Dynamics of Memory in Investor Attention to Energy Market

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Dynamics of Memory in Investor Attention to Energy Market

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Abstract. In this article, we investigate the correlation structure of the time series of investor attention as measured by relative search query volume of stocks in Google. Specifically, we explore - i) Whether the time series has a power law correlated dependence (long range memory) and how does it evolve over time? ii) How does this dependence vary with frequencies of sampled data? iii) Does a cross-correlation dependence exist between local and global investor attention? iv) What happens to this memory structure in case of volatility clustering periods of price and volume? We perform detrended fluctuation analysis and detrended cross-correlation analysis of the time series of investor attention of top 20 energy companies (by their market capitalization). The results confirm the existence of long range dependence in investor attention. The memory dynamics are characterized by persistent and mean-reverting behavior. There is a reasonably high positive cross-correlation dependence between local and global investor attention. Finally, we observe that volatility clustering has little effect on long range dependence structure of investor attention.

Keywords: Investor Attention, Google Trends, Fluctuation Analysis, Power law dependence

1 Introduction

When the New York times reported the breakthrough in cancer research on 3rd May 1998, the stock price of EntreMed's surged by 300 % [1]. Although the article was there in the journal *Nature* and some other newspapers five months back, the market remained under reacted till it appeared in *Times*. This news not only affected EntreMed but other biotechnology firms witnessed a considerable increase in their stock price as well. This suggests that mere an availability of information does not get reflected in prices unless enough attention is paid to it by the relevant people (like investors). Hence, the investor attention must play a crucial role in determining market movement and efficiency. Furthermore, attention is a limited cognitive resource available to us [2]. So, even if there is a huge volume of information available, investors have no choice but to select only specific set of information and make their investment decisions.

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In this article, we study the memory associated with the time series of investor attention. An investigation on whether the time series has noise, short memory or long memory shall have direct implications while modeling the relationships of investor attention and other variables. A number of studies are available on long run memory characteristics of stock market variables like - stock prices [3], [4], stock returns [5], [6], stock volume [7], [8], stock volatility [9], [10] and conditional variance of stock returns [11]. In case the time series has no memory i.e. it's a pure noise, the series cannot be used for any kind of predictive modeling. The existence of short memory in a time series implies that the effect of exogenous variable or shock to the series is short lived and dissipates very fast [12]. Long memory in a time series implies that its autocorrelations decay slowly, making it efficacious for modeling and analyzing the relationship with other variables. Understanding of long memory is important and special because it is often absent in most of the stochastic processes [13]. Existing literature primarily covers the impact of investor attention on other stock market variables, volatility and returns predictability [14], [15], [16]. In a very recent article, Xiaoquian Fan et. al analyzed Baidu search engine based investor attention index and its cross correlations with trading volume and volatility [17]. In this article we analyze noise and long range memory structure for investor attention based on the relative volume of Google search queries.

The main focus of this article is to carry out an in depth analysis of this dependence structure rather than predictions. With respect to memory in investor attention time series, specifically we explore the following - **a) Existence & Dynamics**: Whether the time series has a power law correlated dependence (long range memory) and how does it change over time? **b) Sampling Frequency**: How does the dependence structure vary with frequency of sampled data? **c) Local Vs Global Investor Attention**: Does a cross correlation dependence exist between local and global investor attention? **d) Volatility Clustering**: What happens to the memory structure in case of volatility clustering periods of price and volume? A better understanding of memory in investor attention shall have important implications to value at risk computation, volatility modeling, analyzing market efficiency, risk diversification and policies in energy market.

2 Memory Detection in Time Series

In this section we briefly discuss the notion of 'memory' in a time series and statistical methods for its detection. Let X_t be a sequence of IID random variables such that $E(X_t^2) < \infty$ and $var(X_t)$ is independent of t. Let $\lambda_u = Cov(X_t, X_{t+u})$. The time series is said to have [18] **no memory** if $\lambda_u = 0$ for all $u \neq 0$. It has a **short memory** if λ_u has decays faster or has an exponential decay. In a less stringent sense, X_t has a short memory if $\sum_{u=-\infty}^{u=\infty} |\lambda_u| < \infty$. A **long Memory** exists if λ_u decays slowly or has a power law decay. Again using the mild definition, X_t has a long memory if $\sum_{u=-\infty}^{u=\infty} |\lambda_u| = \infty$.

