects that cannot be captured in a single measure (Amihud and Mendelson, 1991). Aside from that, a lot of sources define liquidity as the ability to trade large quantities quickly, at low cost, and without moving the price of the stock. In recent years, the recognition of liquidity as a desirable characteristic of a stock is increasing. High liquidity risk will lower the price and increase the required return of a security. Thus, creating a good reason for investors to consider liquidity in designing their portfolio strategies (Cooper et al., 1985). Kyle (1985) mentions three elements of liquidity, they are: Tightness refers to the cost of turning over a position in a short period of time. It is measured by the bid-ask spread of assets. Depth refers to the ability of the markets to absorb quantities without having a large effect on price. It is measured with the size of the transaction required to change the price of an asset. Resiliency refers to the speed of the prices to return to their equilibrium after a shock in the market, while the degree of liquidity of a security depends on the nature and extent of both supply and demand. The most liquid securities are likely to be the shares of large corporations, the ownership of which is broadly dispersed.

The concept of investors' recognition itself was first proposed by Merton (1987), he noted that a potential investor must at least know of a firm before deciding whether to purchase a stock or even on whether to acquire additional information. The investors' recognition hypothesis also supported the notation that investors' attention may be relevant for stock pricing and liquidity. The theory then provoked several types of research with matching results. Using the Amihud (2002) illiquidity ratio and Google search volume as the proxy of investors' attention, Bank et al. (2010) conducted a research to find the relation between liquidity and investors' attention. The research resulted in investors' attention (Google search volume) to be positively related to illiquidity. The test also conducted once again with alternative illiquidity measures such as the turnover price impact, the role impact variable, and the relative bid-ask spread. Which, also appear to have similar results, indicating that a stock's liquidity improves with an increased internet search volume.

Bank et al (2010) also discussed the standard market microstructure theory that proposes three sources of illiquidity: explicit trading costs such as fees or taxes, asymmetric information, or inventory risk of market makers. Given the negative relationship between illiquidity and Google search volume (investors' attention), the search volume must be related to one of the three sources of illiquidity. Bank suggests the relationship between search volume and asymmetric information. They believe that the increase in liquidity and trading volume are the results of the reduction in the asymmetric information costs, with the Internet as one of the main causes of reduction. Not only that, but Bank et al. (2010) also found that the effect of Google Search Volume over liquidity appears to be particularly strong for smaller capitalized stocks. Since stocks with higher liquidity usually are stocks from large firms that will be bought anyway without any additional attention towards them. The research is also repeated by Ding and Hou (2015) with S&P 500 stocks that again, show the increase in investors' attention leads to a reduced relative bid-ask spread and a higher turnover rate. Both of the researches are using the Google search volume as investors' attention proxy. Another research with a different proxy (product market advertising) was conducted by (Grullon et al., 2004). Their research results indicated that firms that spend more on advertising to attract investors' attention have a larger number of both individual and institutional investors. They also found that advertising has a stronger effect on individuals than institutions.

The result suggests that advertising helps to attract a disproportionate number of investors who at least in part, make their investment decisions based on familiarity rather than on more fundamental information. Because the investors that are attracted to a firm by such advertising are likely to be uninformed. Thus, it is safe to expect that greater advertising by a firm will decrease the adverse selection costs that thereby will improve market liquidity. Although various researches show a positive relationship between investors' attention and stock liquidity, we must keep in mind that the use of proxies to measure investors' attention might not be 100% accurate. The internet search volume of a firm's name or stock ticker symbol may be considered a broad and probably noisy measure of attention. The measurement errors are possible. Fang and Peress (2009) research resulted in a negative relationship between investors' attention with stock return. That is further backed by Merton (1987) and the impediment to trade theory. But, the usage of the daily newspaper as investors' attention proxy by Fang and Peress (2009) is questionable.

Whereas, Bank et al. (2010) that find a positive relationship between investors' attention and stock return use more reliable proxies. Both of their research with Google Search Volume as investors' attention proxy, found a positive relation between GSV and stock's return. They also stated that the condition only lasts for a short amount of time, and even tend to turn around with underperformance later on. Previous researches of the relationship between investors' attention and liquidity use several investors' attention proxies, such as Google search volume (Bank et al., 2010), (Ding and Hou, 2015), also advertising expenditures (Grullon et al., 2004). Although there are variations in the usage of proxies, the research generates matching results, which is significant and positively related. Not only that, but

Bank et al. (2010) also found that the influence is apparently larger to smaller size firms than larger firms.

3. METHODOLOGY

The sample being used in this research is consist of firms that are listed in Indonesia Stock Exchange (IDX) from 2006 to 2016. The data is divided into two categories: The weekly data frequency and the monthly data frequency. Due to the limitation of each research methodology, the data being used by both return and liquidity research method is a bit different.

Table 1. Sample of the Data

Method	Frequency	Total Firms	Period
Fama French	Weekly	359	July, 2011 - June 2016
	Monthly	359	July, 2006 - June, 2016
Dynamic Panel	Weekly	249	July, 2012 - June, 2015
	Monthly	304	July, 2006 - June, 2016

Source: Google Search Volume

All the weekly and monthly stocks data including the closing price, volume, outstanding shares, bid price, and offer price were obtained from The Indonesia Capital Market Institute (TICMI). While the risk-free rate is used in this research were obtained from the BI Rate provided by Bank Indonesia. The proxy for investors' attention in the form of the Google Search Volume is provided by Google Trends. Google Trends itself is a free platform that allows the user to compare the popularity of search terms or trends. It provides users a way to find out the hottest or developing trends on the internet. But, it is important to understand that the search volume provided by Google Trends for a specific keyword, is not the real total number of searches. In fact, it is the total number of queries that the user enters into Google in a specific area/region. The query index is obtained by normalization through dividing the total query volume of a search term in a specific region with the total number of queries in that region during the time period being examined (Choi & Varian, 2012). The scale of the search result started with a minimum of 0 and a maximum of 100.

