Geomagnetic Storms and the Stock Market

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Abstract

In their paper "Playing the field: Geomagnetic storms and international stock markets" [1] Krivelyova and Robotti find a 14% difference in means for the annualized percentage return between normal days and days affected by geomagnetic storms from 1972 to 2000 for the NASDAQ. We here find a 15.13% difference for the same period. For 2001-2016, a difference of -7.94% is found, contradicting the hypothesis developed in [1].

1 Introduction

A geomagnetic storm (GMS), also known as a solar flare, is a disturbance in the earth magnetosphere caused by a solar wind. These disturbances vary in length and in intensity, with the strongest ones able to affect satellites and radio communications. One of the largest GMS known is the Solar Storm of 1859. Such a GMS would today incur an economic loss to the US alone of $\$0.6 - 2.6$ trillions [2]. It has been known that disturbances in the earth magnetic field have an effect on the orientation and navigation of animals, which develop local maps with their magnetoception sense [3].
The thesis proposed in [1] is based on numerous psychological research papers demonstrating that the human mood is also affected by disturbances in the earth magnetic field [4]. In turn, this change of mood would cause changes in behavior and decision making, which would be seen in the decrease of the price of risky assets. In [1], a difference of up to 14% in annualized return for the period 15/12/1972 - 29/12/2000 is observed between normal days and bad days, the latter defined as days where people's behavior would be affected by the magnetic disturbances.
In this paper, we begin by looking at the correlation between sunspots and GMS and their seasonality. We then go on to analyze the data for the NASDAQ Composite Index, from 15/12/1972 to 30/12/2016, hence covering the range presented in [1] and expanding it. A short conclusion will highlight the main results obtained throughout the experiment and suggest further developments.

2 Sunspots and geomagnetic storms

What causes GMS and how can they affect our magnetosphere? The Space Weather Prediction Center gives the following definition: *"Sunspots are dark areas that become apparent at the sun's photosphere as a result of intense magnetic flux pushing up from further within the solar interior. [...] rapid changes in the magnetic field alignment of sunspot regions are the most likely sources of significant space weather events such as solar flares"* [5]. To quantify the intensity of a GMS, we use the AP index, which is an arithmetic average of 8 daily measurements over 13 observatories located in the northern and southern hemispheres. To test the results found in [1], we follow their definition of a stormy day as a day with an AP>29. We investigate the stability of this choice in section 3.3.1.

The data was taken from the National Geophysical Data Center, which is part of the National Oceanic & Atmospheric Administration (NOAA) [6]. We find that GMS usually last for 2-4 days and there is an average of 35 stormy days per year between 1932 and 2016.

We want to analyze the correlation between the yearly average number of significant geomagnetic storms (AP>29) and the yearly number of sunspots. A display of both phenomena can be found in Figure 1.

As the median of number of sunspots per year is 21 111 (vs. a median of 29 for the number of GMS), the daily average of sunspots for each year was taken.

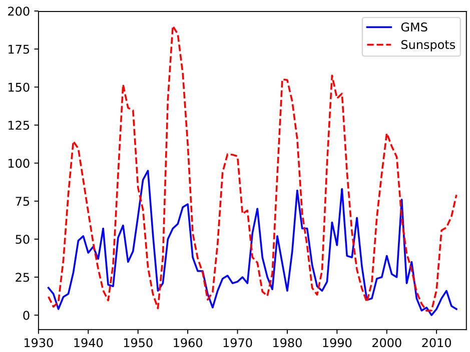


Figure 1: Daily average of sunspots for each year versus the number of geomagnetic storms per year