We analyze the memory structure in the time series using detrended fluctuation and cross correlation analysis. To outline the algorithmic steps involved in these methods, let $\{x_t\}$ and $\{y_t\}$ be two time series with t = 1,2,3,...,N. We denote $m_x = \frac{1}{N}\sum_{i=1}^{i=N}(x_i)$ and $m_y = \frac{1}{N}\sum_{i=1}^{i=N}(y_i)$. A cumulative sum function (called 'profile') for the given time series $\{x_t\}$ and $\{y_t\}$ is constructed as: $X_t = \sum_{i=1}^{i=t}(x_i - m_x)$, $Y_t = \sum_{i=1}^{i=t}(y_i - m_y)$. To perform **detrened cross correlation analysis**, a fluctuation function is obtained using these steps: [19]: a) Partition X_t and Y_t into $\left[T_b = \frac{N}{l}\right]$ non overlapping segments of size l from beginning to end of X_t and Y_t. If the series N is not divisible by l, some points at the end of the series may be left out. Hence another partion of size l is done $\left[T_e = \frac{N}{l}\right]$ from end to beginning on both series. b) Enumerate the partitions as i = 1,2,3,..,$2T = (T_b + T_e)$. For each partition i in $1 < i < 2T$, a least square line is fitted (denoted by $X_{i,t}^{ols}$ and $Y_{i,t}^{ols}$). The detrended covariance is computed as -

$$\psi_i^2(l) = \frac{1}{l}\sum_{j=1}^{l}(\left[X_{(i-1)l+j} - X_{i,j,}^{ols}\right]\left[Y_{(j-1)l+j} - Y_{i,j}^{ols}\right])$$

for i = 1,2,3,...,T_b

$$\psi_i^2(l) = \frac{1}{l}\sum_{j=1}^{l}(\left[X_{(N-(i-T_e)l+j} - X_{i,j,}^{ols}\right]\left[Y_{(N-(i-T_e)l+j} - Y_{i,j}^{ols}\right])$$

for i = T_b+1, T_b+2, ..., $2T$. The detrended cross correlation analysis (DCCA) fluctuation function is given by $\psi_{DCCA}^2(l) = \left\{\frac{1}{2T}\sum_{i=1}^{i=2T}\psi_i^2(l)\right\}^{\frac{1}{2}}$. If only one of the time series is considered, the detrended covariance reduces to detrended variance. The **detrended fluctuation analysis** (DFA) function is given: $\psi_{DFA}^2(l) = \left\{\frac{1}{2T}\sum_{i=1}^{i=2T}\psi_i^2(l)\right\}^{\frac{1}{2}}$. However this method was developed earlier by Peng et. al [20].The main essence of detrended fluctuation function is the fact it follows power law [21] : $\psi_{DFA}^2(l) \propto l^{\alpha}$. If the individual series x_t and y_t are power law correlated then $\psi_{DCCA}^2(l)) \propto l^{\beta}$ [19]. Using DFA and DCCA exponents, detrended cross correlation coefficient (ρ_{DCCA}) for series x_t and y_t is computed as -

$$\rho_{DCCA}(l) = \frac{\psi_{DCCA}^2(l)}{[\psi_{DFA}^2(l)]_{\{x_i\}}[\psi_{DFA}^2(l)]_{\{y_i\}}} \tag{1}$$

The idea of both DFA and DCCA has its root in a method known as "Hurst Rescaled Analysis" [22]. The associated exponent (known as Hurst exponent, H) could be affected by non-stationaries [4], while DFA and DCCA exponents (α and β) works well on non stationary series as well. In our analysis we only use DFA and DCCA to analyze the memory structure of the time series. The interpretations of H and α are similar [23]. For a stationary process the value of H lies between 0 and 1. For H = 0.5, the series is just a white noise (random walk) and has no memory. For $H < 0.5$ the series is anti persistent while $H > 0.5$

shows persistent behavior of the series. The series becomes non-stationary when H crosses 1, however till H=1.5, it exhibits a mean reverting behavior. H = 1.5 reflects that the series is Brown Noise (Brownian motion). When H exceeds 1.5 it represents an explosive process. β is a measure of nature of cross correlation between two series. For a given value of β the primary nature of series remains same but for the interpretation. For example - if $0 < \beta < 0.5$, there is anti persistent cross correlation i.e. increase in one series is marked by a decrease in another. $\rho_{DCCA} = -1, 0, 1$, imply that there complete negative, zero, positive cross correlation respectively between the two series.