Google defines that the data provided by Google Trends is normalized to makes data comparison easier and more accurate. Without normalization, regions with the most search volume would always rank the highest in the total search. While Da used the stock 's ticker symbol, this research uses ordinary firm names as the keyword to obtain Google Search Volume variable. The writer of this research believes that this method will cover a broader scope, that will increase the possibility to capture a potentially relevant audience. The usage of stock ticker symbols as keywords is also avoided to minimizes the possible noise created by similar non-related popular words. A little note to be taken, the firm names are sometimes adjusted to public recognition. The keywords are not solely the firm names, it sometimes needed to be adjusted into more public-friendly names. Because a lot of official listed firm names are different from the names that the public recognition. Further action that needs to be taken to ensure the accuracy of Google Search Volume data was to set up several filters. Google Trends allows users to filter the search data based on region and specific timeframe. To calculate the impact of investors' attention to return, this research uses the model constructed by Fama & French three-factor model. Fama French three-factor model once was formed to test CAPM. The study conducted by Eugene Fama & French (1993) found that there are factors other than the beta that can affect stock returns. They stated that firm size and the market to book ratio appears to also affect the value of average stock return across sectors. The three-factor model introduced by Fama and French stated that return is determined by the market risk premium, size, and book-to-market value. The model is as follows:

$Return_{p,t} – R_f = a + b1\ (R_m-R_f)_t + b2\ (SMB)_t + b3\ (HML)_t + \varepsilon_{p,t}$ .....

The weekly frequency consists of 359 companies with 5 years (July 2011- June 2016) timeframe. While the higher frequency has a very thin to none available search result. Due to the odd search volume, the distribution of the weekly frequency portfolio will be constructed from these requirements:

Portfolio 1 Firms with lowest intensity of search volume data (0-7)

Portfolio 2 Firms with low intensity of search volume data (8-14)

Portfolio 3 Firms with mid-low intensity of search volume data (15-21)

Portfolio 4 Firms with mid-high intensity of search volume data (22-28)

Portfolio 5 Firms with high intensity search volume data (29-35)

Portfolio 6 Firms with highest intensity search volume data

(36-100)

Thus, resulting in the total firms of each portfolio in every year of;

Table 2. Firms in each portfolio sorted by weekly frequency GSV

	PORT1	**PORT2**	**PORT3**	**PORT4**	**PORT5**	**PORT6**
YEAR 1	46	39	63	75	40	96
YEAR 2	44	48	90	63	47	67
YEAR 3	60	95	86	49	29	40
YEAR 4	65	105	80	50	25	34
YEAR 5	77	110	74	46	22	30

While the monthly Google Search distribution for 10 years (July 2006-June 2016) that consists of 359 companies. Based on the search frequency distributions for 10 years, this research will construct the monthly frequency portfolio from these requirements:

Portfolio 1 Firms with lowest intensity of search volume data (0-2)

Portfolio 2 Firms with low intensity of search volume data (3-6)

Portfolio 3 Firms with high intensity of search volume data (7-15)

Portfolio 4 Firms with highest intensity of search volume data (16-100)

Thus, resulting in total firms of each portfolio in every year of;

Table 3. Firms in each portfolio sorted by monthly GSV

	PORT1	**PORT2**	**PORT3**	**PORT4**
YEAR 1	120	33	87	121
YEAR 2	87	51	121	102
YEAR 3	84	80	111	86

YEAR 4		73	101	117		70
YEAR 5		86	108	104		63
YEAR 6	104		124		84	49
YEAR 7	108		125		72	56
YEAR 8	142		116		55	48
YEAR 9	145		114		55	47
YEAR 10	161		100		50	50

The weekly return of each firms will be calculated and combined with other firms in the same portfolio to find the average return for each week in 5 years. The weekly return will calculated:

$$\text{Return}_{i,t} = \frac{(\text{closing price}i{,}t - \text{closing price}i{,}t-1)}{\text{closing price}i{,}t}$$

....

....

Where closing price i,t is the closing price of stock i on day t, and day t-1 is the trading day before day t. While the monthly return is calculated by summing up all the weekly return in a month. All the monthly return of the firms will also be calculated and combined to find the average return of the portfolio for each month in 10 years. The average return of each portfolio then will be subtracted by the risk-free rate to create a time series of the dependent variable. The model itself consists of three independent variables: The market factor is the market risk premium that is calculated from the difference between the return of the market with the return of the risk-free asset

$$R_{m,t} - Rf = \frac{Mt - Mt-1}{Mt-1} - Rf$$

....

Eq. (3)

Where $R_{m,t}$ is the market return in the month t, M_t is the market price in month t, M_{t-1} is the market price in month t-1, and R_f is the risk-free rate. Small minus big is the difference each month between simple average of the average returns on the three small portfolios (S/L, S/M, S/H) and the simple average returns on the three big portfolios (B/L, B/M, B/H) on the year of t to t+1. At the end of June of each year t, all stocks are ranked based on market capitalization. $SMB = (S/L+S/M+S/H)/3 – (B/L+B/M+B/H)/3$

High minus low is the difference between average return of two value portfolios (high book t market value) and average return on two growth portfolios (low book to market value).

$HML = (S/H+B/H)/2 – (S/L+B/L)/2$ ....

The model being used in this research is constructed using several control variables affecting the liquidity, with the independent variable of investors' attention in the form of

Google Search Volume (GSV). Both the weekly and monthly illiquidity model is as follows;

$ILLIQ_{i,t} = c + b_1 ILLIQ_{i,t-1} + b_2 GSV_{i,t-1} + b_3 lnMV_{i,t-1} + b_4 RET_{i,t-1} + b_5 STDV_{i,t-1} + b_6 Trading\ activity_{i,t-1} + b_7 GSV_{i,t-1} \times lnMV_{i,t-1} + c_i + \mu_i + u_{i,t}$ ....

