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Working Paper 2003-5a
March 2003

Working Paper Series

Federal Reserve Bank of Atlanta
Working Paper 2003-5a
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Abstract: This paper documents the impact of geomagnetic storms (GMS) on world and country-specific stock market returns. For the world index and for most of the international indices in our sample, we find that the previous week's unusually high levels of geomagnetic activity have a negative, statistically and economically significant impact on today's stock returns. Our results are consistent with psychological theories of "misattribution of mood," since GMS have been found to negatively affect people's judgment and behavior.

JEL classification: G1

Key words: stock returns, geomagnetic storms, seasonal affective disorders, depression, behavioral finance

The authors have benefited from the suggestions of Lisa Kramer and Mark Kamstra. They also gratefully acknowledge the research assistance of Lisle Cormier. The views expressed here are the authors' and not necessarily those of the Federal Reserve Bank of Atlanta or the Federal Reserve System. Any remaining errors are the authors' responsibility.

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Introduction

While it is the geomagnetic storms that give rise to the beautiful Northern lights, they can also pose a serious threat for commercial and military satellite operators, power companies, astronauts, and they can even shorten the life of oil pipelines in Alaska by increasing pipeline corrosion. Most importantly, intense geomagnetic storms can pose a serious threat for human health. In Russia, as well as in other Eastern and Northern European countries, regular warnings about the intensity of geomagnetic storms have been issued for decades. More recently, the research on geomagnetic storms and their effects started to become more and more important in several other countries such as the United States, the United Kingdom, and Japan. Now, we can get regular updates on the intensity of the geomagnetic activity from the press, the Internet and the Weather Channel.

The pervasive effects of intense geomagnetic storms on human health and behavior is what motivates our investigation of a possible link between geomagnetic storms and the stock market. In this paper, we suggest a plausible and economically reasonable story that relates geomagnetic storms to stock market returns, and provide empirical evidence which is consistent with this story.

A large body of research in psychology has documented a link between depression, anxiety, altered moods, and unusually high levels of geomagnetic activity. Psychological disorders and "bad moods" have been found to be linked to more cautious behavior, including decisions of a financial nature,[1] and substantial misattribution.[2] Through the links between geomagnetic storms[3] (GMS) and altered moods and altered moods and misattribution, above average levels of geomagnetic activity can potentially affect stock market returns. If people are more pessimistic during periods

[1] See, for example, Wong and Carducci (1991).

[2] See, for example, Schwarz (1990).

[3] Geomagnetic storms are worldwide disturbances of the earth's magnetic field, distinct from regular diurnal variations. Geomagnetic storms occur when a mass of plasma containing trapped magnetic fields is ejected from the sun and strikes the earth at its atmosphere.

of intense geomagnetic storms, they may be more incline to sell stocks on stormy days. Specifically, they may incorrectly attribute their bad mood to perceived negative economic prospects rather than environmental conditions. Seminal papers[4] cited by Kamstra, Kramer, and Levi (2003) show that the market clears at prices where marginal buyers are willing to exchange with marginal sellers. According to this principle, market participants directly affected by GMS can influence overall market returns. More pessimistic future prospects would translate into a relatively high demand for riskless assets, causing the price of risky assets to fall or to rise less quickly than otherwise. The implication of this story is a negative causal relationship between patterns in geomagnetic activity and stock market returns.

We find strong empirical support in favor of a GMS effect in stock returns after controlling for market seasonals and other environmental and behavioral factors.[5] The previous week's unusually high levels of geomagnetic activity have a negative and statistically significant effect on today's stock returns for twelve out of thirteen indices in our sample. We provide evidence of substantially higher returns around the world during periods of quiet geomagnetic activity. This effect also appears to be relevant from an economic point of view.

Recent empirical studies in financial economics have documented links between emotions and mood and financial decision making. Lo and Repin (2001) look at the impact of emotions on the decisions of professional securities traders. Our results complement the findings of a seasonal affective disorders (SAD) effect [Kamstra, Kramer, and Levi (2003)] and of a sunshine effect [Saunders (1993), Hirshleifer and Shumway (2003)] on international stock returns at the aggregate level.

In a study on GMS and depression, Ronald W. Kay (1994) found that hospital admissions of predisposed individuals with a diagnosis of depression rose 36.2% during

[4]See Hicks (1963), Bierwag and Grove (1965), and the appendix of "The Equilibrium Prices of Financial Assets" by Van Horne (1984, pp. 70-78) among others.

[5]We would like to thank Mark Kamstra and Lisa Kramer for providing us with most of the data used in this study.

periods of high geomagnetic activity as compared with normal periods.[6] Geomagnetic variations have been correlated with enhanced anxiety, sleep disturbances, altered moods, and greater incidences of psychiatric admissions.

The effects are usually brief but pervasive.[7] For example, on heliomagnetic (solar) exposures, pilots with a high level of anxiety operate at a new, even more intensive homeostatic level[8] which is accompanied by a decreased functional activity of the central nervous system. The latter leads to a sharp decline in flying skills.[9] Kuleshova, Pulinets, Sazanova, and Kharchenko (2001) document a substantial and statistically significant effect of geomagnetic storms on human health. For example, the average number of hospitalized patients with mental and cardiovascular diseases during geomagnetic storms increases approximately two times compared with quiet periods. The frequency of occurrence of myocardial infarction, angina pectoris, violation of cardial rhythm, acute violation of brain blood circulation doubles during storms compared with magnetically quiet periods. Oraevskii, Kuleshova, Gurfinkel, Guseva, and Rapoport (1998) reach similar conclusions by looking at emergency ambulance statistical data accumulated in Moscow during March 1983-October 1984. They examine diurnal numbers of urgent hospitalization of patients in connection with suicides, mental disorders, myocardial infarction, defects of cerebrum vessels and arterial and venous diseases. Comparison of geomagnetic and medical data show that at least

[6] Raps, Stoupel, and Shimshoni (1992) document a significant 0.274 Pearson correlation between monthly numbers of first psychiatric admissions and sudden magnetic disturbances of the ionosphere.

[7] See, for example, Persinger (1987).

[8] Homeostasis is the maintenance of equilibrium, or constant conditions, in a biological system by means of automatic mechanisms that counteract influences tending toward disequilibrium. The development of the concept, which is one of the most fundamental in modern biology, began in the 19th century when the French physiologist Claude Bernard noted the constancy of chemical composition and physical properties of blood and other body fluids. He claimed that this "fixity of the milieu interieur" was essential to the life of higher organisms. The term homeostasis was coined by the 20th-century American physiologist Walter B. Cannon, who refined and extended the concept of self-regulating mechanisms in living systems.

[9] See Usenko (1992).

75% of geomagnetic storms caused increase in hospitalization of patients with the above-mentioned diseases by 30-80% at average. Zakharov and Tyrnov (2001) document an adverse effect of solar activity not only on sick but also on healthy people: "It is commonly agreed that solar activity has adverse effects first of all on enfeebled and ill organisms. In our study we have traced that under conditions of nervous and emotional stresses (at work, in the street, and in cars) the effect may be larger for healthy people. The effect is most marked during the recovery phase of geomagnetic storms and accompanied by the inhibition of the central nervous system".

Geomagnetic storms are classically divided into three components or phases [see, for example, Persinger (1980)]: the sudden commencement or initial phase, the main phase and the recovery phase. The initial phase is associated with compression of the magnetosphere, resulting in an increase in local intensity. This lasts for 2-8 hours. The main phase is associated with erratic but general decreases in background field intensities. This phase lasts for 12-24 hours and is followed by a recovery period that may require tens of hours to a week.