3 Data & Investor Attention Measure

For our analysis we chose 20 largest energy companies by market capitalization [24] listed at New York Stock Exchange. We quantify investor attention using Google search queries for these particular stock. The key idea is that if an investor is searching for a query in Google, this means (s)he is paying attention to it. So Google search could be a revealed measure of attention [25]. Zhi Da et. al showed that the investor attention as measured by relative search volume of stock ticker symbols correlates with existing measures of investor attention [25]. Their results also suggest that search based investor attention is more real time. Amal Aouadi et al. [26] analyzed France stock market and showed that Google search based investor attention is correlated with trading volume of the stock and could be used to model volatility.

To quantify investor attention we use relative search volume time series of 'stock name' instead of 'stock ticker symbol' because the later is likely to capture more of retail investor attention [25]. Further, in our analysis a 'company name' as search query is much more relevant than ticker symbol. For example - stocks like CNOOC Limited has its symbol as 'CEO', so looking at search query time series of 'CEO' gives little information about investor attention to the stock. In fact while looking for time series of a particular stock name, Google gives suggestions whether the entered stock is just a search term or a corporation. We select the time series of the stock name corresponding to corporation. The obtained series is the relative search volume of the stock with respect to the total search volume worldwide over time scaled from 0 to 100. Let R_t be the relative search volume of stock at time t. We define the measure of investor attention ($\mathbb{I}_t$) as $log(1+R_t)$.

We collect the data for R_t for each of the stock using public web facility of Google called "Google Trends". For a given stock, we collect dataset for R_t classified into following categories - **a) Longer time duration, searched locally**: In this case R_t consists of weekly data from second week of April 2012 to last week of April 2017 where search location is restricted to the country of origin for the stock, **b) Longer time duration, searched globally**: In this case R_t is same as above but the search location is worldwide now. **c) Shorter time duration, searched locally**: In this case R_t consists of daily data from 26th

Jan 2017 to 24th April 2017 where search location is restricted to the country of origin for the stock. **d) Shorter time duration, searched globally**: Again, in this case R_t is same as above except the search location is now modified to worldwide now. The key idea behind this classification is to understand the memory dependence structure when investor attention data is sampled at a low & high frequency as well as to see the cross correlations between local and global investor attention for a given stock.

4 Analysis & Results

4.1 Memory in Investor Attention: Existence

To check the existence of memory in investor attention, we perform detrended fluctuation analysis of the time series for both long and short duration. Based on the estimated coefficients we conclude on the existence of long range memory in the series. For each stock we obtain the investor attention by $\mathbb{I}_t = log(1 + R_t)$. We denote $\mathbb{I}_{t,d}$ and $\mathbb{I}_{t,w}$ as investor attention of stock with underlying time series frequency as daily and weekly respectively. The length of time series of $\mathbb{I}_{t,d}$ is 89 while for $\mathbb{I}_{t,w}$ it is 261. In this case, we limit our analysis to investor attention obtained using global search for the stocks (since local search volume could be zero if the language of query entered is non - English). For example, we observe that for Sinopec (a Chinese firm) relative volume of local search query is often zero while globally it has non zero and significant large search volumes (Figure 1). This means investors in China use Chinese search queries or a different search engine (like Baidu).

For any given stock we first compute $\mathbb{I}_{t,d}$ and $\mathbb{I}_{t,w}$. Using the steps outlined in section 2, we obtain the fluctuations (ψ_{DFA}) as a function of window size (l). Using equation (3), we assume a constant k_i for a stock i such that - $\psi^2_{DFA}(l) = k_i l^{\alpha_i}$. Therefore,