The dependent variable, ILLIQ, is obtained through two illiquidity measurements to confirm the robustness of the results.

The first model is the Amihud (2002) Illiquidity measurement which is the daily ratio of absolute stock return to its dollar volume, averaged over some period.

The weekly:

$$ILLIQ = \frac{wRi}{wVOL} \times \frac{1}{\text{Number of observations in the week}}$$

The monthly formula:

Where, wRi is the absolute weekly return of stock i, mRi is the absolute monthly return of stock WVOL is the weekly stock volume, and MVOL is the monthly stock volume.

The second model is the bid-ask spread measurement method. Both the weekly and monthly Bid-ask model is as follows;

Bidaski,t = c + b1Bidaski,t-1 + b2GSVi,t-1 + b3lnMVi,t-1 + b4RETi,t-1 + b5STDVi,t-1 + b6Trading activityi,t-1 + b7GSVi,t-1 × lnMVi,t-1 + ci + µi + ui,t ....

The bid-ask spread is estimated by subtracting the bid price from the corresponding ask price, and dividing the result by the mid-price of stock at the end of trading day.

The weekly: The monthly:

$$S\_REL = \frac{PA - PB}{\left(\frac{PA+PB}{2}\right)} \qquad S\_REL = \frac{mPA - mPB}{\left(\frac{mPA+mPB}{2}\right)}$$

…Eq. (9) (10)

Where PA is the corresponding ask price and PB is the bid price. While mPA and mPB are the average ask price and average bid price in a month.

The two independent variables of main interest from the liquidity model are GSVi,t-1 and GSVi,t-1 × lnMVi,t-1, which allows us to control for the influence of a stock's search volume conditional on its market capitalization. The coefficient signs on both variables are expected to be opposing each other since the impact of illiquidity is weaker for larger firms (Bank et al., 2010). The GSV will be obtained from the Google Trends website without additional process, while the the natural logarithm of market capitalization will be calculated as follows:

lnMV = outstanding shares × current share price ……………

The weekly return will be calculated with similar model to the Fama & French three factor model. While the monthly return is obtained through the sum of all the weekly return. The standard deviation for both weekly and monthly returns (STDVi,t-1) will be calculated as follows:

$$s = \sqrt{\frac{\sum (x - \bar{x})^2}{n - 1}}$$

………………………………

With x as the returns of each period, x represents the mean returns. Another variable is the trading volume TVi,t-1 which is represented in the model by the Trading activityi,t-1. It is calculated as follows:

Trading Activity = Volume/Outstanding Shares …..

A one-month lagged of the dependent variable is also included as ILLIQi,t-1 to account for a dynamic relationship in a stock 's liquidity. All the independent and control variables are one-month lagged to account for a possibly endogenous interdependence between stock's illiquidity and its trading activity, Google Search Volume, or other control variables. In order to avoid bias and inconsistent estimation by the usage of a fixed-effect or random-effect approach, the dynamic panel regression with Generalized Method of Moments

(GMM) approach will be used instead for the illiquidity model. The usage of a dynamic panel model supported by the ability of the model to first differencing to remove unobserved heterogeneity. The model also contains one or more lagged dependent variables, allowing for the modeling of a partial adjustment mechanism. While the Generalized Method of Moments (GMM) approach was chosen to construct a more efficient estimation of the dynamic panel data model.

4. RESULTS AND ANALYSIS

There are 261 observations from 5 years timeframe (2011-2016) that are constructed with 359 firms. Judging by the mean return provided in table 4, the performance of all portfolios are quite bad with the negative mean return. While the standard deviation of all portfolios is larger than the mean return, indicating a more spread-out data.

Table 4. Descriptive Statistics of Weekly Fama French Research Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
PORT1Rf	261	-0.0612472	0.024658	-0.1173785	0.0801956
PORT2Rf	261	-0.0632402	0.0240652	-0.1528453	0.0313496
PORT3Rf	261	-0.064495	0.0224267	-0.1589872	0.0055575
PORT4Rf	261	-0.0628462	0.0261535	-0.1477367	0.077917
PORT5Rf	261	-0.0629906	0.028977	-0.1852271	0.0312015
PORT6Rf	261	-0.062055	0.0270726	-0.1685792	0.0238777
RmRf	261	-0.0640275	0.0275209	-0.1681412	0.0136413
SMB	261	0.005475	0.02203	-0.077846	0.1037987
HML	261	-0.0025811	0.0238567	-0.1118502	0.1606513

The biggest maximum return from all 6 portfolios come from the portfolio with the lowest intensity of search volume data (PORT1). While the lowest minimum return from all 6 portfolios come from a portfolio with high intensity of search volume data (PORT5). The founding, in a way, supports the theory that stocks return is negatively affected by investors' attention. The market factor or the market risk premium is calculated from the difference between the return of the market with the return of the risk-free rate. Table 4.1 shows the average market risk premium of -6.4% with the maximum value ranging from 1.36% to the minimum value of -16.81%. While the standard deviation shows the dispersion of market factor for 2.75%. The size of firms is represented by SMB, with an average value of 0.55% and a standard deviation of 2.2%. While HML represents the ratio of stocks' market value with their book value. The variable average value is -0.25% and the standard deviation is 2.2%. At 120 observations from 10 years timeframe (2006-2016) that is constructed with 359 firms. Different from the portfolios constructed by the weekly frequency of Google (Lin & Chen, 2018).

Search Volume, all 4 portfolios constructed by the monthly frequency of Google Search Volume appears to be quite good with a positive mean. While the standard deviation of all portfolios is larger than the mean return, indicating a more spread- out data. The biggest maximum return from all 4 portfolios come from the portfolio with the highest intensity of search volume data (PORT4). While the lowest minimum return from all 4 portfolios come from a portfolio with the lowest intensity of search volume data (PORT1), contradicting the result of portfolios constructed by weekly Google

Search Volume data.

