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Volatility of the Utilities Industry: Its Causal Relationship to Other Nine Industries

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Abstract: The goal of this study is to investigate the causality relationship between the Utilities industry and the nine other industries. Previous literatures show that volatility of stock prices is informative; Granger causality is applied in this research by using of a leveraged bootstrap test developed by Hacker and Hatemi-J (2006) to examine the behavior of the volatility. The results indicate that causality of the volatility of the Utilities industry on the volatility of seven other industries, except the Information Technology and Telecommunication Services industries. The data also suggest that Financials industry has impact on the Utilities industry.

JEL Classifications: C10, C15, C32, G14

Keywords: Granger Causality, Volatility, S&P 500, Bootstrap, Simulation

1. Introduction

Utilities play a crucial role in our daily lives. Electricity lights our homes as well as businesses, gas cooks our meals in addition to keeping us warm, and water provides clean clothes. Utilities drive many of the gains in productivity and convenience in our daily lives. However, do utilities still have an effect on in the wider economy? Are investors sentimental towards industries in which basic needed services are provided? Anderson et al (2010) find that the Utilities sector does somehow have a significant appeal to investors; they note that the sector contains "old economy" stocks that generally follow fundamentals. If the Utilities sector is sentimental towards investors, then what industry drives the Utilities sector which drives sentiment?

We find evidence that the utilities industry drives and is driven, by other industries. We find evidence to support Anderson et al (2010) notion of "old economy" stocks, and that investors are sentimental towards these stocks. Therefore, we aim to identify the impact of the utilities industry in contributing and leading to changes in nine other industries by examining the behaviors of the

industrial volatility. Our findings offer important insight on the channels in which investors can use to protect their investments, and presents potential solution to policy makers to kick start a stagnant economy.

2. Literature Review

Numerous studies support the importance that the industrial sector has on stock returns. Moskowitz, T. J. and M. Grinblatt (1999) found a strong and persistent industry momentum effect, of which industry momentum appears to be contributing substantially to the profitability of individual stock momentum strategies. Hong, H., W. Torous , et al. (2007) investigated whether the returns of industry portfolios predict stock market movements and found that stock markets react with a delay to information contained in industry returns directly about their fundamentals. They find that information diffuses only gradually across markets. Heston, S. L. and K. G. Rouwenhorst (1994) find that diversification across countries within an industry is found much more effective for risk reduction than industry diversification within a country.

Great deals of studies find that investor sentiment plays a significant role in investment dynamics through the industrial sector. Sayim, M., P. D. Morris, et al. (2013) examined the effect of rational and irrational investor sentiment on the stock return and volatility of US oil and utility industries. They found that investor sentiment had a significant impact on stock return and volatility in these two industries. They also found that the positive rational component of US individual investor sentiment tends to increase stock returns in these industries. Chen et. al. (3013) investigate the effects of investor sentiment on expected industry stock returns and find that asymmetric effects of global sentiment on oil & gas, financials, and health care industry returns become less under optimism, as compared with under pessimism. They further find that higher local sentiment enhances the returns of basic materials, telecommunications, and utilities industries. Cavaglia et al (2000) generally supports the findings of Chen et al (2013) but also finds that in determining global equity returns, industry factors dominate global factors.

Investor sentiment, whether rational, irrational, pessimistic or optimistic, plays an important role in stock returns through industrial sectors. It is important for investors to identify the dynamics of the driving force within these industrial sectors. Current literatures broadly apply only stock returns to examine the response rate of stock prices to the market information. However, we believe that returns reflect only partial market information about the stock. Volatility in many studies has also proved to be a good indicator of future information. Traditional Capital Asset Pricing Model (CAPM) holds the opinion that idiosyncratic risk could be eliminated away by holding a well-diversified investment portfolio; therefore, systematic risk would be the only factor that influences asset prices. However, recent empirical studies have found that the risk intensity of stocks is mainly due to the idiosyncratic risk of individual stocks. This conclusion was different from CAPM's argument that only systematic risk would have an effect on returns. We consider the notion that many previous literatures have indicated, which is, that volatility was informative as well. By using volatility to investigate the speed to which information travels rather than returns is a more direct way.