Tarquini, Perfetto, and Tarquini (1998) analyze the relationship between geomagnetic activity, melatonin and seasonal depression. Specifically, geomagnetic storms, by influencing the activity of the pineal gland, cause imbalances and disruptions of the circadian rhythm of melatonin production, a factor that plays an important role in mood disturbances.[10]

Even if geomagnetic activity is more intense during spring and fall (see Figure II), leading to increased susceptibility for desynchronization of circadian rhythms, geo-

[10]The hormone melatonin is sometimes called the body's built-in biological clock because it coordinates many physical functions in conjunction with the sleep wake cycle. Abnormal melatonin patterns have been closely linked to a variety of behavioral changes and mood disorders. In general, studies have reported decreased nocturnal melatonin levels in patients suffering from depression. An unstable circadian secretion pattern of melatonin is also associated with depression in SAD. The relationship between melatonin, day length variation rate, and geomagnetic field fluctuations has also been analyzed by Bergiannaki, Paparrigopoulus, and Stefanis (1996).

magnetic storms and their effects on human beings are not purely seasonal phenomena.[11]

This evidence complements and contrasts additional medical findings on the link between depression and SAD, a condition that affects many people only during the seasons of relatively fewer hours of daylight. While SAD is characterized by recurrent fall and winter depression, unusually high levels of geomagnetic activity seem to negatively affect people's mood intermittently all year long. Moreover, the response of human beings to a singularly intense geomagnetic storm may continue several days after the perturbation has ceased. In summary, there seems to be a direct causal relationship between geomagnetic storms and common psychological disorders and geomagnetic activity seems to affect people's health with a lag.

Therefore, against the null hypothesis that there is no effect of GMS on stock returns, our alternative hypothesis is that psychological disorders brought on by GMS lead to relatively lower returns the days following intense levels of geomagnetic activity.[12] Medical findings do not allow us to identify a precise lag structure linking geomagnetic storms to psychological disorders, but make it clear that the effects of unusually high levels of geomagnetic activity are more pronounced during the recovery phase of the storms. Hence, we use daily data to empirically investigate the link between stock market returns at time t and GMS indicators at time $t-k$, with choice of k motivated below.

The remainder of the paper is organized as follows. In section I, we discuss geomagnetic storms and misattribution of mood. In section II, we briefly describe international stock returns and other behavioral and environmental variables. In sec-

[11] Our findings don't have much to say about the abnormally low returns around the world during the fall months documented by Kamstra, Kramer, and Levi (2003), about the Halloween effect documented by Bouman and Jacobsen (2001), or about the lunar effect documented by Yuan, Zheng, & Zhu (2001), Rotton and Kelly (1985a, 1985b), Rotton and Rosenberg (1984), and Dichev and Janes (2001).

[12] Notice that the relation between GMS and the stock market is not subject to the criticism of datasnooping. Exploration of whether this pattern exists was stimulated by the psychological hypothesis and the hypothesis was not selected to match a known pattern.

tion III, we explain the construction of the variable intended to capture the influence of GMS on international stock markets. In section IV, we document the statistical and economic significance of the GMS effect, discuss the GMS effect on returns of large capitalization vs. small capitalization stocks, and analyze the excess returns that would arise from trading strategies based on the GMS effect. In section V, we conduct three types of robustness checks: i) We investigate the robustness of our results to the introduction of SAD and other calendar and environmental variables; ii) We consider different estimation techniques; and iii) We examine alternate ways of measuring the GMS effect, control for stock market downturns, and explore the possibility of a seasonal GMS effect in stock returns. We conclude in section VI.

I. Geomagnetic Storms, Misattribution of Mood, and Stock Market Returns

Geomagnetic storms occur when a mass of plasma containing trapped magnetic fields is ejected from the sun and strikes the earth at its atmosphere. This mass, sometimes called a plasma "bubble", travels away from the sun at about 2 million miles per hour. The "bubble" does not follow a straight course but rides the rotating three-dimensional spiral pattern of the sun's magnetic field. If a "bubble" leaves the right place on the sun to reach earth, it travels the 93-million-mile distance in about 40 hours. Though these ejections can happen any time, the sun is stormiest when sunspots are most numerous. Since sunspot activity peaks every 11 years, geomagnetic storms exhibit some cyclicality as well. Figure I shows that geomagnetic storms correlate with sunspots, the annual correlation being 0.4 over the 1932-2000 period.[13]

[13]On the contrary, the daily correlation between GMS and sunspots is only 0.1 over the same period. Data on GMS and sunspots were obtained from the National Geophysical Data Center, which is a part of the National Oceanic & Atmospheric Administration (NOAA). See Section III for a formal definition of the GMS variable and for the exact reference to the web site where all geomagnetic data can be found.

Also notice that the number of sunspots is usually higher than the number of storms, consistent with the idea that the vast majority of plasma "bubbles" miss earth, and many that do reach the earth are too weak to produce a significant storm. Moreover, the sunspots and the GMS cycles are not perfecly synchronized. Physicists at the University of California, San Diego and Japan's Nagoya University, have improved geomagnetic storms predictions dramatically in the past few years by developing a method of detecting and predicting the movements of these geomagnetic storms in the vast region of space between the sun and the earth. Forecasts of geomagnetic activity at different horizons are available from NASA and various other sources.

Geomagnetic storms are predictable and persist for periods of two to four days. On average, we have 35 stormy days a year with a higher concentration of stormy days in March-April and September-October (see Figure II).

Geomagnetic storms have been found to have brief but pervasive effects on human health and have been related to various forms of mood disorders that are connected to melatonin dysregulation in the brain through the activity of the pineal gland. Sandyk, Anninos, and Tsagas (1991), among others, propose magneto and light therapy as a cure for patients with winter depression: "In addition, since the environmental light and magnetic fields, which undergo diurnal and seasonal variations, influence the activity of the pineal gland, we propose that a synergistic effect of light and magnetic therapy in patients with winter depression would be more physiological and, therefore, superior to phototherapy alone". Some of the symptoms caused by GMS are similar to symptoms of SAD and range from sleep disturbances to loss of energy and difficulty concentrating.

Experimental research in psychology has documented a direct link between mood disorders and human behavior. Hirshleifer and Shumway (2003) provide a detailed summary of these studies. For example, Wright and Bower (1992) show that, when people are in bad moods, there is a clear tendency for more pessimistic choices and judgments. Mood mainly affects relatively abstract judgments, about which people lack concrete information.[14] Bad moods also lead to a more detailed and more critical analytical activity [Schwarz (1990), Petty, Gleicher, and Baker (1991)]. Loewenstein (2000) discusses the role of emotions in economic behavior, Johnson and Tversky (1983) find that mood has strong effects on judgments of risk.[15] Frijda (1988), Schwarz (1990), Clore and Parrot (1991), Clore, Schwarz, and Conway (1994), Wilson and Schooler (1991), among others, show that emotions and moods provide information, perhaps unconsciously, to individuals about the environment. An important finding of this literature is that people often attribute their feelings and emotions to the wrong source, leading to incorrect judgments. Specifically, people affected by GMS may be more inclined to sell stocks on stormy days, by incorrectly attributing their bad mood to negative economic prospects rather than bad environmental conditions. Market participants directly affected by GMS can influence overall market returns according to the principle that market equilibrium occurs at prices where marginal buyers are willing to exchange with marginal sellers. Misattribution of mood and pessimistic choices can translate into a relatively higher demand for riskless assets, causing the price of risky assets to fall or to rise less quickly than otherwise. Hence, we anticipate a negative causal relationship between patterns in geomagnetic activity and stock market returns. Moreover, we expect this relationship to show up with some lags, since unusually high levels of geomagnetic activity have been found to increase the incidence of mood disorders during the recovery phase of geomagnetic storms. Based on previous considerations, we expect to see a GMS effect on stock returns, if any, within a week from the origination of an intense geomagnetic storm.

[14] See, for example, Clore, Schwarz, and Conway (1994), and Forgas (1995).

[15] See Loewenstein, Weber, Hsee, and Welch (2001) for a review of several studies in this literature.

II. Data

A. Stock Market Returns

We consider the same stock market indices used by Kamstra, Kramer and Levi (2003): the same four indices from the United States as well as the indices from eight other countries at different latitudes in different hemispheres. As Kamstra, Kramer, and Levi (2003) do, we choose these twelve indices based on the following three criteria: 1) absence of hyper-inflation; 2) sufficiently long time series; 3) large capitalization and representation of a broad range of sectors. In addition, we consider the world market index.