Table 5. Descriptive Statistics of Monthly Fama French Research Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
PORT1Rf	120	0.0109801	0.0535144	-0.1784681	0.1494726
PORT2Rf	120	0.0116579	0.0579146	-0.2082076	0.214081
PORT3Rf	120	0.0108862	0.0637216	-0.2672175	0.1651678
PORT4Rf	120	0.0114106	0.0638138	-0.3092152	0.2173594
RmRf	120	0.0063902	0.0627669	-0.321716	0.194434
SMB	120	0.0120097	0.1056819	-0.9195508	0.3730317
HML	120	-0.0107056	0.0751627	-0.2052811	0.2877264

Table 5 shows the average market risk premium of 0.4% with the maximum value ranging from 19.4% to the minimum value of -32.17%. While the standard deviation shows the dispersion of market factor for 6.27%. SMB average value is 0.55% with a standard deviation of 2.2%. While HML average value is -0.25% with a standard deviation of 2.2%. The Fama & French three-factor model with monthly frequency will follow as table 5. The Dynamic Panel with weekly frequency will show table 6 as follow:

Table 6. Descriptive Statistics of Weekly Dynamic Panel Research Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
ILLIQ	36,153	4.82E-06	0.0000484	0	0.0028889
Bidask	36,153	0.0100597	0.0246759	-0.4	0.3315508
GSV	36,153	22.41056	19.63636	0	100
Return	36,153	0.0013662	0.0787459	0.9540881	9.1

Stdev	36,153	0.2243352	0.2500839	0	4.093582
lnMV	36,153	28.75727	1.912791	24.28998	34.71649
lnMVXGSV	36,153	653.7808	581.0482	0	3336.437
TradingActivity	36,153	0.0018541	0.007737	6.13E-09	0.5545547

The weekly frequency of illiquidity model was created from 249 companies with 3 years timeframe (2012-2015), and the total of 36,153 observations. The two dependent variables are the ILLIQ and bidask, that was alternately tested. The ILLIQ variable stands for Amihud Illiquidity model. With as low as 0.0048% of standard deviation, it shows that there is just a little discrepancy between the lowest and highest value. Bidask represents the illiquidity measurement using the Bid-ask spread method. Acting as an alternative illiquidity measure, Bidask ensures the robustness of the result. The variable itself has a standard deviation of 2.46% and an average value of -1%. There are 5 control variables in the model including; return, stdev, lnMV, trading activity, and last but not least, the lag-1 of the dependent variable (either lag-1 ILLIQ or lag-1 bidask, depending on which currently being tested). And two independent variables; The GSV (Google Search Volume) with 22.4 as the average value of all 249 firms out of 100, falling on the lower criteria of search intensity.

The minimum value itself of 0, appears more often in the observations than the maximum value. Dominating the appearance by appearing in 11,270 observations out of 36,153 total observations, nearly 1/3 of total observations! While the maximum value of 100 only appears in 62 observations out of 36,153 total observations. The second independent variable, lnMVXGSV which supposes to represent the influence of market capitalization to GSV appears with the average value of 653 thousand and a standard deviation of 581 thousand. The lower standard deviation shows that the data are more centered around the mean. Although GSV does not show the real value of search (but instead only showing the query that has been processed), we can conclude that the act of searching firms' names to find firms data using internet does not happen very often. There are several reasons that support the possibility. First of all, the majority of heavy internet users are millennials, while the stocks investment field is mostly crowded by middle-aged investors with steady income that could support their investing activities. Therefore, it is possible that the different generation still prefers old school information sources, or they simply do not bother to use the internet because of the lack of comprehension to do so.

Secondly, looking through the search intensity data of all individual firms, we could see that firms that appear to be searched on google are huge firms in Indonesia, such as; H. M. Sampoerna (HMSP), Astra Agro Lestari (AALI), Sinarmas Multiartha (SMMA), Holcim Indonesia (SMCB), etc. While the smaller firms are only occasionally being searched on when a huge event happen. Resulting in a compilation of a lot of zeroes in the search intensity data, because the majority of people only concentrated in a few huge firms. The average value of return is 0.14%, with a standard deviation of 7.87%. The maximum return is 9.1% that came from SIPD in the week of February 6, 2015, with the difference of 500 from the previous closing price. The standard deviation of return average value is

22.43% with the minimum value of 0. The value of 0 is possible because the weekly standard deviation is obtained through the daily trading data. And sometimes, several firms are being inactive throughout the week which results in 0 return for the whole week or even months.

The natural logarithm of market capitalization has an average value of 28.75 and standard deviation of 1.91. While the merging of market capitalization and Google Search Volume variable shows a lower standard deviation than the average value, meaning that the majority of the data are clustered toward the mean. Last, the trading activity average value is 0.185% with the standard deviation of 0.77%, meaning that the discrepancy of the highest and lowest value is quite big. The monthly frequency of illiquidity model was created from 304 companies with 10 years timeframe (2006-2016), and the total of 28,195 observations. Thus , the Dynamic Panel with monthly frequency;

Table 7. Descriptive Statistics of Monthly Dynamic Panel Research Variables

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
ILLIQ	28,195	2.99E-07	3.10E-06	0	0.0002499
BidAsk	28,195	0.0135933	0.2259434	-1.999999	1.860022
GSV	28,195	10.20294	14.63587	0	100
Return	28,195	0.0174213	0.1833697	-1.33207	9.110099
Stdev	28,195	0.2317965	0.2219483	0	6.26878
lnMV	28,158	28.272	1.993046	22.43163	33.8001
lnMVxGSV	28,158	293.5652	425.3118	0	3151.464
TradingActivity	28,158	0.0085151	0.0307014	6.13E-09	1.279363