Recent literature that attempt to break through the traditional method of returns was performed by Campbell, Lettau, Malkiel and Xu (2001). They successfully divided the volatility of stock returns into market, industry, and firms' idiosyncratic volatility by using a disaggregated approach. Xu and Malkiel (2003) additionally applied both direct a decomposition method and a disaggregated approach method to decompose volatility of stock returns into systematic volatility and idiosyncratic volatility. Xu and Malkiel (2003) found that corporate private information could be reflected to its stock price faster when the institutional investors held a higher percentage of that

company's stock. Busch and Christensen (2011) found that implied volatility contains incremental information about future volatility in the foreign exchange, stock, and bond markets. Furthermore, implied volatility is an unbiased forecast in the foreign exchange and stock markets. Hatemi-J, A. and M. Irandoust (2011) found that the volatility causes returns negatively and returns cause volatility positively.

We seek to find the dynamics of the driving force within industrial sectors, however, we depart from previous studies by applying volatility to investigate the causality between the Utilities industry and other nine industries. Our research will attempt to answer the question of how the Utilities industry, which effects our daily lives, play a causal role in other industries.

3. Data and Methodology

We apply our research to the 416 S&P-500 listed firms that have their fourth quarter earnings announcements of 2010 on December 31st for our research and we obtain data from 25 days before to 20 days after December 31st- Nov 23, 2011 to Jan 31, 2012. General statistical description is showed in the table in appendix.

Due to the nature of our research, namely the use of high frequency data, a more suitable approach is outlined by Campbell, Lettau, Malkiel and Xu (2001). According to the calculation method used in Brandt, Brav, Graham, and Kumar (2010), for each stock j that belongs to industry I on day t, the intraday firm residual can be computed by subtracting the industry-i return:

$$\varepsilon_{ijst} = r_{ijst} - r_{ist}$$

where r_{ijst} is the return of sth 5-minutes interval on day t of stock j that belongs to industry i and r_{ist} is the valued weighted return of industry I in s^{th} 5-minutes interval on day t.

Then we obtained the day-t idiosyncratic volatility (σ_{ijt}^{id}) of stock j in industry I by

$$\sigma_{ijt}^{id} = \sqrt{\sum_{s} \varepsilon_{ijst}^{2}}$$

For industry volatility, by using the daily idiosyncratic volatility estimates for all stocks, we calculate the value weighted average volatility for each industry as:

$$\sigma_{it} = \sum_{j} w_{ij,t-1}\sigma_{ijt}^{id}$$

where w_{ijt} is the day-t weight of stock j belonging to industry-i.

After the volatility of each industry has been computed, we then investigate for Granger causality by using of a leveraged bootstrap test developed by Hacker and Hatemi-J (2006). This test applied the following vector autoregressive model of order p, VAR (p):

$$\sigma_t = \upsilon + A_1\sigma_{t-1} + \cdots + A_p\sigma_{t-p} + e_t \ ,$$

where σ is a two dimensional vector of volatility from two industries. The lag order p can be selected by minimizing an information criterion by Hatemi-J(2003, 2008) which is robust to ARCH effects and performs well when the goal of the VAR model is to conduct ex ante inference. This information criterion is defined as:

$$HJC = \ln\left(det\widehat{\Omega}_j\right) + j\left(\frac{n^2 lnT + 2n^2 \ln(lnT)}{2T}\right), j = 0, \dots, p.$$

where $det\widehat{\Omega}_j$ denoted as the determinant of the estimated maximum likelihood variance-covariance matrix of the residuals in the VAR(j) model. The number of the variables is represented by n and T, and signifies the sample size.

The null hypothesis that *k*th element of σ_t does not Granger-cause the *d*th element of σ_t is defined as

$$\boldsymbol{H_0}\text{: the row } d\text{, column } k \text{ element in } A_r \text{equals 0 for } r = 1, \dots, p.$$

