

Portfolio Management Coursework

FEARS INVESTOR SENTIMENT AND ASSET PRICES

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FEARS INVESTOR SENTIMENT AND ASSET PRICES

Abstract

In this report, we looked at the paper “The Sum of All FEARS Investor Sentiment and Asset Prices” by Zhi Da, Joseph Engelberg and Pengjie Gao. We use daily Internet search volume from millions of households to reveal market-level sentiment. By aggregating the volume of queries related to household concerns (e.g., “recession,” “unemployment,” and “bankruptcy”), we construct a Financial and Economic Attitudes Revealed by Search (FEARS) index as a new measure of investor sentiment. We try to reproduce the result in the paper and construct the FEARS again. The predictive power of out FEARS index was not as good as the authors’ result.

But beyond replication, we also tried several extensions in robustness check. We not only check the influence of the number of words selected, we also do experiments on index updating frequency. In the paper, the author suggested to update the component of the FEARS index every 6 months. In this coursework, we tried to improve our result by:

- 1. Try different updating frequency to see if higher frequency lead to better result.*
- 2. Try construct Fears index by using weighted averaging rather than equal-weight averaging*

After looking at the asset returns, we also tried to find the correlation between FEARS index and other asset classes other than equities. We also tried to work with fund flow to see how the market sentiments influence the investors’ appetites and how the money was channelled. Our finding is similar to the authors’ result, but our FEARS index was not as powerful as stated, partially because of the sub-optimal word selection and time effects.

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Chapter 1: Index Construction

Throughout the project, we found the index construction was the most time-consuming step. We construct our index through following several steps

1.1 Create list of 111 interested words

Our objective is to build a list of search terms that reveal sentiment toward economic conditions. In the introduction paper, we learned about how to extract, filter and organize data.

Step 1:

We follow the recent text analytics literature in finance, which uses the Harvard IV-4 Dictionary and the Lasswell Value Dictionary. These dictionaries place words into various categories, like “positive”, “negative”, “weak”, “strong”, “economic”. Our goal is to filter out economic words with positive and negative directions. The results we obtained are “gold”, “bankrupt”, “oligarchy”, “unemployed” and were built the “primitive” word list (150 words).

Step 2:

We input each primitive word into Google Trends, which, among other things, returns ten “top searches” related to each primitive word. For example, we searched the word “gold” and the results in the related searches “gold price”, “gold rate”, “gold coast”, “gold ring”, and “black gold” because this is how the term “gold” is commonly searched in Google. Our 150 primitive words generate 1,500 related terms, which become 1,453 terms after removing duplicates.

Step 3:

We removed terms with insufficient data and removed terms that are not clearly related to economics or finance. For example, search for “depression” results in the related searches “go bankrupt”, “bankruptcy”, “trump bankrupt”, “file bankruptcy”, “bankruptcy court”, “filing bankruptcy”, etc. We keep the first three terms (which relate to an economic bankruptcy) and remove the last three terms (which relate to computer bankruptcy). This leaves us with 120 search terms.

Because we do not have enough IP to download the related words, during the download process, our team spent 10 days, using 4-5 kinds of codes to express, running on Google Colab, but was intercepted and cooled by Google. Therefore, we did not get the same effect as the author by using the “introduction paper” method.

1.2 Data downloading methodology

We are working with python “pytrends” API to download daily work search frequency data directly from the google website.

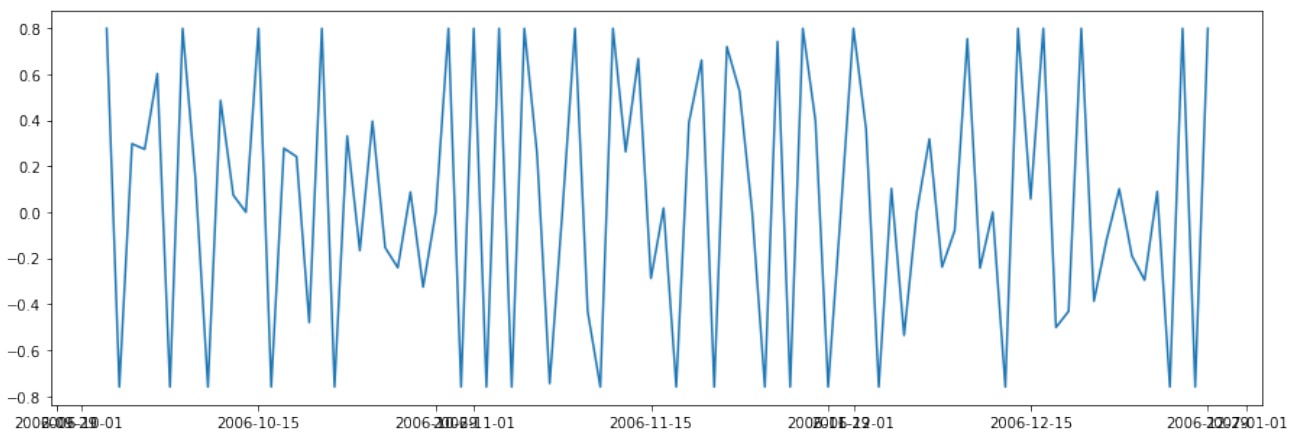
```
words = ['GOLD', 'ECONOMY', 'PRICE OF GOLD', 'THE DEPRESSION', 'CRISIS', 'FRUGAL', 'GDP']
for word in words:
    saved = []
    for year in range(2005, 2020):
        for month in range(1, 13):
            while True:
                try:
                    print('try')
                    time.sleep(3)
                    data = dailydata.get_daily_data(word, year, month, year, month, wait_time=3)
                    saved.append(data)
                    break
                except Exception:
                    continue
            print(str(year)+' '+str(month))

    while True:
        try:
            print('try')
            time.sleep(3)
            data = dailydata.get_daily_data(word, 2020, 1, 2020, 1, wait_time=3)
            saved.append(data)
            break
        except Exception:
            continue
    new = pd.concat(saved, axis=0)
    new.to_csv('{} .csv'.format(word))
```

The first problem we were facing was the way of downloading daily data. Google automatically select frequency for the users. If we want to download 15 years directly, google will force user to download monthly data. Hence, in order to get daily search frequency data, we need to constantly send downloading request on each month and then merge them manually.

The second problem was the upper limit of the number of downloading requests that google is imposed to all python user. We need to constantly create new python agent to bypass the weekly requesting limits and to avoid blacklist of IP address.

We save each word as an independent csv file in the folder “111_google_trends”. Finally, after all the 111 words was downloaded, we merge the data together to form our final dataset “111_daily_trends.csv”. These files contain the original unprocessed daily google search frequency for all the 111 interested words. The image below shows the daily frequency percentage change of the search item “Price of gold”



1.3 Data Cleaning and Pre-processing

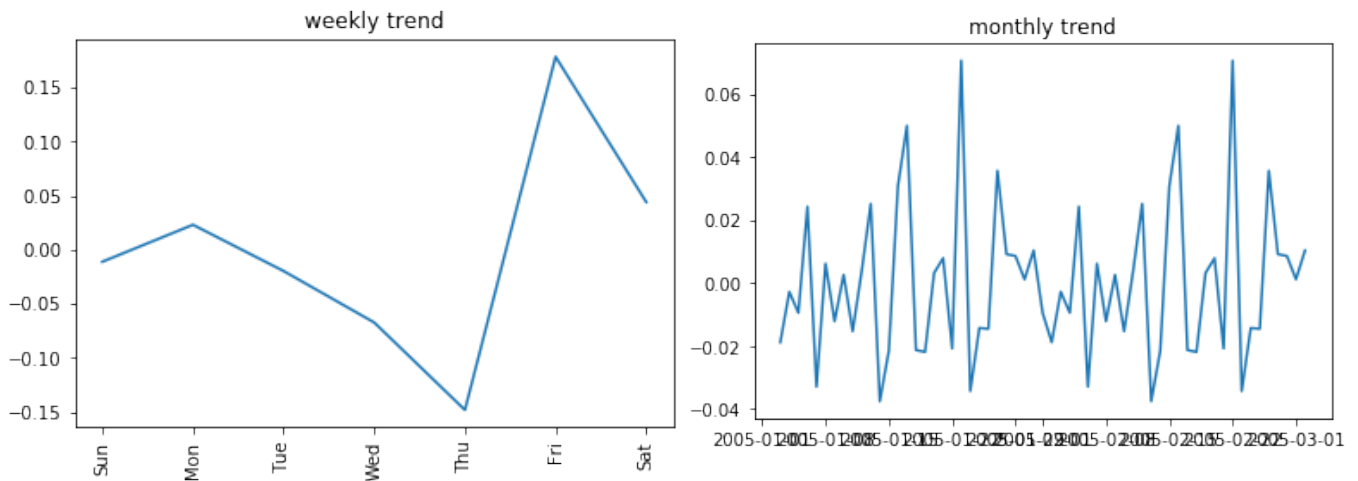
The data need to be processed for the following several steps in order to improve index accuracy:

Remove outliers and extreme movement:

There is a situation where the search volume yester day is only 1 and the next day is 12 which makes the movement too extreme. We need to winsorize at 5% level at every time series (2.5% in each tail of every 111 words)

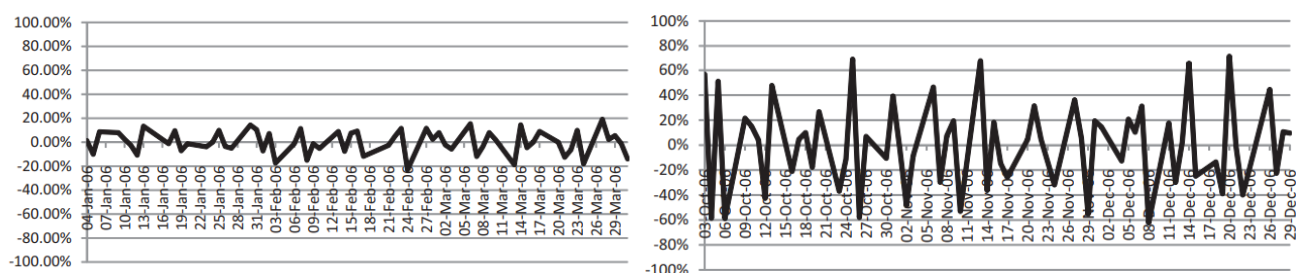
Remove weekly and monthly seasonality:

There is a weekly trend where people tends to research more on weekends and less on weekday because people have more free time to use the internet in weekends than in working day. Hence the search volume change in this context will have no realistic meaning. Hence, we need to we regress search volume change on weekday dummies and month dummies and only keep the residual.



Remove heteroscedasticity:

Finally, to address heteroscedasticity and make each times-series comparable, we standardize each of the time series by scaling each by the time-series standard deviation as in Baker and Wurgler (2006). The image below shows how different words have different level of percentage change. Heteroscedasticity do exist.



This leaves us with an adjusted (winsorized, deseasonalized, and standardized) daily change in search volume, $ASVI_{it}$, for each of our 118 terms.

1.4 Identify the 30 most important term and merge into final index by averaging (6-month)

First of all, we first create FEARS index with components that are updated every 6 month. For example, at the end of June 2009, we run a **regression** of **ASVI** on contemporaneous market return (SP500 return) during the period January 1, 2004 to June 30, 2009, for each of our 118 search terms. Then we rank the t-statistic on **ASVI** from this regression from most negative ($i=1$) to most positive ($i=118$). We select the thirty most negative terms and use these terms to form our FEARS index for the period from July 1, 2009, to December 31, 2009.

Formally, we define FEARS on day t as:

$$FEARS_t = \sum_{i=1}^{30} R^i(\Delta ASV I_t)$$

$R^i(\Delta ASV I_t)$ is the change in search volume of each word. And we average over the percentage change of 30 selected word. i represents the i^{th} most negative word. And then we could form the final FEARS index.

1.5 Construct other data:

We also included The Chicago Board Options Exchange (CBOE) daily market volatility index (VIX), a high-frequency measure of concurrent macroeconomic conditions from the Federal Reserve Bank of Philadelphia and a news-based measure of economic policy uncertainty (EPU) recently developed by Baker.

And this is out final dataset:

```
merged_data.head()
```

	SP500	EPU	ADS	VIX	static_fears	6month_dynamic_fears
2005-07-05	0.008794	0.668818	-0.144097	0.024265	0.695029	0.450887
2005-07-06	-0.008375	-0.678372	-0.156650	0.049279	-0.270910	-0.357042
2005-07-07	0.002449	0.002929	-0.171888	0.017771	0.077164	0.484266
2005-07-08	0.011611	0.166195	-0.190854	-0.086939	-0.326078	-0.111118
2005-07-11	0.006235	-1.006852	-0.322447	-0.014958	-0.461740	-0.300328

Chapter 2: FEARS and Asset Returns

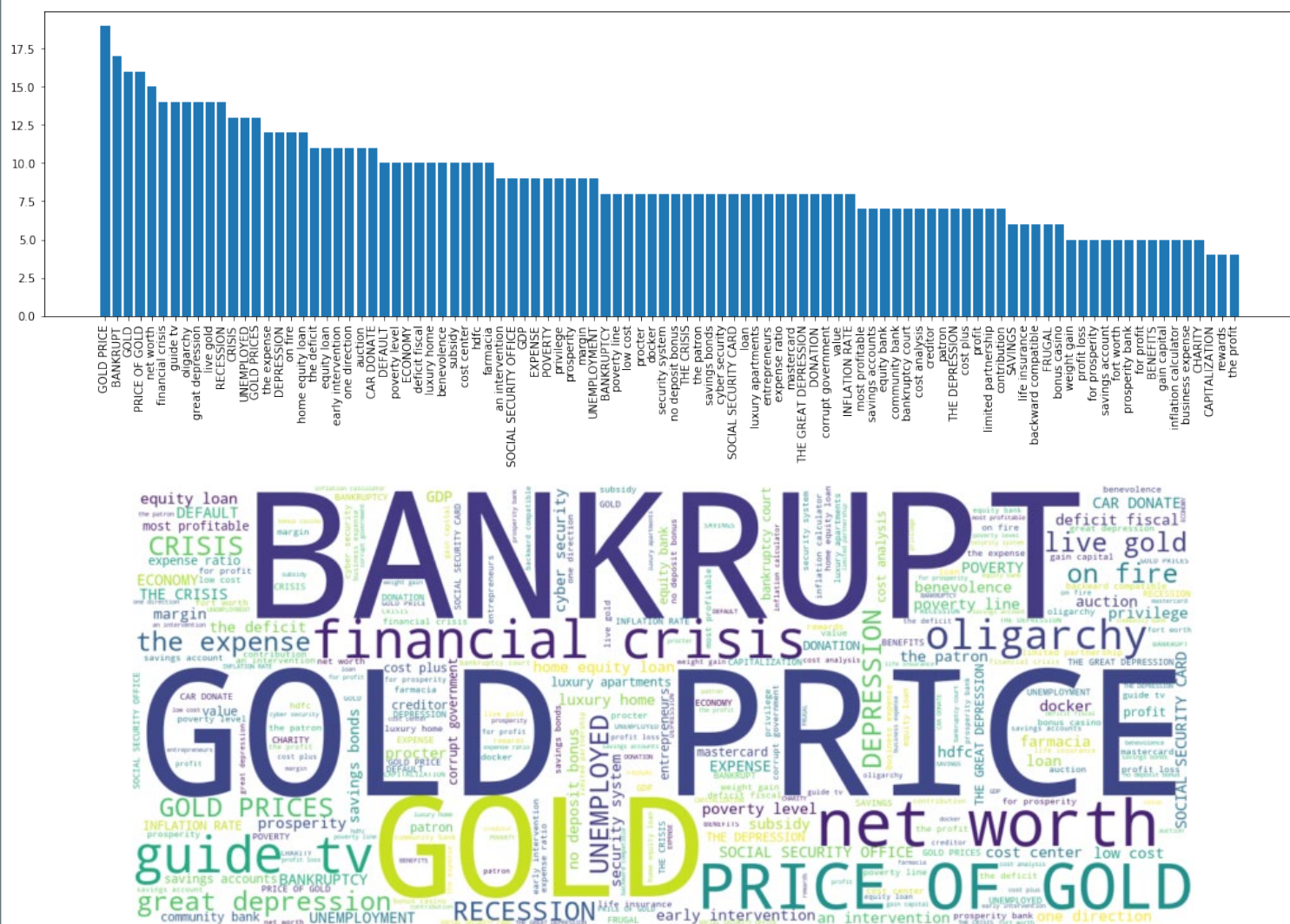
We first examine the relationship between FEARS and returns across various asset classes. We then examine how this relationship varies when we consider different index updating frequency.

2.1 6-month updating frequency FEARS and average returns of SP500

We look for evidence of return reversals by running the following regressions:

$$return_{i,t+k} = \beta_0 + \beta_1 FEARS_t + \sum_m \gamma_m Control_{i,t}^m + u_{i,t+k}.$$

Where $return_{i,t+k}$ denotes the asset i 's return on day $t + k$, and we consider Control variables ($Control_{i,t}^m$) include lagged asset-class returns, changes in a news-based measure of economic policy uncertainty (EPU), the CBOE volatility index (VIX), and changes in the Aruoba-Diebold-Scotti (ADS) business conditions index. We calculate bootstrapped standard errors, and our statistical inference is conservative. We found that the following words are used to construct FEARS index and they have significantly different frequency. The word with more used frequency are more powerful in predicting the asset returns.



And the regression result is below:

Ret(t+0)				Ret(t+1)			
	coef	t	P> t		coef	t	P> t
const	0.000300	1.890	0.059	const	0.000300	1.398	0.162
EPU	-0.000100	-0.514	0.607	EPU	-0.000500	-1.254	0.210
ADS	-0.000300	-1.343	0.180	ADS	0.000033	0.107	0.915
VIX	-0.119300	-60.825	0.000	VIX	-0.006200	-1.452	0.147
6month_dynamic_fears	-0.000071	-0.134	0.894	6month_dynamic_fears	0.001300	1.609	0.108
t	-0.032700	-2.702	0.007	t	-0.132100	-5.069	0.000
t-1	-0.018500	-1.523	0.128	t-1	-0.069600	-3.905	0.000
t-2	0.050200	4.131	0.000	t-2	0.019500	1.095	0.274
t-3	-0.005000	-0.411	0.681	t-3	-0.021900	-1.222	0.222
t-4	-0.023100	-1.917	0.055	t-4	-0.049600	-2.784	0.005
t-5				t-5	0.002300	0.128	0.898
0	1			0	1		
5 No. Observations:	3190			5 No. Observations:	3190		
2	3			2	3		
1 Adj. R-squared:	0.545			1 Adj. R-squared:	0.017		
Ret(t+2)				Ret(t+3)			
	coef	t	P> t		coef	t	P> t
const	0.0003	1.506	0.132	const	0.000300	1.237	0.216
EPU	0.0008	1.863	0.063	EPU	0.000200	0.494	0.621
ADS	0.0003	0.953	0.341	ADS	0.000085	0.274	0.784
VIX	-0.0048	-1.129	0.259	VIX	0.003300	0.768	0.443
6month_dynamic_fears	-0.0009	-1.120	0.263	6month_dynamic_fears	-0.000200	-0.279	0.780
t	-0.0807	-3.080	0.002	t	0.047500	1.809	0.070
t-1	0.0276	1.541	0.123	t-1	-0.020900	-1.166	0.244
t-2	-0.0243	-1.354	0.176	t-2	-0.049700	-2.763	0.006
t-3	-0.0462	-2.569	0.010	t-3	0.007000	0.387	0.699
t-4	0.0064	0.358	0.721	t-4	-0.020800	-1.159	0.247
t-5	-0.0254	-1.424	0.154	t-5	0.020800	1.164	0.244
0	1			0	1		
5 No. Observations:	3190			5 No. Observations:	3190		
2	3			2	3		
1 Adj. R-squared:	0.007			1 Adj. R-squared:	0.002		
Ret(t+4)				Ret(t+5)			
	coef	t	P> t		coef	t	P> t
const	0.000300	1.217	0.224	const	0.000300	1.186	0.236
EPU	-0.000200	-0.391	0.696	EPU	-0.000039	-0.095	0.925
ADS	0.000069	0.220	0.826	ADS	0.000035	0.112	0.910
VIX	0.003300	0.768	0.443	VIX	-0.000800	-0.193	0.847
6month_dynamic_fears	0.000300	0.389	0.697	6month_dynamic_fears	0.000400	0.529	0.597
t	-0.010300	-0.392	0.695	t	-0.051300	-1.952	0.051
t-1	-0.053100	-2.954	0.003	t-1	0.011300	0.628	0.530
t-2	0.008100	0.450	0.653	t-2	-0.024200	-1.343	0.179
t-3	-0.024300	-1.346	0.178	t-3	0.020400	1.129	0.259
t-4	0.016400	0.911	0.362	t-4	-0.015000	-0.835	0.404
t-5	-0.020400	-1.143	0.253	t-5	0.040900	2.292	0.022
0	1			0	1		
5 No. Observations:	3190			5 No. Observations:	3190		
2	3			2	3		
1 Adj. R-squared:	0.002			1 Adj. R-squared:	0.002		

Similar to what is written by the author the search terms that compose the FEARS index were selected based on their historical correlation with the market. The first table suggests that they continue to be correlated out of sample when $k=0$. But in our cases, none of the cases above shows that the FEARS index is significant in predicting the future market return. The problem may comes from the word selected for constructing the FEARS

index. This shows FEARS index is very sensitive to the pool of the 100+ candidate words that are used to construct the index.

But on the other hand, our FEARS index successfully reconstruct the change in fund flow which proves the inefficient market hypothesis, where the investor tends to overreact to bad news. Hence, we see a negative correlation in at $k=0$ (the first table), which means the investor search more negative words, the market is less confident and people tends to sell which leads to drop in price. Then on the day after, at $k=1$, the market realised it is overreacted and hence buy some shares buy which push up the price again. That why the coefficient of fears is negative in the first day and the negative in the second day.

Of course, such a short-term reversal can also be caused by a liquidity shock as in Campbell, Grossman and Wang (1993; GSW hereafter). As Baker and Stein (2004) point out, as sentiment and liquidity are intertwined, the difference between a sentiment-based story as in DSSW and a liquidity-based story as in GSW boils down how we view liquidity shocks and noise traders. Tetlock (2007) even goes so far as to say that “the difference between DSSW and CGW is philosophical rather than economic.” Our results remain interesting even under the liquidity interpretation, as they suggest high-frequency investor sentiment, as measured by our FEARS, can be a powerful trigger of a liquidity shock.

As a result, we may conclude that our FEARS index though reveals the relation between market sentiments and stock returns, but non of our regression is significant in predicting future returns. The reason may be:

1. Our 111 words selected for constructing the fears index as not as powerful as the author's ones
2. The predictive power of google search sentiments are less significant now.

Hence, we proposed two possible **improvements** showing in the next section.

2.2 Construct 6-month updating FEARS index with components weighted by frequency

Previously, the FEARS index was constructed by averaging all search terms with equal weights despite some word may appears more frequently and hence more powerful than others. Hence, the new formula is

$$FEARS_t = \sum_{i=1}^{30} W_i \times R^i(\Delta ASVI_t) \quad \text{and} \quad W_i = \frac{F_i}{\sum_{j=1}^{30} F_j}$$

Where all other terms remains the same and W_i represents the weight of this word and F_i represent the frequency word i appears throughout the 15 years from 2005 to 2020. And then I run the same regression and got the following:

Ret(t+0)				Ret(t+1)			
	coef	t	P> t		coef	t	P> t
const	0.0003	1.754	0.080	const	0.00030	1.267	0.205
EPU	-0.0001	-0.513	0.608	EPU	-0.00050	-1.292	0.196
ADS	-0.0003	-1.365	0.172	ADS	0.00003	0.098	0.922
VIX	-0.1193	-60.813	0.000	VIX	-0.00620	-1.465	0.143
6month_dynamic_fears	0.0006	0.845	0.398	6month_dynamic_fears	0.00060	0.551	0.582
t				t	-0.13240	-5.079	0.000
t-1	-0.0328	-2.710	0.007	t-1	-0.06910	-3.876	0.000
t-2	-0.0181	-1.493	0.136	t-2	0.01910	1.068	0.286
t-3	0.0504	4.150	0.000	t-3	-0.02090	-1.164	0.244
t-4	-0.0051	-0.420	0.674	t-4	-0.04890	-2.745	0.006
t-5	-0.0232	-1.927	0.054	t-5	0.00260	0.148	0.883
	0	1			0	1	
5 No. Observations:	3190			5 No. Observations:	3190		
	2	3			2	3	
1 Adj. R-squared:	0.545			1 Adj. R-squared:	0.016		
Ret(t+2)				Ret(t+3)			
	coef	t	P> t		coef	t	P> t
const	0.0004	1.911	0.056	const	0.000200	1.070	0.285
EPU	0.0008	1.897	0.058	EPU	0.000200	0.499	0.618
ADS	0.0003	1.024	0.306	ADS	0.000075	0.242	0.809
VIX	-0.0048	-1.119	0.263	VIX	0.003300	0.770	0.442
6month_dynamic_fears	-0.0029	-2.758	0.006	6month_dynamic_fears	0.001200	1.135	0.257
t	-0.0795	-3.039	0.002	t	0.047100	1.793	0.073
t-1	0.0275	1.536	0.125	t-1	-0.021100	-1.179	0.239
t-2	-0.0253	-1.410	0.159	t-2	-0.048900	-2.720	0.007
t-3	-0.0481	-2.676	0.007	t-3	0.007400	0.410	0.682
t-4	0.0062	0.345	0.730	t-4	-0.021000	-1.174	0.241
t-5	-0.0252	-1.418	0.156	t-5	0.020500	1.150	0.250
	0	1			0	1	
5 No. Observations:	3190			5 No. Observations:	3190		
	2	3			2	3	
1 Adj. R-squared:	0.009			1 Adj. R-squared:	0.003		

We could see that the result was actually worse and it even fails to show the negative relation between the returns and the Fears index. Hence, we decide this is not a great approach.