ILLIQ as the dependent variable shows an average value as low as 0.0000299%, and a standard deviation of 0.00031%. While bidask, as another dependent variable shows an average value of 1.359% and standard deviation of 22.59%. The Google Search Volume (GSV) variable average value is lower than the weekly frequency with 10.2 and a standard deviation of 14.63. Similar with weekly frequency, minimum value with 0 search intensity appears more often than the maximum value of 100. The minimum value of 0 appears in 6728 observations out of 28,195 total observations. While the maximum value of 100 appears in 58 observations out of 28,195 total observations. The percentage of the appearance of 0 search intensity is actually lower in the monthly frequency with 23.86%. While the weekly frequency holds a 31.17% portion out of total observations. This prove earlier observation that the search process mostly triggered by a certain event, not equally distributed all the time. A firm might get zero or low search intensity on the first or second week, but suddenly get so many internet searches by the end of the month because of a certain event. Which resulted in a positive result of search intensity instead of zero for monthly frequency, but not for the weekly frequency.

The average value of return is 1.74% with a standard deviation of 18.33%. While the natural logarithm of market capitalization average value is 28.272 and the standard deviation is 1.99. The standard deviation of the market capitalization and google search volume merger is higher than the average value with 425.3118 while the average value itself is 293.5652. The last variable, trading activity, has an average value of 0.85% and a standard deviation of 0.03%. In order to test the heteroskedasticity problem in Fama French model, the ARCH (Autoregressive Conditional Heteroskedasticity) test will be used. The hypothesis for ARCH test is:

H0 = There is no heteroskedasticity problem

H1 = There is heteroskedasticity problem

Thus the result will be presented as below:

Table 8. Heteroskedasticity Test for Weekly Frequency Fama French Model

EMPIRICAL MODEL	PROB > CHI2	CONCLUSION
PORT1	0.9275	Homoscedasticity
PORT2	0.0327	Heteroscedasticity
PORT3	0.0005	Heteroscedasticity
PORT4	0.5448	Homoscedasticity
PORT5	0.1394	Homoscedasticity
PORT6	0.0003	Heteroscedasticity

Table 9 summarize all the intercept from 6 portfolios regression model. The alpha (a) or intercept in the model represents the return of portfolio beyond what would be expected, given the asset's exposure to risk factors.

Returnp,t – Rf = a + b1 (Rm-Rf)t + b2 (SMB)t + b3 (HML)t + εp,t ....Eq. (14)

In short, it measures the abnormal risk adjusted performance of the portfolio, or we could say, represents the abnormal return.

The empirical results will be presented as follow:

Table 9. Intercept of All Models in Weekly Frequency

Variable	Coefficient	Std. Error	t-Statistic	Prob

PORT1 (C)	-0.026967	0.003110	-8.671174	0.0000
PORT2 (C)	-0.021928	0.002662	-8.237352	0.0000
PORT3 (C)	-0.021444	0.001682	-12.74607	0.0000
PORT4 (C)	-0.021824	0.003048	-7.159408	0.0000
PORT5 (C)	-0.018577	0.00334	-5.561241	0.0000
PORT6 (C)	-0.005253	0.00216	-2.431862	0.0150
PORT6 - PORT1	0.021714	0.00378652	5.734560	0.0000

To verify the hypothesis that an increase in investors' attention measured by Google Trends will lead to higher returns of corresponding stock, we need an upward slope. And portfolio with the highest search intensity needs to showcase the highest or high abnormal rate of return. Below is the graph created from the intercept value data in table 4.6.

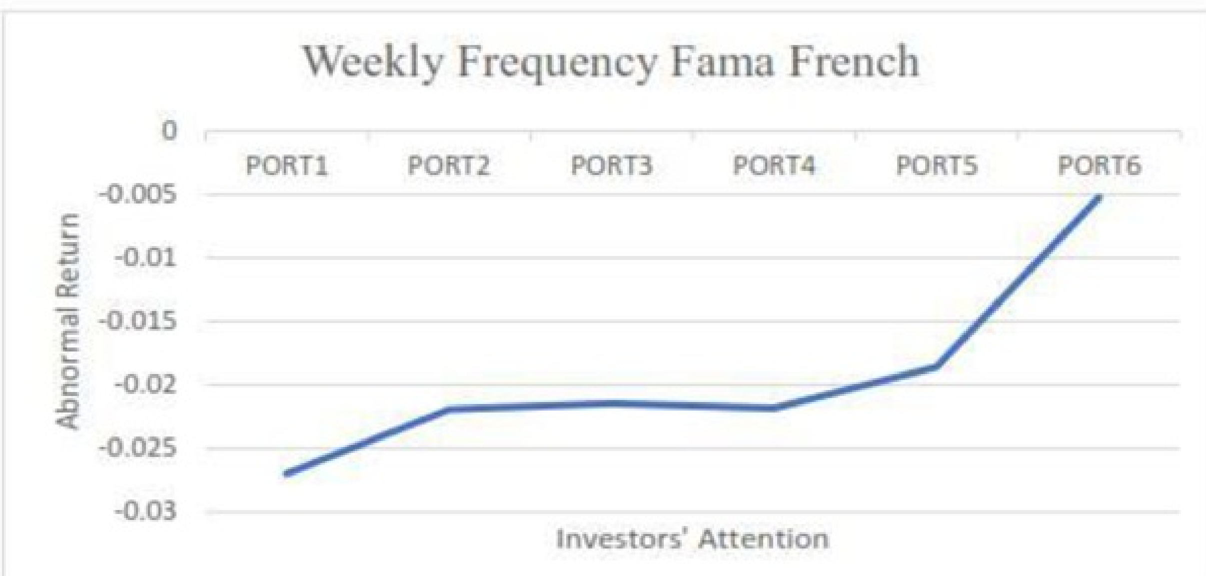

Figure 1. Abnormal Return of Weekly Frequency Fama French

Figure 1 along with table 9 shows that the intercept from all 6 portfolios creates an upward slope. As we can see from both the table and graph, all portfolios' alpha/ intercept is actually in a negative value, which means that all portfolios underperformed the market. The cause might be the portfolio management using Google Search Volume data itself, which creates portfolios that are not optimally diversified. Although all portfolios that were sorted by different search intensity could not generate a positive alpha, it does not disregard an upward trend that was shaped by the intercept. Meaning, that there is, still, an impact of investors' attention toward stock 's return. Not only that, the coefficient from PORT6-PORT1shows a 2% difference between the two portfolios, Which means that PORT6 which was constructed from firms with the highest search intensity (x), has a 2% higher return than other portfolios.