In order to test the above null hypothesis, we apply a Wald test. First, we introduce the following denotations:

$$Y \coloneqq (\sigma_1, \dots, \sigma_T)(n \times T)\ martix, D\colon \big(\upsilon, A_1, \dots, A_p\big)\big(n \times (1 + n \times p)\big)\ matrix,$$

$$Z_t \coloneqq \begin{bmatrix} 1 \\ \sigma_t \\ \sigma_{t-1} \\ \dots \\ \sigma_{t-p} \end{bmatrix} \big((1 + n \times p) \times 1\big)\ matrix, for\ t = 1, \dots T.$$

$$Z \coloneqq (Z_0, \dots, Z_{T-1})\big((1 + n \times p) \times T\big)\ matrix, and\ \varepsilon \coloneqq (e_1, \dots, e_T)(n \times T)\ matrix,$$

where *n* is the number of variables - which is two in our case - and *T* is the sample size. By using these denotations, the VAR(*p*) model can be reformulated as:

$$Y = DZ + \varepsilon$$

Secondly, the null hypothesis of non-Granger causality can be expressed as

$$H_0\colon C\beta = 0$$

This null hypothesis will be tested via the following Wald test statistics:

$$Wald = (C\beta)'[C((Z'Z)^{-1} \otimes S_U)C']^{-1}(C\beta) \sim \chi_p^2,$$

where $\beta = vec(D)$ and vec is the column-stacking operator; the notation $\otimes$ represents the Kronecker product (that is, element by all elements matrix multiplication), and C is a $(p \times n)(1 + p \times n)$ indicator matrix with elements consisting of ones and zeros. The elements in each row of C takes a value of one if related parameter in β is zero under the null hypothesis, and they take a value of zero if there is no such restriction under the null. S_U represents the variance-covariance matrix of the unrestricted VAR model. That is, $S_U = (\hat{\varepsilon}'_U \hat{\varepsilon}_U)/(T - c)$, where c is the number of estimated parameters. When the assumption of normality is fulfilled, the Wald test statistics defined above is asymptotically distributed as χ^2 with the number of degrees of freedom equal to the number of restrictions under the null hypothesis (in our case, it will equal to *p*).

It should be pointed out that financial market data for emerging markets are usually characterized by non-normality and with time-varying volatilities. Under such circumstances the Wald test based on asymptotic critical values would not perform accurately. We implement a new causality test method developed by Hacker and Hatemi-J (2006), which is robust to non-normality as well as time-varying volatility. In order to conduct this test, the following steps are taken:

I. Estimate the VAR model using the selected lag order, p, and obtain the estimated residuals ($\hat{e}_t$).

II. Then, generate the simulated data, denoted by σ_t^*, as following:

$$\sigma_t^* = \hat{A}_0 + \hat{A}_1\sigma_{t-1} + \dots + \hat{A}_p\sigma_{t-p} + \hat{e}_t^*$$

where the circumflex above a variable represents its estimated values. The variable $\hat{e}_t^*$ is the bootstrapped residuals, which are based on T random draws with replacement from the regressions' modified residuals (to be defined below). These residuals are mean adjusted in each independent draw to make sure that the expected value of the residuals will be zero. The regressions' raw residuals are modified by using *leverages* as suggested by Hacker and Hatemi-J (2006) in order to have constant variance. To be more specific about the leveraged modification, it is necessary to introduce more notations. First, we define $Y_{-p} = (\sigma_{1-L}, \dots, \sigma_{T-p})$ and let $Y_{i,-p}$be the *i*th row of Y_{-p}. Thus, $Y_{i,-p}$ is defined as a row vector of the lag p values for variables σ_{it} during the sample period $t = 1, \dots, T$. We then define $V = (Y'_{-1}, \dots, Y'_{-p})$ and $V_i = (Y'_{i,-1}, \dots, Y'_{i,-p})$ for $i = 1, 2$. For the equation that generates σ_{1t}, the independent variable matrix for the regression is V_1; this equation is restricted by the null hypothesis non-Granger causality. For the equation that generates σ_{2t}, the independent variable matrix for the regression is V; this equation is not restricted by the null hypothesis non-Granger causality and includes the lag values of all variables in the VAR model. We define the $T \times 1$ leverages vectors for σ_{1t} and σ_{2t} as:

$$l_1 = diag(V_1(V'_1V_1)^{-1}V'_1) \text{ and } l_1 = diag(V(V'V)^{-1}V').$$

These leverages are used to modify the residuals in order to take into account that effect of ARCH. The modified residual for σ_{it} is produced as:

$$\hat{u}_{it}^m = \frac{\hat{u}_{it}}{\sqrt{1 - l_{it}}},$$

where l_{it} it the element of l_i, and $\hat{u}_{it}$ is the raw residual from the regression for σ_{it}.