2.3 Construct FEARS index with different updating frequency

In the paper, author updates the FEARS index every 6 month to decide the component for next 6 months. Here we decide to investigate how the t-value and the words chosen were changed when we pick different updating frequency.

One-month frequency:

```
=====
Ret(t+0)
               coef      t  P>|t|
const          0.0002    1.607 0.108
EPU            -0.0002   -0.732 0.464
ADS            -0.0002   -1.069 0.285
VIX            -0.1232  -61.980 0.000
6month_dynamic_fears -0.0003   -0.783 0.434
t-1            -0.0322   -2.686 0.007
t-2            -0.0204   -1.696 0.090
t-3             0.0502    4.178 0.000
t-4            -0.0062   -0.514 0.607
t-5            -0.0229   -1.924 0.054
               0      1
5  No. Observations: 3190
               2      3
1  Adj. R-squared:  0.554
=====
```

```
=====
Ret(t+1)
               coef      t  P>|t|
const          0.0003    1.249 0.212
EPU            -0.0005   -1.260 0.208
ADS            0.0001    0.356 0.722
VIX            -0.0057   -1.303 0.193
6month_dynamic_fears 0.0010    1.582 0.114
t              -0.1330   -5.049 0.000
t-1            -0.0670   -3.760 0.000
t-2             0.0151    0.845 0.398
t-3            -0.0238   -1.331 0.183
t-4            -0.0487   -2.737 0.006
t-5             0.0037    0.212 0.832
               0      1
5  No. Observations: 3190
               2      3
1  Adj. R-squared:  0.017
=====
```

Three-month Frequency

```
=====
Ret(t+0)
               coef      t  P>|t|
const          0.0002    1.685 0.092
EPU            -0.0002   -0.715 0.475
ADS            -0.0002   -1.075 0.283
VIX            -0.1226  -61.676 0.000
6month_dynamic_fears -0.0005   -1.105 0.269
t-1            -0.0330   -2.747 0.006
t-2            -0.0194   -1.613 0.107
t-3             0.0500    4.149 0.000
t-4            -0.0062   -0.519 0.604
t-5            -0.0226   -1.891 0.059
               0      1
5  No. Observations: 3190
               2      3
1  Adj. R-squared:  0.552
=====
```

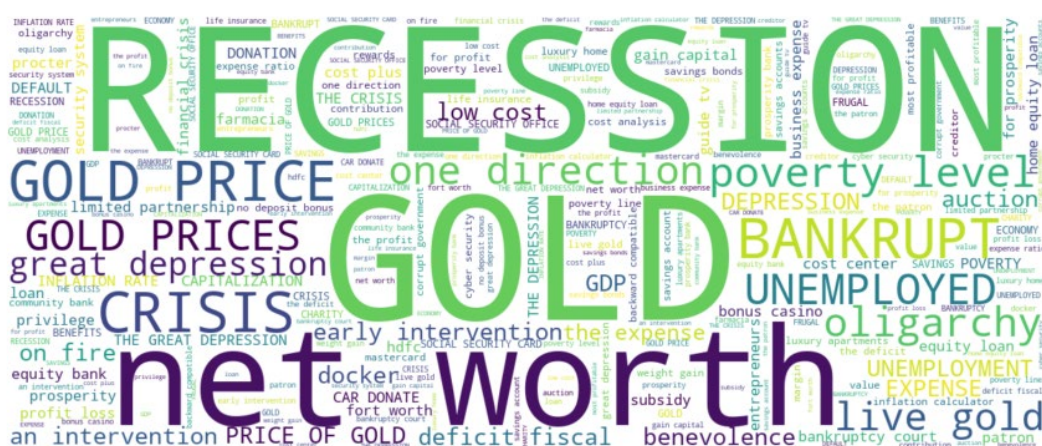
```
=====
Ret(t+1)
               coef      t  P>|t|
const          0.0003    1.360 0.174
EPU            -0.0005   -1.302 0.193
ADS            0.0001    0.324 0.746
VIX            -0.0056   -1.278 0.201
6month_dynamic_fears 0.0004    0.496 0.620
t              -0.1329   -5.060 0.000
t-1            -0.0661   -3.707 0.000
t-2             0.0152    0.850 0.395
t-3            -0.0236   -1.316 0.188
t-4            -0.0486   -2.725 0.006
t-5             0.0026    0.147 0.883
               0      1
5  No. Observations: 3190
               2      3
1  Adj. R-squared:  0.016
=====
```

One-year Frequency

```
=====
Ret(t+0)
               coef      t  P>|t|
const          0.0003    1.796 0.073
EPU            -0.0002   -0.686 0.493
ADS            -0.0002   -1.397 0.162
VIX            -0.1181  -60.731 0.000
6month_dynamic_fears -0.0002   -0.318 0.750
t-1            -0.0338   -2.787 0.005
t-2            -0.0189   -1.557 0.119
t-3             0.0507    4.172 0.000
t-4            -0.0040   -0.333 0.739
t-5            -0.0233   -1.931 0.054
               0      1
5  No. Observations: 3190
               2      3
1  Adj. R-squared:  0.544
=====
```

```
=====
Ret(t+1)
               coef      t  P>|t|
const          0.000300    1.293 0.196
EPU            -0.000700   -1.622 0.105
ADS            0.000019    0.079 0.937
VIX            -0.005900   -1.399 0.162
6month_dynamic_fears -0.001700   -1.913 0.056
t              -0.132100   -5.075 0.000
t-1            -0.068300   -3.835 0.000
t-2             0.021300    1.195 0.232
t-3            -0.019800   -1.108 0.268
t-4            -0.050400   -2.834 0.005
t-5             0.002800    0.159 0.873
               0      1
5  No. Observations: 3190
               2      3
1  Adj. R-squared:  0.018
=====
```

One-month frequency:



Three-month frequency:



One-year frequency



We could see that 3-month updating frequency FEARS index has better performance than 6-month and 1-year updating frequency FEARS index, we may conclude that higher frequency do leading to better prediction result. However, the prediction improvement is still very limited. One of the reasons is that the word we choose are largely unchanged no matter which frequency we picked.

Chapter 3: FEARS and returns of other asset classes

In this section we will study the relationship between FEARS index and returns of other asset classes such as ETF. We obtained ETF daily data from “cn.investing.com” (Investing.com - Stock Market Quotes & Financial News, 2020). Similar to the previous sections, we chose the FEARS update frequency to be 6 months and perform regression on different datasets.

Panel A: Fears and SPY

	Return(t)	Return (t+1)	Return (t+2)	Return (t+3)
FEARS	0.0003	-0.0003	-0.0002	0.0003
FEARS (p-value)	0.061	0.774	0.836	0.127
Control	-0.016	-0.023	-0.018	-0.0004
Control (p-value)	Yes	Yes	Yes	Yes
Observations	0.284	0.352	0.231	0.4366
Adjusted R^2	3190	3190	3190	3190
	0.547	0.015	0.01	0.002

Panel B: Fears and IWB

	Return (t)	Return (t+1)	Return (t+2)	Return (t+3)
FEARS	0.0003	0.0003	0.0003	0.0003
FEARS (p-value)	0.052	-0.019	0.104	0.192
Control	-0.013	-0.014	-0.014	-0.002
Control (p-value)	Yes	Yes	Yes	Yes
Observations	0.278	0.295	0.248	0.454
Adjusted R^2	3190	3190	3190	3190
	0.553	0.011	0.007	0.002

Panel C: Fears and IWM

	Return (t)	Return (t+1)	Return (t+2)	Return (t+3)
FEARS	0.0003	0.0003	0.0003	0.0003
FEARS (p-value)	0.113	0.292	0.198	0.278
Control	-0.162	-0.191	-0.087	-0.078
Control (p-value)	Yes	Yes	Yes	Yes
Observations	0.271	0.375	0.420	0.597
Adjusted R^2	3190	3190	3190	3190
	0.485	0.008	0.004	0.002

Table 1 FEARS and returns of other asset classes

From the Panel A table, we see that FEARS index is significant and has positive correlation with SPY return when $k=0$. However, for $k>0$, FEARS index becomes less significant.

From the Panel B table, we see that FEARS index is significant and has positive correlation with IWB for most of k . This shows that IWB is more affected by FEARS index and its component words.

Panel C table shows similar result as Panel A table. FEARS index is significant and has positive correlation with IWM return when $k=0$. However, for $k>0$, FEARS index becomes less significant. This make sense since IWM has higher expense ratio, thus riskier than IWB. Investors of IWM are less risk adverse so they tend to not affected by FEARS words.

Chapter 4: FEARS and Fund Flows

In this section, we studied the relationship between FEARS index and Fund Flows. Asset prices are affected by trading. We obtained mutual fund flow data from YCharts (YCharts, 2020) for mutual funds including US Mutual Fund, US Bond Mutual Fund and US Equity Mutual Fund.

There is one data issue. We were only able to obtain monthly data rather than daily data. Hence, we used linear interpolation to fill missing values for each month. However, since we have many missing values, we expected the result to be less accurate. We run the following regression:

$$flow_{i,t+k} = \beta_0 + \beta_1 FEARS_t + \sum_m \gamma_m Control_{i,t}^m + u_{i,t+k}$$

where fund class i includes bond and equity funds. Control variables ($Control_{i,t}^m$) include as usual VIX, ΔEPU , ΔADS , and five lags of market returns. The results of these regressions are reported in Table 2.

Panel A: US Mutual Fund Flows

	Flow(t)	Flow(t+1)	Flow(t+2)	Flow(t+3)
FEARS	0.000039	-0.0003	-0.0002	-0.0005
FEARS (p-value)	0.969	0.774	0.836	0.656
Control	0.0719	0.06475	0.05224	0.04572
Control (p-value)	Yes	Yes	Yes	Yes
Observations	3190	3190	3190	3190
Adjusted R^2	0.299	0.298	0.171	0.117

Panel B: US Bond Fund Flows

	Flow(t)	Flow(t+1)	Flow(t+2)	Flow(t+3)
FEARS	-0.0004	-0.0005	-0.0004	-0.0006
FEARS (p-value)	0.801	0.788	0.819	0.727
Control	0.0321	0.0305	0.0326	0.0277
Control (p-value)	Yes	Yes	Yes	Yes
Observations	3190	3190	3190	3190
Adjusted R^2	0.037	0.037	0.023	0.014

Panel C: Equity Mutual Fund Flows

	Flow(t)	Flow(t+1)	Flow(t+2)	Flow(t+3)
FEARS	-0.0003	0.000061	-0.0002	0.000013
FEARS (p-value)	0.748	0.952	0.882	0.990
Control	0.068	0.062	0.053	0.046
Control (p-value)	Yes	Yes	Yes	Yes
Observations	3190	3190	3190	3190
Adjusted R^2	0.205	0.206	0.13	0.093

Table 2 Sentiment and Fund flows

We found that our FEARS index has less significant incremental predictive power for future daily fund flow of US Mutual Fund, US Bond Mutual Fund Flows and US Equity Mutual Fund Flows.

From Panel A, we see that the coefficient on FEARS is statistically insignificant for days $t + 1$ (p-value > 10%), $t + 2$ (p-value > 10%) and $t + 3$ (p-value > 10%) in the US Mutual Fund Flows regressions. However, coefficients are all negative, which shows that investors tend to withdraw from US Mutual Fund after they saw jumps in FEARS, and such an outflow persists for the next two days.

From Panel A, we see that the coefficient on FEARS is negative on each day we consider ($t = 0, 1, 2, 3$, and 4) and is not statistically significant for days $t + 1$ (p-value $> 10\%$), $t + 2$ (p-value $> 10\%$) and $t + 3$ (p-value $> 10\%$). Similar to US Mutual Fund, investors withdraw from US Bond Fund after jumps in FEARS.

In the US Mutual Equity Fund Flows regressions, the coefficient on FEARS is statistically insignificant. We don't see clear correlation between US Mutual Equity fund flow and FEARS index. The table shows random trend regression coefficients.

From below are the codes we used for our entire projects.

part 1 Important words selection

April 15, 2020

```
[1]: !pip install pytrends
```

Collecting pytrends

Downloading <https://files.pythonhosted.org/packages/74/a4/c1b1242be7d31650c6d9128a776c753db18f0e83290aaea0dd80dd31374b/pytrends-4.7.2.tar.gz>

Requirement already satisfied: requests in /usr/local/lib/python3.6/dist-packages (from pytrends) (2.21.0)

Requirement already satisfied: pandas in /usr/local/lib/python3.6/dist-packages (from pytrends) (1.0.3)

Requirement already satisfied: lxml in /usr/local/lib/python3.6/dist-packages (from pytrends) (4.2.6)

Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.6/dist-packages (from requests->pytrends) (2019.11.28)

Requirement already satisfied: chardet<3.1.0,>=3.0.2 in /usr/local/lib/python3.6/dist-packages (from requests->pytrends) (3.0.4)

Requirement already satisfied: idna<2.9,>=2.5 in /usr/local/lib/python3.6/dist-packages (from requests->pytrends) (2.8)

Requirement already satisfied: urllib3<1.25,>=1.21.1 in /usr/local/lib/python3.6/dist-packages (from requests->pytrends) (1.24.3)

Requirement already satisfied: numpy>=1.13.3 in /usr/local/lib/python3.6/dist-packages (from pandas->pytrends) (1.18.2)

Requirement already satisfied: python-dateutil>=2.6.1 in /usr/local/lib/python3.6/dist-packages (from pandas->pytrends) (2.8.1)

Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.6/dist-packages (from pandas->pytrends) (2018.9)

Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.6/dist-packages (from python-dateutil>=2.6.1->pandas->pytrends) (1.12.0)

Building wheels for collected packages: pytrends

Building wheel for pytrends (setup.py) ... done

Created wheel for pytrends: filename=pytrends-4.7.2-cp36-none-any.whl size=14261

sha256=11e3167bf3735d71b2d2dc225fffd36cfd06ce7fb15cd622d28898e55558bd3

Stored in directory: /root/.cache/pip/wheels/64/ae/af/51d48fbbca0563036c6f80999b7ce3f097fa591fd165047baf

Successfully built pytrends

Installing collected packages: pytrends

Successfully installed pytrends-4.7.2

```
[2]: !pip install --upgrade --user git+https://github.com/GeneralMills/pytrends
```

```
Collecting git+https://github.com/GeneralMills/pytrends
  Cloning https://github.com/GeneralMills/pytrends to /tmp/pip-req-build-
gar92s2r
  Running command git clone -q https://github.com/GeneralMills/pytrends /tmp
/pip-req-build-gar92s2r
Requirement already satisfied, skipping upgrade: requests in
/usr/local/lib/python3.6/dist-packages (from pytrends==4.7.2) (2.21.0)
Requirement already satisfied, skipping upgrade: pandas>=0.25 in
/usr/local/lib/python3.6/dist-packages (from pytrends==4.7.2) (1.0.3)
Requirement already satisfied, skipping upgrade: lxml in
/usr/local/lib/python3.6/dist-packages (from pytrends==4.7.2) (4.2.6)
Requirement already satisfied, skipping upgrade: chardet<3.1.0,>=3.0.2 in
/usr/local/lib/python3.6/dist-packages (from requests->pytrends==4.7.2) (3.0.4)
Requirement already satisfied, skipping upgrade: idna<2.9,>=2.5 in
/usr/local/lib/python3.6/dist-packages (from requests->pytrends==4.7.2) (2.8)
Requirement already satisfied, skipping upgrade: certifi>=2017.4.17 in
/usr/local/lib/python3.6/dist-packages (from requests->pytrends==4.7.2)
(2019.11.28)
Requirement already satisfied, skipping upgrade: urllib3<1.25,>=1.21.1 in
/usr/local/lib/python3.6/dist-packages (from requests->pytrends==4.7.2) (1.24.3)
Requirement already satisfied, skipping upgrade: python-dateutil>=2.6.1 in
/usr/local/lib/python3.6/dist-packages (from pandas>=0.25->pytrends==4.7.2)
(2.8.1)
Requirement already satisfied, skipping upgrade: pytz>=2017.2 in
/usr/local/lib/python3.6/dist-packages (from pandas>=0.25->pytrends==4.7.2)
(2018.9)
Requirement already satisfied, skipping upgrade: numpy>=1.13.3 in
/usr/local/lib/python3.6/dist-packages (from pandas>=0.25->pytrends==4.7.2)
(1.18.2)
Requirement already satisfied, skipping upgrade: six>=1.5 in
/usr/local/lib/python3.6/dist-packages (from python-
dateutil>=2.6.1->pandas>=0.25->pytrends==4.7.2) (1.12.0)
Building wheels for collected packages: pytrends
  Building wheel for pytrends (setup.py) ... done
  Created wheel for pytrends: filename=pytrends-4.7.2-cp36-none-any.whl
size=14820
sha256=2c11ae4a5aa600fc5499410593a1dbf374f99cc80093cf3e94e1848c62d1622f
  Stored in directory: /tmp/pip-ephem-wheel-cache-
jvpyj061/wheels/f6/49/f7/a4785ff2079f1cc793186a60d40863c5d4ee9863e2b315a0bd
Successfully built pytrends
Installing collected packages: pytrends
Successfully installed pytrends-4.7.2
```

```
[3]: !pip install pytrendsdaily
```

Collecting pytrendsdaily

Downloading <https://files.pythonhosted.org/packages/52/23/74025f57678fbbb5d9a59e07a74957a15480bad01aba98e048572be7955a/pytrendsdaily-1.0.0-py3-none-any.whl>

Requirement already satisfied: pandas>=0.23.0 in /usr/local/lib/python3.6/dist-packages (from pytrendsdaily) (1.0.3)

Requirement already satisfied: pytrends>=4.4.0 in /root/.local/lib/python3.6/site-packages (from pytrendsdaily) (4.7.2)

Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.6/dist-packages (from pandas>=0.23.0->pytrendsdaily) (2018.9)

Requirement already satisfied: numpy>=1.13.3 in /usr/local/lib/python3.6/dist-packages (from pandas>=0.23.0->pytrendsdaily) (1.18.2)

Requirement already satisfied: python-dateutil>=2.6.1 in /usr/local/lib/python3.6/dist-packages (from pandas>=0.23.0->pytrendsdaily) (2.8.1)

Requirement already satisfied: requests in /usr/local/lib/python3.6/dist-packages (from pytrends>=4.4.0->pytrendsdaily) (2.21.0)

Requirement already satisfied: lxml in /usr/local/lib/python3.6/dist-packages (from pytrends>=4.4.0->pytrendsdaily) (4.2.6)

Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.6/dist-packages (from python-dateutil>=2.6.1->pandas>=0.23.0->pytrendsdaily) (1.12.0)

Requirement already satisfied: urllib3<1.25,>=1.21.1 in /usr/local/lib/python3.6/dist-packages (from requests->pytrends>=4.4.0->pytrendsdaily) (1.24.3)

Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.6/dist-packages (from requests->pytrends>=4.4.0->pytrendsdaily) (2019.11.28)

Requirement already satisfied: idna<2.9,>=2.5 in /usr/local/lib/python3.6/dist-packages (from requests->pytrends>=4.4.0->pytrendsdaily) (2.8)

Requirement already satisfied: chardet<3.1.0,>=3.0.2 in /usr/local/lib/python3.6/dist-packages (from requests->pytrends>=4.4.0->pytrendsdaily) (3.0.4)

Installing collected packages: pytrendsdaily

Successfully installed pytrendsdaily-1.0.0

```
[0]: import pandas as pd
      from pytrends.request import TrendReq
      pytrend = TrendReq()
      from pytrends import dailydata
      from pytrendsdaily import getDailyData
```

```
[5]: from google.colab import files
      uploaded = files.upload()
```

<IPython.core.display.HTML object>

Saving inquirerbasic.csv to inquirerbasic.csv

```
[6]: import io
      df2 = pd.read_csv(io.BytesIO(uploaded['inquirerbasic.csv']))
      List = df2['Entry']
```

List

```
[6]: 0      ABUNDANCE
      1      ACCRUE
      2      ADVANTAGE
      3      AFFLUENCE
      4      AFFLUENT
```

```
      ...
     145     VAGRANT
     146     VALUABLE
     147     WARFARE
     148     WASTE
     149     WORTH
```

Name: Entry, Length: 150, dtype: object

```
[0]: l=[]
      count=[]
      n = int(len(List))
```

```
[0]: for i in range(n):
      pytrend.build_payload(kw_list=[List[i]])
      related_queries = pytrend.related_queries()
      d1 = related_queries[List[i]]
      d2 = d1['top']
      d3 = d2['query']
      d4 = d3.tolist()
      n4 = len(d4)
      if n4<10:
          for j in range(n4):
              l.append(d4[j])
      else:
          for j in range(10):
              l.append(d4[j])
```

```
[9]: len(l)
```

```
[9]: 1473
```

```
[10]: res = []
      [res.append(x) for x in l if x not in res]
      len(res)
```

```
[10]: 1446
```

```
[11]: data = dailydata.get_daily_data(res[1],2020,3,2020,3,wait_time=1)
```

in abundance:2020-03-01 2020-03-31

```
[12]: sum(data[res[1]+'_unscaled'])
```

```
[12]: 1595
```

```
[13]: r = len(res)
      for i in range (0,600):
          try:
              data = dailydata.get_daily_data(res[i],2020,3,2020,3,wait_time=1,)
              count.append(sum(data[res[i]+'_unscaled']))
          except:
              count.append(0)
```

abundance of:2020-03-01 2020-03-31
in abundance:2020-03-01 2020-03-31
abundance meaning:2020-03-01 2020-03-31
an abundance:2020-03-01 2020-03-31
what is abundance:2020-03-01 2020-03-31
abundance definition:2020-03-01 2020-03-31
in abundance meaning:2020-03-01 2020-03-31
relative abundance:2020-03-01 2020-03-31
abundance of katherines:2020-03-01 2020-03-31
life abundance:2020-03-01 2020-03-31
accrue to:2020-03-01 2020-03-31
accrue interest:2020-03-01 2020-03-31
accrue meaning:2020-03-01 2020-03-31
accrue definition:2020-03-01 2020-03-31
accrue annual leave:2020-03-01 2020-03-31
accrued:2020-03-01 2020-03-31
what is accrue:2020-03-01 2020-03-31
accrue holiday:2020-03-01 2020-03-31
accrual:2020-03-01 2020-03-31
accrue define:2020-03-01 2020-03-31
the advantage:2020-03-01 2020-03-31
advantage and disadvantage:2020-03-01 2020-03-31
hp:2020-03-01 2020-03-31
medicare advantage:2020-03-01 2020-03-31
hp ink advantage:2020-03-01 2020-03-31
hp deskjet:2020-03-01 2020-03-31
hp deskjet ink advantage:2020-03-01 2020-03-31
take advantage:2020-03-01 2020-03-31
competitive advantage:2020-03-01 2020-03-31
staples advantage:2020-03-01 2020-03-31
affluence meaning:2020-03-01 2020-03-31
disney affluence:2020-03-01 2020-03-31
affluence disney:2020-03-01 2020-03-31
disneyland affluence:2020-03-01 2020-03-31
disneyland:2020-03-01 2020-03-31
school of affluence:2020-03-01 2020-03-31
what is affluence:2020-03-01 2020-03-31
famine affluence and morality:2020-03-01 2020-03-31
affluence define:2020-03-01 2020-03-31

asterix:2020-03-01 2020-03-31
affluent definition:2020-03-01 2020-03-31
definition:2020-03-01 2020-03-31
affluent society:2020-03-01 2020-03-31
affluent danube:2020-03-01 2020-03-31
what is affluent:2020-03-01 2020-03-31
affluent du danube:2020-03-01 2020-03-31
define affluent:2020-03-01 2020-03-31
synonyme:2020-03-01 2020-03-31
affluent synonym:2020-03-01 2020-03-31
meaning of affluent:2020-03-01 2020-03-31
stay afloat:2020-03-01 2020-03-31
afloat meaning:2020-03-01 2020-03-31
keep afloat:2020-03-01 2020-03-31
arbory afloat:2020-03-01 2020-03-31
afloat definition:2020-03-01 2020-03-31
class afloat:2020-03-01 2020-03-31
nsips afloat:2020-03-01 2020-03-31
nsips:2020-03-01 2020-03-31
staying afloat:2020-03-01 2020-03-31
afloat mac:2020-03-01 2020-03-31
baggage allowance:2020-03-01 2020-03-31
tax allowance:2020-03-01 2020-03-31
carers allowance:2020-03-01 2020-03-31
personal allowance:2020-03-01 2020-03-31
attendance allowance:2020-03-01 2020-03-31
disability:2020-03-01 2020-03-31
disability allowance:2020-03-01 2020-03-31
attendance:2020-03-01 2020-03-31
job seekers allowance:2020-03-01 2020-03-31
car allowance:2020-03-01 2020-03-31
aristocracy definition:2020-03-01 2020-03-31
aristocracy meaning:2020-03-01 2020-03-31
democracy:2020-03-01 2020-03-31
oligarchy:2020-03-01 2020-03-31
what is aristocracy:2020-03-01 2020-03-31
monarchy:2020-03-01 2020-03-31
government:2020-03-01 2020-03-31
aristocracy government:2020-03-01 2020-03-31
aristocrat:2020-03-01 2020-03-31
the aristocrat:2020-03-01 2020-03-31
aristocrat definition:2020-03-01 2020-03-31
aristocrat meaning:2020-03-01 2020-03-31
aristocracy:2020-03-01 2020-03-31
aristocrat bags:2020-03-01 2020-03-31
an aristocrat:2020-03-01 2020-03-31
aristocrat restaurant:2020-03-01 2020-03-31
aristocrat menu:2020-03-01 2020-03-31