U.S. stock market indices are obtained from CRSP; international indices are from Datastream. All of the indices are value-weighted and do not include dividends. The four US indices that we consider are the NASDAQ, the S&P500,[16] the Amex, and the NYSE. For the United States, we also considered CRSP indices of returns including dividends and we found qualitatively identical results in all cases. The remaining eight countries included in our study are Australia (All Ordinaries, Sydney), Britain (FTSE 100, London), Canada (TSE 300, Toronto), Germany (DAX 30, Frankfurt), Japan (NIKKEI 225, Tokyo), New Zealand (Capital 40, Auckland), South Africa (Datastream Global Index, Johannesburg), and Sweden (Veckans Affärer, Stockholm).[17] The world index is also from Datastream.[18]

The longest time series that we consider is the US S&P500 which spans approximately 70 years. For South Africa we choose the Datastream Global Index of 70 large-cap stocks in that country, which spans approximately 30 years. Table I displays summary statistics for the stock market data used in this study. Notice that the time spans widely vary across countries. Negative skewness and high kurtosis

[16] The starting date for the S&P500 is dictated by GMS data availability.

[17] The Datastream codes for these series are, in the order, AUSTOLD, FTSE100, TTOCOMP, DAXINDX, JAPDOWA, NZ40CAP, TOTXTSA, and VECWALL.

[18] The Datastream code for this series is TOTMKWD.

represent common characteristics of all the indices in our sample. Average daily percentage returns range from 0.013 for New Zealand to 0.063 for Sweden. Daily percentage standard deviations of returns range from 0.74 for the world index to 1.34 for South Africa. The Australian index experienced the largest daily loss, while the S&P 500 experienced the largest daily gain.

B. Calendar, Environmental, and Behavioral Variables

The calendar variables we consider are a tax dummy and a Monday dummy. The tax year starts on January 1 in the US, Canada, Germany, Japan, and Sweden. The tax year starts on April 6 in Britain, on July first in Australia, on March 1 in South Africa, and on April 1 in New Zealand.[19] For Britain, since the tax year ends on April 5, the tax-year dummy equals 1 for the last trading day before April 5 and the first 5 trading days starting on April 5 or immediately thereafter. Tax-year dummies for the other countries are analogously constructed. Monday is a dummy variable which equals 1 when period t is the trading day following a weekend (usually a Monday) and 0 otherwise.

We now describe the additional control variables that we will use in Section V to perform robustness checks.

As in Kamstra, Kramer, and Levi (2003), we test for a GMS effect in stock return data by controlling for the following environmental variables: i) Percentage cloud cover ; ii) Millimeters of precipitation; and iii) Temperature in degrees Celsius. All of these environmental factors are measured in the city of the exchange. All of the climate data were obtained from the IRI/LDEO Climate Data Library operated jointly by the International Research Institute for Climate Prediction and the Lamont-Doherty Earth Observatory of Columbia University: ingrid.ldeo.columbia.edu. Saunders (1993) and Hirshleifer and Shumway (2003) present evidence of a relation between sunshine and market returns for the US and for 26 international stock markets,

[19]See Ernst & Young International, Ltd. *1999 Worldwide Executive Tax Guide*, 1998.

respectively. Cao and Wei (2001) find a link between temperature and stock market returns in eight international markets. Our results build on the psychology literature linking GMS to depression as well as the economics literature linking environmental factors to stock market returns.

Following Kamstra, Kramer and Levi (2003), we also include the SAD variable in our empirical specification in Section V.

Kamstra, Kramer and Levi (2003) explain how to construct the seasonal affective disorders (SAD) variable, which is aimed to capture the different number of hours of daylight during the four seasons of the year. Consistent with clinical evidence, Kamstra, Kramer and Levi (2003) define SAD as follows:

$$SAD_t = \begin{cases} H_t - 12 & \text{for trading days in fall and winter} \\ 0 & \text{otherwise} \end{cases}$$

where

$$H_t = \begin{cases} 24 - 7.72 \cdot arccos[-tan\frac{(2\pi\delta)}{360}tan(\lambda_t)] & \text{in the Northern Hemisphere} \\ 7.72 \cdot arccos[-tan\frac{(2\pi\delta)}{360}tan(\lambda_t)] & \text{in the Southern Hemisphere .} \end{cases}$$

"$arccos$" is the arc cosine, δ is the latitude, and λ_t, the sun's declination angle, is defined as

$$\lambda_t = 0.4102 \cdot sin[-tan(\frac{2\pi}{365})(julian_t - 80.25)] \ .$$

"$julian_t$" is a variable that ranges from 1 to 365 (366 in a leap year), representing the number of the day in the year.

III. Measuring the Effect of Geomagnetic Storms

The vast majority of empirical studies on GMS and psychological disorders use either the Ap or the Kp index to capture the intensity of the environmental magnetic field.

These are planetary indices and represent averages across 13 different observatories between 44 degrees and 60 degrees northern or southern geomagnetic latitude.

We choose the Ap index as a proxy for geomagnetic activity.[20] Values of the Ap index with corresponding geomagnetic field conditions are reported in the table below:

Geomagnetic Activity Index

Ap Index	Geomagnetic Field Conditions
0-29	Quiet or Unsettled Activity
30-49	Minor Storm
50-99	Major Storm
≥ 100	Severe Storm

The Ap index series is the arithmetic average of 8 daily ap values of the geomagnetic conditions, recorded at three hour intervals. To express the effect of GMS on stock returns in calendar days instead of trading days, we first match stock return data with the desired lags of the continuous GMS variable.

Values of the Ap index below 30 refer to relatively quiet geomagnetic activity levels. Consistent with several findings in the medical literature according to which depressive disorders are mainly associated with levels of unusually high levels of geomagnetic activity, we focus on environmental magnetic storms that are characterized by values of the Ap index above 29.

Accordingly, we construct a GMS dummy variable as follows:

$$D_{t-k}^{GMS} = \begin{cases} 1 & \text{for GMS} > 29 \\ 0 & \text{for GMS} \leq 29 \end{cases} \tag{1}$$

where GMS $= AM(\text{ap})$ at time $t-k$ and AM denotes the arithmetic mean.

[20] The geomagnetic data can be downloaded from the National Geophysical Data Center, which is a part of the National Oceanic & Atmospheric Administration (NOAA):

ftp : //ftp.ngdc.noaa.gov/STP/GEOMAGNETIC_DATA/INDICES/KP_AP/.

Our GMS measure has a few advantages over the SAD variable used by Kamstra, Kramer, and Levi (2003) and over the sunshine variable used by Hirshleifer and Shumway (2003). First, differently than SAD and sunshine, GMS is not highly seasonal. As a consequence, our results are less likely to be driven by other seasonal patterns that have been identified in stock return data as well. Second, differently than SAD and sunshine, GMS is a planetary variable and does not have to be measured in the cities where the stock exchanges are located.

Ap index data start on January 1, 1932 and end on October 31, 2002. Days of intense geomagnetic storms represent, on average, 10% percent of our sample. On average, three days a month can be classified as stormy days. Moreover, the GMS as well as the D_{t-k}^{GMS} variables exhibit strong positive autocorrelation and partial autocorrelation up to lag four. Figure II shows that geomagnetic storms are not a purely seasonal phenomenon. Even if there are peaks in March and April, and September and October[21], geomagnetic activity seems to follow a smooth sinusoidal pattern across all months of the calendar year.

Consistent with several psychological findings, we look at the differences in returns the week following unusually high levels of geomagnetic activity. Figure III displays the average daily return on the world index during 'bad' days and 'normal' days. We define the six calendar days following a geomagnetic storm as 'bad' days. We define the remaining calendar days as 'normal' days.[22] As an example, consider the situation where a storm hits at time t. Then, days $t+1, \ldots, t+6$ would be characterized as 'bad' days. Suppose that day $t+1$ is also a stormy day. By systematically keeping the six day window fixed, days $t+1, \ldots, t+7$ would now be considered 'bad' days. The difference in means is 6.7% in terms of annualized percentage returns and is highly statistically significant.[23] Figure IV displays, for each stock market index, the

[21] The semiannual variation in geomagnetic activity is well established in geomagnetic data. See Russell and McPherron (1973) for a review of the proposed explanations.