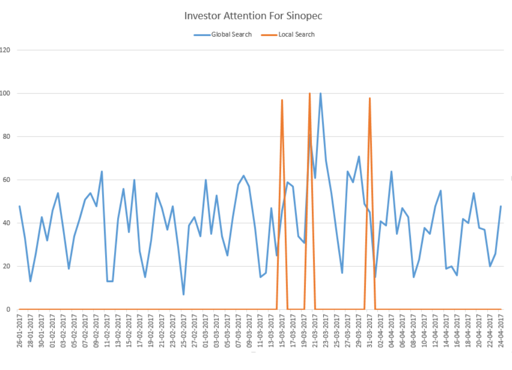

Fig. 1. Local and Global Search Trends For Query "Sinopec"

$$log(\psi^2_{DFA}(l)) = log(k_i) + \alpha_i * log(l) \quad (2)$$

To obtain α_i for a given stock, we fit a linear model using ordinary least squares between $log(\psi^2_{DFA}(l))$ as dependent variable and $log(l)$ as independent variable. Since, we are interested in whether the $\mathbb{I}_{t,d}$ or $\mathbb{I}_{t,w}$ has memory or its just a noise, we do an hypothesis testing to check whether obtained α_i is statistically different from 0.5 (case when it is a pure noise). For this we use a null hypothesis $H_0 : \alpha_i = 0.5$ and alternate hypothesis as $H_A : \alpha_i \neq 0.5$. Wald statistic for this test is defined as: $W = \left(\frac{\alpha_i - 0.5}{\sigma_\alpha}\right)^2$, where σ_{α_i} is the standard error of α_i. Figure 2 shows the plot of logarithm of fluctuation function vs logarithm of window size for the stock Sinopec. To obtain the fluctuation function we vary window size from 5 to 85 for $\mathbb{I}_{t,d}$ and 5 to 250 for $\mathbb{I}_{t,w}$. It is evident (from Table 1 & Table 2) that for both the series the null hypothesis of pure noise is rejected. We observe that the DFA exponent for $\mathbb{I}_{t,d}$ is 0.34, suggesting that the series is anti-persistent i.e. it exhibits a mean reverting behavior. However $\mathbb{I}_{t,w}$ has DFA exponent as 0.90 (Table 2) indicating a long term dependence in the investor attention and is near to the edge of non-stationarity. We carry out the same analysis for global investor attention of all the stocks. It is evident that more often than not Wald test rejects null of pure noise in investor attention. This confirms the existence of power law correlated structure implying a long term memory in the time series of investor attention.

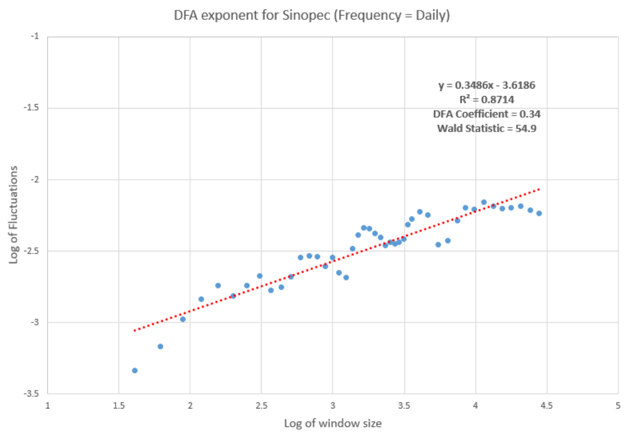

Fig. 2. DFA coefficient estimation for investor attention (for 3 months) for "Sinopec"

4.2 Memory in Investor Attention: Dynamics

To explore the dynamics of memory across time we carry out a rolling window analysis for both 90 day & and 5 years series of investor attention based on global