what is aristocrat:2020-03-01 2020-03-31
aristocratic meaning:2020-03-01 2020-03-31
aristocratic definition:2020-03-01 2020-03-31
aristocratic names:2020-03-01 2020-03-31
what is aristocratic:2020-03-01 2020-03-31
aristocratic family:2020-03-01 2020-03-31
meaning of aristocratic:2020-03-01 2020-03-31
aristocratic government:2020-03-01 2020-03-31
aristocratic meaning in hindi:2020-03-01 2020-03-31
associate degree:2020-03-01 2020-03-31
sales associate:2020-03-01 2020-03-31
the associate:2020-03-01 2020-03-31
associate with:2020-03-01 2020-03-31
associate professor:2020-03-01 2020-03-31
research associate:2020-03-01 2020-03-31
associate login:2020-03-01 2020-03-31
business associate:2020-03-01 2020-03-31
associate kiosk:2020-03-01 2020-03-31
associate manager:2020-03-01 2020-03-31
backer board:2020-03-01 2020-03-31
de backer:2020-03-01 2020-03-31
tile backer:2020-03-01 2020-03-31
tile backer board:2020-03-01 2020-03-31
tile board:2020-03-01 2020-03-31
backer rod:2020-03-01 2020-03-31
baker:2020-03-01 2020-03-31
cerveja:2020-03-01 2020-03-31
cerveja backer:2020-03-01 2020-03-31
hardie backer:2020-03-01 2020-03-31
forward:2020-03-01 2020-03-31
forward and backward:2020-03-01 2020-03-31
backward compatibility:2020-03-01 2020-03-31
backward class:2020-03-01 2020-03-31
backward classes:2020-03-01 2020-03-31
xbox backward:2020-03-01 2020-03-31
backwards:2020-03-01 2020-03-31
backward compatible:2020-03-01 2020-03-31
xbox one backward:2020-03-01 2020-03-31
xbox one:2020-03-01 2020-03-31
economic backwardness:2020-03-01 2020-03-31
backwardness meaning:2020-03-01 2020-03-31
social backwardness:2020-03-01 2020-03-31
economic backwardness in historical perspective:2020-03-01 2020-03-31
scholastic backwardness:2020-03-01 2020-03-31
backwardness synonym:2020-03-01 2020-03-31
go bankrupt:2020-03-01 2020-03-31
bankruptcy:2020-03-01 2020-03-31
going bankrupt:2020-03-01 2020-03-31

went bankrupt:2020-03-01 2020-03-31
to go bankrupt:2020-03-01 2020-03-31
what is bankrupt:2020-03-01 2020-03-31
50 cent:2020-03-01 2020-03-31
50 cent bankrupt:2020-03-01 2020-03-31
bank bankrupt:2020-03-01 2020-03-31
trump bankrupt:2020-03-01 2020-03-31
file bankruptcy:2020-03-01 2020-03-31
chapter 7 bankruptcy:2020-03-01 2020-03-31
bankruptcy court:2020-03-01 2020-03-31
chapter 7:2020-03-01 2020-03-31
how to bankruptcy:2020-03-01 2020-03-31
bankruptcy attorney:2020-03-01 2020-03-31
filing bankruptcy:2020-03-01 2020-03-31
after bankruptcy:2020-03-01 2020-03-31
chapter 13:2020-03-01 2020-03-31
chapter 13 bankruptcy:2020-03-01 2020-03-31
bargain hunt:2020-03-01 2020-03-31
bargain outlet:2020-03-01 2020-03-31
home bargain:2020-03-01 2020-03-31
bargain booze:2020-03-01 2020-03-31
bargain store:2020-03-01 2020-03-31
best bargain:2020-03-01 2020-03-31
bargain shop:2020-03-01 2020-03-31
bargain box:2020-03-01 2020-03-31
plea bargain:2020-03-01 2020-03-31
bargain barn:2020-03-01 2020-03-31
the beggar:2020-03-01 2020-03-31
beggar meaning:2020-03-01 2020-03-31
blind beggar:2020-03-01 2020-03-31
virtual beggar:2020-03-01 2020-03-31
the blind beggar:2020-03-01 2020-03-31
begger:2020-03-01 2020-03-31
indian beggar:2020-03-01 2020-03-31
beggar king:2020-03-01 2020-03-31
beggars:2020-03-01 2020-03-31
beggar in hindi:2020-03-01 2020-03-31
the benefactor:2020-03-01 2020-03-31
gta benefactor:2020-03-01 2020-03-31
estado benefactor:2020-03-01 2020-03-31
benefactor meaning:2020-03-01 2020-03-31
gta 5:2020-03-01 2020-03-31
gta 5 benefactor:2020-03-01 2020-03-31
el benefactor:2020-03-01 2020-03-31
benefactor serrano:2020-03-01 2020-03-31
benefactor schafter:2020-03-01 2020-03-31
the beneficiary:2020-03-01 2020-03-31
beneficiary status:2020-03-01 2020-03-31

beneficiary bank:2020-03-01 2020-03-31
insurance beneficiary:2020-03-01 2020-03-31
insurance:2020-03-01 2020-03-31
what is beneficiary:2020-03-01 2020-03-31
beneficiary meaning:2020-03-01 2020-03-31
trust beneficiary:2020-03-01 2020-03-31
beneficiary account:2020-03-01 2020-03-31
add beneficiary:2020-03-01 2020-03-31
child benefit:2020-03-01 2020-03-31
benefits:2020-03-01 2020-03-31
housing benefit:2020-03-01 2020-03-31
benefit brow:2020-03-01 2020-03-31
my benefit:2020-03-01 2020-03-31
cost benefit:2020-03-01 2020-03-31
child tax benefit:2020-03-01 2020-03-31
benefit calculator:2020-03-01 2020-03-31
security benefit:2020-03-01 2020-03-31
benefit cosmetics:2020-03-01 2020-03-31
benevolence meaning:2020-03-01 2020-03-31
benevolence definition:2020-03-01 2020-03-31
benevolent:2020-03-01 2020-03-31
define benevolence:2020-03-01 2020-03-31
what is benevolence:2020-03-01 2020-03-31
her benevolence:2020-03-01 2020-03-31
benevolence synonym:2020-03-01 2020-03-31
meaning of benevolence:2020-03-01 2020-03-31
definition of benevolence:2020-03-01 2020-03-31
meaning benevolent:2020-03-01 2020-03-31
meaning:2020-03-01 2020-03-31
benevolent definition:2020-03-01 2020-03-31
the benevolent:2020-03-01 2020-03-31
benevolent fund:2020-03-01 2020-03-31
benevolent society:2020-03-01 2020-03-31
define benevolent:2020-03-01 2020-03-31
benevolent association:2020-03-01 2020-03-31
what is benevolent:2020-03-01 2020-03-31
bequeath meaning:2020-03-01 2020-03-31
bequeath definition:2020-03-01 2020-03-31
to bequeath:2020-03-01 2020-03-31
define bequeath:2020-03-01 2020-03-31
will:2020-03-01 2020-03-31
what is bequeath:2020-03-01 2020-03-31
bequest:2020-03-01 2020-03-31
bequeath synonym:2020-03-01 2020-03-31
meaning of bequeath:2020-03-01 2020-03-31
betroth meaning:2020-03-01 2020-03-31
betroth definition:2020-03-01 2020-03-31
define betroth:2020-03-01 2020-03-31

betrothed:2020-03-01 2020-03-31
ratify:2020-03-01 2020-03-31
betrothal:2020-03-01 2020-03-31
betrothal meaning:2020-03-01 2020-03-31
betrothal definition:2020-03-01 2020-03-31
betrothal ring:2020-03-01 2020-03-31
what is betrothal:2020-03-01 2020-03-31
engagement:2020-03-01 2020-03-31
betrothal ceremony:2020-03-01 2020-03-31
betrothal in tamil:2020-03-01 2020-03-31
betrothal tamil meaning:2020-03-01 2020-03-31
meaning of betrothal:2020-03-01 2020-03-31
betrothal meaning in tamil:2020-03-01 2020-03-31
blackmail mom:2020-03-01 2020-03-31
blackmail video:2020-03-01 2020-03-31
sister blackmail:2020-03-01 2020-03-31
blackmail movie:2020-03-01 2020-03-31
brother blackmail:2020-03-01 2020-03-31
blackmail song:2020-03-01 2020-03-31
black:2020-03-01 2020-03-31
blackmail stories:2020-03-01 2020-03-31
blackmail 2018:2020-03-01 2020-03-31
blackmail illegal:2020-03-01 2020-03-31
casino:2020-03-01 2020-03-31
casino bonus:2020-03-01 2020-03-31
no deposit bonus:2020-03-01 2020-03-31
bonus code:2020-03-01 2020-03-31
casino bonus no deposit:2020-03-01 2020-03-31
casino deposit bonus:2020-03-01 2020-03-31
ah bonus:2020-03-01 2020-03-31
ah:2020-03-01 2020-03-31
bonus card:2020-03-01 2020-03-31
no deposit bonus codes:2020-03-01 2020-03-31
boom beach:2020-03-01 2020-03-31
the boom:2020-03-01 2020-03-31
sonic boom:2020-03-01 2020-03-31
sonic:2020-03-01 2020-03-31
ue boom:2020-03-01 2020-03-31
baby boom:2020-03-01 2020-03-31
boom boom song:2020-03-01 2020-03-31
boom boom boom song:2020-03-01 2020-03-31
boom boom lyrics:2020-03-01 2020-03-31
boom boom boom lyrics:2020-03-01 2020-03-31
the breadwinner:2020-03-01 2020-03-31
breadwinner meaning:2020-03-01 2020-03-31
breadwinner movie:2020-03-01 2020-03-31
the breadwinner movie:2020-03-01 2020-03-31
breadwinner book:2020-03-01 2020-03-31

the breadwinner book:2020-03-01 2020-03-31
breadwinner definition:2020-03-01 2020-03-31
what is breadwinner:2020-03-01 2020-03-31
breadwinners:2020-03-01 2020-03-31
parvana breadwinner:2020-03-01 2020-03-31
corruption:2020-03-01 2020-03-31
to bribe:2020-03-01 2020-03-31
bribe meaning:2020-03-01 2020-03-31
the bribe:2020-03-01 2020-03-31
bribe money:2020-03-01 2020-03-31
bribery:2020-03-01 2020-03-31
bribe definition:2020-03-01 2020-03-31
what is bribe:2020-03-01 2020-03-31
bribe in hindi:2020-03-01 2020-03-31
bribe hindi meaning:2020-03-01 2020-03-31
broke girls:2020-03-01 2020-03-31
broke up:2020-03-01 2020-03-31
2 broke girls:2020-03-01 2020-03-31
broke girl:2020-03-01 2020-03-31
young dumb:2020-03-01 2020-03-31
young dumb broke:2020-03-01 2020-03-31
heart broke:2020-03-01 2020-03-31
young dumb and broke:2020-03-01 2020-03-31
two broke girls:2020-03-01 2020-03-31
broke lyrics:2020-03-01 2020-03-31
baby bum:2020-03-01 2020-03-31
baby bum bum:2020-03-01 2020-03-31
bum bum song:2020-03-01 2020-03-31
bum bum bum song:2020-03-01 2020-03-31
my bum:2020-03-01 2020-03-31
little bum:2020-03-01 2020-03-31
baby little bum:2020-03-01 2020-03-31
bum bum tam tam:2020-03-01 2020-03-31
bum bum tam:2020-03-01 2020-03-31
kim bum:2020-03-01 2020-03-31
best buy:2020-03-01 2020-03-31
where:2020-03-01 2020-03-31
walmart:2020-03-01 2020-03-31
buy buy baby:2020-03-01 2020-03-31
target:2020-03-01 2020-03-31
buy a car:2020-03-01 2020-03-31
best buy canada:2020-03-01 2020-03-31
buy and sell:2020-03-01 2020-03-31
best buy credit card:2020-03-01 2020-03-31
best buy near me:2020-03-01 2020-03-31
to capitalize:2020-03-01 2020-03-31
how to capitalize:2020-03-01 2020-03-31
capitalize title:2020-03-01 2020-03-31

capitalize on:2020-03-01 2020-03-31
when to capitalize:2020-03-01 2020-03-31
capitalize first letter:2020-03-01 2020-03-31
when do you capitalize:2020-03-01 2020-03-31
capitalized:2020-03-01 2020-03-31
capitalize seasons:2020-03-01 2020-03-31
string capitalize:2020-03-01 2020-03-31
charitable trust:2020-03-01 2020-03-31
charitable foundation:2020-03-01 2020-03-31
charitable donations:2020-03-01 2020-03-31
charity:2020-03-01 2020-03-31
charitable giving:2020-03-01 2020-03-31
charitable contributions:2020-03-01 2020-03-31
charitable donation:2020-03-01 2020-03-31
charitable organizations:2020-03-01 2020-03-31
charitable deduction:2020-03-01 2020-03-31
charitable fund:2020-03-01 2020-03-31
charity shop:2020-03-01 2020-03-31
charity shops:2020-03-01 2020-03-31
charity jobs:2020-03-01 2020-03-31
charity commission:2020-03-01 2020-03-31
charities:2020-03-01 2020-03-31
charity work:2020-03-01 2020-03-31
what is charity:2020-03-01 2020-03-31
charity navigator:2020-03-01 2020-03-31
cancer charity:2020-03-01 2020-03-31
charity donation:2020-03-01 2020-03-31
flights:2020-03-01 2020-03-31
cheap flights:2020-03-01 2020-03-31
cheap hotels:2020-03-01 2020-03-31
cheap tickets:2020-03-01 2020-03-31
cheap hotel:2020-03-01 2020-03-31
cheap flight:2020-03-01 2020-03-31
cheap cars:2020-03-01 2020-03-31
cheap holidays:2020-03-01 2020-03-31
cheap air:2020-03-01 2020-03-31
cheap insurance:2020-03-01 2020-03-31
the colony:2020-03-01 2020-03-31
first colony:2020-03-01 2020-03-31
colony house:2020-03-01 2020-03-31
colony bank:2020-03-01 2020-03-31
defence colony:2020-03-01 2020-03-31
old colony:2020-03-01 2020-03-31
colony hotel:2020-03-01 2020-03-31
beach colony:2020-03-01 2020-03-31
the colony tx:2020-03-01 2020-03-31
lost colony:2020-03-01 2020-03-31
the commoner:2020-03-01 2020-03-31

commoner pittsburgh:2020-03-01 2020-03-31
commoner meaning:2020-03-01 2020-03-31
commoner definition:2020-03-01 2020-03-31
the commoner pittsburgh:2020-03-01 2020-03-31
commoner 5e:2020-03-01 2020-03-31
barry commoner:2020-03-01 2020-03-31
what is a commoner:2020-03-01 2020-03-31
commoner tucson:2020-03-01 2020-03-31
commoner menu:2020-03-01 2020-03-31
community college:2020-03-01 2020-03-31
community center:2020-03-01 2020-03-31
community credit union:2020-03-01 2020-03-31
community bank:2020-03-01 2020-03-31
community centre:2020-03-01 2020-03-31
community first:2020-03-01 2020-03-31
community services:2020-03-01 2020-03-31
community hospital:2020-03-01 2020-03-31
community service:2020-03-01 2020-03-31
community care:2020-03-01 2020-03-31
compensate for:2020-03-01 2020-03-31
to compensate:2020-03-01 2020-03-31
compensate meaning:2020-03-01 2020-03-31
compensate definition:2020-03-01 2020-03-31
what is compensate:2020-03-01 2020-03-31
compensation:2020-03-01 2020-03-31
compensate synonym:2020-03-01 2020-03-31
what does compensate:2020-03-01 2020-03-31
compensate define:2020-03-01 2020-03-31
meaning of compensate:2020-03-01 2020-03-31
workers compensation:2020-03-01 2020-03-31
flight compensation:2020-03-01 2020-03-31
what is compensation:2020-03-01 2020-03-31
compensation plan:2020-03-01 2020-03-31
claim compensation:2020-03-01 2020-03-31
deferred compensation:2020-03-01 2020-03-31
workers compensation insurance:2020-03-01 2020-03-31
work compensation:2020-03-01 2020-03-31
va compensation:2020-03-01 2020-03-31
injury compensation:2020-03-01 2020-03-31
contribute to:2020-03-01 2020-03-31
to contribute to:2020-03-01 2020-03-31
contribute in:2020-03-01 2020-03-31
contribute to ira:2020-03-01 2020-03-31
401k:2020-03-01 2020-03-31
contribute definition:2020-03-01 2020-03-31
contribute to or in:2020-03-01 2020-03-31
contribution:2020-03-01 2020-03-31
roth ira:2020-03-01 2020-03-31

contribute meaning:2020-03-01 2020-03-31
contribution to:2020-03-01 2020-03-31
ira contribution:2020-03-01 2020-03-31
contribution limits:2020-03-01 2020-03-31
sss:2020-03-01 2020-03-31
sss contribution:2020-03-01 2020-03-31
ira contribution limits:2020-03-01 2020-03-31
contribution margin:2020-03-01 2020-03-31
hsa contribution:2020-03-01 2020-03-31
cooperative bank:2020-03-01 2020-03-31
the cooperative:2020-03-01 2020-03-31
cooperative society:2020-03-01 2020-03-31
the cooperative bank:2020-03-01 2020-03-31
credit cooperative:2020-03-01 2020-03-31
cooperative bank login:2020-03-01 2020-03-31
cooperative learning:2020-03-01 2020-03-31
cooperative housing:2020-03-01 2020-03-31
what is cooperative:2020-03-01 2020-03-31
cooperative credit union:2020-03-01 2020-03-31
corrupt file:2020-03-01 2020-03-31
corrupt files:2020-03-01 2020-03-31
corrupt countries:2020-03-01 2020-03-31
corrupted:2020-03-01 2020-03-31
corrupt data:2020-03-01 2020-03-31
corrupt a file:2020-03-01 2020-03-31
most corrupt countries:2020-03-01 2020-03-31
corrupt definition:2020-03-01 2020-03-31
corrupt government:2020-03-01 2020-03-31
low cost:2020-03-01 2020-03-31
cost of living:2020-03-01 2020-03-31
cost plus:2020-03-01 2020-03-31
voli low cost:2020-03-01 2020-03-31
opportunity cost:2020-03-01 2020-03-31
fixed cost:2020-03-01 2020-03-31
cost control:2020-03-01 2020-03-31
marginal cost:2020-03-01 2020-03-31
jet cost:2020-03-01 2020-03-31
cost of sales:2020-03-01 2020-03-31
costliness meaning:2020-03-01 2020-03-31
costly car:2020-03-01 2020-03-31
expensive:2020-03-01 2020-03-31
more costly:2020-03-01 2020-03-31
costly phone:2020-03-01 2020-03-31
world costly car:2020-03-01 2020-03-31
costly meaning:2020-03-01 2020-03-31
costly mobile:2020-03-01 2020-03-31
costly cars:2020-03-01 2020-03-31
very costly:2020-03-01 2020-03-31

costly bike:2020-03-01 2020-03-31
the crisis:2020-03-01 2020-03-31
la crisis:2020-03-01 2020-03-31
financial crisis:2020-03-01 2020-03-31
water crisis:2020-03-01 2020-03-31
infinite crisis:2020-03-01 2020-03-31
cuban missile crisis:2020-03-01 2020-03-31
crisis center:2020-03-01 2020-03-31
crisis on infinite earths:2020-03-01 2020-03-31
midlife crisis:2020-03-01 2020-03-31
crisis action:2020-03-01 2020-03-31
creditor:2020-03-01 2020-03-31
the debtor:2020-03-01 2020-03-31
creditor debtor:2020-03-01 2020-03-31
debtor meaning:2020-03-01 2020-03-31
what is debtor:2020-03-01 2020-03-31
debt:2020-03-01 2020-03-31
debtor definition:2020-03-01 2020-03-31
debtor and creditor:2020-03-01 2020-03-31
what is a debtor:2020-03-01 2020-03-31
default password:2020-03-01 2020-03-31
by default:2020-03-01 2020-03-31
default browser:2020-03-01 2020-03-31
what is default:2020-03-01 2020-03-31
set as default:2020-03-01 2020-03-31
default gateway:2020-03-01 2020-03-31
bravely default:2020-03-01 2020-03-31
default ip address:2020-03-01 2020-03-31
c# default:2020-03-01 2020-03-31
make google default:2020-03-01 2020-03-31
attention:2020-03-01 2020-03-31
deficit attention:2020-03-01 2020-03-31
deficit disorder:2020-03-01 2020-03-31
budget deficit:2020-03-01 2020-03-31
budget:2020-03-01 2020-03-31
deficit de atencion:2020-03-01 2020-03-31
calorie deficit:2020-03-01 2020-03-31
fiscal deficit:2020-03-01 2020-03-31
attention deficit disorder:2020-03-01 2020-03-31
what is deficit:2020-03-01 2020-03-31
tax depreciation:2020-03-01 2020-03-31
depreciation rate:2020-03-01 2020-03-31
what is depreciation:2020-03-01 2020-03-31
depreciation cost:2020-03-01 2020-03-31
depreciation expense:2020-03-01 2020-03-31
depreciation method:2020-03-01 2020-03-31
car depreciation:2020-03-01 2020-03-31
asset depreciation:2020-03-01 2020-03-31

accounting depreciation:2020-03-01 2020-03-31
accumulated:2020-03-01 2020-03-31
great depression:2020-03-01 2020-03-31
anxiety:2020-03-01 2020-03-31
the great depression:2020-03-01 2020-03-31
depression symptoms:2020-03-01 2020-03-31
what is depression:2020-03-01 2020-03-31
depression and anxiety:2020-03-01 2020-03-31
depression test:2020-03-01 2020-03-31
depression help:2020-03-01 2020-03-31
depression quotes:2020-03-01 2020-03-31
depression signs:2020-03-01 2020-03-31
destitute meaning:2020-03-01 2020-03-31
destitute definition:2020-03-01 2020-03-31
define destitute:2020-03-01 2020-03-31
meaning of destitute:2020-03-01 2020-03-31
destitute synonym:2020-03-01 2020-03-31
what is destitute:2020-03-01 2020-03-31
definition of destitute:2020-03-01 2020-03-31
destitute meaning in hindi:2020-03-01 2020-03-31
what does destitute mean:2020-03-01 2020-03-31
world domination:2020-03-01 2020-03-31
domination video:2020-03-01 2020-03-31
black domination:2020-03-01 2020-03-31
domination game:2020-03-01 2020-03-31
total domination:2020-03-01 2020-03-31
downhill domination:2020-03-01 2020-03-31
domination meaning:2020-03-01 2020-03-31
domination hard:2020-03-01 2020-03-31
emperor domination:2020-03-01 2020-03-31
global domination:2020-03-01 2020-03-31
blood donate:2020-03-01 2020-03-31
where to donate:2020-03-01 2020-03-31
plasma:2020-03-01 2020-03-31
donate plasma:2020-03-01 2020-03-31
donate money:2020-03-01 2020-03-31
donate hair:2020-03-01 2020-03-31
donate clothes:2020-03-01 2020-03-31
my donate:2020-03-01 2020-03-31
donate to charity:2020-03-01 2020-03-31
blood donation:2020-03-01 2020-03-31
plasma donation:2020-03-01 2020-03-31
donation near me:2020-03-01 2020-03-31
organ donation:2020-03-01 2020-03-31
donation center:2020-03-01 2020-03-31
goodwill donation:2020-03-01 2020-03-31
goodwill:2020-03-01 2020-03-31
donation pick up:2020-03-01 2020-03-31

salvation army donation:2020-03-01 2020-03-31
wish:2020-03-01 2020-03-31
wish economize:2020-03-01 2020-03-31
wish economize comprando:2020-03-01 2020-03-31
farmacia economize:2020-03-01 2020-03-31
economize agua:2020-03-01 2020-03-31
economize rondonopolis:2020-03-01 2020-03-31
economize telefone:2020-03-01 2020-03-31
drogaria economize:2020-03-01 2020-03-31
economize definition:2020-03-01 2020-03-31
farmacia economize rondonopolis:2020-03-01 2020-03-31
endow meaning:2020-03-01 2020-03-31
to endow:2020-03-01 2020-03-31
endowment:2020-03-01 2020-03-31
endow with:2020-03-01 2020-03-31
endow me:2020-03-01 2020-03-31
endow define:2020-03-01 2020-03-31
endow synonym:2020-03-01 2020-03-31
endowed:2020-03-01 2020-03-31
meaning of endow:2020-03-01 2020-03-31
endowment meaning:2020-03-01 2020-03-31
business:2020-03-01 2020-03-31
entrepreneurial business:2020-03-01 2020-03-31
entrepreneur:2020-03-01 2020-03-31
entrepreneurship:2020-03-01 2020-03-31
what is entrepreneurial:2020-03-01 2020-03-31
entrepreneurial development:2020-03-01 2020-03-31
entrepreneurial definition:2020-03-01 2020-03-31
entrepreneurial meaning:2020-03-01 2020-03-31
entrepreneurial skills:2020-03-01 2020-03-31
private equity:2020-03-01 2020-03-31
equity fund:2020-03-01 2020-03-31
home equity:2020-03-01 2020-03-31

```
[14]: len(count)
```

```
[14]: 600
```

```
[0]: count2=count
```

```
[0]: df = pd.DataFrame(count)  
df.to_csv('fears.csv', index=False)
```



```
In [1]: !pip install pytrends
```

```
Collecting pytrends
  Downloading https://files.pythonhosted.org/packages/74/a4/c1b1242be7d31650c6d9128a776c753db18f0e83290aaea0dd80dd31374b/pytrends-4.7.2.tar.gz
Requirement already satisfied: requests in c:\users\lunarhero\anaconda3\lib\site-packages (from pytrends) (2.21.0)
Requirement already satisfied: pandas in c:\users\lunarhero\anaconda3\lib\site-packages (from pytrends) (0.23.4)
Requirement already satisfied: lxml in c:\users\lunarhero\anaconda3\lib\site-packages (from pytrends) (4.2.5)
Requirement already satisfied: idna<2.9,>=2.5 in c:\users\lunarhero\anaconda3\lib\site-packages (from requests->pytrends) (2.8)
Requirement already satisfied: urllib3<1.25,>=1.21.1 in c:\users\lunarhero\anaconda3\lib\site-packages (from requests->pytrends) (1.24.1)
Requirement already satisfied: chardet<3.1.0,>=3.0.2 in c:\users\lunarhero\anaconda3\lib\site-packages (from requests->pytrends) (3.0.4)
Requirement already satisfied: certifi>=2017.4.17 in c:\users\lunarhero\anaconda3\lib\site-packages (from requests->pytrends) (2019.11.28)
Requirement already satisfied: python-dateutil>=2.5.0 in c:\users\lunarhero\anaconda3\lib\site-packages (from pandas->pytrends) (2.7.5)
Requirement already satisfied: pytz>=2011k in c:\users\lunarhero\anaconda3\lib\site-packages (from pandas->pytrends) (2018.7)
Requirement already satisfied: numpy>=1.9.0 in c:\users\lunarhero\anaconda3\lib\site-packages (from pandas->pytrends) (1.18.1)
Requirement already satisfied: six>=1.5 in c:\users\lunarhero\anaconda3\lib\site-packages (from python-dateutil>=2.5.0->pandas->pytrends) (1.12.0)
Building wheels for collected packages: pytrends
  Running setup.py bdist_wheel for pytrends: started
  Running setup.py bdist_wheel for pytrends: finished with status 'done'
  Stored in directory: C:\Users\lunarhero\AppData\Local\pip\Cache\wheels\64\ae\af\51d48fbbca0563036c6f80999b7ce3f097fa591fd165047baf
Successfully built pytrends
Installing collected packages: pytrends
Successfully installed pytrends-4.7.2
```