[22] The choice of this window is motivated in the next section.

[23] We also split our 30 year sample into three subsamples: the 70', the 80', and the 90'. We found that the GMS effect in stock returns was very robust during the 80' and the 90' and somewhat less

average daily returns during 'bad' days and 'normal' days. The differences in means are substantial for several indices in our sample. This preliminary analysis seems to provide the rational for a deeper investigation of a GMS effect in stock returns using regression techniques.

IV. Influence of the Geomagnetic Storms Effect

A. Estimation: Controlling for GMS

We first run separate time series regressions for the thirteen indices in our dataset to capture the differential effect of each lag of the GMS variable on returns at time t. Returns are regressed on a constant and the GMS dummy:

$$r_t = \alpha + \beta_{GMS} D_{t-k}^{GMS} + \epsilon_t. \tag{2}$$

Variables are defined as follows: r_t is the period t return for a given country's index; D_{t-k}^{GMS} is a dummy variable which equals 1 if a storm occurred on day $t-k$ and 0 otherwise. Table II documents a widespread GMS effect across countries one to six calendar days after relatively high recorded levels of geomagnetic activity. In this table, we use Ordinary Least Squares (OLS) techniques to estimate equation (2) separately for each lag and each country. A "$\surd$" means that the different lags of the GMS variable negatively and statistically significantly affect stock market returns at least at the 10% level using one-sided heteroskedasticity-robust White (1980) standard errors. Notice that, with the exception of Germany, all the stock market returns in our sample are negatively affected by GMS at different lags. Table II clearly shows that lags 5 and 6 of the GMS variable affect the different stock market indices more than any other lag of the GMS variable. As a consequence, for expositional purposes, we present regression results using lag 5 and 6 of the GMS variable.[24] In separate

robust during the 70'.

[24]Notice that, while lags 5 and 6 of the GMS variable explain r_t for most of the countries in our sample, several other lags of our GMS variable show up significantly for different countries.

regressions (available from the authors on request), we considered lags of the GMS variable ranging from 0 up to 14. Lags equal to 0 or greater than 6 always delivered statistically insignificant results for all countries. These empirical results fully support the clinical finding that geomagnetic storms cause depressive disorders among people within a week from hitting the atmosphere.

Regression results using $D^{GMS}_{t-5,t-6}$ ($D^{GMS}_{t-5,t-6}$ is a dummy variable which equals 1 if a storm occurred on day $t-5$ or $t-6$ and 0 otherwise) for each of the thirteen indices are reported in Table III. We use OLS to estimate equation (2) and we account for heteroskedasticity by reporting robust standard errors. The parameter estimates on the GMS variable have the right negative sign for all countries and all indices and are statistically significant for ten indices out of thirteen. The three exceptions are represented by Australia, Germany and South Africa. The GMS estimated coefficients for Germany, Australia, and South Africa are negative but insignificant. These findings complement recent evidence provided by Kamstra, Kramer, and Levi (2003) of a weak SAD effect for Australia, Germany and South Africa.

B. Estimation: Economic Significance

We present the economic significance of the GMS effect in Table IV.

Table IV shows the average annual percentage return due to GMS and the entire unconditional annual percentage return. The return due to GMS is negative in all countries, ranging from -0.8 percent to -4.4 percent. The size of the GMS effect appears to be similar across all indices, and the return due to GMS exceeds the entire unconditional annual return only in the case of New Zealand. As an example, consider an investor able to obtain an average annual return of 96.8 dollars for each 1000 US dollars invested in the FTSE 100. In absence of a GMS effect in stock returns, she would have earned an average annual return of 139 dollars instead of 96.8 dollars for each 1000 dollars invested in the British index.

C. Estimation: Controlling for GMS and Well-Known Calendar Effects

As in the previous subsection, we run separate time series regressions for the nine countries in our dataset.[25] Returns are regressed on a constant, a Monday dummy, a dummy variable for a tax-loss selling effect, and the GMS dummy:

$$r_t \quad = \quad \alpha + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{GMS} D_{t-5,t-6}^{GMS} + \epsilon_t. \tag{3}$$

With the exception of the following new variables, all variables in this equation are defined as in equation (2). D_t^{Monday} is a dummy variable which equals 1 when period t is the trading day following a weekend (usually a Monday) and equals 0 otherwise; D_t^{Tax} is a dummy variable which equals 1 for a given country when period t is in the trading day or first five trading days of the tax year and equals 0 otherwise. Again, we use OLS techniques to estimate equation (3) and report one-sided heteroskedasticity-robust White (1980) standard errors.

Table V shows that the GMS effect in stock returns is robust to the introduction of other controls, the size and the precision of the GMS coefficient estimates being virtually unchanged. Regarding other aspects of the estimation, we find that the Monday dummy and the tax-loss dummy are significant for most of the countries in our sample.

Following Hirshleifer and Shumway (2003), we also examine whether the sign of an index return on a particular day is associated with GMS. For each country, we estimate separate Logit models, where the dependent variable equals zero if r_t is negative and equals one if r_t is positive. The sets of explanatory variables are the same as in our OLS regressions. The results (available on request from the authors) are consistent with our OLS findings and indicate a negative association between lagged values of GMS and the sign of an index return across all indices. This negative association is also significant at conventional confidence levels for 11 out of 12 indices.

[25]We drop the emphasis on the world index because of the country-specific regressions we run.

Overall, this is consistent with a GMS-induced pattern in returns as more pessimistic investors increase their demand for riskless assets, causing the price of risky assets to fall or to rise less quickly than otherwise. Intense geomagnetic storms not only appear to affect people's mood during their recovery phase but also seem to affect international stock returns a few days after reaching unusually high levels.

In summary, the empirical results of this section document a significant GMS effect in stock returns around the world, which appears to be statistically as well as economically significant.

D. The GMS Effect on Returns of Large Cap vs. Small Cap Stocks

In this section, we examine whether the GMS effect on stock returns is related to stock size. This test is motivated by the empirical finding that institutional ownership is positively correlated with stock capitalization, small cap stocks being held mostly by individuals.[26] Since investment decisions of individual investors are more likely to be affected by emotions and mood than those of institutional investors who trade and rebalance their portfolio using a specified set of rules, we expect the GMS effect to be more pronounced in the pricing of smaller cap stocks.

Given data availability, we focus on US stock market indices. We form ten stock portfolios based on market capitalization for stocks traded on NASDAQ, and NYSE, AMPEX, and NASDAQ.[27] The sample period ranges from July 5, 1962 to December 29, 2000 for NYSE/AMEX/NASDAQ, and from December 18, 1972 to December 29, 2000 for NASDAQ.

[26] See, for example, Gompers and Metrick (2001).

[27] The Center for Research in Security Prices (CRSP) ranks all NYSE companies by market capitalization and divides them in to ten equally populated portfolios; based on their market capitalization, AMEX and NASDAQ stocks are then placed into the deciles determined by the NYSE breakpoints. CRSP portfolios 1-2, for example, represent large-cap issues, whereas portfolios 9-10 represent CRSP's benchmark micro-caps.

Table VI reports the results from estimating equation (2) for each decile portfolio. The GMS effect is more pronounced for smaller cap stocks than for very large cap stocks. For example, regression results indicate that the GMS coefficient estimate for the first NASDAQ decile portfolio is equal to -0.01 with standard error of 0.024, while the GMS coefficient estimate for the tenth NASDAQ decile portfolio is equal to -0.07 with standard error of 0.04. The results for NYSE/AMEX/NASDAQ are qualitatively similar. The GMS coefficient on the first decile turns out to be the smallest across deciles. The magnitude of the regression coefficients increases, even if not monotonically, going from the first to the tenth decile. The precision of the GMS coefficient estimates is low for the first decile, and it increases as we move towards smaller cap stocks. Figure V shows the difference between returns during 'normal' days and returns during 'bad' days. The differences in returns generally increase as we move from large capitalization stocks to small capitalization stocks. In summary, our evidence suggests that the GMS effect is stronger for smaller cap stocks.