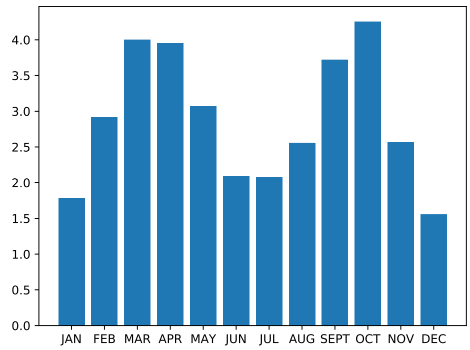


Figure 2: Daily average of GMS for each month, from 1932 to 2014

Note that even though the data on GMS was complete until mid 2017, the number of sunspots are only available until 2014. Hence the cut-off at the latter date.
Using the Fisher transformation, we find a maximum annual correlation between the GMS and sunspots for lag 2, with $\rho = 0.58^{+0.07}_{-0.08}$. This gives us a z-score of 5.88, allowing us to statistically confirm our visual intuition and reject the null hypothesis at close to 6σ. As mentioned in [1], the annual correlation (at lag 0) over the 1932-2000 period is 0.395.
In Figure 2, the data show a seasonal effect on the occurences of GMS over the period 1932-2014.

3 NASDAQ data

3.1 Structure of the data

The data retrieved from Thomson Reuters Datastream for the NASDAQ Composite Index consist of closing prices from 15/12/1972 to 31/12/2016. The dataset gives a closing price for all weekdays in this period, but an opening price only from 11/10/1984 on.
From 1972 to 2016, there are 382 holidays within the 11 492 weekdays. Even though this represents only 3.44% more data points, the more we could algorithmically pinpoint and remove holidays, the more it became apparent these days were strongly influencing our results. Eventually, we removed all days where the NASDAQ was closed. The final dataset on which our analysis is based contains 11 110 trading days.

3.2 Summary statistics of NASDAQ returns

We report the summary statistics for daily returns in Table 1.
The first two rows allow us to compare our results with the ones from the original paper [1]. In it, they state their data for US stock market indices come from the Center for Research and Security Prices (CRSP), whereas our data are from the Reuters Datastream info. Surprisingly and significantly, [1] states a maximum continuously compounded daily return of 10.575%. This is clearly a mistake as can be cross checked on Yahoo [7] and the Wall Street Journal [8]. In total, neither the standard deviation, maximum value, skewness nor kurtosis match our computations. A check of these statistical values on the historical data available on Yahoo comforts our computation, as the former lie extremely close to our results. After many tries, we were in no way able to reproduce the results stated in [1]. The kurtosis presented by [1] being 24% higher than the results obtained through Reuters Datastream and Yahoo, we can question how such a discrepancy is possible. We suggest the authors of the paper may have made a mistake while computing daily return.
This makes us question the validity of all the other results listed in [1] as the whole paper lies on computing (the difference in) returns for stormy versus normal trading days.

Country Period	Mean	Standard Deviation	Min	Max	Skewness	Kurtosis
US : NASDAQ (results from [1]) 15/12/1972 - 29/12/2000 (7085 obs.)	0.047	1.095	-11.350	10.573	-0.48	15.069
US : NASDAQ 15/12/1972 - 29/12/2000 (7085 obs.)	0.047	1.087	-11.350	10.476	-0.50	12.118
US : NASDAQ 01/01/2001 - 30/12/2016(4025 obs.)	0.032	1.502	-9.142	14.173	0.24	6.563
US : NASDAQ 15/12/1972 - 30/12/2016(11110 obs.)	0.042	1.253	-11.350	14.173	-0.06	9.588

Table 1: Summary of NASDAQ Returns

3.3 Returns during stormy days versus normal days

Let us now turn to the most important result of [1]: a 14% difference in means for the annualized percentage return between normal and bad days from 1972 to 2000 for the NASDAQ is found. As in [1], we define "bad" days as the 6 calendar days that follow a geomagnetic storm with an AP index larger than 29. The remaining days are labeled as "normal" days. To illustrate, if a storm hits on day t, then the calendar days $t+1, ..., t+7$ are defined as "bad" days.
Between 1972 and 2000 (7085 observations), there are 789 stormy days (11.13%) that hit on a trading day, and 2601 bad days (36.71%). Between 1972 and 2016 (11 110 observations), we have 994 stormy days (8.9%), and 3361 bad days (30.25%). This decrease of GMS can be seen in Figure 1: the GMS have been more frequent from 1972 to 2000 than from 2000 to 2016.
We summarize our results for the mean in annualized percentage returns for bad and normal days in Table 2.