Section 1: Index Construction

Step 1: construct static Fears index using the 30 words demonstrated on the paper

```
In [50]: import pandas as pd
import numpy as np
import datetime
import os
import matplotlib.pyplot as plt
import scipy.stats
import statsmodels.api as sm

from wordcloud import WordCloud
```

```
In [20]: word_list = ['RECESSION', 'GOLD PRICE', 'DEPRESSION', 'GREAT DEPRESSION', 'GOLD', 'ECONOMY', 'PRICE OF GOLD', 'THE DEPRESSION', 'CRISIS']

In [23]: for word in word_list:
          data = dailydata.get_daily_data(word, 2005, 1, 2020, 1, wait_time=2)
          data.to_csv(r'C:\Users\lunarhero\Documents\imperial college\MSC_Mathfin\portfolio management\saved_data\{}.csv'.format(word))

RECESSION:2017-12-01 2017-12-31
RECESSION:2018-01-01 2018-01-31
RECESSION:2018-02-01 2018-02-28
RECESSION:2018-03-01 2018-03-31
RECESSION:2018-04-01 2018-04-30
RECESSION:2018-05-01 2018-05-31
RECESSION:2018-06-01 2018-06-30
RECESSION:2018-07-01 2018-07-31
RECESSION:2018-08-01 2018-08-31
RECESSION:2018-09-01 2018-09-30
RECESSION:2018-10-01 2018-10-31
RECESSION:2018-11-01 2018-11-30
RECESSION:2018-12-01 2018-12-31

-----
timeout                                Traceback (most recent call last)
~\Anaconda3\lib\site-packages\urllib3\connectionpool.py in _make_request(self, conn, method, url, timeout, chunked, **httplib
_request_kw)
```

```
In [ ]: # from pytrends import dailydata
# word_list = ['GOLD', 'ECONOMY', 'PRICE OF GOLD', 'THE DEPRESSION', 'CRISIS', 'FRUGAL', 'GDP', 'CHARIT
Y', 'BANKRUPTCY', 'UNEMPLOYMENT', 'INFLATION RATE', 'BANKRUPT', 'THE GREAT DEPRESSION', 'CAR DONAT
E', 'CAPITALIZATION', 'EXPENSE', 'DONATION', 'SAVINGS', 'SOCIAL SECURITY CARD', 'THE CRISIS', 'DEFAULT', 'BENEFITS', 'UNEMPLOYED', 'POVERTY', 'SOCIAL SECURITY OFFICE']
# for word in word_list:
#     from pytrends import dailydata
#     data = dailydata.get_daily_data(word, 2005, 1, 2020, 1, wait_time=3)
#     data.to_csv(r'C:\Users\Lunarhero\Documents\imperial college\MSC_Mathfin\portfolio manageme
nt\saved_data\{}.csv'.format(word))
```

GOLD:2005-01-01 2005-01-31

The request failed: Google returned a response with code 429.

Trying again in 60 seconds.

```

In [2]: def update_df2(this_df,df):
        '''
        This function aims to merge two time series into one dataframe
        And it also fill missing dates with extra column
        '''
        try:
            df['date']=pd.to_datetime(df['date'], format='%Y-%m-%d')
        except:
            try:
                df['date']=pd.to_datetime(df['date'], format='%d/%m/%Y')
            except:
                df['date']=pd.to_datetime(df['date'])
        df=df.set_index('date')
        df.index = pd.DatetimeIndex(df.index)
        #remove the duplicated index
        df = df[~df.index.duplicated()]
        df = df.reindex(idx)
        try:
            df=df.drop(['_id'], axis=1)
        except:
            pass

        # merge two data
        if len(this_df)==0:
            if len(df)!=0:
                this_df=df
        else:
            this_df=pd.concat([this_df,df],axis=1)
        return this_df

# setup necessaty parameter

idx = pd.date_range('2005-01-01', '2020-01-31')

def load_daily_index(path = 'saved_data/',file_name='daily_trends.csv',force_update=False,debug=False):
    csv_files = []
    xlsx_files = []

    def action1(cache=[]):
        for r, d, f in os.walk(path):
            for file in f:
                if '.csv' in file:
                    csv_files.append(os.path.join(r, file))
                if '.xlsx' in file:
                    xlsx_files.append(os.path.join(r, file))
        # concate and merge all the dataframes
        for file in csv_files:
            if debug==True:
                print('\r'+file,end='')
            df=pd.read_csv(file).iloc[:,[0,5]]
            cache = update_df2(cache,df)

        for file in xlsx_files:
            df=pd.read_excel(file).iloc[:,[0,5]]
            cache = update_df2(cache,df)
        # save daily data to one csv
        cache.to_csv('merged_data/'+file_name)
        return cache

    if force_update == False:
        try:
            this_df = pd.read_csv('merged_data/'+file_name,index_col=0)
        except:
            this_df = action1()
    else:
        this_df = action1()
    return this_df

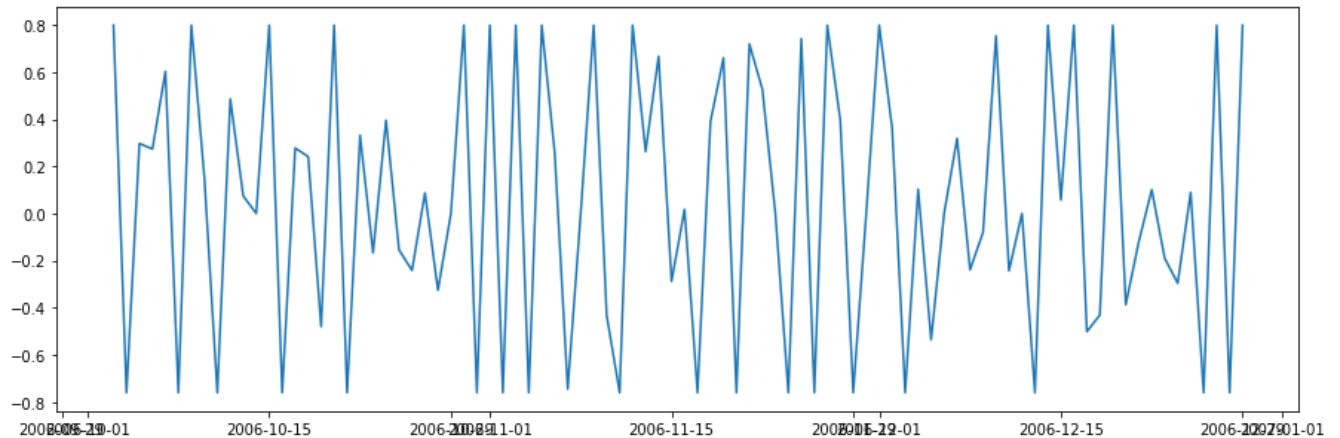
```

In []:

```
In [123]: # this is the 30 words that is shown by the paper
daily_trends=load_daily_index(force_update=False)
daily_trends.index = pd.DatetimeIndex(daily_trends.index)
```

```
In [124]: daily_trends = daily_trends.replace({0:1}) # replace 0 search with 1 to avoid problem
return_ratio = np.log(daily_trends.iloc[1:, :]) - np.log(daily_trends.iloc[:-1, :].values)
for column in list(return_ratio):
    return_ratio.loc[:, column] = scipy.stats.mstats.winsorize(return_ratio.loc[:, column].values,
limits=[0.05, 0.05])
```

```
In [125]: plt.figure(figsize=(15,5))
plt.plot(pd.date_range('2006-10-03', '2006-12-29'), return_ratio.loc['2006-10-03': '2006-12-29', 'PRICE OF GOLD'].values)
plt.show()
```



Now remove the seasonality

```

In [126]: from statsmodels.tsa.seasonal import seasonal_decompose

data = return_ratio.loc[:, 'PRICE OF GOLD']
weekly = seasonal_decompose(data, freq=7)
plt.plot(weekly.seasonal[3:10])
plt.xticks(weekly.seasonal[3:10].index, ['Sun', 'Mon', 'Tue', 'Wed', 'Thu', 'Fri', 'Sat'], rotation='vertical')
plt.title('weekly trend')

plt.show()
data = data - weekly.seasonal
monthly = seasonal_decompose(data, freq=30)
data = data - monthly.seasonal

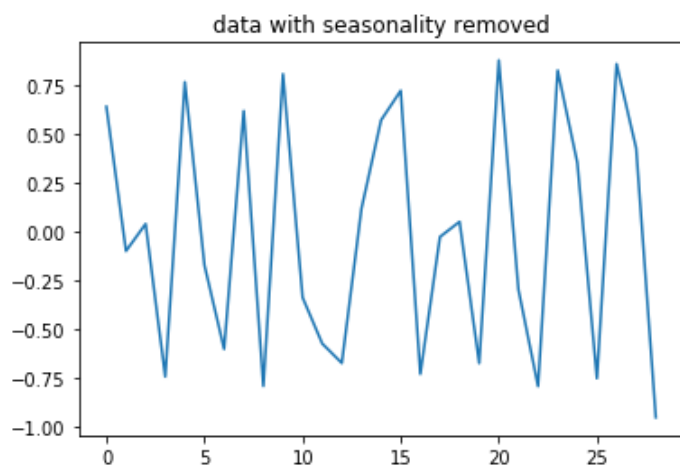
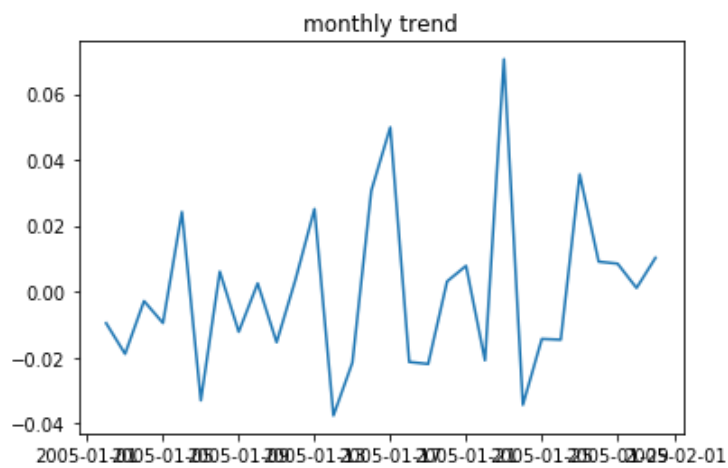
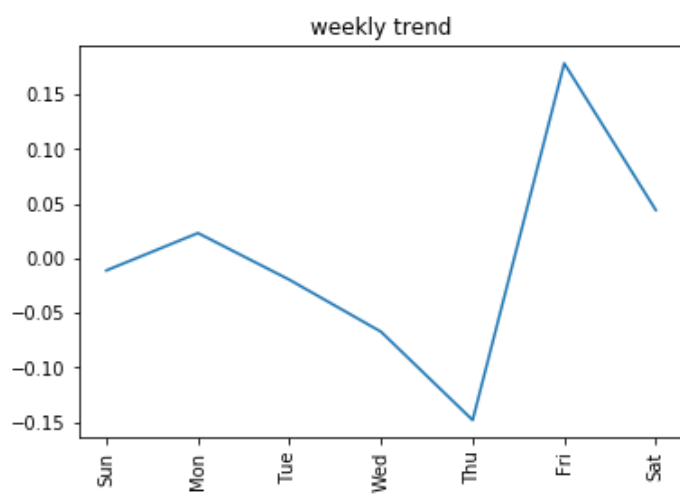
plt.plot(monthly.seasonal[:30])
plt.title('monthly trend')
plt.show()

plt.plot(data.values[1:30])
plt.title('data with seasonality removed')
plt.show()

def remove_seasonality(data):
    weekly = seasonal_decompose(data, freq=7)
    r = data - weekly.seasonal
    monthly = seasonal_decompose(r, freq=30)
    r = r - monthly.seasonal
    return r

# remove seasonality on weekly and monthly dummy, and standardized by scaling each on standard deviation
original_return = return_ratio.copy()
for column in list(return_ratio):
    return_ratio.loc[:, column] = remove_seasonality(return_ratio.loc[:, column])
    return_ratio.loc[:, column] /= np.std(return_ratio.loc[:, column].values)

```

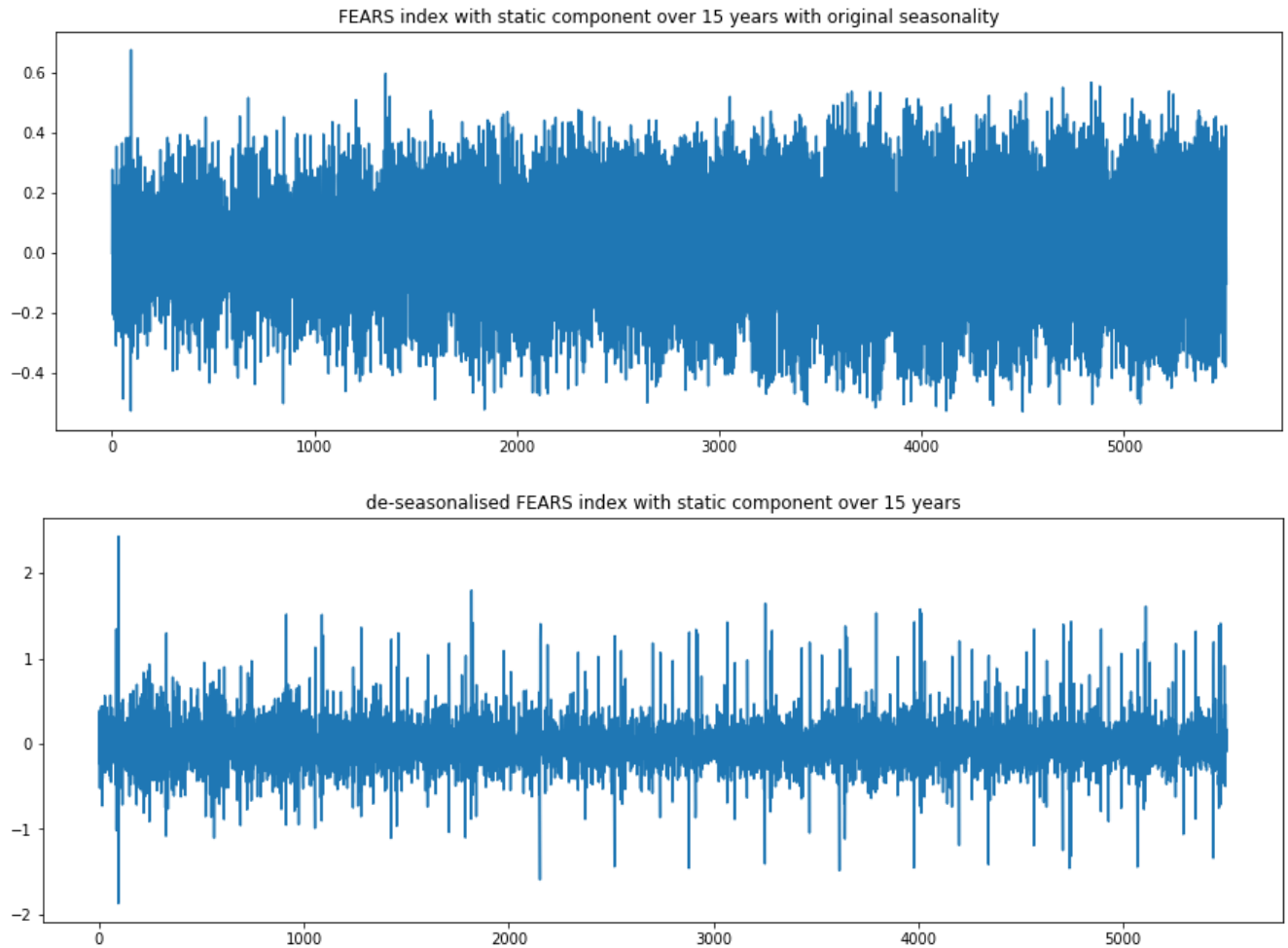


```
In [156]: return_ratio['fears_index'] = return_ratio.sum(axis=1)/30
original_return['fears_index'] = original_return.sum(axis=1)/30
```

this is how detrend static index looks like

```
In [8]: plt.figure(figsize=(15,5))
plt.plot(original_return.fears_index.values)
plt.title('FEARS index with static component over 15 years with original seasonality')
plt.show()

plt.figure(figsize=(15,5))
plt.plot(return_ratio.fears_index.values)
plt.title('de-seasonalised FEARS index with static component over 15 years')
plt.show()
```



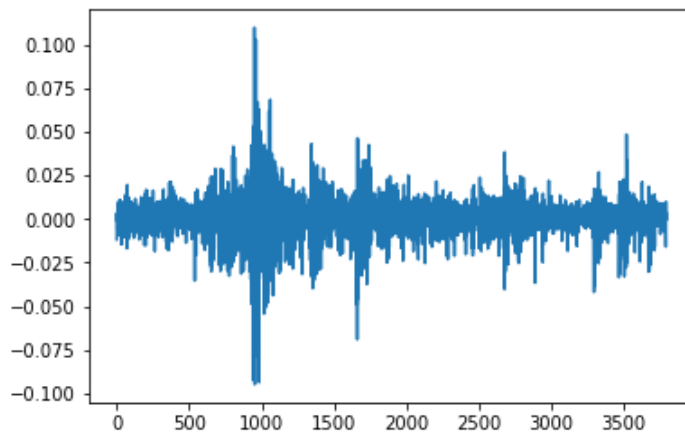
Step 2: construct all other relevant data:

including: sp500 EPU,ADS,VIX

```
In [9]: SP500=pd.read_csv('merged_data/SP500.csv').iloc[:,[0,4]]
SP500['Date']=pd.to_datetime(SP500['Date'], format='%Y-%m-%d')
SP500=SP500.set_index('Date')
SP500.columns=['SP500']
SP500 = np.log(SP500.iloc[1:,:])-np.log(SP500.iloc[:-1,:].values)
```

```
In [192]: plt.plot(SP500.values)
```

```
Out[192]: [<matplotlib.lines.Line2D at 0x27de7de5348>]
```



```
In [10]: EPU=pd.read_excel('merged_data/All_Daily_Policy_Data.xlsx')
EPU['Date']=pd.to_datetime(EPU['Date'], format='%d/%m/%Y')
EPU = EPU.set_index('Date')
EPU.columns=['EPU']
EPU = np.log(EPU.iloc[1:, :]) - np.log(EPU.iloc[: -1, :].values)

ADS=pd.read_excel('merged_data/ADS_Index_Most_Current_Vintage.xlsx', index_col=0)
ADS.columns=['ADS']
ADS = (ADS.iloc[1:, :]-ADS.iloc[: -1, :].values).divide(ADS.iloc[: -1, :].values)

VIX = pd.read_csv('merged_data/vixcurrent.csv').iloc[:, [0, 4]]
VIX['Date']=pd.to_datetime(VIX['Date'], format='%m/%d/%Y')
VIX = VIX.set_index('Date')
VIX.columns=['VIX']
VIX = np.log(VIX.iloc[1:, :]) - np.log(VIX.iloc[: -1, :].values)
```

Step 3: construct dynamic Fears index selecting from 120 words and with variable updating frequency

in the paper, the author worked with updating frequency of 6 months, but we could do better than that :-)