E. Trading Strategies

Figures III and IV show that returns during 'normal' days are substantially higher than returns on 'bad' days for most of the stock market indices in our sample. A natural question related to this empirical finding is whether we can use the information displayed in Figures III and IV to build exploitable trading strategies. In forming simple trading strategies based on the GMS effect, we face transaction costs as the main problem. Even though geomagnetic storms are predictable, their frequency, intensity, and persistence varies over time. Shortening the calendar window that we use to define 'bad' days would help us to pinpoint the days characterized by particularly low (and often negative) returns, but would significantly increase the number of transactions that we have to make.

One simple trading strategy based on our six day calendar window described above would be the following. An individual might try to hold the world market portfolio during ‘normal’ days and switch his investments towards safer assets such as the 3-month Eurodollar deposits[28] during ‘bad’ days. This trading strategy would require rebalancing the GMS-based portfolio on average 26 times a year. Ignoring transaction costs, this trading rule would generate an average annual return of 7.5 percent, while a buy and hold policy would yield a 6.4 percent annual return. The GMS-based portfolio would also deliver a standard deviation which is 14 percent lower than the standard deviation of the benchmark portfolio. However, no individual investor can ignore transaction costs.[29] By referring to Huang and Stoll (1997), Hirshleifer and Shumway (2003) approximate transaction costs with the cost of trading one S&P 500 futures contract as a fraction of the contract's value and come up with an estimate of one basis point per transaction. With costs of 2 basis points roundtrip, our GMS strategy would generate an average annual return of 7.25 percent, while the buy and hold policy would always yield a 6.4 percent annual return.[30] The break even point is represented by 8 basis points roundtrip. In this latter case, the GMS-based strategy and the buy and hold strategy would deliver almost identical annual returns. Even if our GMS-based strategy seems to produce small trading gains, an individual could increase the expected return to his investments by altering the timing of trades which would have been made anyway – executing stock purchases scheduled for ‘normal’ days on ‘bad’ days and delaying stock sales planned for ‘bad’ days on ‘normal’ days.

There might be more effective ways of taking advantage of the GMS effect in stock returns. One possibility would be to use derivative securities as a hedging

[28] The 3-month Eurodollar deposit rate is from the Board of Governors of the Federal Reserve System. The series spans the entire length of the return on the world market portfolio.

[29] Berkowitz et al. (1988) estimate the cost of a transaction on the NYSE to be 0.23 percent. One of the largest institutional investors world wide, the Rebecco Group, estimates transaction costs in France 0.3%, Germany 0.5%, Italy, 0.4%, Japan 0.3%, the Netherlands 0.3%, and the United States 0.25%. In the UK, the costs of a buy or sell transaction are 0.75% or 0.25%, respectively. Solnik (1993) estimates round-trip transaction costs of 0.1% on future contracts.

[30] Specifically, we deduct from the GMS-based portfolio return one basis point for switching from stocks to bonds and another basis point for switching from bonds to stocks.

device. Trading against incoming storms by buying put options on stock market indices might turn out to be a valid strategy.

V. Robustness Checks

In this section, we provide several robustness checks. First, we analyze the robustness of our regression results to the introduction of SAD and other environmental variables used by Kamstra, Kramer, and Levi (2003) and Hirshleifer and Shumway (2003). Second, we jointly model the mean and the variance of stock returns via Maximum likelihood. Finally, we look at the sensitivity of our results to alternate ways of defining the GMS variable, we allow for the possibility of a seasonal GMS effect in stock returns, and we control for the October 1987 stock market crash and for major downturns in world market returns.

A. Controlling for GMS and Other Calendar, Environmental, and Behavioral Variables

In this section, we evaluate the robustness of our results to the introduction of other calendar, behavioral, and environmental variables. As in Table III, we run separate time series regressions for the nine countries in our dataset. Returns are regressed on a constant, a Monday dummy, a dummy variable for a tax-loss selling effect, the GMS dummy, the SAD measure, cloud cover, precipitation, and temperature:

$$\begin{aligned} r_t &= \alpha + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{GMS} D_{t-5,t-6}^{GMS} + \beta_{SAD} SAD_t + \\ &\quad \beta_{Cloud} Cloud_t + \beta_{Prec} Prec_t + \beta_{Temp} Temp_t + \epsilon_t \,. \end{aligned} \tag{4}$$

With the exception of the following new variables, all variables in this equation are defined as in equation (3). SAD_t is the Seasonal Affective Disorders variable defined in subsection B of section II. The environmental factors, each measured in the city of the exchange, are percentage cloud cover ($Cloud_t$), millimeters of precipitation ($Prec_t$), and temperature in degrees Celsius ($Temp_t$).

The regression results are reported in Table VII. Notice that the size of the GMS regression coefficients is virtually unchanged when comparing this set of results to the empirical findings of Table III and Table V. The GMS coefficient estimates continue to be highly statistically significant. Hence, the SAD effect in stock returns documented by Kamstra, Kramer, and Levi (2003) does not seem to wipe out the effect of the GMS variable on international stock market returns.

Environmental factors such as cloud cover, precipitation, and temperature appear to be mostly insignificant, while the SAD effect documented by Kamstra, Kramer, and Levi (2003) appears to be fairly robust for several indices in our sample. Specifically, the SAD coefficient estimate is positive in all countries and is significant at least at the 10% level for six indices out of twelve. The Monday dummy and the tax-loss dummy continue to be highly statistically significant for most of the countries in our sample.

B. Maximum Likelihood Model

We previously addressed the possibility of heteroskedasticity by using White (1980) standard errors. In this section, we explicitly account for the heteroskedasticity in stock returns by estimating a Maximum Likelihood model which jointly models the mean and the variance of the returns. We estimate the following Asymmetric Component Model:

$$\begin{aligned} r_t &= \alpha + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{GMS} D_{t-5,t-6}^{GMS} + \epsilon_t & (5) \\ \sigma_t^2 - q_t &= \delta(\epsilon_{t-1}^2 - q_{t-1}) + \eta(\epsilon_{t-1}^2 - q_{t-1}) D_{t-1} + \nu(\sigma_{t-1}^2 - q_{t-1}) & (6) \\ q_t &= \omega + \gamma(q_{t-1} - \omega) + \phi(\epsilon_{t-1}^2 - \sigma_{t-1}^2) & (7) \\ \epsilon_t &\sim (0, \sigma_t^2) \\ D_{t-1} &= \begin{cases} 1 & \text{if } \epsilon_{t-1} < 1 \\ 0 & \text{otherwise}. \end{cases} \end{aligned}$$

Equation (5) represents the mean equation. Equations (6) and (7), in the order, represent the transitory and permanent equations. With the exception of the following new variables, all variables are defined as before. The conditional variance of ϵ_t is represented by σ_t^2. The model accounts for autoregressive clustering of stock market return volatility with the ϵ_{t-1}^2 and σ_{t-1}^2 terms, and allows for asymmetric response to negative shocks with the interactive dummy variable D_{t-1}. q_t takes the place of ω (a constant for all time) and is the time-varying long-run volatility.

This specification combines the Component Model, which allows mean reversion to a varying level q_t, with the Sign-GARCH or Threshold GARCH of Glosten *et al.* (1993). We focus on this model because it has been shown to capture important characteristics of stock returns and to be more reliable than several alternative specifications.

Panels A, B, and C of Table VIII display our results. With the exception of some minor quantitative changes, the Maximum Likelihood results are very similar to the results reported above.[31] Log-likelihood values, R^2, and F-statistics p-values are reported at the bottom of the tables. The coefficients on the GMS variable slightly decrease in magnitude but, overall, remain strongly statistically significant. In summary, we still see large and economically significant effects due to GMS.

C. Other Measures for GMS, Seasonality, and Stock Market Downturns

All of the detailed estimation results described in this subsection are provided in the appendix available from the authors. First, we analyzed an alternate measure of the geomagnetic storms variable. We considered the continuous Ap series and found weaker results, consistent with the clinical finding that only unusually high levels of geomagnetic activity affect people's moods.