Stock Name	DFA Exponent	$R_{Squared}$	Sd_{Error}	Wald Statistic	P Value
Exxonmobil	0.4359	0.9291	0.0184	12.1934	0.0011
Royal Dutch	0.3395	0.9244	0.0148	117.5224	0.0000
Chevron	0.3452	0.9192	0.0156	98.3467	0.0000
Petrochina	0.2864	0.7039	0.0283	56.8750	0.0000
Total SA	0.6054	0.8817	0.0338	9.7144	0.0033
Schlumberger	0.2335	0.8325	0.0160	278.5484	0.0000
British Petroleum	0.3486	0.8714	0.0204	54.9230	0.0000
Sinopec	0.4825	0.8429	0.0318	0.3045	0.5839
Petrobras	0.4473	0.8945	0.0234	5.0672	0.0295
Conco Phillips	0.3716	0.5840	0.0478	7.2129	0.0102
ENI	0.1779	0.5513	0.0245	173.1554	0.0000
Enterprise Products	0.4601	0.8230	0.0325	1.5019	0.2270
Statoil	0.8162	0.8936	0.0429	54.2219	0.0000
EOG Resources	0.3235	0.8580	0.0201	77.3600	0.0000
CNOOC Limited	0.5332	0.8713	0.0313	1.1292	0.2939
Suncor Energy	0.3534	0.9106	0.0169	75.4474	0.0000
Kinder Morgan	0.4800	0.7820	0.0386	0.2672	0.6079
Occidental Petroleum	0.6091	0.9398	0.0235	21.5404	0.0000
Halliburton	0.2469	0.8833	0.0137	341.8434	0.0000
Phillips 66	0.7697	0.9690	0.0210	164.8613	0.0000

Table 1. DFA Exponents For Investor Attention (90 day Period)

Stock Name	DFA Exponent	$R_{Squared}$	Sd_{Error}	Wald Statistic	P Value
Exxonmobil	0.8085	0.9543	0.0179	298.0700	0.0000
Royal Dutch	0.9214	0.9303	0.0255	273.3864	0.0000
Chevron	1.1181	0.9745	0.0183	1146.7347	0.0000
Petrochina	0.9053	0.9155	0.0278	212.9451	0.0000
Total SA	0.8237	0.9669	0.0154	441.5677	0.0000
Schlumberger	0.9949	0.8210	0.0469	111.2002	0.0000
British Petroleum	0.9665	0.9277	0.0272	293.0681	0.0000
Sinopec	0.9011	0.9308	0.0248	261.3366	0.0000
Petrobras	1.1102	0.9628	0.0220	766.0020	0.0000
Conco Phillips	0.9839	0.9563	0.0212	518.9868	0.0000
ENI	0.6126	0.8886	0.0219	26.4150	0.0000
Enterprise Products	0.6503	0.8818	0.0241	39.0325	0.0000
Statoil	1.0556	0.9380	0.0274	410.5673	0.0000
EOG Resources	0.7491	0.9179	0.0226	121.0644	0.0000
CNOOC Limited	0.6927	0.9512	0.0158	147.8458	0.0000
Suncor Energy	0.6855	0.8659	0.0272	46.3254	0.0000
Kinder Morgan	0.8919	0.9472	0.0213	339.4692	0.0000
Occidental Petroleum	0.8680	0.9266	0.0247	222.3952	0.0000
Halliburton	1.1109	0.8871	0.0400	232.9367	0.0000
Phillips 66	0.6761	0.8182	0.0322	29.9242	0.0000

Table 2. DFA Exponents For Investor Attention (5 years Period)

search volume for the stock. For a 90 day period the rolling window consists of 22 days and for a 5 year period, 24 quarters are taken. For each stock we take 65 and 217 rolling windows for 90 days and 5 year period respectively. We compute DFA coefficients for each rolling window using the method discussed in section 2. The dynamics of power law dependence is shown in Figure 3 for a subset of stocks. The dynamics of this dependence structure is observed to persistent and short lived in nature. This means as we progress across rolling windows for a given stock, a large change is followed by a large change and small change is followed by a small change. From the plot, it is clear that direction of changes DFA exponent varies rapidly thereby changing the extent of dependence quickly. This characteristic brings down the predictability of investor attention which could lead to higher efficiency in the market. Similar pattern is observed for both 90 days and a 5 year period.

4.3 Sampling Frequency & Dependence Structure

We have considered the investor attention at two different frequencies. As mentioned earlier, for a short term investor attention we consider 90 days data measured daily and for a long term investor attention we consider 5 years data measured weekly.