I put this step here because I need the SP500 data to do regression in order to update FEARS index components.

```
In [61]: # first read the data

all_daily_trends = load_daily_index(path = '111_google_trend/', file_name='111_daily_trends.csv',
force_update=False, debug=True)
all_daily_trends = all_daily_trends.loc[:, (all_daily_trends.isna().sum() < 100).values] # remove
column with too many missing value
select_column = [x for x in list(all_daily_trends) if not '.' in x] # remove duplicates
all_daily_trends = all_daily_trends.loc[:, select_column] # remove column with too many missing
value
```

```
In [60]:
```

```
In [ ]:
```



```
In [62]: all_daily_trends = all_daily_trends.replace({0:1}) # replace 0 search with 1 to avoid problem
all_return_ratio = np.log(all_daily_trends.iloc[1:,:])-np.log(all_daily_trends.iloc[:-1,:].values)

for column in list(all_return_ratio):
    # winsorize data
    all_return_ratio.loc[:,column] = scipy.stats.mstats.winsorize(all_return_ratio.loc[:,column].values, limits=[0.05, 0.05])
    # remove seasonality
    all_return_ratio.loc[:,column] = remove_seasonality(all_return_ratio.loc[:,column])
    # remove heteroscedasticity
    all_return_ratio.loc[:,column] /= np.std(all_return_ratio.loc[:,column].values)
all_return_ratio.index = pd.DatetimeIndex(all_return_ratio.index)
```

```

In [63]: def create_dynamic_index(frequency,all_return_ratio,SP500,descending=False):
'''
    frequency decides the frequency of index updates
    all_return_ratio is the data we want to select from
    SP500 is the index we want to regress on
    descending false represent we select 30 most negatively corrected terms, ascending represent
    s the positive most negative terms

    output:
    merged_data is the dataset we finally used for the regression
    fre_dictionary saved the frequency of each word to be included into the Fears Index
'''
all_return_with_Fears = all_return_ratio.copy()
start_date = pd.Timestamp(year=2005, month=1, day=2).date()
end_date = start_date + pd.Timedelta(frequency,unit='M')
next_end_date = end_date + pd.Timedelta(frequency,unit='M')
fre_dictionary = {}

while next_end_date<pd.Timestamp(year=2020, month=1, day=30).date():
    print('\r now end time is '+str(end_date),end='')
    # seperate the dataset into several time segements

    selected_data = all_return_ratio.loc[pd.date_range(start_date,end_date),:]

    # includes return data
    word_choices = list(selected_data)
    selected_data_SP500 = selected_data.join(SP500,how='inner')
    ranking = []

    # run regression on all 104 words within this selected periods
    for word in word_choices:
        X = sm.add_constant(selected_data_SP500.loc[:,[word]])
        model = sm.OLS(selected_data_SP500.loc[:,['SP500']], X).fit() # run regression
        t_stats = pd.read_html(model.summary().tables[1].as_html(),header=0,index_col=0)[0][
't'][1]
        ranking.append([t_stats,word]) # save word and t statistics

    # select the 30 most negative words
    ranking.sort(reverse=descending)

    negative_30_words = [ranking[i][1] for i in range(30)]
    for word in negative_30_words:
        if word in fre_dictionary:
            fre_dictionary[word]+=1
        else:
            fre_dictionary[word]=1
    this_fears_index = selected_data.loc[:,negative_30_words].sum(axis=1)/30

    # update the fears index
    all_return_with_Fears.loc[(all_return_with_Fears.index>pd.Timestamp(end_date)) & (all_r
eturn_with_Fears.index<=pd.Timestamp(next_end_date)), 'FEARS'] = this_fears_index.values
    start_date = end_date
    end_date = next_end_date
    next_end_date = next_end_date + pd.Timedelta(frequency,unit='M')
    Fears_index = all_return_with_Fears.loc[all_return_with_Fears.FEARS.isna()!=True,['FEARS']]
    plt.figure(figsize=(15,5))
    plt.plot(Fears_index)
    plt.title('de-seasonalised FEARS index with dynamic component over 15 years')
    plt.show()

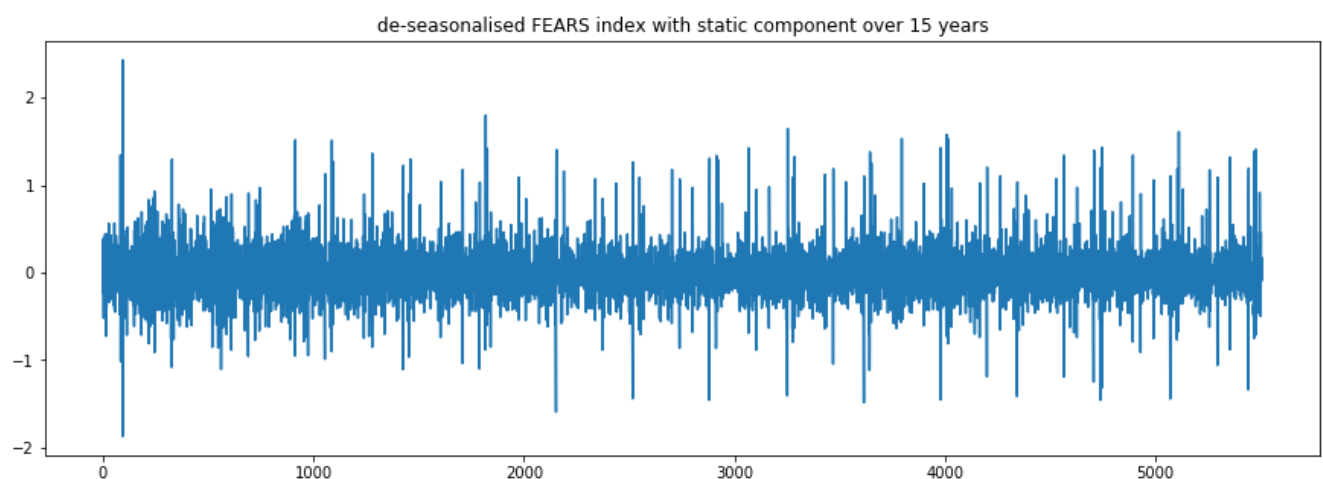
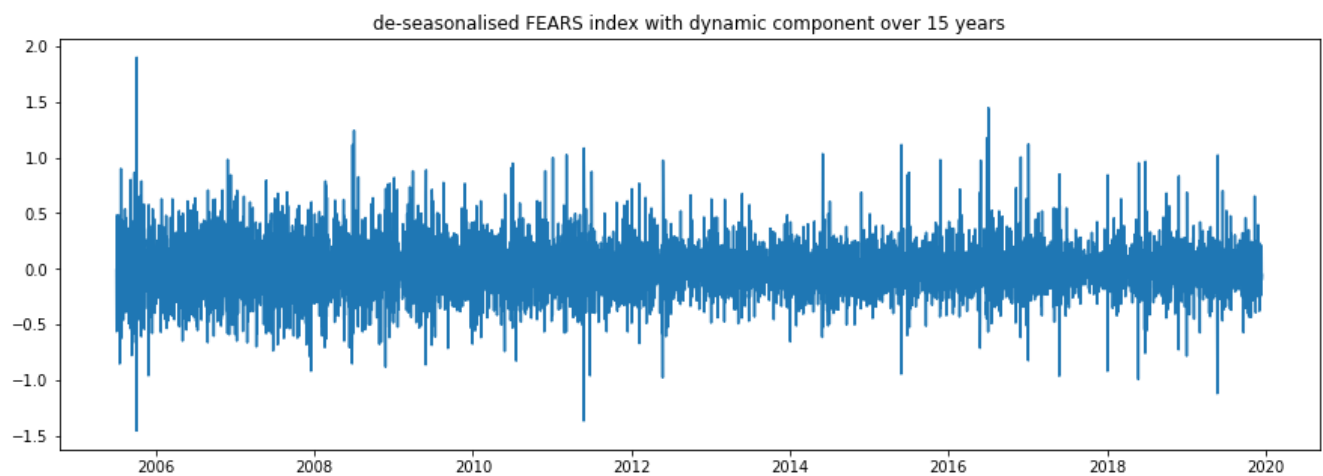
    plt.figure(figsize=(15,5))
    plt.plot(return_ratio.fears_index.values)
    plt.title('de-seasonalised FEARS index with static component over 15 years')
    plt.show()
    merged_data= SP500.join(EPU,how='inner')
    merged_data= merged_data.join(ADS,how='inner')
    merged_data= merged_data.join(VIX,how='inner')
    merged_data= merged_data.join(return_ratio.fears_index,how='inner')
    merged_data= merged_data.join(Fears_index,how='inner').rename(columns={'fears_index':'static
_fears','FEARS':'6month_dynamic_fears'})

    return merged_data,fre_dictionary

```

```
In [64]: merged_data,word_freq = create_dynamic_index(6, all_return_ratio,SP500)
```

now end time is 2019-06-16



Step 4: Check the merged dataset

```
In [65]: merged_data.head()
```

Out[65]:

	SP500	EPU	ADS	VIX	static_fears	6month_dynamic_fears
2005-07-05	0.008794	0.668818	-0.144097	0.024265	0.695029	0.450887
2005-07-06	-0.008375	-0.678372	-0.156650	0.049279	-0.270910	-0.357042
2005-07-07	0.002449	0.002929	-0.171888	0.017771	0.077164	0.484266
2005-07-08	0.011611	0.166195	-0.190854	-0.086939	-0.326078	-0.111118
2005-07-11	0.006235	-1.006852	-0.322447	-0.014958	-0.461740	-0.300328

look at the relation between return and FEARS indes as well as some control parameters

```

In [32]: def train_ndelay(merged_data,n=1,start = 0, end = 3200-5):
    trained_data = merged_data.iloc[(start+5):end,[0,1,2,3,5]].copy()
    if n!=0:
        trained_data.loc[:, 't'] = merged_data.iloc[(start+5):end,0].values

    trained_data.loc[:, 't-1'] = merged_data.iloc[(start+4):(end-1),0].values
    trained_data.loc[:, 't-2'] = merged_data.iloc[(start+3):(end-2),0].values
    trained_data.loc[:, 't-3'] = merged_data.iloc[(start+2):(end-3),0].values
    trained_data.loc[:, 't-4'] = merged_data.iloc[(start+1):(end-4),0].values
    trained_data.loc[:, 't-5'] = merged_data.iloc[start:(end-5),0].values
    X = sm.add_constant(trained_data.iloc[:,1:])
    model = sm.OLS(merged_data.iloc[(start+5+n):(end+n),0].values, X).fit()
    print('')
    print('=====')
    print('Ret(t+{})'.format(n))
    print(pd.read_html(model.summary().tables[1].as_html(),header=0,index_col=0)[0].loc[:,['coef', 't', 'P>|t|']])
    print(pd.read_html(model.summary().tables[0].as_html())[0].iloc[[5],[0,1]])
    print(pd.read_html(model.summary().tables[0].as_html())[0].iloc[[1],[2,3]])
    print('=====')
    print('')
    return None

for n in range(6):
    train_ndelay(merged_data,n)

```

```

=====
Ret(t+0)
               coef      t  P>|t|
const          0.000300   1.890  0.059
EPU            -0.000100  -0.514  0.607
ADS            -0.000300  -1.343  0.180
VIX            -0.119300 -60.825  0.000
6month_dynamic_fears -0.000071 -0.134  0.894
t-1            -0.032700  -2.702  0.007
t-2            -0.018500  -1.523  0.128
t-3             0.050200   4.131  0.000
t-4            -0.005000  -0.411  0.681
t-5            -0.023100  -1.917  0.055
               0      1
5  No. Observations:  3190
               2      3
1  Adj. R-squared:    0.545
=====

```

```

=====
Ret(t+1)
               coef      t  P>|t|
const          0.000300   1.398  0.162
EPU            -0.000500  -1.254  0.210
ADS            0.000033   0.107  0.915
VIX            -0.006200  -1.452  0.147
6month_dynamic_fears 0.001300   1.609  0.108
t              -0.132100  -5.069  0.000
t-1            -0.069600  -3.905  0.000
t-2             0.019500   1.095  0.274
t-3            -0.021900  -1.222  0.222
t-4            -0.049600  -2.784  0.005
t-5             0.002300   0.128  0.898
               0      1
5  No. Observations:  3190
               2      3
1  Adj. R-squared:    0.017
=====

```

```

=====
Ret(t+2)
               coef      t  P>|t|
const          0.0003   1.506  0.132
EPU            0.0008   1.863  0.063
ADS            0.0003   0.953  0.341
VIX            -0.0048  -1.129  0.259
6month_dynamic_fears -0.0009 -1.120  0.263
t              -0.0807  -3.080  0.002
t-1             0.0276   1.541  0.123
t-2            -0.0243  -1.354  0.176
t-3            -0.0462  -2.569  0.010
t-4             0.0064   0.358  0.721
t-5            -0.0254  -1.424  0.154
               0      1
5  No. Observations:  3190
               2      3
1  Adj. R-squared:    0.007
=====

```

```

=====
Ret(t+3)
               coef      t  P>|t|
const          0.000300   1.237  0.216
EPU            0.000200   0.494  0.621
ADS            0.000085   0.274  0.784
VIX            0.003300   0.768  0.443
6month_dynamic_fears -0.000200 -0.279  0.780
t              0.047500   1.809  0.070
t-1            -0.020900  -1.166  0.244

```

t-2	-0.049700	-2.763	0.006
t-3	0.007000	0.387	0.699
t-4	-0.020800	-1.159	0.247
t-5	0.020800	1.164	0.244

0 1

5 No. Observations: 3190

2 3

1 Adj. R-squared: 0.002

=====

=====

Ret(t+4)

	coef	t	P> t
const	0.000300	1.217	0.224
EPU	-0.000200	-0.391	0.696
ADS	0.000069	0.220	0.826
VIX	0.003300	0.768	0.443
6month_dynamic_fears	0.000300	0.389	0.697
t	-0.010300	-0.392	0.695
t-1	-0.053100	-2.954	0.003
t-2	0.008100	0.450	0.653
t-3	-0.024300	-1.346	0.178
t-4	0.016400	0.911	0.362
t-5	-0.020400	-1.143	0.253

0 1

5 No. Observations: 3190

2 3

1 Adj. R-squared: 0.002

=====

=====

Ret(t+5)

	coef	t	P> t
const	0.000300	1.186	0.236
EPU	-0.000039	-0.095	0.925
ADS	0.000035	0.112	0.910
VIX	-0.000800	-0.193	0.847
6month_dynamic_fears	0.000400	0.529	0.597
t	-0.051300	-1.952	0.051
t-1	0.011300	0.628	0.530
t-2	-0.024200	-1.343	0.179
t-3	0.020400	1.129	0.259
t-4	-0.015000	-0.835	0.404
t-5	0.040900	2.292	0.022

0 1

5 No. Observations: 3190

2 3

1 Adj. R-squared: 0.002

=====

Step 2: construct FEARS index with componentes weighted averaging


```

In [162]: def create_dynamic_index_weighted(frequency,all_return_ratio,SP500,descending=False):
'''
    frequency decides the frequency of index updates
    all_return_ratio is the data we want to select from
    SP500 is the index we want to regress on
    descending false represent we select 30 most negatively corrected terms, ascending represent
    s the positive most negative terms

    output:
    merged data is the dataset we finally used for the regression
    fre_dictionary saved the frequency of each word to be included into the Fears Index
'''

start_date = pd.Timestamp(year=2005, month=1, day=2).date()
end_date = start_date + pd.Timedelta(frequency,unit='M')
next_end_date = end_date + pd.Timedelta(frequency,unit='M')
historical_select = []
fre_dictionary = {}
while next_end_date<pd.Timestamp(year=2020, month=1, day=30).date():
    print('\r now end time is '+str(end_date),end='')
    # seperate the dataset into several time segements

    selected_data = all_return_ratio.loc[pd.date_range(start_date,end_date),:]

    # includes return data
    word_choices = list(selected_data)
    selected_data_SP500 = selected_data.join(SP500,how='inner')
    ranking = []

    # run regression on all 104 words within this selected periods
    for word in word_choices:
        X = sm.add_constant(selected_data_SP500.loc[:,[word]])
        model = sm.OLS(selected_data_SP500.loc[:,['SP500']], X).fit() # run regression
        t_stats = pd.read_html(model.summary().tables[1]).as_html(),header=0,index_col=0)[0][
't'][1]
        ranking.append([t_stats,word]) # save word and t statistics

    # select the 30 most negative words and record number of occurance
    ranking.sort(reverse=descending)
    negative_30_words = [ranking[i][1] for i in range(30)]
    for word in negative_30_words:
        if word in fre_dictionary:
            fre_dictionary[word]+=1
        else:
            fre_dictionary[word]=1

    historical_select.append(negative_30_words)
    start_date = end_date
    end_date = next_end_date
    next_end_date = next_end_date + pd.Timedelta(frequency,unit='M')

all_return_with_Fears = all_return_ratio.copy()
#reset start ending date
start_date = pd.Timestamp(year=2005, month=1, day=2).date()
end_date = start_date + pd.Timedelta(frequency,unit='M')
next_end_date = end_date + pd.Timedelta(frequency,unit='M')
i=0

while next_end_date<pd.Timestamp(year=2020, month=1, day=30).date():
    #calculate the weighted sum
    total_fre = sum([fre_dictionary[word] for word in historical_select[i]])
    list_of_value=[fre_dictionary[word]/total_fre for word in historical_select[i]]
    this_fears_index = selected_data.loc[:,historical_select[i]].dot(list_of_value)
    # update the fears index
    all_return_with_Fears.loc[(all_return_with_Fears.index>pd.Timestamp(end_date)) & (all_r
eturn_with_Fears.index<=pd.Timestamp(next_end_date)),'FEARS'] = this_fears_index.values

```

```

start_date = end_date
end_date = next_end_date
next_end_date = next_end_date + pd.Timedelta(frequency,unit='M')
i+=1

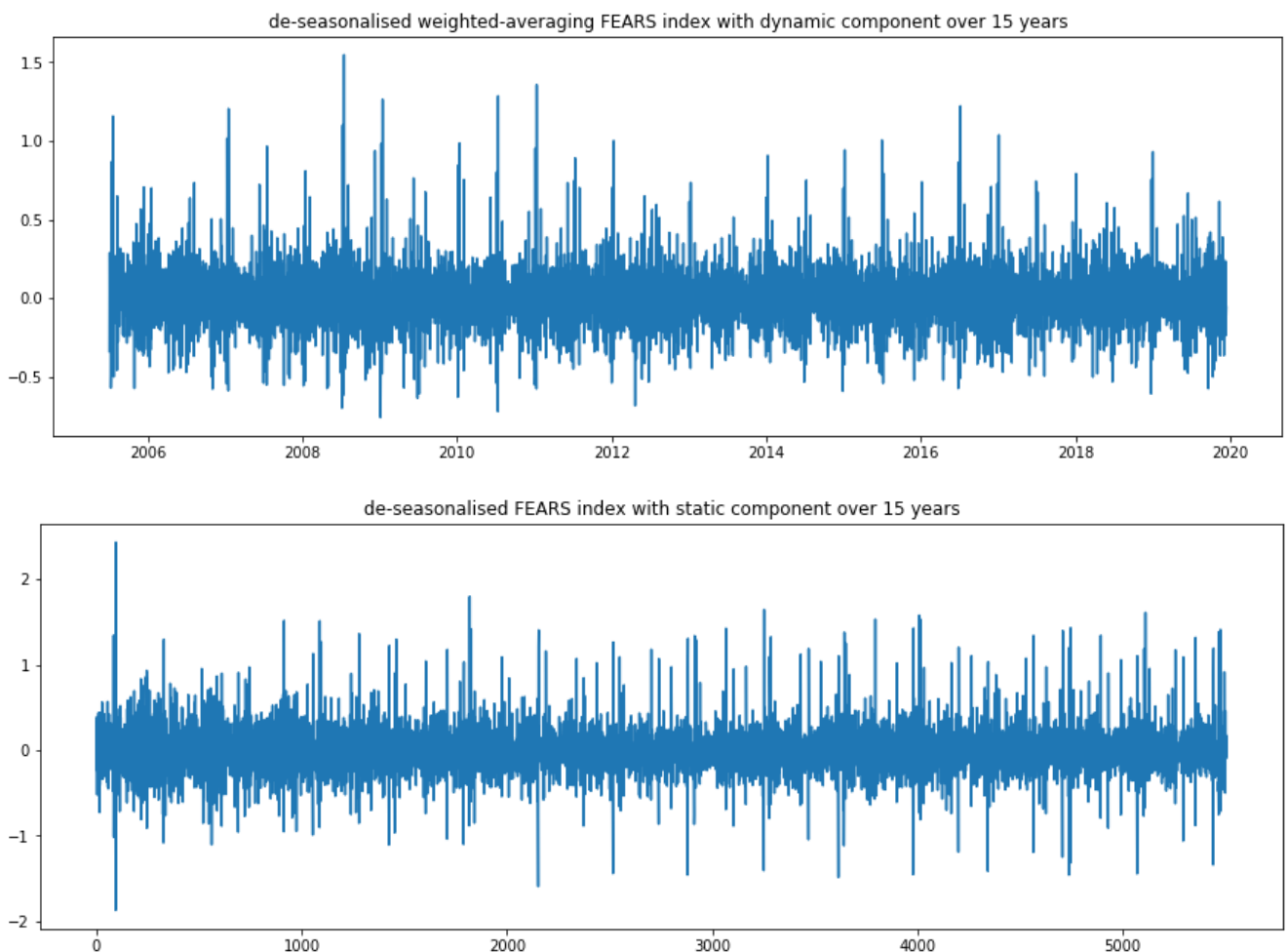
Fears_index = all_return_with_Fears.loc[all_return_with_Fears.FEARS.isna()!=True,['FEARS']]
plt.figure(figsize=(15,5))
plt.plot(Fears_index)
plt.title('de-seasonalised weighted-averaging FEARS index with dynamic component over 15 years')
plt.show()

plt.figure(figsize=(15,5))
plt.plot(return_ratio.fears_index.values)
plt.title('de-seasonalised FEARS index with static component over 15 years')
plt.show()
merged_data= SP500.join(EPU,how='inner')
merged_data= merged_data.join(ADS,how='inner')
merged_data= merged_data.join(VIX,how='inner')
merged_data= merged_data.join(return_ratio.fears_index,how='inner')
merged_data= merged_data.join(Fears_index,how='inner').rename(columns={'fears_index':'static_fears','FEARS':'6month_dynamic_fears'})
return merged_data,fre_dictionary

```

In [163]: merged_data,word_freq = create_dynamic_index_weighted(6, all_return_ratio, SP500)

now end time is 2019-06-16



```
In [164]: for n in range(6):  
          train_ndelay(merged_data,n)
```

```

=====
Ret(t+0)
               coef      t  P>|t|
const          0.0003    1.754 0.080
EPU            -0.0001   -0.513 0.608
ADS            -0.0003   -1.365 0.172
VIX            -0.1193  -60.813 0.000
6month_dynamic_fears  0.0006    0.845 0.398
t-1            -0.0328   -2.710 0.007
t-2            -0.0181   -1.493 0.136
t-3             0.0504    4.150 0.000
t-4            -0.0051   -0.420 0.674
t-5            -0.0232   -1.927 0.054
               0      1
5  No. Observations: 3190
               2      3
1  Adj. R-squared:  0.545
=====

```

```

=====
Ret(t+1)
               coef      t  P>|t|
const          0.00030    1.267 0.205
EPU            -0.00050   -1.292 0.196
ADS            0.00003    0.098 0.922
VIX            -0.00620   -1.465 0.143
6month_dynamic_fears  0.00060    0.551 0.582
t              -0.13240   -5.079 0.000
t-1            -0.06910   -3.876 0.000
t-2             0.01910    1.068 0.286
t-3            -0.02090   -1.164 0.244
t-4            -0.04890   -2.745 0.006
t-5             0.00260    0.148 0.883
               0      1
5  No. Observations: 3190
               2      3
1  Adj. R-squared:  0.016
=====

```

```

=====
Ret(t+2)
               coef      t  P>|t|
const          0.0004    1.911 0.056
EPU            0.0008    1.897 0.058
ADS            0.0003    1.024 0.306
VIX            -0.0048   -1.119 0.263
6month_dynamic_fears -0.0029   -2.758 0.006
t              -0.0795   -3.039 0.002
t-1             0.0275    1.536 0.125
t-2            -0.0253   -1.410 0.159
t-3            -0.0481   -2.676 0.007
t-4             0.0062    0.345 0.730
t-5            -0.0252   -1.418 0.156
               0      1
5  No. Observations: 3190
               2      3
1  Adj. R-squared:  0.009
=====

```

```

=====
Ret(t+3)
               coef      t  P>|t|
const          0.000200    1.070 0.285
EPU            0.000200    0.499 0.618
ADS            0.000075    0.242 0.809
VIX            0.003300    0.770 0.442
6month_dynamic_fears  0.001200    1.135 0.257
t              0.047100    1.793 0.073
t-1            -0.021100   -1.179 0.239

```

```

t-2      -0.048900 -2.720  0.007
t-3      0.007400  0.410  0.682
t-4     -0.021000 -1.174  0.241
t-5      0.020500  1.150  0.250
          0      1
5  No. Observations:  3190
          2      3
1  Adj. R-squared:   0.003
=====

```

```

=====
Ret(t+4)
          coef      t  P>|t|
const      0.000300  1.172  0.241
EPU       -0.000200 -0.400  0.689
ADS        0.000068  0.217  0.829
VIX        0.003300  0.765  0.445
6month_dynamic_fears  0.000200  0.167  0.867
t         -0.010400 -0.396  0.692
t-1       -0.052900 -2.948  0.003
t-2        0.008000  0.444  0.657
t-3       -0.024000 -1.331  0.183
t-4        0.016500  0.921  0.357
t-5       -0.020300 -1.139  0.255
          0      1
5  No. Observations:  3190
          2      3
1  Adj. R-squared:   0.002
=====