Second, we explored the possibility of a purely seasonal GMS effect in stock re-

[31] Results available from the authors show that the precision of the coefficient estimates increases when we allow for a GARCH term in the mean equation. The magnitude of the coefficient estimates is virtually unchanged.

turns. Specifically, we interacted a dummy 0,1 variable (1 in March/April and September/October, 0 otherwise) with our continuous GMS variable, as measured by the Ap index. We found evidence of a weaker but non negligible GMS seasonal effect in stock returns around the world.[32]

Third, we controlled for the October 1987 stock market crash. For each country,[33] we dummied out the whole month of October 1987 and found no substantial changes in the magnitude and in the precision of the coefficient estimates.

Finally, for each country, we dummied out all the years with negative returns. The size and the precision of the GMS coefficient estimates did not change. These results make it clear that the empirical regularity under examination is not driven by the chance that peaks in solar activity coincide with years of unusually low stock market returns.

VI. Conclusions

This paper provides evidence of a large GMS effect on stock market returns around the world, even after controlling for the influence of other environmental factors and well-known market seasonals. The world and country-specific stock returns appear to be negatively affected by geomagnetic storms during their recovery phase. This effect is statistically and economically significant, and seems to generate some trading gains. The size of the GMS effect is similar within and across countries, ranging from -0.77% to -4.4% of average annual returns.

We also document a more pronounced GMS effect in the pricing of smaller capitalization stocks. We rationalize this finding by noticing that institutional ownership is higher for large cap stocks, small cap stocks being held mostly by individuals. Since investment decisions of individual investors are more likely to be affected by senti-

[32]The use of the seasonal interaction dummy substantially reduces the number of stormy days in our sample. As expected, size and precision of the coefficient estimates turn out to be smaller.

[33]New Zealand was not included since our sample for this country starts in 1991.

ments and mood than those of institutional investors, we expect the GMS effect to be bigger for small cap stocks.[34]

Overall, results are consistent with some of the recent findings in the psychology literature, are robust to different measures to capture the GMS effect, and do not appear to be an artifact of heteroskedastic patterns in stock returns.

As a supporting argument, we used clinical studies showing that geomagnetic storms have a profound effect on people's moods; and in turn people's moods have been found to be related to human behavior, judgments and decisions about risk. By using related medical and psychological arguments, our results complement recent findings of a significant SAD effect [Kamstra, Kramer, and Levi (2003)] and of a significant sunshine effect [Hirshleifer and Shumway (2003)] in stock market returns.

This paper represents an attempt of establishing a link between psychology and economics. Future research should further explore the relation between people's mood and behavior in a financial setting, possibly controlling for cross-country differences. We believe that a better understanding of investor moods and emotions will shed more light on the daily movements in international stock returns.

[34]Daily data on the trading behavior of mutual funds and individual investors might shed more light on the differential impact of GMS on small cap vs. large cap stocks.

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Table I

Summary Statistics of International Stock Returns

We report summary statistics of daily (continuously compounded) returns on the world index and on the nine country indices. Indices are value-weighted. All returns are in percentage points per day and are denominated in local currency.

Country Period	Mean	Standard Deviation	Min	Max	Skewness	Kurtosis
WORLD 1973/01/02 - 2002/10/31 (7732 obs.)	0.025	0.743	-9.756	7.608	-0.472	13.042
US: NASDAQ 1972/12/15 - 2000/12/29 (7085 obs.)	0.047	1.095	-11.350	10.573	-0.480	15.069
US: S&P500 1932/01/07 - 2000/12/29 (18219 obs.)	0.030	1.065	-20.467	15.366	-0.355	22.621
US: AMEX 1962/07/03 - 2000/12/29 (9694 obs.)	0.032	0.840	-12.746	10.559	-0.862	19.396
US: NYSE 1962/07/03 - 2000/12/29 (9694 obs.)	0.035	0.842	-18.359	8.791	-1.155	31.740
Canada 1969/01/02 - 2001/12/18 (8311 obs.)	0.023	0.853	-10.295	9.878	-0.752	16.957
Sweden 1982/09/14 - 2001/12/18 (4832 obs.)	0.063	1.245	-8.986	9.777	-0.251	9.008
UK 1984/01/03 - 2001/12/06 (4531 obs.)	0.037	1.010	-13.029	7.597	-0.928	15.279
Japan 1950/04/04 - 2001/12/06 (12852 obs.)	0.037	1.119	-16.135	12.430	-0.339	13.817
Australia 1980/01/02 - 2001/12/18 (5568 obs.)	0.034	1.005	-28.761	9.786	-4.873	133.934
New Zealand 1991/07/01 - 2001/12/18 (2639 obs.)	0.013	0.973	-13.307	9.475	-0.854	21.735
South Africa 1973/01/02 - 2001/12/06 (7406 obs.)	0.054	1.343	-14.528	13.574	-0.717	12.682
Germany 1965/01/04 - 2001/12/12 (9313 obs.)	0.025	1.105	-13.710	8.872	-0.503	11.614

Table II

Selecting the Lags of the GMS Variable

For all the indices in our sample (indices do not include dividend distributions and are value-weighted), we use the following equation:

$$r_t = \alpha + \beta_{GMS} D_{t-k}^{GMS} + \epsilon_t$$

to evaluate the statistical significance of the lags of the GMS variable. $\surd$ means that the lag under investigation negatively and statistically significantly affects stock market returns at least at the 10% level using one-sided heteroskedasticity-robust standard errors. k varies between 1 and 6. Lags equal to zero or beyond 6 (not reported in the table) never turn out to be statistically significant.

Country Indices	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
WORLD	√					√
NASDAQ	√		√	√	√	√
S&P500	√					√
AMEX	√	√	√		√	√
NYSE	√	√			√	√
Canada	√		√		√	√
Sweden					√	√
UK		√			√	√
Japan						√
Australia		√	√			√
New Zealand						√
South Africa						√
Germany						

Table III

Estimation Results for Each Index: Controlling for GMS

We report regression results for all indices using the following equation:

$$r_t = \alpha + \beta_{GMS} D^{GMS}_{t-5,t-6} + \epsilon_t .$$

Indices do not include dividend distributions and are value-weighted. Heteroskedasticity robust standard errors are reported in parentheses. One, two, and three asterisks denote significance at the 10 percent, 5 percent, and 1 percent levels respectively.

Index	α	β_{GMS}
WORLD	0.035*** (0.009)	−0.059*** (0.025)
NASDAQ	0.059*** (0.014)	−0.073** (0.037)
S&P500	0.035*** (0.009)	−0.031* (0.021)
AMEX	0.044*** (0.009)	−0.084*** (0.026)
NYSE	0.044*** (0.009)	−0.057** (0.027)
UK	0.054*** (0.016)	−0.111*** (0.047)
Canada	0.032*** (0.010)	−0.053** (0.028)
Germany	0.028** (0.012)	−0.021 (0.032)
Sweden	0.081*** (0.019)	−0.111** (0.050)
Australia	0.042*** (0.014)	−0.053 (0.044)
Japan	0.046*** (0.011)	−0.051** (0.027)
New Zealand	0.027* (0.020)	−0.092** (0.052)
South Africa	0.058*** (0.017)	−0.020 (0.043)

Table IV

Economic Significance of the GMS Effect Based on Regression Results

This Table displays the average annual percentage return and the annual percentage return due to GMS. For each trading day, we determine the value of the GMS dummy variable and multiply it by that country's GMS variable estimate (from Table III). Then we adjust the value to obtain an annualized percentage return. In the case of the column for the annualized return due to the GMS variable, significance is based on robust standard errors associated with the parameter estimates from Table III. In the case of the average return column, significance is based on standard errors for a mean daily return different from zero.