III. Next, we iterate the bootstrap simulation 10,000 times and the *W* test statistic is calculated thereafter each simulation. From this procedure, we can construct an approximate distribution for the *W* test statistic. Subsequent to these 10,000 estimations we determine the (α)th upper quintile of the distribution of the bootstrapped *W* statistics and find the α-level of significant "bootstrap critical values" (c_α^*). The simulations are conducted by using the module written in Gauss by Hacker and Hatemi-J (2009a) which is available online.

We compare the calculated W statistic using the original simulated data (not the data that is generated via bootstrap simulations). Note that if the calculated W statistics is higher than the bootstrap critical values c_α^*, we then rejected the null hypothesis of non-Granger causality at the α-level of significance.

4. Empirical Results

We used the bootstrap simulation here to compute our own critical values based on the empirical distribution of the data set, which does not require normality. For example, from the results Table showed on the next page, we can see the calculated W statistics for the causal effect of volatility of Utilities industry on the volatility of Energy industry, 4.003, is higher than the estimated critical values that generated by simulation on a 10% significance level and less than the 1% and 5% simulated significance levels. We then can conclude that these data show that the volatility of the Utilities industry does have an impact on the volatility of the Energy industry under a 10% significance level. The causality of the Energy industry volatility on the volatility of the Utility industry, for instance, has a calculated W statistics of 0.960, which is lower than all three 1%, 5% and 10% simulated significance levels. This result implies that there exists a uni-direction causality between the Utilities industry and Energy industry. Furthermore, we also find that

volatility from seven out of nine other industries are affected by the volatility of the Utilities industry, except the Information Technology and Telecommunication Services industries. In addition, only the Financials industry has an impact on the Utilities industry.

Table 1. The results of test for causality using the leveraged bootstrap test

Null hypothesis	calculated W statistics	bootstrap critical value		
		1%	5%	10%
Utilities ≠> Energy	4.003*	7.612	4.258	2.949
Energy ≠> Utilities	0.960	7.394	4.120	2.860
Utilities ≠> Materials	3.842*	7.764	4.336	3.044
Materials ≠> Utilities	0.154	7.279	4.262	2.935
Utilities ≠> Industrials	3.766*	6.614	3.952	2.901
Industrials ≠> Utilities	0.430	6.554	4.078	2.994
Utilities ≠> Consumer Discretionary	7.895***	7.025	3.988	2.771
Consumer Discretionary ≠> Utilities	0.252	7.204	4.095	2.868
Utilities ≠> Consumer Staples	3.403*	7.812	4.095	2.876
Consumer Staples ≠> Utilities	1.794	7.340	4.087	2.880
Utilities ≠> Health Care	12.573***	7.066	4.075	2.846
Health Care ≠> Utilities	0.461	7.348	4.114	2.861
Utilities ≠> Financials	7.026**	7.622	4.094	2.807
Financials ≠> Utilities	3.981*	7.313	4.122	2.880
Utilities ≠> Information Technology	0.651	7.024	4.033	2.868
Information Technology ≠> Utilities	0.061	6.638	3.950	2.859
Utilities ≠> Telecommunication Services	2.698	7.017	4.062	2.861
Telecommunication Services ≠> Utilities	0.344	7.000	3.981	2.829

Notes: 1. Utilities ≠ > Energy is denoted as Utilities volatility does not cause Energy volatility.

2. *, **, and *** indicate that the null hypothesis is rejected at 10%, 5%, and 1% statistical significance levels, respectively.

5. Conclusion

The main objective of this research is to investigate if there is causality between the volatility of Utilities industry and the volatility of nine other industries by using a causality test method developed by Hacker and Hatemi-J (2006) which is robust to non-normality and ARCH. As noted, if investors are sentimental towards "old economy" stocks, and if these stocks have an effect on the wider economy, then what drives these stocks, and what are drivers of these stocks?

We tested volatility based on the calculation method used in Brandt, Brav, Graham, and Kumar (2010) for 416 S&P 500 firms during the period Nov 23, 2011 to Jan 31, 2012. According to causality test results, there is causality of the volatility of Utilities industry on the volatility of seven out of nine other industries, except Information Technology and Telecommunication Services. Also, Utilities industry market was affected only by Financials industry. It is not difficult to imagine that the Utilities are not as crucial in Information Technology and Telecommunication Services as in seven other industries.