Country Period	Annualized Return	Annualized Return Bad Days	Annualized Return Normal Days	Difference
US : NASDAQ 15/12/1972 - 29/12/2000	18.76	9.42	24.55	15.13
US : NASDAQ 01/01/2001 - 30/12/2016	12.54	19.02	11.09	-7.94
US : NASDAQ 15/12/1972 - 30/12/2016	16.48	11.52	18.69	7.17

Table 2: Annualized percentage returns during normal and bad days for the NASDAQ

Looking now at the daily returns for normal days versus bad days, we obtain the results given in Figure 3. The period 1972-2000 has an average daily return for normal days of 0.060%, which corresponds to the result stated in [1]. However, the daily average for bad days are about 3 times larger than what is found on page 49 in [1]. As we have used the same condition on the AP index as well as the same lags to define bad days as in [1], the discrepancy is hard to explain. We refer again to the incoherent results from [1] that we listed in the first line of Table 1.

For the period 2001-2016, we unexpectedly see the opposite effect that [1] had predicted: now the daily average returns during bad days (0.047%) are much better than during normal days (0.028%). This measure contradicts strongly the hypothesis proposed in [1] that people sell stocks on stormy days attributing their pessimism to inexistent economic conditions rather than bad environmental conditions.

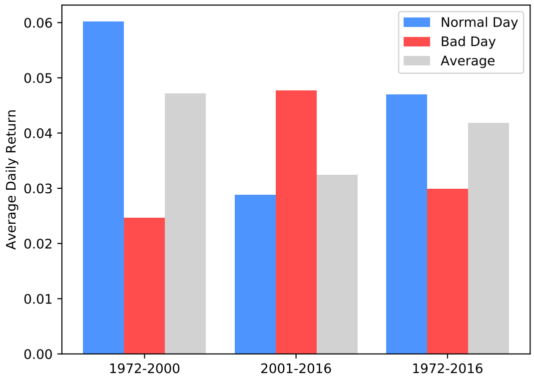


Figure 3: Average daily return for the three defined periods for a cut-off at AP> 29

3.3.1 Remark on the stability of the results

In [1], the AP cut-off to define bad days is set at AP>29. This choice is motivated as follows :*"The GMS proxy is motivated by several findings in the medical literature according to which depressive disorders are mainly associated with unusually high levels of geomagnetic activity. Values of the AP index below 30 refer to relatively quiet geomagnetic activity levels. Hence, we focus on environmental magnetic storms that are characterized by values of the AP index above 29"*. The only article later mentioned to sustain the association of depression and GMS gives no clear value for the cut-off on the AP index [4].
In an article on the official NOAA website [9], a stormy day is defined as having an AP≥40 (i.e. AP>39). This questions the validity of the cut-off used in [1] (AP>29). Running our analysis on different cut-offs, we notice that the results displayed in Figure 3 vary widely. As stated in Table 2, the difference in annualized return between normal and bad days is 15.13% for the period 1972-2000 with a cut-off at AP>29. For a cut-off at AP>28, This difference falls to 12.58% as can be shown in Figure 5a. For AP>30, the difference is now 20.25% (Figure 5b), at AP>35 the difference is 30.31% (Figure 5c), and at AP>39 we obtain 29.34% (Figure 5d).