We delved deeper into obtained DFA exponents to spot any differences in pattern or values for $\mathbb{I}_{t,d}$ & $\mathbb{I}_{t,w}$. We partitioned the estimated DFA exponents into four intervals - a) **(0 - 0.4)**: Anti-persistent, b)**(0.4 - 0.6)**: Almost Pure Noise, c) **(0.6 - 1.0)**: Persistent & d) **(1 - 1.5)**: Non Stationary. DFA exponent for each rolling window for a given stock falls exactly in one of the partitions. For both $\mathbb{I}_{t,d}$ & $\mathbb{I}_{t,w}$, we compute the probability of a rolling window falling into one of these partitions using the relative frequency approach. From the computed probabilities we observe that for a 5 year period $Prob(Persistent)$ is consistently higher than $Prob(Antipersistent)$ for all stocks. This suggests that at low frequency (i.e. weekly), the investor attention has a long range dependence with near non stationary structure making the predictability difficult and thereby boosting market efficiency. However at a high frequency (i.e. daily), $Prob(Antipersistent)$ is relatively higher than $Prob(Persistent)$ for almost all the stocks. This means for most of the rolling windows the series is stationary and mean reverting indicating higher predictability and lesser efficiency in the market. The results remain same when estimated DFA exponents are compared for full time period [Figure 4]. For nearly all stocks low frequency investor attention is closer to 1 while it is less than 0.5 for high frequency investor attention.

4.4 Local and Global Investor Attention

To investigate the cross correlation structure between local and global investor attention we compute $\rho_{DCCA}(l)$ as defined by equation 4. We perform this analysis on $\mathbb{I}_{t,w}$ for a five year period. Local investor attention is the time series based on search queries for the stock at country of origin as the geographical location

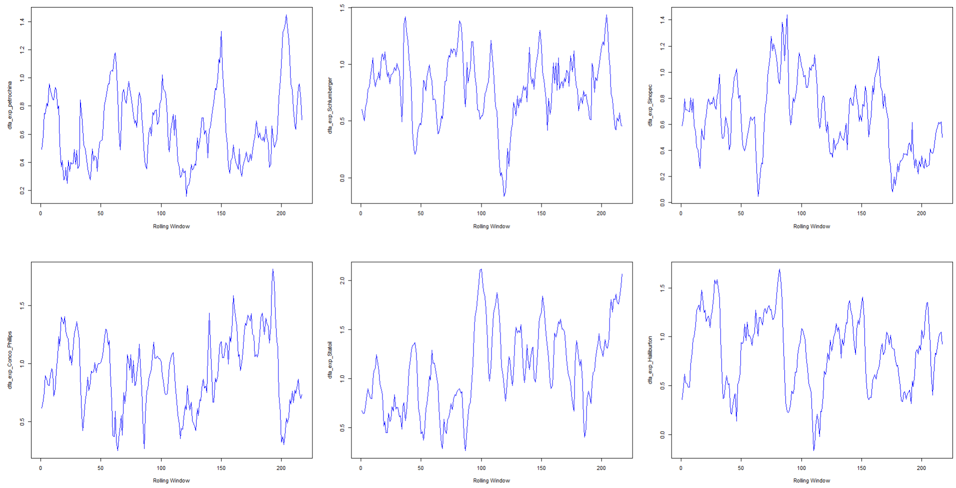

Fig. 3. Memory Dynamics For Investor Attention For Stocks (5 year period) (Left to Right, Top : Petrochina, Schlumberger, Sinopec & Bottom: Conco Phillips, Statoil, Halliburton)

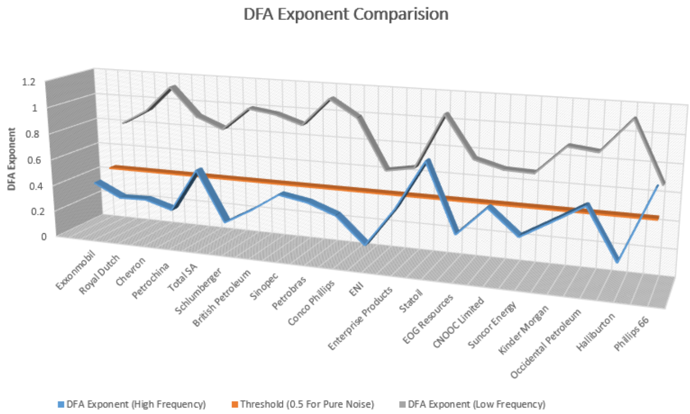

Fig. 4. Dependence Structure At High and Low Frequency

while for global investor attention the location is chosen to be worldwide. An important point the note here is that $\rho_{DCCA}(l)$ is calculated at a given scale. We have a total of 261 observations and we chose $l = 20$. One may calculate $\rho_{DCCA}(l)$ at different scales and then average it out. This value will only be slightly different. We expect the cross correlations to be positive and should be reasonably high. This is because an important news related to the stock draws local and global investors attention. However depending on the stock and it's