As we saw in the 2007 financial crisis, there was a tremendous flight to safety/quality as a result of inability to assess risk in the financial industry. Investors had no way of calculating the risk of unknown intangible assets held by these companies. As a result, there was a gargantuan shift towards tangible assets such as those presented in the utilities sector. Our findings support the

notion that investors are sentimental towards "old economy" stocks and view these stocks as substantially 'risk assessable'. These findings are important for investors and for policy makers alike. Identifying a causal relationship in industries provides a means for investors to hedge against any macroeconomic downturns. Identifying a relationship allows policy makers to identify channels, which would allow them to kick-start a stagnant economy.

References

[1] Anderson, K., Brooks, C., Katsaris, A. (2010). "Speculative bubbles in the S&P 500: was the tech bubble confined to the tech sector?", *Journal of Empirical Finance*, 17(3): 345-361.

[2] Balcilar, M., & Ozdemir, Z. A. (2013). "The causal nexus between oil prices and equity market in the U.S.: A regime switching model", *Energy Economics*, 39(C): 271-282.

[3] Brandt, M. W., Brav, A., Graham, J. R., & Kumar, A. (2010). "The idiosyncratic volatility puzzle: Time trend or speculative episodes?", *Review of Financial Studies*, 23(2): 863-899.

[4] Busch, T., Christensen, B. J., and Nielsen, M. G. (2011). "The role of implied volatility in forecasting future realized volatility and jumps in foreign exchange, stock, and bond markets", *Journal of Econometrics*, 160(1): 48-57.

[5] Campbell, J. Y., Lettau, M., Malkiel, B. G., & Xu, Y. (2001). "Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk", *The Journal of Finance*, 56(1): 1-43.

[6] Cavaglia, S.& Brightman, C. & Aked, M.(2000). "The increasing importance of industry factors", *Financial Analysts Journal*, 56(5): 41-54.

[7] Chen, Mei-Ping, Chen, Pei-Fen, Lee, Chien-Chiang (2013). "Asymmetric effects of investor sentiment on industry stock returns: Panel data evidence", *Emerging Markets Review*, 14 (March): 35-54.

[8] Hacker, R. S., & Hatemi-J, A. (2006). "Tests for causality between integrated variables using asymptotic and bootstrap distributions: theory and application", *Applied Economics*, 38(13): 1489-1500.

[9] Hatemi-J, A., & Irandoust, M. (2011). "The dynamic interaction between volatility and returns in the US stock market using leveraged bootstrap simulations", *Research in International Business and Finance*, 25(3): 329-334.

[10] Hatemi-J, A., & S. Hacker, R. (2009). "Can the LR test be helpful in choosing the optimal lag order in the VAR model when information criteria suggest different lag orders?", *Applied Economics*, 41(9): 1121-1125.

[11] Heston, S. L., & Rouwenhorst, K. G. (1994). "Does industrial structure explain the benefits of international diversification?", *Journal of Financial Economics*, 36(1): 3-27.

[12] Hong, H., Torous, W., & Valkanov, R. (2007). "Do industries lead stock markets?", *Journal of Financial Economics*, 83(2): 367-396.

[13] Moskowitz, T. J., & Grinblatt, M. (1999). "Do industries explain momentum?", *The Journal of Finance*, 54(4): 1249-1290.

[14] Sayim, M., Morris, P. D., & Rahman, H. (2013). "The effect of US individual investor sentiment on industry-specific stock returns and volatility", *Review of Behavioral Finance*, 5(1): 58-76.

[15] Xu, Y., & Malkiel, B. G. (2003). "Investigating the Behavior of Idiosyncratic Volatility", *The Journal of Business*, 76(4): 613-645.

Appendix:
General statistical description

Industry	Number of companies observed	Average of daily return	Average of daily Volatility
Energy	40	-0.00034	0.00851
Materials	29	-0.00024	0.01016
Industrials	55	-0.00052	0.01079
Consumer Discretionary	46	-0.00041	0.01014
Consumer Staples	25	-0.00052	0.00662
Health Care	48	-0.00050	0.00809
Financials	79	-0.00034	0.01076
Information Technology	54	-0.00037	0.00883
Telecommunication Services	8	-0.00085	0.00627
Utilities	32	-0.00073	0.00602