In corresponding with the hypothesis by Bank et al. (2010), Portfolio 1 which consists of firms with the lowest search intensity actually generated the lowest value of intercept. While Portfolio 2, Portfolio 3, and Portfolio 4 which represent the low, mid-low, and mid-high search intensity show an increase in the value of intercept compared to Portfolio 1, but are quite indifferent between each other. All the 3 portfolios might as well be considered to shows the same value of abnormal return, representing the medium search intensity. Portfolio 5 that consists of firms with high search intensity shows a few points increase. Whereas Portfolio 6 which consists of firms with the highest search intensity, shows a difference of 0.01332 higher abnormal return from Portfolio 5, and even a difference of 0.02171 higher abnormal return from Portfolio 1. In conclusion, a portfolio with the highest search intensity actually performs better than the rest, with a slight underperformance of -0.5%. Thus, proving consistency with the H1 that, an increase in investors' attention measured by the Google Trends will lead to higher returns of the corresponding stock. While to test auto-correlation problems, the Arellano-Bond test will be used. The hypothesis for the Arellano-Bond test is:

H0 = There is no auto-correlation problem

H1 = There is auto-correlation problem

Below is the result of the auto-correlation test for each empirical model:

Table 10. Auto-correlation Test for Weekly Frequency Dynamic Panel

Empirical Model	Order	Prob > z	Conclusion
ILLIQ	1	0.0000	No Auto-correlation
	2	0.3249	
BidAsk	1	0.0000	Auto-correlation
	2	0.0000	

In conclusion, the first illiquidity model using the Amihud illiquidity measurement appears to have no auto-correlation problem. While the second model using the Bid-ask spread illiquidity measurement appears to have auto-correlation problems[1]. Thus, the second model of weekly frequency illiquidity using bid-ask spread measurement will be dropped from further discussion.

Based on table 11 below, the model of the illiquidity will become:

ILLIQi,t = c + b1ILLIQi,t-1 + b2GSVi,t-1 + + b3Returni,t-1 + b4Stdevi,t-1 + b5lnMVi,t-1 + b6GSVi,t-1 × lnMVi,t-1 +

b7TradingActivity,t-1 + ci + μi + ui,t ....

Table 11. Weekly Frequency Illiquidity Regression Model

	Inliquidity			
Variable	**Coefficient**	**Std. Error**	**z**	**P > |z|**
ILLIQ	0.0813942	0.0318551	2.56	0.011
GSV	-1.15E-06	7.50E-07	-1.53	0.126
Return	1.88E-06	5.95E-06	0.32	0.752
Stdev	-4.73E-07	3.40E-06	-0.14	0.889
lnMV	-0.0000107	0.00000326	-3.29	0.001
lnMVxGSV	3.92E-08	2.58E-08	1.52	0.129
TradingActivity	-0.0000201	0.0000163	-1.24	0.217

Table 11 shows the Google Search Volume with p-value bigger than the confidence level of 5%. Which means, it fails to support the hypothesis that, an increase in investors' attention measured by the Google Trend will lead to higher liquidity of the corresponding stock. The table shows that after all, the Google Search Volume does not affect illiquidity at all. Meanwhile, table 11 shows a negative relationship between market capitalization lnMV and stock's illiquidity. Which, is well in line with the results of other literature, as for example with (Amihud, 2002). Although nearly all other variables in the model appears to not affect illiquidity, except for the illiquidity lag-1 itself and the market capitalization (lnMV). For the importance of the research, we will only focus in discussing the main variable, Google Search Volume (GSV). Liquidity is defined as an elusive concept, but an attempt to solidify it explains that, a stock is said to be liquid if the act of selling shares can be done with little-to-none impact on the stock's price. There are several factors that has been considered affecting the liquidity by investors, but the elusiveness of the concept itself makes room for new possible factors. Which, this research proposed in the form of Google Search Volume.

But, based on the model created from 249 firms in the timeframe of 3 years, the influence of GSV (if there is really any) is failed to be detected. Which might happen because of several reasons; One, due to the limitation of the research tools available, the model only uses 249 firms from an approximate of 564 firms listed in IDX per 2016. The reduction was made not only because of the limitation of the research tools, but also in order to eliminate delisting stocks, stocks that have been sleeping for a long time (too illiquid to provide any resourceful information), or stocks with recent initial public offering that again, could not provide much resourceful information due to the short trading frequency available. The reductions caused the stocks in the data to be quite undiversified. The data is composed of stocks with good trading activities, ones that we might say to be in the liquid side more than the illiquid side. And as stated by Bank et. al. (2010), the impact of public attention as indicated by Internet search volume (GSV) for larger firms are weaker. The large firms with liquid stocks do not really get affected by any increase or decrease in the search, because no matter what happens, people would still buy their stocks. They have such a big trading volume available, many buyers and sellers, that resulting in narrow bid-ask spread. That means it is possible the model failed to capture the correlation between GSV and illiquidity due to the data being too concentrated on larger firms with liquid stocks, which, like Bank et. al. (2010) stated, have a weaker correlation with GSV.