```

```

=====
Ret(t+5)
          coef      t  P>|t|
const      0.000200  1.103  0.270
EPU       -0.000045 -0.108  0.914
ADS        0.000032  0.103  0.918
VIX       -0.000800 -0.197  0.844
6month_dynamic_fears  0.000400  0.413  0.679
t         -0.051500 -1.959  0.050
t-1        0.011400  0.636  0.525
t-2       -0.024200 -1.344  0.179
t-3        0.020800  1.154  0.249
t-4       -0.014800 -0.823  0.410
t-5        0.041000  2.297  0.022
          0      1
5  No. Observations:  3190
          2      3
1  Adj. R-squared:   0.002
=====

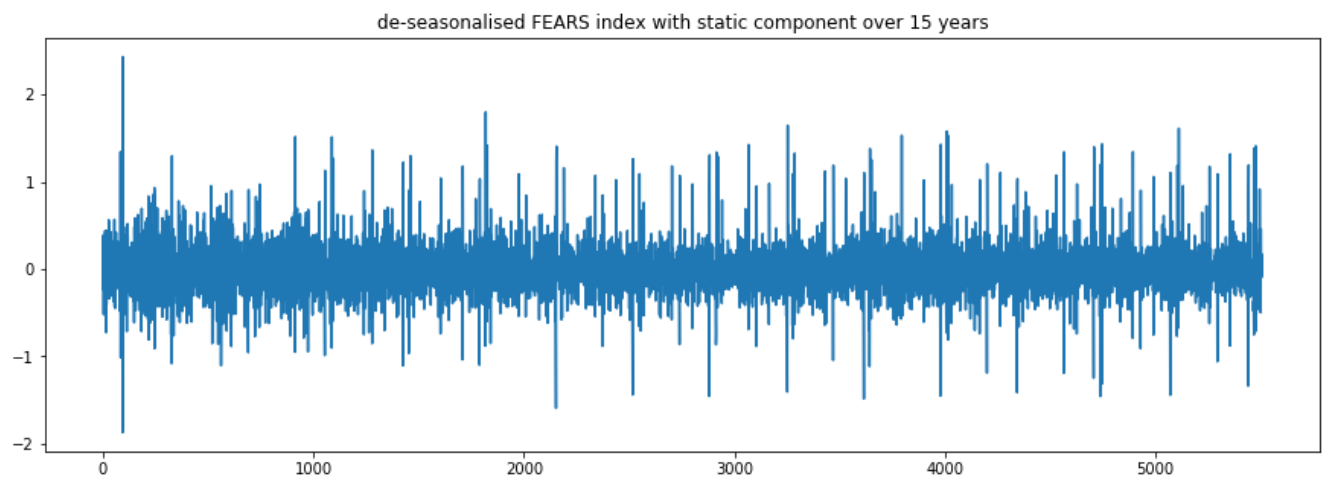
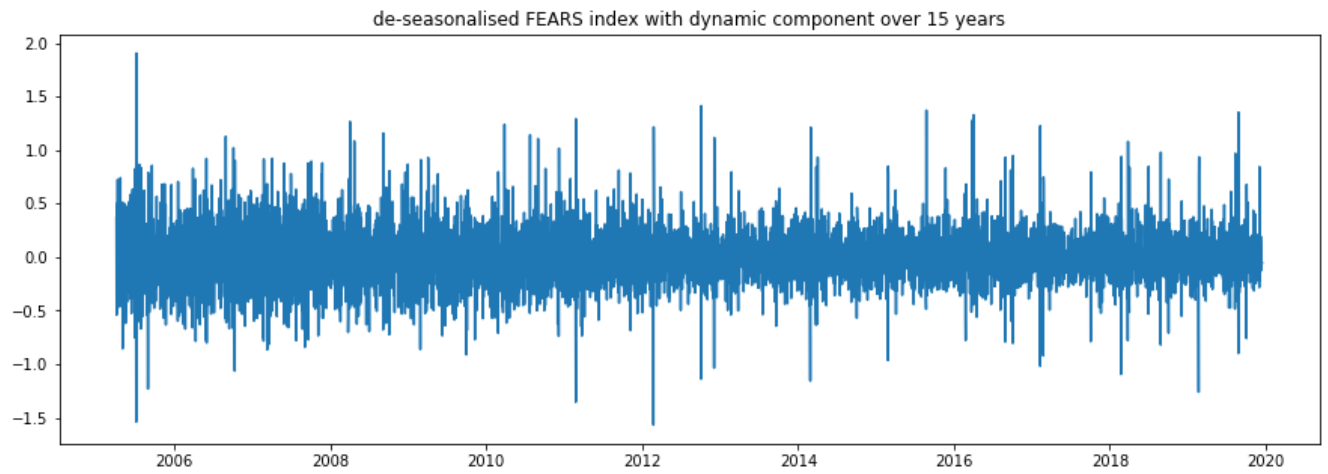
```

step3: check result with other frequency

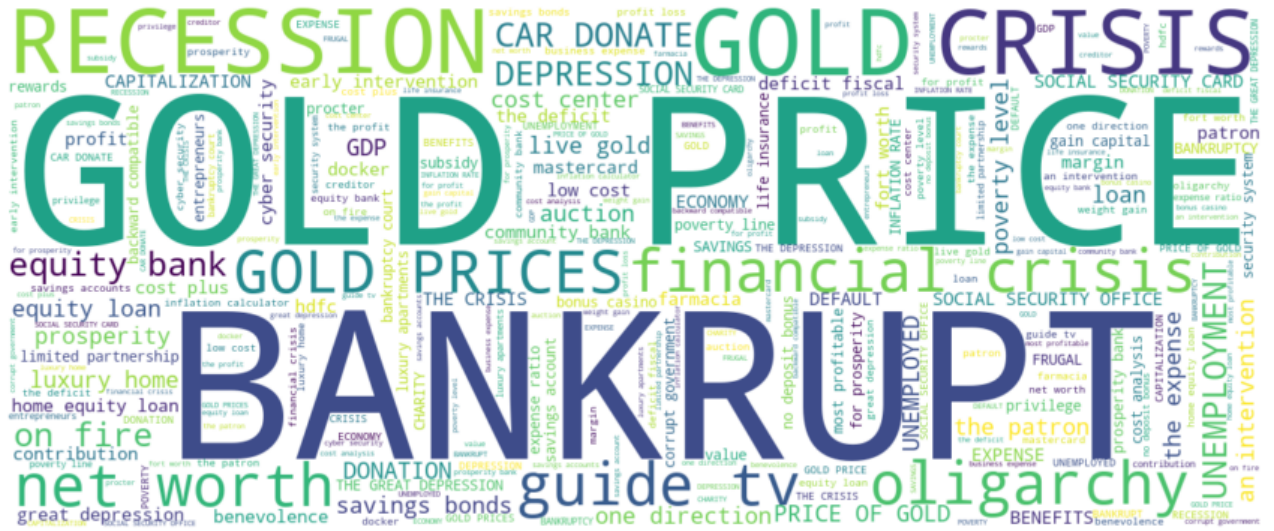
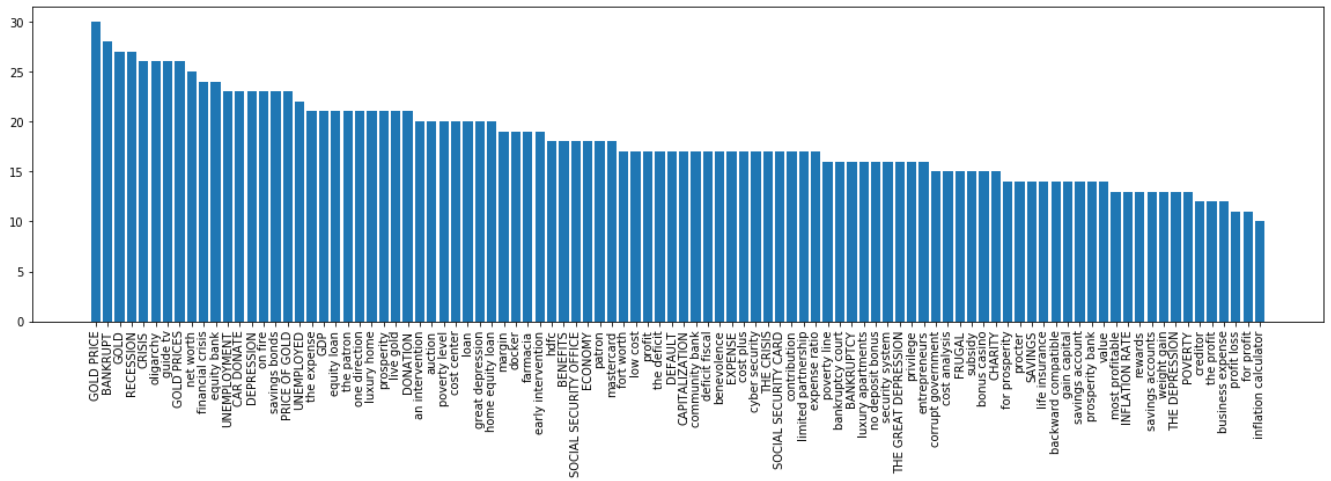
3 month frequency

```
In [70]: merged_data, word_freq = create_dynamic_index(3, all_return_ratio, SP500)
```

now end time is 2019-09-15



```
visualise_frequency(word_freq)
```



```
In [72]: for n in range(6):  
         train_ndelay(merged_data,n)
```



```

=====
Ret(t+0)
               coef      t  P>|t|
const          0.0002   1.685  0.092
EPU            -0.0002  -0.715  0.475
ADS            -0.0002  -1.075  0.283
VIX            -0.1226 -61.676  0.000
6month_dynamic_fears -0.0005  -1.105  0.269
t-1            -0.0330  -2.747  0.006
t-2            -0.0194  -1.613  0.107
t-3             0.0500   4.149  0.000
t-4            -0.0062  -0.519  0.604
t-5            -0.0226  -1.891  0.059
               0      1
5  No. Observations:  3190
               2      3
1  Adj. R-squared:    0.552
=====

```

```

=====
Ret(t+1)
               coef      t  P>|t|
const          0.0003   1.360  0.174
EPU            -0.0005  -1.302  0.193
ADS             0.0001   0.324  0.746
VIX            -0.0056  -1.278  0.201
6month_dynamic_fears 0.0004   0.496  0.620
t              -0.1329  -5.060  0.000
t-1            -0.0661  -3.707  0.000
t-2             0.0152   0.850  0.395
t-3            -0.0236  -1.316  0.188
t-4            -0.0486  -2.725  0.006
t-5             0.0026   0.147  0.883
               0      1
5  No. Observations:  3190
               2      3
1  Adj. R-squared:    0.016
=====

```

```

=====
Ret(t+2)
               coef      t  P>|t|
const          0.0003   1.529  0.126
EPU            0.0007   1.819  0.069
ADS            0.0002   0.779  0.436
VIX            -0.0052  -1.193  0.233
6month_dynamic_fears 0.0002   0.227  0.820
t              -0.0785  -2.972  0.003
t-1             0.0241   1.348  0.178
t-2            -0.0262  -1.457  0.145
t-3            -0.0463  -2.569  0.010
t-4             0.0062   0.346  0.730
t-5            -0.0269  -1.509  0.131
               0      1
5  No. Observations:  3190
               2      3
1  Adj. R-squared:    0.006
=====

```

```

=====
Ret(t+3)
               coef      t  P>|t|
const          0.000300   1.269  0.204
EPU            0.000200   0.412  0.680
ADS            0.000059   0.192  0.848
VIX            0.006200   1.418  0.156
6month_dynamic_fears 0.001000   1.321  0.187
t              0.057200   2.162  0.031
t-1           -0.024000  -1.339  0.181

```

t-2	-0.049800	-2.770	0.006
t-3	0.006400	0.356	0.722
t-4	-0.021600	-1.202	0.229
t-5	0.021900	1.227	0.220

0 1

5 No. Observations: 3190

2 3

1 Adj. R-squared: 0.003

=====

=====

Ret(t+4)

	coef	t	P> t
const	0.000300	1.261	0.208
EPU	-0.000100	-0.338	0.735
ADS	0.000031	0.099	0.921
VIX	0.003700	0.851	0.395
6month_dynamic_fears	-0.000500	-0.734	0.463
t	-0.010900	-0.413	0.680
t-1	-0.051700	-2.877	0.004
t-2	0.009200	0.510	0.610
t-3	-0.025000	-1.384	0.167
t-4	0.018700	1.040	0.298
t-5	-0.017700	-0.989	0.323

0 1

5 No. Observations: 3190

2 3

1 Adj. R-squared: 0.002

=====

=====

Ret(t+5)

	coef	t	P> t
const	0.000300	1.233	0.217
EPU	-0.000030	-0.074	0.941
ADS	-0.000017	-0.055	0.956
VIX	-0.001200	-0.264	0.792
6month_dynamic_fears	-0.000300	-0.352	0.725
t	-0.051600	-1.950	0.051
t-1	0.012600	0.704	0.482
t-2	-0.024400	-1.358	0.175
t-3	0.023400	1.296	0.195
t-4	-0.012100	-0.677	0.499
t-5	0.042400	2.374	0.018

0 1

5 No. Observations: 3190

2 3

1 Adj. R-squared: 0.002

=====

one month frequency

```
In [73]: merged_data,word_freq = create_dynamic_index(1, all_return_ratio, SP500)
```

now end time is 2007-01-22

[illegible]

[illegible]

[illegible]

[illegible]


```
C:\Users\richard\Anaconda3\lib\site-packages\scipy\stats\stats.py:1416: UserWarning: kurtosistest only valid for n>=20 ... continuing anyway, n=17
  "anyway, n=%i" % int(n))

now end time is 2009-01-11
```

[illegible]

[illegible]

[illegible]

[illegible]

```
C:\Users\richard\Anaconda3\lib\site-packages\scipy\stats\stats.py:1416: UserWarning: kurtosistest only valid for n>=20 ... continuing anyway, n=19
  "anyway, n=%i" % int(n))

now end time is 2013-01-20
```

[illegible]

[illegible]

[illegible]

[illegible]

```
C:\Users\richard\Anaconda3\lib\site-packages\scipy\stats\stats.py:1416: UserWarning: kurtosistest only valid for n>=20 ... continuing anyway, n=19
  "anyway, n=%i" % int(n))
```

```
now end time is 2017-01-29
```

[illegible]

[illegible]

[illegible]

[illegible]

```
C:\Users\richard\Anaconda3\lib\site-packages\scipy\stats\stats.py:1416: UserWarning: kurtosistest only valid for n>=20 ... continuing anyway, n=19
  "anyway, n=%i" % int(n))
```

```
now end time is 2019-02-18
```


[illegible]

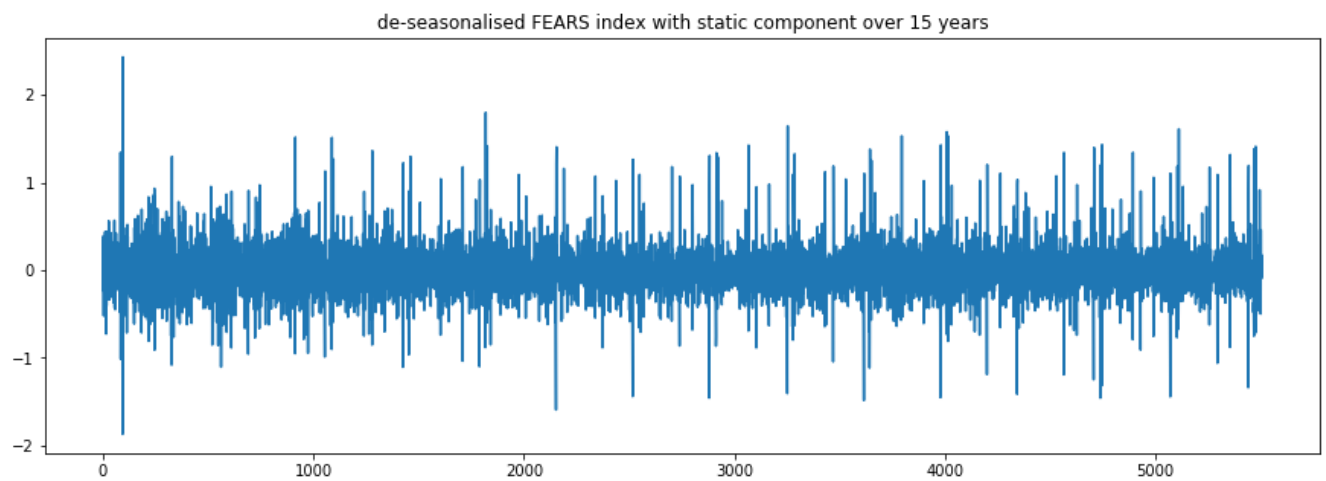
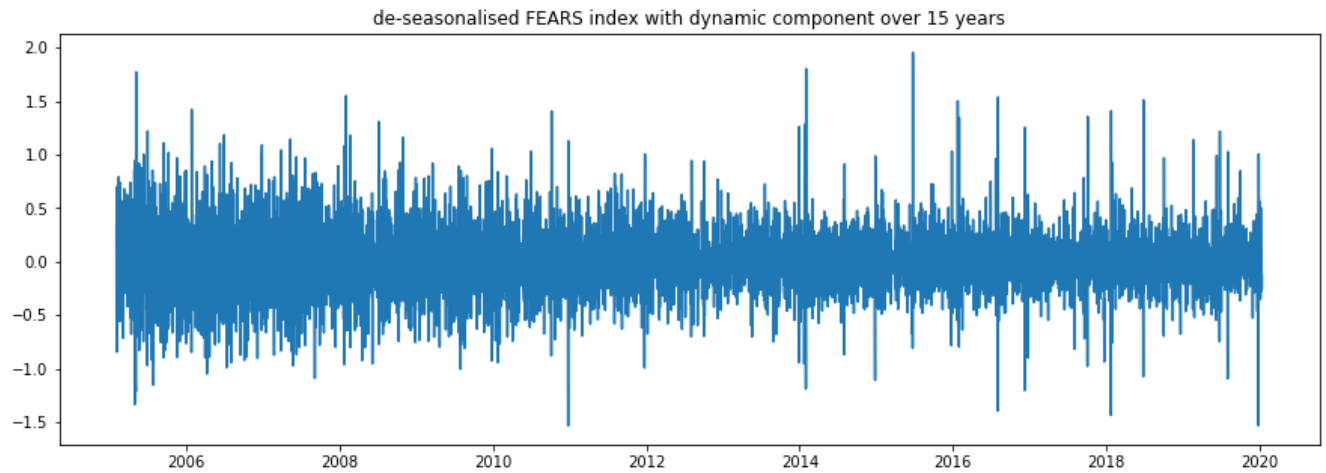
[illegible]

[illegible]

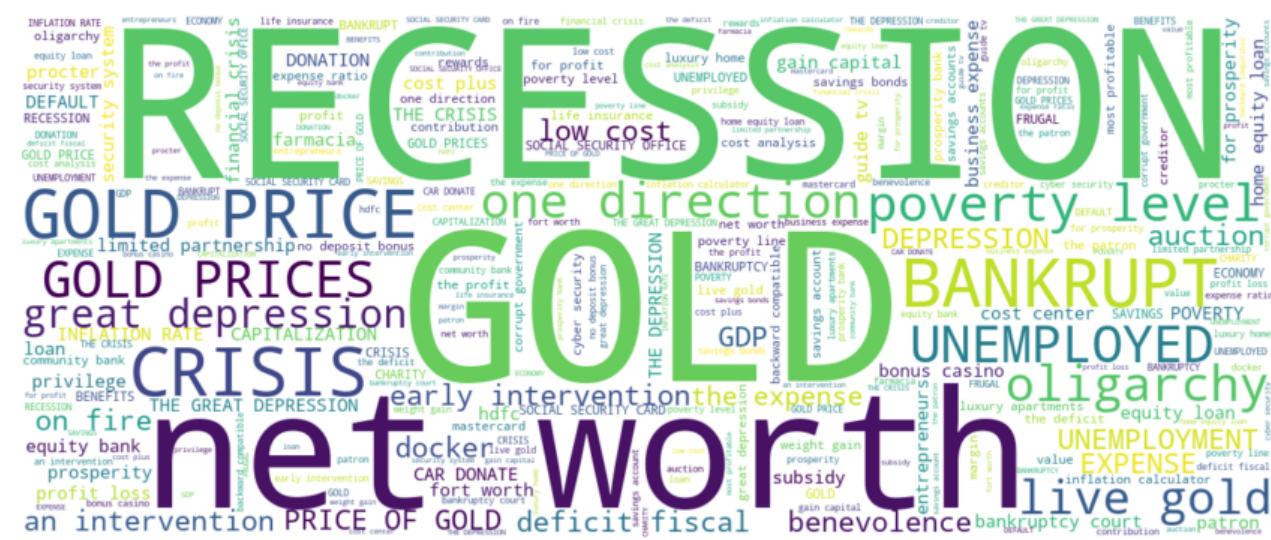
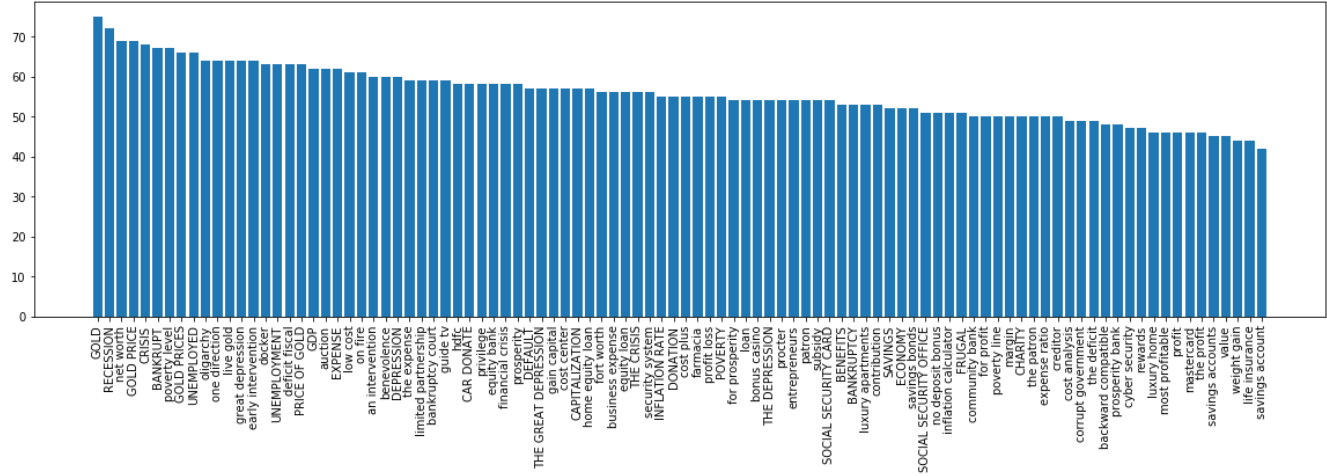
[illegible]

```
C:\Users\richard\Anaconda3\lib\site-packages\scipy\stats\stats.py:1416: UserWarning: kurtosistest only valid for n>=20 ... continuing anyway, n=19
  "anyway, n=%i" % int(n))
```

now end time is 2019-12-15



```
In [74]: visualise_frequency(word_freq)
```



```
In [75]: for n in range(6):  
         train_ndelay(merged_data,n)
```

```

=====
Ret(t+0)
               coef      t  P>|t|
const          0.0002   1.607  0.108
EPU            -0.0002  -0.732  0.464
ADS            -0.0002  -1.069  0.285
VIX            -0.1232 -61.980  0.000
6month_dynamic_fears -0.0003  -0.783  0.434
t-1            -0.0322  -2.686  0.007
t-2            -0.0204  -1.696  0.090
t-3             0.0502   4.178  0.000
t-4            -0.0062  -0.514  0.607
t-5            -0.0229  -1.924  0.054
               0      1
5  No. Observations: 3190
               2      3
1  Adj. R-squared:  0.554
=====

```

```

=====
Ret(t+1)
               coef      t  P>|t|
const          0.0003   1.249  0.212
EPU            -0.0005  -1.260  0.208
ADS             0.0001   0.356  0.722
VIX            -0.0057  -1.303  0.193
6month_dynamic_fears 0.0010   1.582  0.114
t              -0.1330  -5.049  0.000
t-1            -0.0670  -3.760  0.000
t-2             0.0151   0.845  0.398
t-3            -0.0238  -1.331  0.183
t-4            -0.0487  -2.737  0.006
t-5             0.0037   0.212  0.832
               0      1
5  No. Observations: 3190
               2      3
1  Adj. R-squared:  0.017
=====

```

```

=====
Ret(t+2)
               coef      t  P>|t|
const          0.0003   1.445  0.149
EPU            0.0007   1.747  0.081
ADS            0.0002   0.769  0.442
VIX            -0.0048  -1.080  0.280
6month_dynamic_fears -0.0004  -0.600  0.548
t              -0.0769  -2.902  0.004
t-1             0.0242   1.350  0.177
t-2            -0.0257  -1.434  0.152
t-3            -0.0460  -2.555  0.011
t-4             0.0065   0.360  0.719
t-5            -0.0272  -1.524  0.128
               0      1
5  No. Observations: 3190
               2      3
1  Adj. R-squared:  0.006
=====

```

```

=====
Ret(t+3)
               coef      t  P>|t|
const          0.000200   1.157  0.247
EPU            0.000200   0.416  0.677
ADS            0.000057   0.185  0.853
VIX            0.006400   1.458  0.145
6month_dynamic_fears -0.000023 -0.035  0.972
t              0.058000   2.186  0.029
t-1            -0.023600  -1.316  0.188

```


t-2	-0.048800	-2.713	0.007
t-3	0.006300	0.352	0.725
t-4	-0.022300	-1.244	0.214
t-5	0.022900	1.282	0.200
	0	1	

5 No. Observations: 3190

	2	3
--	---	---

1 Adj. R-squared: 0.003

=====

=====

Ret(t+4)

	coef	t	P> t
const	0.00020	1.145	0.252
EPU	-0.00010	-0.340	0.734
ADS	0.00003	0.095	0.924
VIX	0.00360	0.809	0.419
6month_dynamic_fears	0.00090	1.330	0.184
t	-0.01080	-0.407	0.684
t-1	-0.05260	-2.928	0.003
t-2	0.00900	0.502	0.616
t-3	-0.02560	-1.421	0.155
t-4	0.01890	1.055	0.291
t-5	-0.01740	-0.973	0.331
	0	1	

5 No. Observations: 3190

	2	3
--	---	---

1 Adj. R-squared: 0.002

=====

=====

Ret(t+5)

	coef	t	P> t
const	2.000000e-04	1.111	0.267
EPU	-4.458000e-07	-0.001	0.999
ADS	-2.408000e-05	-0.078	0.938
VIX	-6.000000e-04	-0.144	0.886
6month_dynamic_fears	-9.138000e-05	-0.142	0.887
t	-4.910000e-02	-1.849	0.065
t-1	1.250000e-02	0.696	0.486
t-2	-2.510000e-02	-1.396	0.163
t-3	2.300000e-02	1.277	0.202
t-4	-1.200000e-02	-0.668	0.504
t-5	4.130000e-02	2.314	0.021
	0	1	