Stock Name	P(Antipersistent) (90 days)	P(Antipersistent) (5 years)	P (Persistent) (90 days)	P (Persistent) (5 years)	ρ_{DCCA}
Exxonmobil	0.4308	0.1198	0.0923	0.3364	0.86
Royal Dutch	0.3231	0.0507	0.2154	0.4194	0.36
Chevron	0.5385	0.0138	0.0615	0.4378	0.92
Petrochina	0.6462	0.2028	0.0462	0.4286	NA
Total SA	0.4154	0.0507	0.2000	0.5346	0.79
Schlumberger	0.7385	0.0783	0.0000	0.5161	0.35
British Petroleum	0.3231	0.2212	0.2308	0.4700	0.54
Sinopec	0.3846	0.2074	0.2615	0.4424	NA
Petrobras	0.5077	0.0092	0.2000	0.3088	0.99
Conco Phillips	0.6462	0.0553	0.1692	0.4009	0.86
ENI	0.9077	0.0507	0.0000	0.4562	0.94
Enterprise Products	0.7077	0.1429	0.0923	0.3456	0.93
Statoil	0.3538	0.0230	0.2769	0.3318	0.46
EOG Resources	0.5231	0.1751	0.0462	0.2719	0.98
CNOOC Limited	0.6000	0.3502	0.0923	0.3226	NA
Suncor Energy	0.4154	0.0876	0.0769	0.5392	0.94
Kinder Morgan	0.5231	0.1060	0.1077	0.4147	0.81
Occidental Petroleum	0.3231	0.0691	0.2154	0.5023	0.80
Halliburton	0.7846	0.1429	0.0000	0.3180	0.94
Phillips 66	0.3231	0.0599	0.2462	0.3364	0.78

Table 3. DFA Exponents & ρ_{DCCA} For Investor Attention

importance of information related to stock, the intensity of attention may vary. In Table 3 (last column), we enlist all the cross correlation values. As expected the correlations are positive, some of them are high and most of them are above 0.5. For a few stock correlations cannot be computed because search volume is very small (due to non English search queries). In our case, all three happens to be Chinese stocks indicating the investors in China uses queries in 'Chinese' to collect stock information.

4.5 Volatility Clustering and Investor Attention

From the estimated DFA exponents and rolling window analysis we have seen that the long range memory has persistent and short lived nature. We also observed that the extent of dependence is changing rapidly across rolling windows. In this part we analyze if the dependence structure changes during returns or volume volatility clustering periods. Given the dynamics of memory of investor attention, the long range dependence should not have much variation under such periods and intrinsic memory structure should be retained. However, it is very much possible investor attention can affect the returns or volume volatility (as discussed by Daniel Andrei and Michael Hasler [27]).

For a given window, we measure returns volatility by taking standard deviation of log returns and log volumes. We observe that memory structure is retained during volatility clustering periods. To validate this proposition we check correlations between volatility between DFA exponents and volatility for all stocks. The results suggest that there is a small negative correlation (~ 0.2) between the two for most of the stocks. To confirm this further we carry out Granger causality tests with lag 3 and check for both ways causality. The null hypothesis that volatility doesn't Granger cause dependence structure (or vice versa) is failed to get rejected in almost of all the cases. Hence, the results are in favor of the proposition that volatility clustering has little effect on long dependence of investor attention.

5 Conclusions

In this article we investigated the long range dependence of investor attention for top 20 stocks from energy market. Google search queries are revealed measure of attention and we used the relative search query volume to quantify the investor attention. Our results suggest that investor attention is indeed power law correlated and has long term dependence in its time series at both high and low frequencies. Further we observed that at high frequencies, investor attention is stationary and anti-persistent indicating a higher predictability. Dynamics of long range investor attention indicates that extent of dependence is changing rapidly and is short lived and persisting in nature. Detrended cross correlation analysis reveals that there is a reasonably high cross correlations between local and global investor attention. Finally, by using Granger Causality tests we see that the returns and volume volatility clustering has little effect on long range dependence structure of investor attention time series.

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