Country	Annual % Return Due to GMS	Average Annual % Return
WORLD	−2.42*** (0.025)	6.46*** (0.008)
NASDAQ	−3.00** (0.037)	12.47*** (0.013)
S&P500	−1.24* (0.021)	7.79*** (0.008)
AMEX	−3.09*** (0.026)	8.33*** (0.009)
NYSE	−2.10** (0.027)	9.14*** (0.009)
Canada	−2.08** (0.028)	5.92*** (0.009)
Sweden	−4.44** (0.050)	17.05*** (0.018)
UK	−4.22*** (0.047)	9.68** (0.015)
Japan	−2.13** (0.027)	9.69*** (0.001)
Australia	−2.17 (0.044)	8.60*** (0.013)
New Zealand	−3.43** (0.052)	3.30 (0.019)
South Africa	−0.81 (0.043)	14.45*** (0.016)
Germany	−0.77 (0.032)	6.45** (0.011)

Table V

Regression Results for Each Index: Controlling for GMS and Well-Known Calendar Effects

We report regression results for all indices using the following equation:

$$r_t = \alpha + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{GMS} D_{t-5,t-6}^{GMS} + \epsilon_t \,.$$

Indices do not include dividend distributions and are value-weighted. Heteroskedasticity robust standard errors are reported in parentheses. One, two, and three asterisks denote significance at the 10 percent, 5 percent, and 1 percent levels respectively. R^2 and F-statistics with corresponding p-values are displayed in the last two columns of the table.

Index	α	β_{Monday}	β_{Tax}	β_{GMS}	R^2	$F-stat$ ($p-value$)
NASDAQ	0.102*** (0.015)	−0.234*** (0.034)	0.235*** (0.088)	−0.073** (0.037)	0.009	17.96 (0.00)
S&P500	0.069*** (0.009)	−0.180*** (0.022)	0.093** (0.051)	−0.031* (0.021)	0.005	24.00 (0.00)
AMEX	0.084*** (0.010)	−0.234*** (0.023)	0.363*** (0.068)	−0.083*** (0.026)	0.02	43.78 (0.00)
NYSE	0.065*** (0.010)	−0.114*** (0.024)	0.085* (0.066)	−0.056** (0.027)	0.004	8.41 (0.00)
UK	0.073*** (0.017)	−0.111*** (0.039)	0.141* (0.091)	−0.112*** (0.047)	0.004	4.79 (0.00)
Canada	0.053*** (0.011)	−0.121*** (0.024)	0.158** (0.076)	−0.052** (0.028)	0.005	10.71 (0.00)
Germany	0.051** (0.013)	−0.143*** (0.031)	0.257*** (0.092)	−0.018 (0.031)	0.004	10.02 (0.00)
Sweden	0.078*** (0.021)	−0.025 (0.048)	0.354*** (0.151)	−0.111** (0.050)	0.003	3.49 (0.01)
Australia	0.045*** (0.015)	−0.033 (0.034)	0.146** (0.073)	−0.049 (0.044)	0.001	2.15 (0.09)
Japan	0.051*** (0.011)	−0.039* (0.028)	0.099* (0.075)	−0.050** (0.027)	0.001	2.38 (0.06)
New Zealand	0.066*** (0.021)	−0.208*** (0.053)	0.135 (0.138)	−0.096** (0.052)	0.009	6.84 (0.00)
South Africa	0.082*** (0.018)	−0.123*** (0.041)	0.010 (0.105)	−0.019 (0.043)	0.001	3.13 (0.02)

Table VI

Returns on Large Cap vs. Small Cap Stocks

The table displays the GMS coefficient estimates for NASDAQ, and NYSE, AMEX and NASDAQ size deciles (1=large,...,10=small). Regression results are obtained using our basic specification:

$$r_t = \alpha + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{GMS} D_{t-5,t-6}^{GMS} + \epsilon_t \,.$$

Indices do not include dividend distributions and are value-weighted. Heteroskedasticity robust standard errors are reported in parenthesis. One, two, and three asterisks denote significance at the 10 percent, 5 percent, and 1 percent levels respectively.

Decile	NASDAQ	NYSE+AMEX+NASDAQ
1	−0.012 (0.024)	−0.035* (0.022)
2	−0.052** (0.024)	−0.057*** (0.022)
3	−0.080*** (0.024)	−0.054*** (0.023)
4	−0.058** (0.025)	−0.068*** (0.023)
5	−0.074*** (0.026)	−0.051** (0.024)
6	−0.083*** (0.027)	−0.066*** (0.024)
7	−0.076*** (0.029)	−0.070*** (0.025)
8	−0.086*** (0.031)	−0.070*** (0.025)
9	−0.087*** (0.034)	−0.071*** (0.025)
10	−0.073** (0.041)	−0.053** (0.029)

Table VII

Regression Results for Each Index: Controlling for GMS and Well-Known Calendar, Environmental and Behavioral Effects

We report regression results for all indices using the following equation:

$$r_t = \alpha + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{GMS} D_{t-5,t-6}^{GMS} + \beta_{SAD} SAD_t + \beta_{Cloud} Cloud_t + \beta_{Prec} Prec_t + \beta_{Temp} Temp_t + \epsilon_t \,.$$

Returns on the NASDAQ (NAS), S&P500 (SP), AMEX (AM), NYSE (NY), Canadian (CAN), Swedish (SWE), British (UK), Japanese (JAP), Australian (AUS), New Zealander (NZ), South African (SA), and German (GER) stock market indices do not include dividend distributions and are value-weighted. Heteroskedasticity robust standard errors are reported in parentheses. One, two, and three asterisks denote significance at the 10 percent, 5 percent, and 1 percent levels respectively. R^2 and F-statistics with corresponding p-values are displayed in the last two columns of the table.

Index	α	β_{Monday}	β_{Tax}	β_{GMS}	β_{SAD}	β_{Cloud}	β_{Prec}	β_{Temp}	R^2	$F-stat$ ($p-value$)
NAS	−0.098 (0.145)	−0.234*** (0.034)	0.189** (0.092)	−0.069** (0.037)	0.042** (0.024)	0.296* (0.209)	−0.003 (0.004)	0.002 (0.003)	0.010	8.70 (0.00)
SP	−0.095 (0.106)	−0.180*** (0.022)	0.079* (0.052)	−0.028* (0.021)	0.032** (0.015)	0.197* (0.152)	−0.002 (0.003)	0.003** (0.002)	0.005	11.55 (0.00)
AM	0.020 (0.107)	−0.234*** (0.023)	0.332*** (0.069)	−0.082*** (0.026)	0.014 (0.016)	0.143 (0.154)	−0.003 (0.003)	−0.001 (0.002)	0.020	20.41 (0.00)
NY	0.001 (0.111)	−0.114*** (0.024)	0.054 (0.068)	−0.055** (0.027)	0.017 (0.016)	0.110 (0.159)	−0.001 (0.003)	−0.000 (0.002)	0.004	4.75 (0.00)
UK	0.301** (0.175)	−0.111*** (0.039)	0.158** (0.093)	−0.109*** (0.047)	0.023** (0.013)	0.330 (0.266)	−0.016* (0.010)	−0.003 (0.004)	0.007	3.62 (0.00)
CAN	−0.119 (0.125)	−0.120*** (0.024)	0.104* (0.078)	−0.048** (0.028)	0.038** (0.016)	0.314* (0.242)	−0.003 (0.003)	0.000 (0.001)	0.006	6.67 (0.00)
GER	0.178* (0.137)	−0.143*** (0.031)	0.222*** (0.094)	−0.016 (0.031)	0.007 (0.013)	−0.240 (0.239)	0.001 (0.013)	−0.000 (0.003)	0.004	4.95 (0.00)
SWE	0.375** (0.190)	−0.023 (0.048)	0.255** (0.155)	−0.112** (0.050)	0.009 (0.012)	−0.485** (0.292)	0.001 (0.016)	−0.003 (0.003)	0.005	3.02 (0.00)
AUS	0.095 (0.214)	−0.033 (0.034)	0.132** (0.076)	−0.044 (0.043)	0.035* (0.027)	−0.334 (0.323)	−0.005** (0.002)	0.007 (0.006)	0.002	1.73 (0.09)
JAP	0.054 (0.133)	−0.040* (0.028)	0.050 (0.077)	−0.049** (0.027)	0.008 (0.020)	0.079 (0.162)	−0.004* (0.003)	−0.003* (0.002)	0.001	2.61 (0.01)
NZ	−0.300 (0.540)	−0.208*** (0.053)	0.132 (0.138)	−0.092** (0.053)	0.015 (0.023)	0.399 (0.781)	0.002 (0.003)	0.007 (0.007)	0.009	3.15 (0.00)
SA	−0.263* (0.189)	−0.124*** (0.041)	0.012 (0.107)	−0.018 (0.043)	0.101* (0.065)	0.138 (0.223)	−0.002 (0.005)	0.015* (0.010)	0.002	1.87 (0.07)