5 No. Observations: 3190

	2	3
--	---	---

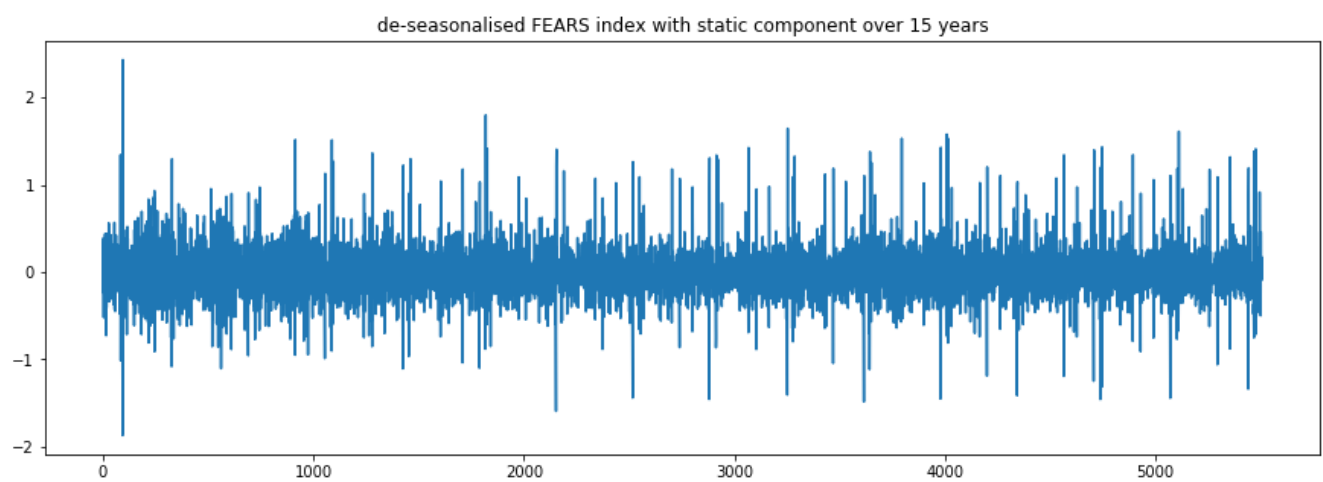
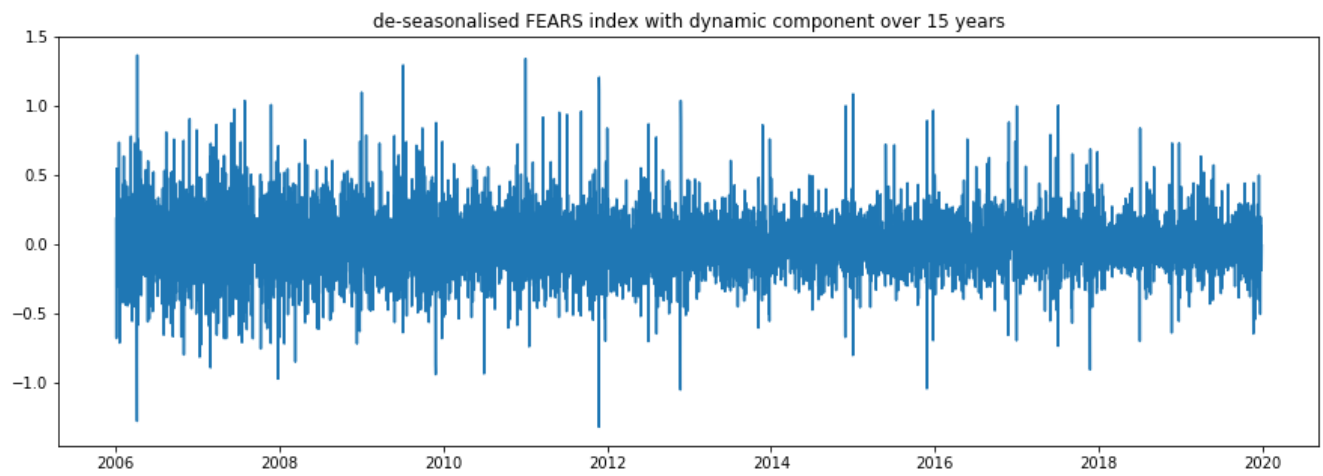
1 Adj. R-squared: 0.002

=====

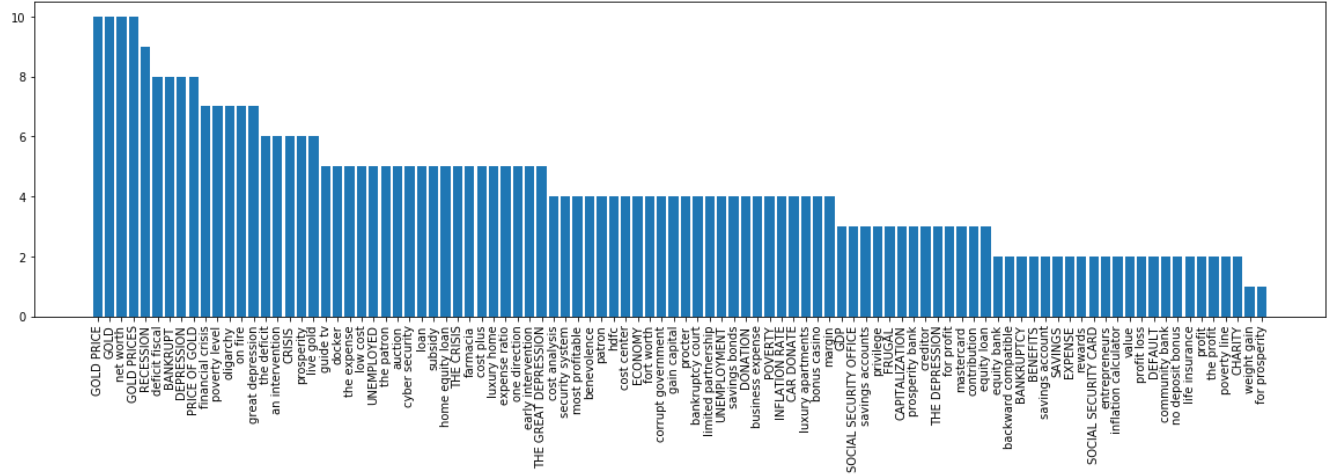
one year frequency

```
In [97]: merged_data, word_freq = create_dynamic_index(12, all_return_ratio, SP500)
```

now end time is 2018-12-30



```
In [98]: visualise_frequency(word_freq)
```



```
In [100]: for n in range(6):  
          train_ndelay(merged_data,n)
```

```

=====
Ret(t+0)
               coef      t  P>|t|
const          0.0003    1.796  0.073
EPU            -0.0002   -0.686  0.493
ADS            -0.0002   -1.397  0.162
VIX            -0.1181  -60.731  0.000
6month_dynamic_fears -0.0002   -0.318  0.750
t-1            -0.0338   -2.787  0.005
t-2            -0.0189   -1.557  0.119
t-3             0.0507    4.172  0.000
t-4            -0.0040   -0.333  0.739
t-5            -0.0233   -1.931  0.054
               0      1
5  No. Observations:  3190
               2      3
1  Adj. R-squared:    0.544
=====

```

```

=====
Ret(t+1)
               coef      t  P>|t|
const          0.000300    1.293  0.196
EPU            -0.000700   -1.622  0.105
ADS            0.000019    0.079  0.937
VIX            -0.005900   -1.399  0.162
6month_dynamic_fears -0.001700   -1.913  0.056
t              -0.132100   -5.075  0.000
t-1            -0.068300   -3.835  0.000
t-2             0.021300    1.195  0.232
t-3            -0.019800   -1.108  0.268
t-4            -0.050400   -2.834  0.005
t-5             0.002800    0.159  0.873
               0      1
5  No. Observations:  3190
               2      3
1  Adj. R-squared:    0.018
=====

```

```

=====
Ret(t+2)
               coef      t  P>|t|
const          0.0003    1.551  0.121
EPU            0.0009    2.151  0.032
ADS            0.0002    0.795  0.427
VIX            -0.0053   -1.254  0.210
6month_dynamic_fears -0.0002   -0.222  0.825
t              -0.0827   -3.161  0.002
t-1             0.0303    1.689  0.091
t-2            -0.0232   -1.293  0.196
t-3            -0.0483   -2.685  0.007
t-4             0.0068    0.380  0.704
t-5            -0.0245   -1.374  0.170
               0      1
5  No. Observations:  3190
               2      3
1  Adj. R-squared:    0.007
=====

```

```

=====
Ret(t+3)
               coef      t  P>|t|
const          0.0003    1.274  0.203
EPU            0.0003    0.807  0.420
ADS            0.0001    0.576  0.565
VIX            0.0028    0.666  0.506
6month_dynamic_fears -0.0002   -0.250  0.803
t              0.0478    1.820  0.069
t-1            -0.0199   -1.110  0.267

```

t-2	-0.0509	-2.833	0.005
t-3	0.0073	0.404	0.686
t-4	-0.0200	-1.113	0.266
t-5	0.0165	0.926	0.355

0 1

5 No. Observations: 3190

2 3

1 Adj. R-squared: 0.002

=====

=====

Ret(t+4)

	coef	t	P> t
const	0.00030	1.225	0.220
EPU	-0.00020	-0.493	0.622
ADS	0.00005	0.210	0.834
VIX	0.00290	0.674	0.500
6month_dynamic_fears	0.00150	1.685	0.092
t	-0.01210	-0.460	0.646
t-1	-0.05540	-3.083	0.002
t-2	0.00860	0.481	0.631
t-3	-0.02320	-1.286	0.198
t-4	0.01230	0.688	0.492
t-5	-0.01770	-0.993	0.321

0 1

5 No. Observations: 3190

2 3

1 Adj. R-squared: 0.002

=====

=====

Ret(t+5)

	coef	t	P> t
const	0.000200	1.157	0.248
EPU	-0.000200	-0.492	0.623
ADS	-0.000037	-0.157	0.875
VIX	0.000400	0.106	0.916
6month_dynamic_fears	-0.000100	-0.122	0.903
t	-0.047200	-1.798	0.072
t-1	0.011800	0.660	0.510
t-2	-0.023700	-1.318	0.188
t-3	0.016000	0.886	0.376
t-4	-0.012600	-0.702	0.483
t-5	0.039200	2.196	0.028

0 1

5 No. Observations: 3190

2 3

1 Adj. R-squared: 0.002

=====

FEARS_Index_(Other_Asset_Class)

April 15, 2020

1 FEARS_Index_(Other_Asset_Class)

```
[0]: !pip install pytrends
```

```
[0]: import pandas as pd
import numpy as np
import datetime
import os
import matplotlib.pyplot as plt
import scipy.stats
import statsmodels.api as sm
```

```
[0]: def update_df2(this_df,df):
    '''
    This function aims to merge two time series into one dataframe
    And it also fill missing dates with extra column
    '''
    try:
        df['date']=pd.to_datetime(df['date'], format='%Y-%m-%d')
    except:
        try:
            df['date']=pd.to_datetime(df['date'], format='%d/%m/%Y')
        except:
            df['date']=pd.to_datetime(df['date'])
    df=df.set_index('date')
    df.index = pd.DatetimeIndex(df.index)
    #remove the duplicated index
    df = df[~df.index.duplicated()]
    df = df.reindex(idxs)
    try:
        df=df.drop(['_id'], axis=1)
    except:
        pass

    # merge two data
    if len(this_df)==0:
        if len(df)!=0:
            this_df=df
```

```

else:
    this_df=pd.concat([this_df,df],axis=1)
return this_df

# setup necessary parameter

idx = pd.date_range('2005-01-01', '2020-01-31')

def load_daily_index(path = 'merged_data/',file_name='daily_trends.
→csv',force_update=False,debug=False):
    csv_files = []
    xlsx_files = []

    def action1(cache=[]):
        for r, d, f in os.walk(path):
            for file in f:
                if '.csv' in file:
                    csv_files.append(os.path.join(r, file))
                if '.xlsx' in file:
                    xlsx_files.append(os.path.join(r, file))
        # concate and merge all the dataframes
        for file in csv_files:
            if debug==True:
                print('\r'+file,end='')
            df=pd.read_csv(file).iloc[:,[0,5]]
            cache = update_df2(cache,df)

            for file in xlsx_files:
                df=pd.read_excel(file).iloc[:,[0,5]]
                cache = update_df2(cache,df)
        # save daily data to one csv
        cache.to_csv('merged_data/'+file_name)
        return cache

    if force_update == False:
        try:
            this_df = pd.read_csv('merged_data/'+file_name,index_col=0)
        except:
            this_df = action1()
    else:
        this_df = action1()
    return this_df

```

[0]: *# this is the 30 words that is shown by the paper*
daily_trends=load_daily_index(force_update=False)


```
daily_trends.index = pd.DatetimeIndex(daily_trends.index)
```

```
[0]: daily_trends = daily_trends.replace({0:1}) # replace 0 search with 1 to avoid
      ↪problem
      return_ratio = np.log(daily_trends.iloc[1:,:]) - np.log(daily_trends.iloc[:-1,:])
      ↪values
      for column in list(return_ratio):
          return_ratio.loc[:,column] = scipy.stats.mstats.winsorize(return_ratio.loc[:,
      ↪column].values, limits=[0.05, 0.05])
```

1.0.1 Now remove the seasonality

```
[6]: from statsmodels.tsa.seasonal import seasonal_decompose

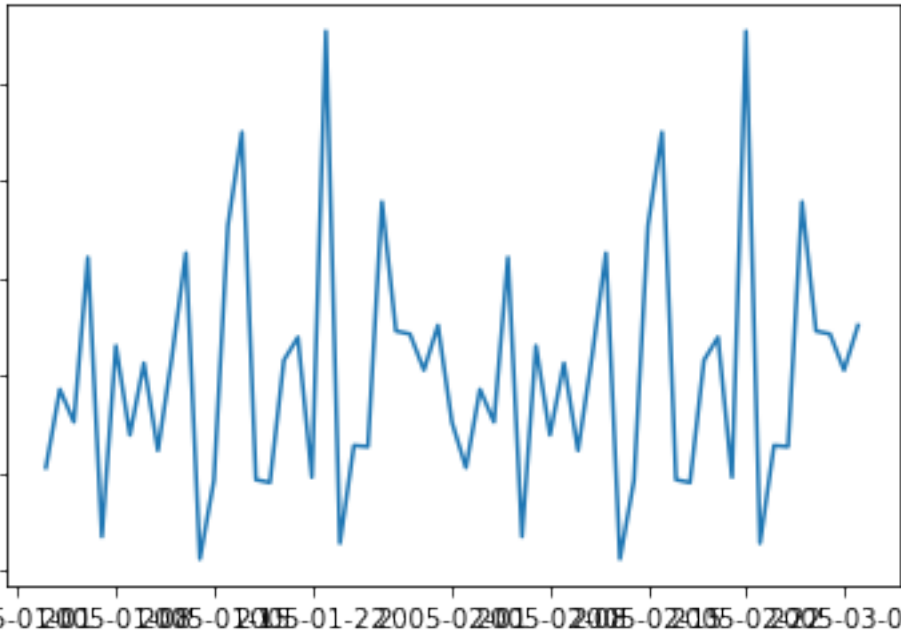
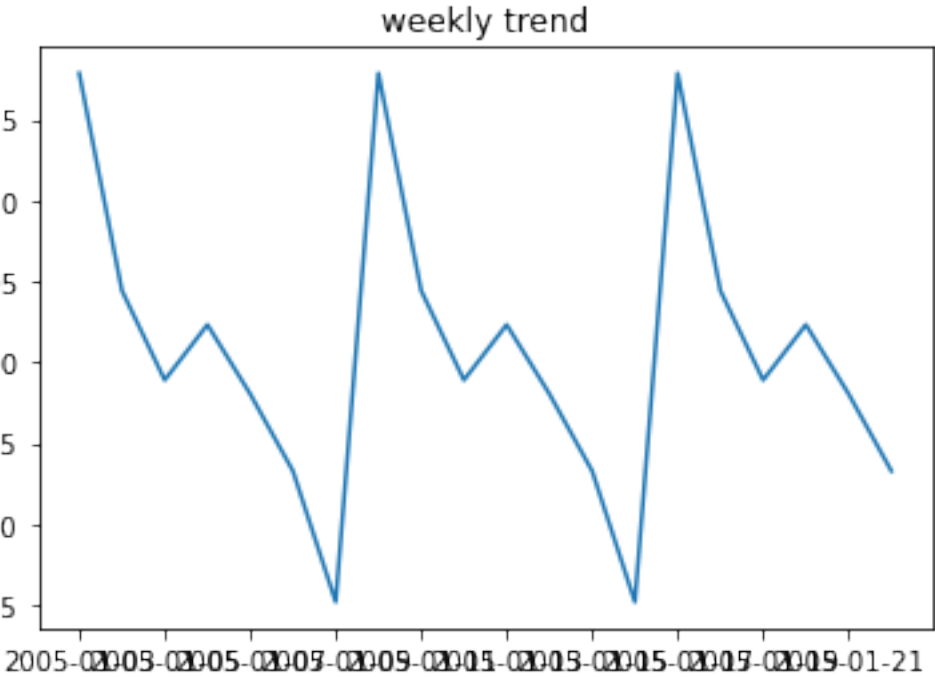
      data = return_ratio.loc[:, 'PRICE OF GOLD']
      weekly = seasonal_decompose(data, freq=7)
      plt.plot(weekly.seasonal[1:21])
      plt.title('weekly trend')
      plt.show()
      data = data - weekly.seasonal
      monthly = seasonal_decompose(data, freq=30)
      data = data - monthly.seasonal

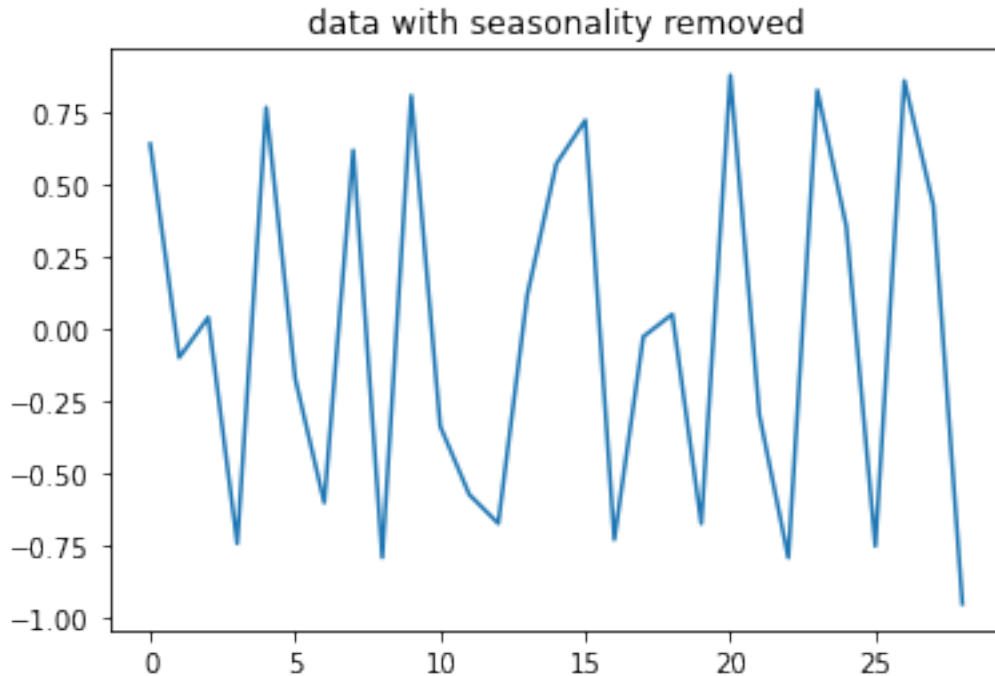
      plt.plot(monthly.seasonal[1:60])
      plt.title('monthly trend')
      plt.show()

      plt.plot(data.values[1:30])
      plt.title('data with seasonality removed')
      plt.show()

      def remove_seasonality(data):
          weekly = seasonal_decompose(data, freq=7)
          r = data - weekly.seasonal
          monthly = seasonal_decompose(r, freq=30)
          r = r - monthly.seasonal
          return r

      # remove seasonality on weekly and monthly dummy, and standardized by scaling
      ↪each on standard deviation
      original_return = return_ratio.copy()
      for column in list(return_ratio):
          return_ratio.loc[:,column] = remove_seasonality(return_ratio.loc[:,column])
          return_ratio.loc[:,column] /= np.std(return_ratio.loc[:,column].values)
```





```
[0]: return_ratio['fears_index'] = return_ratio.sum(axis=1)/30
      original_return['fears_index'] = original_return.sum(axis=1)/30
```

```
[0]: SPY=pd.read_csv('merged_data/SPY.csv').iloc[:,[0,4]]
      SPY['Date']=pd.to_datetime(SPY['Date'], format='%Y-%m-%d')
      SPY=SPY.set_index('Date')
      SPY.columns=['SPY']
      SPY = np.log(SPY.iloc[1:,:])-np.log(SPY.iloc[:-1,:].values)
```

```
IWB=pd.read_csv('merged_data/IWB.csv').iloc[:,[0,4]]
IWB['Date']=pd.to_datetime(IWB['Date'], format='%Y-%m-%d')
IWB=IWB.set_index('Date')
IWB.columns=['IWB']
IWB = np.log(IWB.iloc[1:,:])-np.log(IWB.iloc[:-1,:].values)
```

```
IWM=pd.read_csv('merged_data/IWM.csv').iloc[:,[0,4]]
IWM['Date']=pd.to_datetime(IWM['Date'], format='%Y-%m-%d')
IWM=IWM.set_index('Date')
IWM.columns=['IWM']
IWM = np.log(IWM.iloc[1:,:])-np.log(IWM.iloc[:-1,:].values)
```

```
[0]: EPU=pd.read_excel('merged_data/All_Daily_Policy_Data.xlsx')
      EPU['Date']=pd.to_datetime(EPU['Date'], format='%d/%m/%Y')
      EPU = EPU.set_index('Date')
      EPU.columns=['EPU']
      EPU = np.log(EPU.iloc[1:,:])-np.log(EPU.iloc[:-1,:].values)
```

```

ADS=pd.read_excel('merged_data/ADS_Index_Most_Current_Vintage.xlsx',index_col=0)
ADS.columns=['ADS']
ADS = (ADS.iloc[1:,:]-ADS.iloc[:-1,:].values).divide(ADS.iloc[:-1,:].values)

VIX = pd.read_csv('merged_data/vixcurrent.csv').iloc[:,[0,4]]
VIX['Date']=pd.to_datetime(VIX['Date'], format='%m/%d/%Y')
VIX = VIX.set_index('Date')
VIX.columns=['VIX']
VIX = np.log(VIX.iloc[1:,:])-np.log(VIX.iloc[:-1,:].values)

```

```

[0]: # first read the data
all_daily_trends = load_daily_index(path = '111_google_trend/
    →',file_name='111_daily_trends.csv', force_update=False,debug=True)
all_daily_trends = all_daily_trends.loc[:,(all_daily_trends.isna().sum()<100).
    →values] # remove column with too many missing value

[0]: all_daily_trends = all_daily_trends.replace({0:1}) # replace 0 search with 1 to
    →avoid problem
all_return_ratio = np.log(all_daily_trends.iloc[1:,:])-np.log(all_daily_trends.
    →iloc[:-1,:].values)

for column in list(all_return_ratio):
    # winsorize data
    all_return_ratio.loc[:,column] = scipy.stats.mstats.
    →winsorize(all_return_ratio.loc[:,column].values, limits=[0.05, 0.05])
    # remove seasonality
    all_return_ratio.loc[:,column] = remove_seasonality(all_return_ratio.loc[:
    →,column])
    # removeheteroscedasticity
    all_return_ratio.loc[:,column] /= np.std(all_return_ratio.loc[:,column].
    →values)
all_return_ratio.index = pd.DatetimeIndex(all_return_ratio.index)

[0]: def create_dynamic_index_SPY(frequency,all_return_ratio,SPY):
    all_return_with_Fears = all_return_ratio.copy()
    start_date = pd.Timestamp(year=2005, month=1, day=2).date()
    end_date = start_date + pd.Timedelta(frequency*30,unit='D')
    next_end_date = end_date + pd.Timedelta(frequency*30,unit='D')

    while next_end_date<pd.Timestamp(year=2020, month=1, day=30).date():
        print('\r now end time is '+str(end_date),end='')
        # seperate the dataset into several time segements
        selected_data = all_return_ratio.loc[pd.date_range(start_date,end_date),:
    →]

    # includes return data

```

```

word_choices = list(selected_data)
selected_data_SPY = selected_data.join(SPY,how='inner')
ranking = []

# run regression on all 104 words within this selected periods
for word in word_choices:
    X = sm.add_constant(selected_data_SPY.loc[:,[word]])
    model = sm.OLS(selected_data_SPY.loc[:,['SPY']], X).fit()    # run
→regression
    t_stats = pd.read_html(model.summary().tables[1]).
→as_html(),header=0,index_col=0)[0]['t'][1]
    ranking.append([t_stats,word])    # save word and t statistics

# select the 30 most negative words
ranking.sort()
negative_30_words = [ranking[i][1] for i in range(30)]
this_fears_index = selected_data.loc[:,negative_30_words].sum(axis=1)/30

# update the fears index
all_return_with_Fears.loc[(all_return_with_Fears.index>=pd.
→Timestamp(end_date)) & (all_return_with_Fears.index<=pd.
→Timestamp(next_end_date)), 'FEARS'] = this_fears_index.values
start_date = end_date
end_date = next_end_date
next_end_date = next_end_date + pd.Timedelta(frequency*30,unit='D')
Fears_index = all_return_with_Fears.loc[all_return_with_Fears.FEARS.isna()!
→=True,['FEARS']]
return Fears_index

```

```

[0]: def create_dynamic_index_IWB(frequency,all_return_ratio,IWB):
    all_return_with_Fears = all_return_ratio.copy()
    start_date = pd.Timestamp(year=2005, month=1, day=2).date()
    end_date = start_date + pd.Timedelta(frequency*30,unit='D')
    next_end_date = end_date + pd.Timedelta(frequency*30,unit='D')

    while next_end_date<pd.Timestamp(year=2020, month=1, day=30).date():
        print('\r now end time is '+str(end_date),end='')
        # seperate the dataset into several time segments
        selected_data = all_return_ratio.loc[pd.date_range(start_date,end_date),:]
→]

        # includes return data
        word_choices = list(selected_data)
        selected_data_IWB = selected_data.join(IWB,how='inner')
        ranking = []