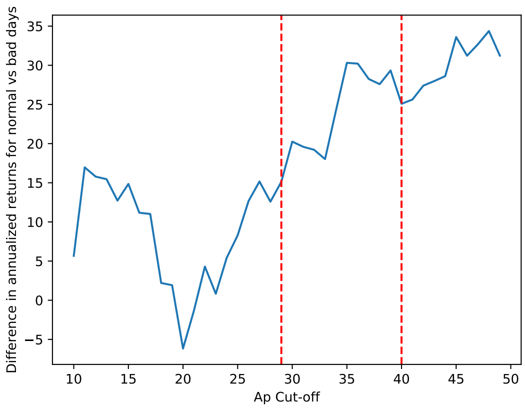
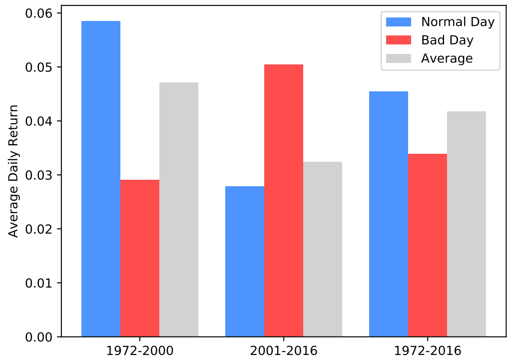
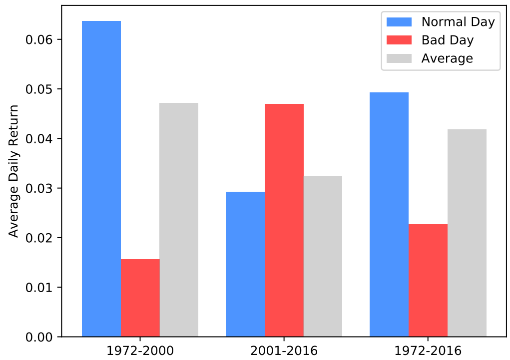


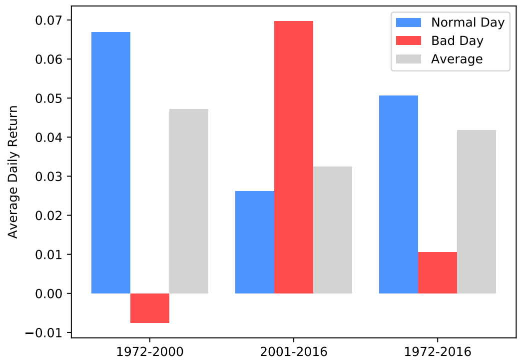
Figure 4: Evolution of the difference in annualized returns between normal and bad days for different cut-offs



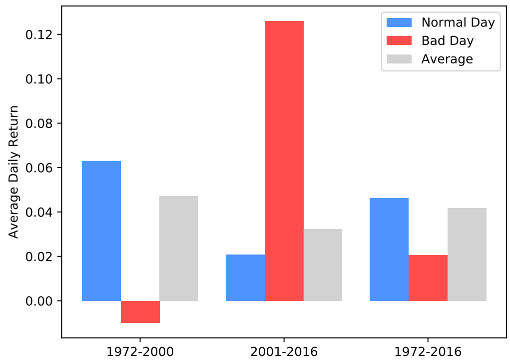
(a) AP>28



(b) AP>30



(c) AP>35



(d) AP>39

Figure 5: Illustration of the instability of the AP cut-off

4 Conclusion

We found a statistically significant value for the correlation of GMS and sunspots. Nevertheless, the results of [1] about the NASDAQ index could only be partially reproduced. Even though a difference in return between normal and bad days could be found, the values computed do not match with the findings of [1]. Moreover, their prediction is overturned for the period 2001-2016. Also, the cut-off parameter AP to define which days are counted as stormy days (and hence defining which days are considered bad) is not strongly motivated in [1].
One key factor that could contribute to the apparent elimination of correlation between bad days and lower returns for the period 2001-2016 could be found in the increase of the algorithmic trading percentage of market volume. Between 2003 and 2012, this percentage grew from 15% to 85% [10]. Thus, a large portion of the trades cannot be linked to a human decision on the day of the trade, but may well have been coded and back tested well before. Based on these findings, it would today perhaps be more relevant to study the causality between GMS and their effects on the power grid, which would in turn affect transition speeds of trades for High Frequency Firms.

References

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