The second reason that might be the cause of the model 's failure to find a correlation between GSV and illiquidity, is the free-float regulation in Indonesia. Free-float refers to the number of outstanding shares that are available to the public for trade. Different from market capitalization, free float is the percentage of shares excluding the entities investing for control reasons rather than for investment purposes (government, corporations, key employees, and other strategic investors). Free float in a certain sense lessens the chance of majority shareholders to exert excessive influence on their firms. An increase in free float makes it easier for regular shareholders to trade the firms' shares and also increase share liquidity. Ding et al. (2015) stated that higher free float is associated with more trading activities which lead to higher liquidity. They argue that free float can increase liquidity through its influence on information asymmetries. But, in an environment with weak investor protection and poor corporate governance system, the investor has higher uncertainty because of the lack of reliable public information, particularly at the firm level. Less protective environments lead to wider bid-ask spreads and thinner depths, due to the associated higher information asymmetries in the environment.

Compared to the United States, Indonesia as an emerging market can be characterized as a lack of strong investor protection and developed system. Not only that, the free-float rate regulation for a firm in Indonesia is very low compared to other emerging market countries. Indonesia establishes a 7.5% rate from total market capitalization. While the Philippines set the minimum free float rate of 20%, Malaysia with 25%, and India also with 25%. With the lower transparency in Indonesia 's market, it means that it is fairly easier for firms in Indonesia to exert excessive influences in their stocks, or borderline manipulation. Which might be the problem of why the model could not capture the correlation between GSV and illiquidity. Because after all, the majority of the influences come from the company itself instead of the public investors that do the act of search. Although there are actually two models of illiquidity to be tested for each frequency, the bid-ask spread model needed to be dropped since it has the problem of autocorrelation that could not be dealing with due to research tools limitation. So, in conclusion, based on the Amihud illiquidity measurement model in weekly frequency, there is no correlation between GSV and illiquidity or the model failed to prove that an increase in investors' attention measured by the Google Trend will lead to higher liquidity of the corresponding stock.

5. THE RESULTS OF THE MONTHLY FREQUENCY DATA

The model is tested once again with monthly frequency data in order to ensure or explain further the result presented by weekly frequency data.

The result of the heteroskedasticity test for each empirical model:

Table 12. Heteroskedasticity Test for Monthly Frequency Fama French Model

EMPIRICAL MODEL	PROB > CHI2	CONCLUSION
PORT1	0.0607	Homoscedasticity
PORT2	0.3577	Homoscedasticity
PORT3	0.1665	Homoscedasticity
PORT4	0.4662	Homoscedasticity

In order to test the heteroskedasticity problem in Fama French model, the ARCH (Autoregressive Conditional Heteroskedasticity) test will be used. The hypothesis for ARCH test is:

H0 = There is no heteroskedasticity problem

H1 = There is heteroskedasticity problem

Therefore, all the model shows no heteroskedasticity problems.

Table 13. Intercept of All Models in Monthly Frequency

Variable	Coefficient	Std. Error	t-Statistic	Prob
PORT1 (C)	0.012973	0.004450	2.915198	0.0043
PORT2 (C)	0.014372	0.004851	2.962754	0.0037
PORT3 (C)	0.013756	0.005261	2.614699	0.0101
PORT4 (C)	0.014787	0.005266	2.807886	0.0059
PORT4 - PORT1	0.00181465	0.00364138	0.498341004	0.619187

As we can see from table 13, the portfolios that were arranged using monthly GSV data do not show any significant difference in the value of intercept (alpha). This implies that the phenomenon is only visible in bigger frequencies data. The founding is in line with Da discovery that found an increase in GSV for Russell 300 stocks predicts higher stock prices in the next 2 weeks, but an eventual price reversal within the year. The monthly frequency model could not capture the phenomenon since it only lasts for a while, or even less than in 2 weeks. Below is the graph created from the intercept value data in table 13. Although the graph shows an upward slope, the difference between PORT1 and PORT4 as shown by table 13, proves that the difference is not significant enough.

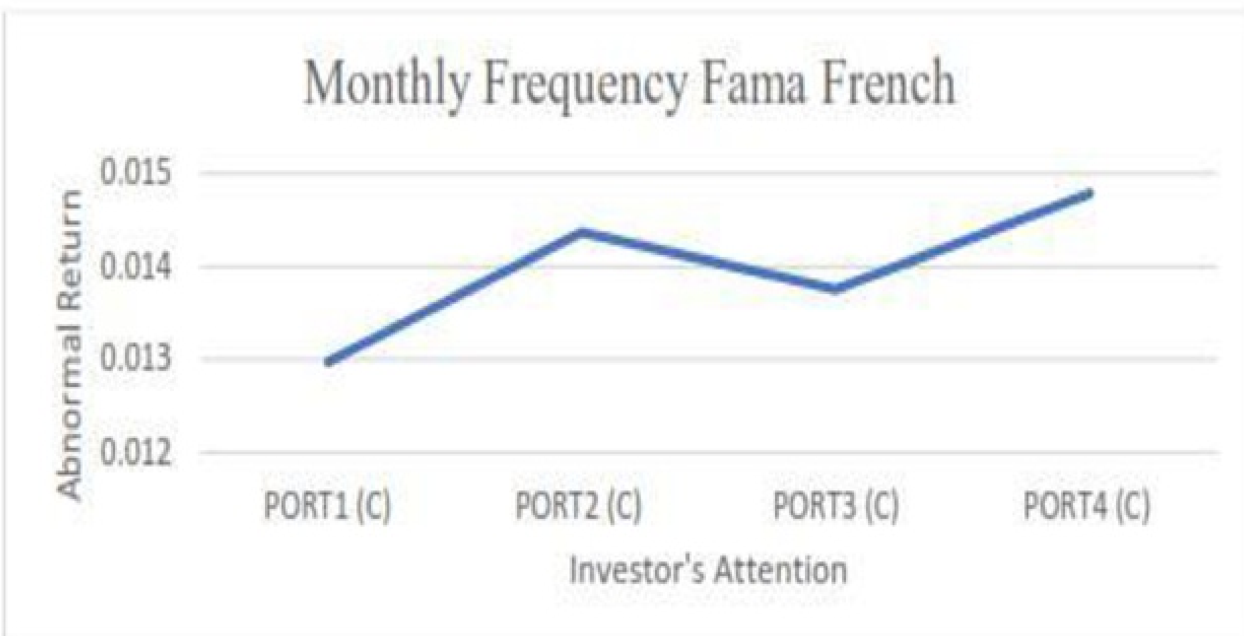

Fig 2. Abnormal Return of Monthly Frequency Fama French

To test auto-correlation probl ems , the Arellano-Bond test will be used. The hypothesis for Arellano-Bond test is:

H0 = There is no auto-correlation problem

H1 = There is auto-correlation problem

The result of the auto-correlation test for each empirical model as follow:

Table 14. Auto-correlation Test for Monthly Frequency Dynamic Panel

Empirical Model	Order	Prob > z	Conclusion
ILLIQ	1	0.0021	No Auto-correlation
	2	0.2304	
BidAsk	1	0.0000	No Auto-correlation
	2	0.6928	

In conclusion, both models of Amihud Illiquidity measurement or Bid-ask measurement does not have auto-correlation problems. Table 15 shows the regression result. Although the number of firms included is different from the weekly frequency, with 304 total firms and 10 years timeframe (July 2006 – June 2016), the result is in line with variable GSV as insignificant. But the market capitalization (lnMV) variable which appears as significant in the weekly frequency model, now appears as insignificant. In fact, all the control and independent variables appear as insignificant.

Table 15. Monthly Frequency Illiquidity Regression Model

		ILLIQUIDITY		
Variable	**Coefficient**	**Std. Error**	**Z**	**P > |z|**
ILLIQ	0.0167477	0.0173525	0.97	0.334
GSV	-2.29E-08	4.58E-08	-0.50	0.617
Return	-2.15E-07	1.34E-07	-1.60	0.110

Stdev	-5.93E-08	2.97E-07	-0.20	0.841
lnMV	2.12E-07	2.52E-07	0.84	0.400
lnMVxGSV	7.35E-10	1.61E-09	0.46	0.649
TradingActivity	-1.01E-06	5.71E-07	-1.76	0.078

The difference in the significance of control variables might be caused by the difference in the list of firms included in the data set. The additional input (and different timeframe) produced a different result. However, it still concludes to the same conclusion that there is no correlation between GSV and illiquidity. Other than the factors that have been discussed in the weekly frequency section, another factor that might cause the failure in capturing the phenomenon is that the Google Search Volume of a firm's name may be considered a broad and probably noisy measure of attention. It is possible that several firm names are messed up with other popular words that do not have any relation whatsoever with the company. In addition to the monthly illiquidity model, there is still one more model using alternative illiquidity measurement to again, test the robustness of the result.

Table 16. Monthly Frequency Illiquidity (Bid-Ask) Regression Model

		BID-ASK		
Variable	**Coefficient**	**Std. Error**	**Z**	**P > |z|**
Bidask	0.1135479	0.0217462	5.22	0.000
GSV	0.0045392	0.0040244	1.13	0.259
Return	0.0200797	0.0124430	1.61	0.107
Stdev	0.0372316	0.0211506	1.76	0.078

lnMV	-0.5830350	0.0084765	-6.88	0.000
lnMVxGSV	-0.0001426	0.0001391	-1.03	0.305
TradingActivity	0.1032649	0.0971119	1.06	0.288

The bid-ask model appears to support the earlier results that there is no correlation between GSV and Illiquidity in Indonesia's stock market. But in addition, the Market Capitalization (lnMV) appears to be significant. In conclusion, we could conclude that Market Capitalization is proven to be significant and positively related to illiquidity, while our independent variable, the GSV is insignificant in all weekly or monthly models.

6. CONCLUSION

This research was conducted to find out the relation, or impact of investors' attention toward return and liquidity in Indonesia's stock market. By using the Fama French three-factor model, the writer of this research tested the relationship between investors' attention, measured by Google Search Volume as the proxy, and stock return. While the relationship between investors' attention and liquidity was tested using dynamic panel model. The model was created using two data frequencies; 5 years timeframe for the weekly frequency, and 10 years timeframe (2006-2016) for the monthly frequency. The number of firms being tested is different in each model with the minimum amount of 249 firms, and a maximum of 359 firms. This research found that investors' attention (measured by GSV) is positively related to stock return. Stocks with higher GSV appears to outperform stocks with lower GSV. Although the impact does not last for long, proven by how the model with monthly frequency could not capture the phenomenon.

On the other hand, GSV appears to be insignificant to stock's liquidity. Both models with a weekly or monthly frequency also model with Amihud illiquidity measurement or bid-ask spread method failed to show the relation between GSV and stock's illiquidity. In fact, only market capitalization appears to be significant and negatively related to illiquidity in the model. In conclusion, Google Search Volume primarily captures the attention of investors, resulting in a short-term buying pressure that creates a higher return. This result is in line with previous researches by Barber and Odean (2007), Bank et al. (2010), and others. But, an increase in Google Search Volume fails to reduce information asymmetry that leads to an increase in liquidity. Some several limitations in this research found, whereas the most significant one as; despite the accuracy of Google Search Volume to capture attention than other proxies (extreme return, trading volume, media coverage, etc.), it does not fully and precisely represent the investors' attention. Because it basically computes all the act of search, but unable to filter the outcome with their demographic or profession. Researchers, students, and other professions might do the act of search as well, not just specifically investors, and there are no possible ways to differentiate the result. At least, the researchers suggest that the problem might be able to be diminished with the usage of more filter for the Google Search Volume data, so the outcome will only show the search intensity under Business and Industries category.

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