```

```

        # run regression on all 104 words within this selected periods
        for word in word_choices:
            X = sm.add_constant(selected_data_IWB.loc[:, [word]])
            model = sm.OLS(selected_data_IWB.loc[:, ['IWB']], X).fit()    # run
→ regression
            t_stats = pd.read_html(model.summary().tables[1]).
→ as_html(), header=0, index_col=0)[0][ 't' ][1]
            ranking.append([t_stats, word])    # save word and t statistics

        # select the 30 most negative words
        ranking.sort()
        negative_30_words = [ranking[i][1] for i in range(30)]
        this_fears_index = selected_data.loc[:, negative_30_words].sum(axis=1)/30

        # update the fears index
        all_return_with_Fears.loc[(all_return_with_Fears.index>=pd.
→ Timestamp(end_date)) & (all_return_with_Fears.index<=pd.
→ Timestamp(next_end_date)), 'FEARS'] = this_fears_index.values
        start_date = end_date
        end_date = next_end_date
        next_end_date = next_end_date + pd.Timedelta(frequency*30, unit='D')
        Fears_index = all_return_with_Fears.loc[all_return_with_Fears.FEARS.isna()!
→ =True, ['FEARS']]
        return Fears_index

```

```

[0]: def create_dynamic_index_IWM(frequency, all_return_ratio, IWM):
    all_return_with_Fears = all_return_ratio.copy()
    start_date = pd.Timestamp(year=2005, month=1, day=2).date()
    end_date = start_date + pd.Timedelta(frequency*30, unit='D')
    next_end_date = end_date + pd.Timedelta(frequency*30, unit='D')

    while next_end_date<pd.Timestamp(year=2020, month=1, day=30).date():
        print('\r now end time is '+str(end_date), end='')
        # seperate the dataset into several time segments
        selected_data = all_return_ratio.loc[pd.date_range(start_date, end_date), :
→ ]

        # includes return data
        word_choices = list(selected_data)
        selected_data_IWM = selected_data.join(IWM, how='inner')
        ranking = []

        # run regression on all 104 words within this selected periods
        for word in word_choices:
            X = sm.add_constant(selected_data_IWM.loc[:, [word]])

```

4. FEARS and Fund Flows

April 15, 2020

1 4. FEARS and Fund Flows

```
[0]: !pip install pytrends
```

```
[0]: import pandas as pd
import numpy as np
import datetime
import os
import matplotlib.pyplot as plt
import scipy.stats
import statsmodels.api as sm
```

2 Data Cleansing to fill missing value

```
[0]: df=pd.read_csv('raw_data/US Mutual Fund Flows.csv')
df['Open'].interpolate(method='linear', inplace=True)
df['Open'].fillna(method='bfill',inplace=True)
df['High'].interpolate(method='linear', inplace=True)
df['High'].fillna(method='bfill',inplace=True)
df['Low'].interpolate(method='linear', inplace=True)
df['Low'].fillna(method='bfill',inplace=True)
df['Close'].interpolate(method='linear', inplace=True)
df['Close'].fillna(method='bfill',inplace=True)
df['Adj Close'].interpolate(method='linear', inplace=True)
df['Adj Close'].fillna(method='bfill',inplace=True)
df.to_csv('merged_data/Mutual.csv', index=False)
```

```
[0]: df=pd.read_csv('raw_data/US Bond Mutual Fund Flows.csv')
df['Open'].interpolate(method='linear', inplace=True)
df['Open'].fillna(method='bfill',inplace=True)
df['High'].interpolate(method='linear', inplace=True)
df['High'].fillna(method='bfill',inplace=True)
df['Low'].interpolate(method='linear', inplace=True)
df['Low'].fillna(method='bfill',inplace=True)
df['Close'].interpolate(method='linear', inplace=True)
df['Close'].fillna(method='bfill',inplace=True)
```

```
df['Adj Close'].interpolate(method='linear', inplace=True)
df['Adj Close'].fillna(method='bfill', inplace=True)
df.to_csv('merged_data/Bond.csv', index=False)
```

```
[0]: df=pd.read_csv('raw_data/US Equity Mutual Fund Flows.csv')
df['Open'].interpolate(method='linear', inplace=True)
df['Open'].fillna(method='bfill', inplace=True)
df['High'].interpolate(method='linear', inplace=True)
df['High'].fillna(method='bfill', inplace=True)
df['Low'].interpolate(method='linear', inplace=True)
df['Low'].fillna(method='bfill', inplace=True)
df['Close'].interpolate(method='linear', inplace=True)
df['Close'].fillna(method='bfill', inplace=True)
df['Adj Close'].interpolate(method='linear', inplace=True)
df['Adj Close'].fillna(method='bfill', inplace=True)
df.to_csv('merged_data/Equity.csv', index=False)
```

```
[0]: def update_df2(this_df,df):
    '''
    This function aims to merge two time series into one dataframe
    And it also fill missing dates with extra column
    '''
    try:
        df['date']=pd.to_datetime(df['date'], format='%Y-%m-%d')
    except:
        try:
            df['date']=pd.to_datetime(df['date'], format='%d/%m/%Y')
        except:
            df['date']=pd.to_datetime(df['date'])
    df=df.set_index('date')
    df.index = pd.DatetimeIndex(df.index)
    #remove the duplicated index
    df = df[~df.index.duplicated()]
    df = df.reindex(idxx)
    try:
        df=df.drop(['_id'], axis=1)
    except:
        pass

    # merge two data
    if len(this_df)==0:
        if len(df)!=0:
            this_df=df
    else:
        this_df=pd.concat([this_df,df],axis=1)
    return this_df

# setup necessary parameter
```



```

idx = pd.date_range('2005-01-01', '2020-01-31')

def load_daily_index(path = 'merged_data/',file_name='daily_trends.
→csv',force_update=False,debug=False):
    csv_files = []
    xlsx_files = []

    def action1(cache=[]):
        for r, d, f in os.walk(path):
            for file in f:
                if '.csv' in file:
                    csv_files.append(os.path.join(r, file))
                if '.xlsx' in file:
                    xlsx_files.append(os.path.join(r, file))
        # concate and merge all the dataframes
        for file in csv_files:
            if debug==True:
                print('\r'+file,end='')
            df=pd.read_csv(file).iloc[:,[0,5]]
            cache = update_df2(cache,df)

        for file in xlsx_files:
            df=pd.read_excel(file).iloc[:,[0,5]]
            cache = update_df2(cache,df)
        # save daily data to one csv
        cache.to_csv('merged_data/'+file_name)
        return cache

    if force_update == False:
        try:
            this_df = pd.read_csv('merged_data/'+file_name,index_col=0)
        except:
            this_df = action1()
    else:
        this_df = action1()
    return this_df

```

```

[0]: # this is the 30 words that is shown by the paper
daily_trends=load_daily_index(force_update=False)
daily_trends.index = pd.DatetimeIndex(daily_trends.index)

```

```

[0]: daily_trends = daily_trends.replace({0:1}) # replace 0 search with 1 to avoid
→problem
return_ratio = np.log(daily_trends.iloc[1:,:])-np.log(daily_trends.iloc[:-1,:]).
→values)

```

```

for column in list(return_ratio):
    return_ratio.loc[:,column] = scipy.stats.mstats.winsorize(return_ratio.loc[:,
→,column].values, limits=[0.05, 0.05])

```

2.0.1 Now remove the seasonality

```

[38]: from statsmodels.tsa.seasonal import seasonal_decompose

data = return_ratio.loc[:, 'PRICE OF GOLD']
weekly = seasonal_decompose(data, freq=7)
plt.plot(weekly.seasonal[1:21])
plt.title('weekly trend')
plt.show()
data = data - weekly.seasonal
monthly = seasonal_decompose(data, freq=30)
data = data - monthly.seasonal

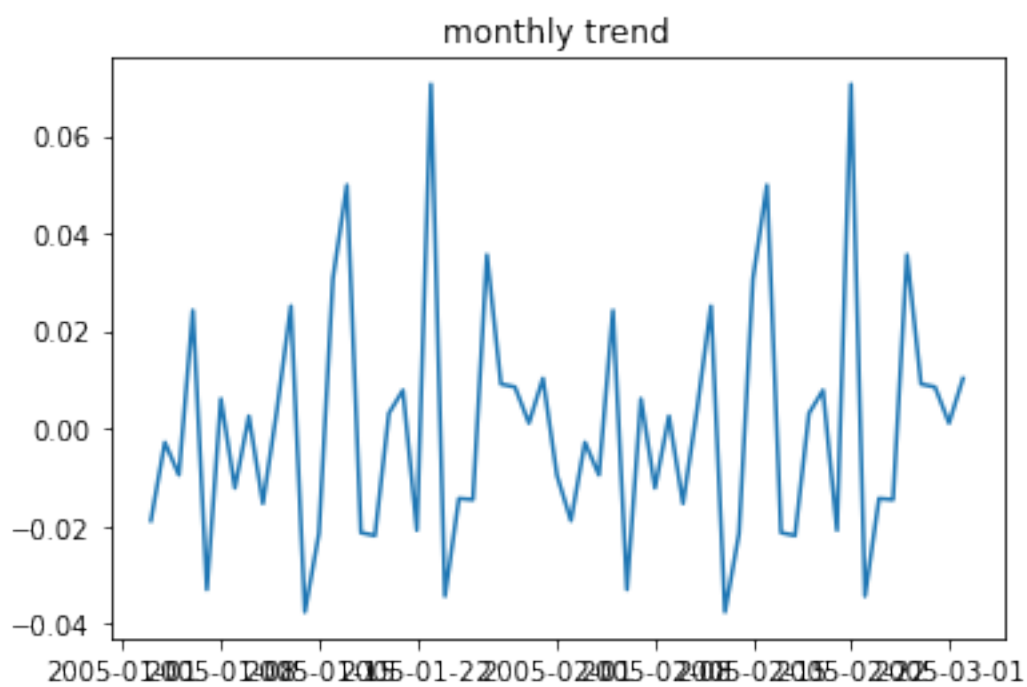
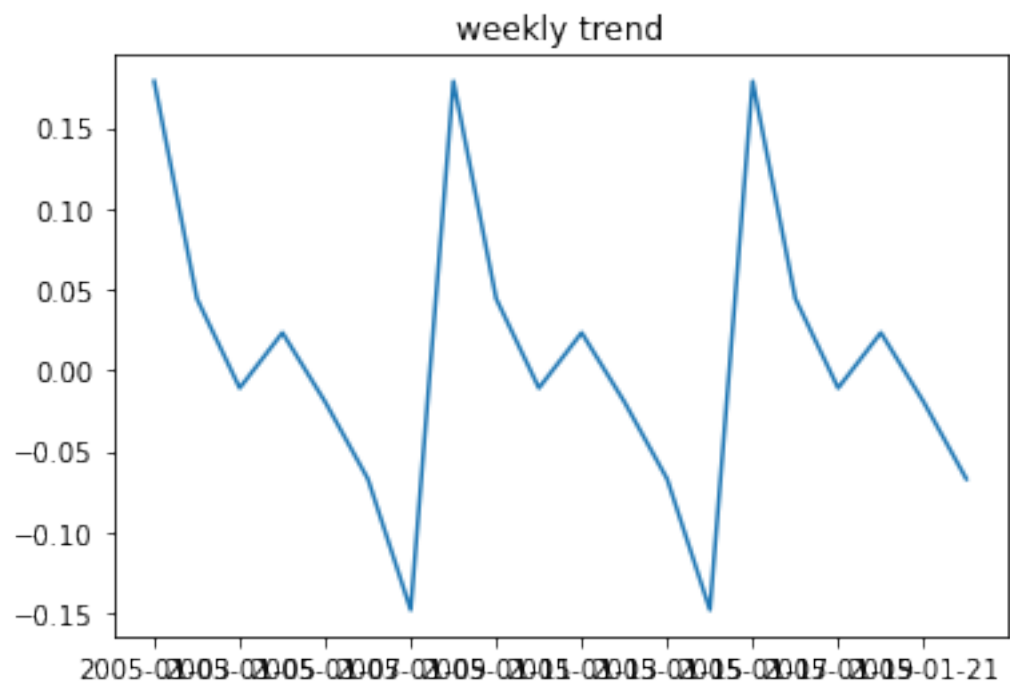
plt.plot(monthly.seasonal[1:60])
plt.title('monthly trend')
plt.show()

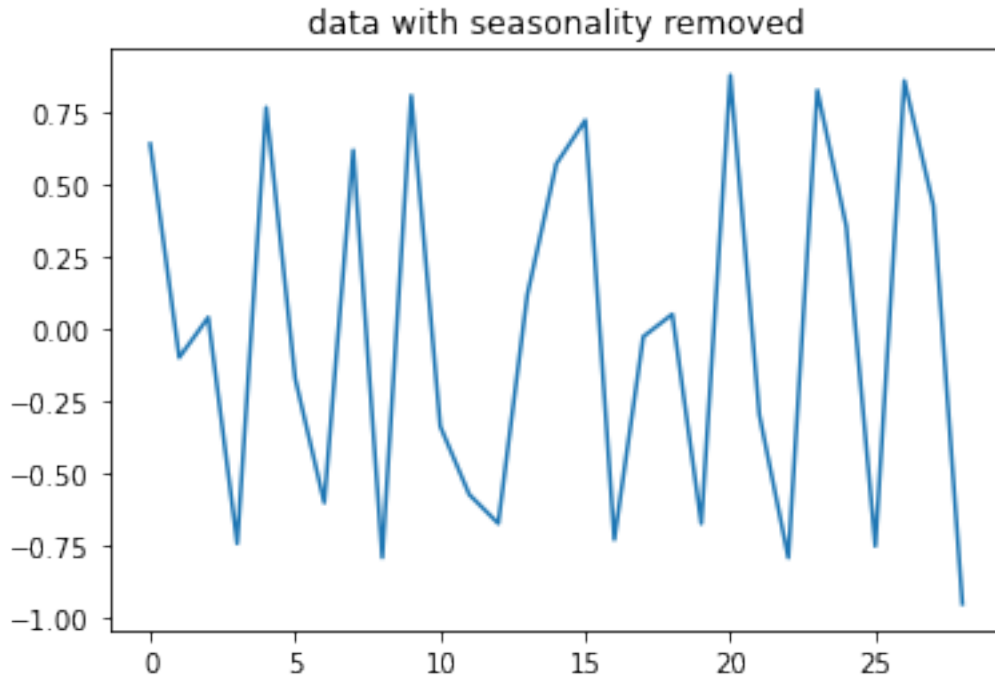
plt.plot(data.values[1:30])
plt.title('data with seasonality removed')
plt.show()

def remove_seasonality(data):
    weekly = seasonal_decompose(data, freq=7)
    r = data - weekly.seasonal
    monthly = seasonal_decompose(r, freq=30)
    r = r - monthly.seasonal
    return r

# remove seasonality on weekly and monthly dummy, and standardized by scaling
→ each on standard deviation
original_return = return_ratio.copy()
for column in list(return_ratio):
    return_ratio.loc[:,column] = remove_seasonality(return_ratio.loc[:,column])
    return_ratio.loc[:,column] /= np.std(return_ratio.loc[:,column].values)

```





```
[0]: return_ratio['fears_index'] = return_ratio.sum(axis=1)/30
      original_return['fears_index'] = original_return.sum(axis=1)/30
```

2.1 Step 2: construct all other relevant data

```
[0]: Mutual=pd.read_csv('merged_data/Mutual.csv').iloc[:,[0,4]]
      Mutual['Date']=pd.to_datetime(Mutual['Date'], format='%Y-%m-%d')
      Mutual=Mutual.set_index('Date')
      Mutual.columns=['Mutual']
      Mutual = np.log(Mutual.iloc[1:,:])-np.log(Mutual.iloc[:-1,:].values)

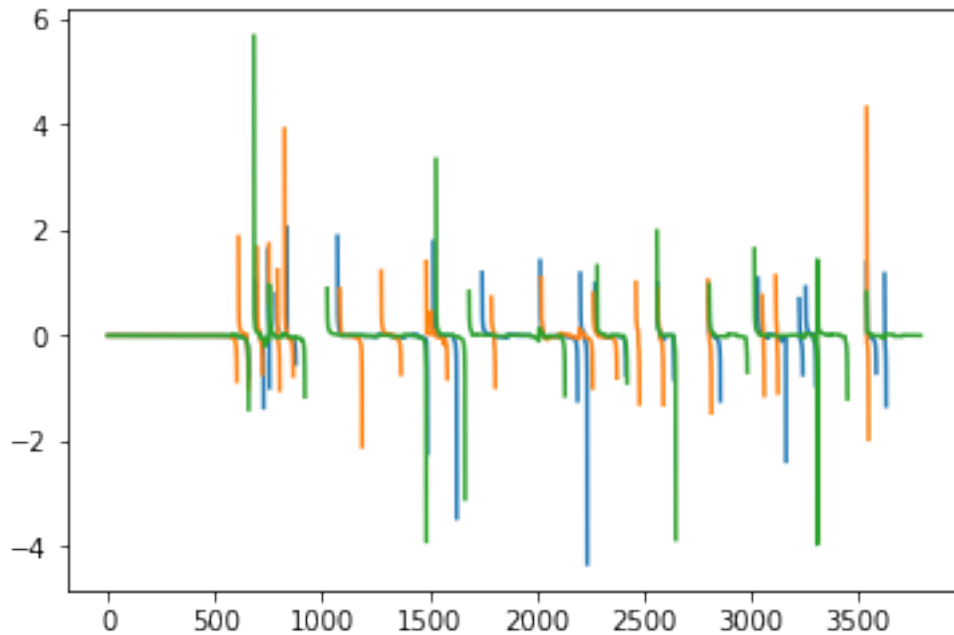
      Equity=pd.read_csv('merged_data/Equity.csv').iloc[:,[0,4]]
      Equity['Date']=pd.to_datetime(Equity['Date'], format='%Y-%m-%d')
      Equity=Equity.set_index('Date')
      Equity.columns=['Equity']
      Equity = np.log(Equity.iloc[1:,:])-np.log(Equity.iloc[:-1,:].values)

      Bond=pd.read_csv('merged_data/Bond.csv').iloc[:,[0,4]]
      Bond['Date']=pd.to_datetime(Bond['Date'], format='%Y-%m-%d')
      Bond=Bond.set_index('Date')
      Bond.columns=['Bond']
      Bond = np.log(Bond.iloc[1:,:])-np.log(Bond.iloc[:-1,:].values)
```

```
[17]: plt.plot(Mutual.values)
      plt.plot(Equity.values)
```

```
plt.plot(Bond.values)
```

[17]: [



```
[0]: EPU=pd.read_excel('merged_data/All_Daily_Policy_Data.xlsx')
EPU['Date']=pd.to_datetime(EPU['Date'], format='%d/%m/%Y')
EPU = EPU.set_index('Date')
EPU.columns=['EPU']
EPU = np.log(EPU.iloc[1:,:])-np.log(EPU.iloc[:-1,:].values)

ADS=pd.read_excel('merged_data/ADS_Index_Most_Current_Vintage.xlsx',index_col=0)
ADS.columns=['ADS']
ADS = (ADS.iloc[1:,:]-ADS.iloc[:-1,:].values).divide(ADS.iloc[:-1,:].values)

VIX = pd.read_csv('merged_data/vixcurrent.csv').iloc[:,[0,4]]
VIX['Date']=pd.to_datetime(VIX['Date'], format='%m/%d/%Y')
VIX = VIX.set_index('Date')
VIX.columns=['VIX']
VIX = np.log(VIX.iloc[1:,:])-np.log(VIX.iloc[:-1,:].values)
```

2.2 Step 3: construct dynamic Fears index selecting from 120 words and with variable updating frequency

2.2.1 in the paper, the author worked with updating frequency of 6 months, but we could do better than that :-)

2.2.2 I put this step here because I need the SPY data to do regression in order to update FEARS index components.

```
[0]: # first read the data
all_daily_trends = load_daily_index(path = '111_google_trend/
    →',file_name='111_daily_trends.csv', force_update=False,debug=True)
all_daily_trends = all_daily_trends.loc[:,(all_daily_trends.isna().sum()<100).
    →values] # remove column with too many missing value

[0]: all_daily_trends = all_daily_trends.replace({0:1}) # replace 0 search with 1 to
    →avoid problem
all_return_ratio = np.log(all_daily_trends.iloc[1:,:])-np.log(all_daily_trends.
    →iloc[:-1,:].values)

for column in list(all_return_ratio):
    # winsorize data
    all_return_ratio.loc[:,column] = scipy.stats.mstats.
    →winsorize(all_return_ratio.loc[:,column].values, limits=[0.05, 0.05])
    # remove seasonality
    all_return_ratio.loc[:,column] = remove_seasonality(all_return_ratio.loc[:
    →,column])
    # removeheteroscedasticity
    all_return_ratio.loc[:,column] /= np.std(all_return_ratio.loc[:,column].
    →values)
all_return_ratio.index = pd.DatetimeIndex(all_return_ratio.index)

[0]: def create_dynamic_index_Mutual(frequency,all_return_ratio,Mutual):
    all_return_with_Fears = all_return_ratio.copy()
    start_date = pd.Timestamp(year=2005, month=1, day=2).date()
    end_date = start_date + pd.Timedelta(frequency*30,unit='D')
    next_end_date = end_date + pd.Timedelta(frequency*30,unit='D')

    while next_end_date<pd.Timestamp(year=2020, month=1, day=30).date():
        print('\r now end time is '+str(end_date),end='')
        # seperate the dataset into several time segements
        selected_data = all_return_ratio.loc[pd.date_range(start_date,end_date),:
    →]

        # includes return data
        word_choices = list(selected_data)
        selected_data_Mutual = selected_data.join(Mutual,how='inner')
```

```

ranking = []

# run regression on all 104 words within this selected periods
for word in word_choices:
    X = sm.add_constant(selected_data_Mutual.loc[:, [word]])
    model = sm.OLS(selected_data_Mutual.loc[:, ['Mutual']], X).fit() #_
→run regression
    t_stats = pd.read_html(model.summary().tables[1]).
→as_html(), header=0, index_col=0)[0]['t'][1]
    ranking.append([t_stats, word]) # save word and t statistics

# select the 30 most negative words
ranking.sort()
negative_30_words = [ranking[i][1] for i in range(30)]
this_fears_index = selected_data.loc[:, negative_30_words].sum(axis=1)/30

# update the fears index
all_return_with_Fears.loc[(all_return_with_Fears.index >= pd.
→Timestamp(end_date)) & (all_return_with_Fears.index <= pd.
→Timestamp(next_end_date)), 'FEARS'] = this_fears_index.values
start_date = end_date
end_date = next_end_date
next_end_date = next_end_date + pd.Timedelta(frequency*30, unit='D')
Fears_index = all_return_with_Fears.loc[all_return_with_Fears.FEARS.isna()!
→=True, ['FEARS']]
return Fears_index

```

```

[0]: def create_dynamic_index_Equity(frequency, all_return_ratio, Equity):
    all_return_with_Fears = all_return_ratio.copy()
    start_date = pd.Timestamp(year=2005, month=1, day=2).date()
    end_date = start_date + pd.Timedelta(frequency*30, unit='D')
    next_end_date = end_date + pd.Timedelta(frequency*30, unit='D')

    while next_end_date < pd.Timestamp(year=2020, month=1, day=30).date():
        print('\r now end time is ' + str(end_date), end='')
        # separate the dataset into several time segments
        selected_data = all_return_ratio.loc[pd.date_range(start_date, end_date), :]
→]

        # includes return data
        word_choices = list(selected_data)
        selected_data_Equity = selected_data.join(Equity, how='inner')
        ranking = []

        # run regression on all 104 words within this selected periods
        for word in word_choices:

```

```

        X = sm.add_constant(selected_data_Equity.loc[:, [word]])
        model = sm.OLS(selected_data_Equity.loc[:, ['Equity']], X).fit()    #
→run regression

        t_stats = pd.read_html(model.summary().tables[1]).
→as_html(), header=0, index_col=0)[0]['t'][1]

        ranking.append([t_stats, word])    # save word and t statistics

    # select the 30 most negative words
    ranking.sort()
    negative_30_words = [ranking[i][1] for i in range(30)]
    this_fears_index = selected_data.loc[:, negative_30_words].sum(axis=1)/30

    # update the fears index
    all_return_with_Fears.loc[(all_return_with_Fears.index>=pd.
→Timestamp(end_date)) & (all_return_with_Fears.index<=pd.
→Timestamp(next_end_date)), 'FEARS'] = this_fears_index.values

    start_date = end_date
    end_date = next_end_date
    next_end_date = next_end_date + pd.Timedelta(frequency*30, unit='D')
    Fears_index = all_return_with_Fears.loc[all_return_with_Fears.FEARS.isna()!
→=True, ['FEARS']]
    return Fears_index

```

```

[0]: def create_dynamic_index_Bond(frequency, all_return_ratio, Bond):
    all_return_with_Fears = all_return_ratio.copy()
    start_date = pd.Timestamp(year=2005, month=1, day=2).date()
    end_date = start_date + pd.Timedelta(frequency*30, unit='D')
    next_end_date = end_date + pd.Timedelta(frequency*30, unit='D')

    while next_end_date<pd.Timestamp(year=2020, month=1, day=30).date():
        print('\r now end time is '+str(end_date), end='')
        # seperate the dataset into several time segments
        selected_data = all_return_ratio.loc[pd.date_range(start_date, end_date), :
→]

        # includes return data
        word_choices = list(selected_data)
        selected_data_Bond = selected_data.join(Bond, how='inner')
        ranking = []

        # run regression on all 104 words within this selected periods
        for word in word_choices:
            X = sm.add_constant(selected_data_Bond.loc[:, [word]])
            model = sm.OLS(selected_data_Bond.loc[:, ['Bond']], X).fit()    # run
→regression

```