Table VIII.A

Maximum Likelihhod Estimation: NASDAQ, S&P500, AMEX, and NYSE

We report maximum likelihood results using the following Asymmetric Component Model:

$$
\begin{aligned}
r_t &= \alpha + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{GMS} D_{t-5,t-6}^{GMS} + +\epsilon_t \\
\sigma_t^2 - q_t &= \delta(\epsilon_{t-1}^2 - q_{t-1}) + \eta(\epsilon_{t-1}^2 - q_{t-1}) D_{t-1} + \nu(\sigma_{t-1}^2 - q_{t-1}) \\
q_t &= \omega + \gamma(q_{t-1} - \omega) + \phi(\epsilon_{t-1}^2 - \sigma_{t-1}^2) \\
\epsilon_t &\sim (0, \sigma_t^2) \\
D_{t-1} &= \begin{cases} 1 & \text{if } \epsilon_{t-1} < 1 \\ 0 & \text{otherwise}. \end{cases}
\end{aligned}
$$

One, two, and three asterisks denote significance at the 10 percent, 5 percent, and 1 percent levels respectively.

Parameter	NASDAQ	S&P500	AMEX	NYSE
α	0.114*** (0.009)	0.069*** (0.006)	0.106*** (0.006)	0.077*** (0.000)
β_{Monday}	−0.217*** (0.024)	−0.123*** (0.011)	−0.175*** (0.015)	−0.106*** (0.012)
β_{Tax}	0.299*** (0.061)	0.039* (0.030)	0.318*** (0.045)	0.064** (0.036)
β_{GMS}	−0.064*** (0.022)	−0.014 (0.013)	−0.060*** (0.006)	−0.041*** (0.005)
δ	0.032* (0.020)	−0.001 (0.004)	0.137*** (0.025)	−0.021*** (0.007)
η	0.141*** (0.031)	0.097*** (0.005)	0.027 (0.035)	0.109*** (0.007)
ν	0.728*** (0.039)	0.866*** (0.006)	0.261*** (0.108)	0.865*** (0.013)
ω	0.655*** (0.146)	0.658*** (0.068)	0.935*** (0.342)	0.722*** (0.143)
γ	0.995*** (0.002)	0.998*** (0.000)	0.991*** (0.004)	0.997*** (0.001)
ϕ	0.033*** (0.005)	0.025*** (0.002)	0.107*** (0.012)	0.045*** (0.004)
Log Likelihood	−8594.785	−22429.97	−9921.511	−10636.07

Table VIII.B

Maximum Likelihhod Estimation: UK, Canada, Germany, and Sweden

We report maximum likelihood results using the following Asymmetric Component Model:

$$\begin{aligned}
r_t &= \alpha + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{GMS} D_{t-5,t-6}^{GMS} + \epsilon_t \\
\sigma_t^2 - q_t &= \delta(\epsilon_{t-1}^2 - q_{t-1}) + \eta(\epsilon_{t-1}^2 - q_{t-1}) D_{t-1} + \nu(\sigma_{t-1}^2 - q_{t-1}) \\
q_t &= \omega + \gamma(q_{t-1} - \omega) + \phi(\epsilon_{t-1}^2 - \sigma_{t-1}^2) \\
\epsilon_t &\sim (0, \sigma_t^2) \\
D_{t-1} &= \begin{cases} 1 & \text{if } \epsilon_{t-1} < 1 \\ 0 & \text{otherwise}. \end{cases}
\end{aligned}$$

One, two, and three asterisks denote significance at the 10 percent, 5 percent, and 1 percent levels respectively.

Parameter	UK	Canada	Germany	Sweden
α	0.095*** (0.015)	0.068*** (0.008)	0.052*** (0.005)	0.122*** (0.018)
β_{Monday}	−0.129*** (0.031)	−0.112*** (0.015)	−0.155*** (0.015)	−0.072** (0.031)
β_{Tax}	0.061 (0.097)	0.122*** (0.037)	0.267*** (0.044)	0.427*** (0.072)
β_{GMS}	−0.086*** (0.034)	−0.029* (0.018)	−0.003 (0.009)	−0.094*** (0.034)
δ	0.011 (0.018)	0.140*** (0.015)	0.054*** (0.008)	0.169*** (0.023)
η	−0.042** (0.020)	0.007 (0.015)	0.081*** (0.010)	−0.148*** (0.024)
ν	−0.365 (0.462)	0.437*** (0.043)	0.835*** (0.011)	−0.369*** (0.097)
ω	1.043*** (0.092)	0.782*** (0.086)	1.083*** (0.207)	1.588*** (0.143)
γ	0.971*** (0.006)	0.992*** (0.001)	0.999*** (0.000)	0.970*** (0.004)
ϕ	0.097*** (0.008)	0.060*** (0.003)	0.016*** (0.002)	0.116*** (0.008)
Log Likelihood	−6012.155	−8924.513	−12779.630	−7183.455

Table VIII.C

Maximum Likelihhod Estimation: Australia, Japan, New Zealand, and South Africa

We report maximum likelihood results using the following Asymmetric Component Model:

$$
\begin{aligned}
r_t &= \alpha + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{GMS} D_{t-5,t-6}^{GMS} + \epsilon_t \\
\sigma_t^2 - q_t &= \delta(\epsilon_{t-1}^2 - q_{t-1}) + \eta(\epsilon_{t-1}^2 - q_{t-1}) D_{t-1} + \nu(\sigma_{t-1}^2 - q_{t-1}) \\
q_t &= \omega + \gamma(q_{t-1} - \omega) + \phi(\epsilon_{t-1}^2 - \sigma_{t-1}^2) \\
\epsilon_t &\sim (0, \sigma_t^2) \\
D_{t-1} &= \begin{cases} 1 & \text{if } \epsilon_{t-1} < 1 \\ 0 & \text{otherwise}. \end{cases}
\end{aligned}
$$

One, two, and three asterisks denote significance at the 10 percent, 5 percent, and 1 percent levels respectively.

Parameter	Australia	Japan	New Zealand	South Africa
α	0.052*** (0.013)	0.069*** (0.008)	0.062*** (0.020)	0.111*** (0.001)
β_{Monday}	−0.029* (0.022)	0.011 (0.012)	−0.164*** (0.035)	−0.148*** (0.023)
β_{Tax}	0.119** (0.070)	0.151*** (0.039)	0.020 (0.103)	0.028 (0.097)
β_{GMS}	−0.004 (0.027)	−0.005 (0.013)	−0.101** (0.059)	−0.074*** (0.024)
δ	0.094*** (0.013)	0.108*** (0.007)	0.048* (0.037)	0.110*** (0.011)
η	0.074*** (0.012)	0.054*** (0.007)	0.047 (0.038)	0.092*** (0.015)
ν	0.711*** (0.012)	0.775*** (0.008)	0.239 (0.199)	0.641*** (0.016)
ω	0.736*** (0.020)	1.480*** (0.311)	0.940*** (0.073)	1.945*** (0.124)
γ	0.976*** (0.008)	0.999*** (0.000)	0.947*** (0.012)	0.993*** (0.001)
ϕ	0.007** (0.004)	0.025*** (0.002)	0.117*** (0.016)	0.021*** (0.003)
Log Likelihood	−7047.929	−17423.920	−3405.935	−11932.960

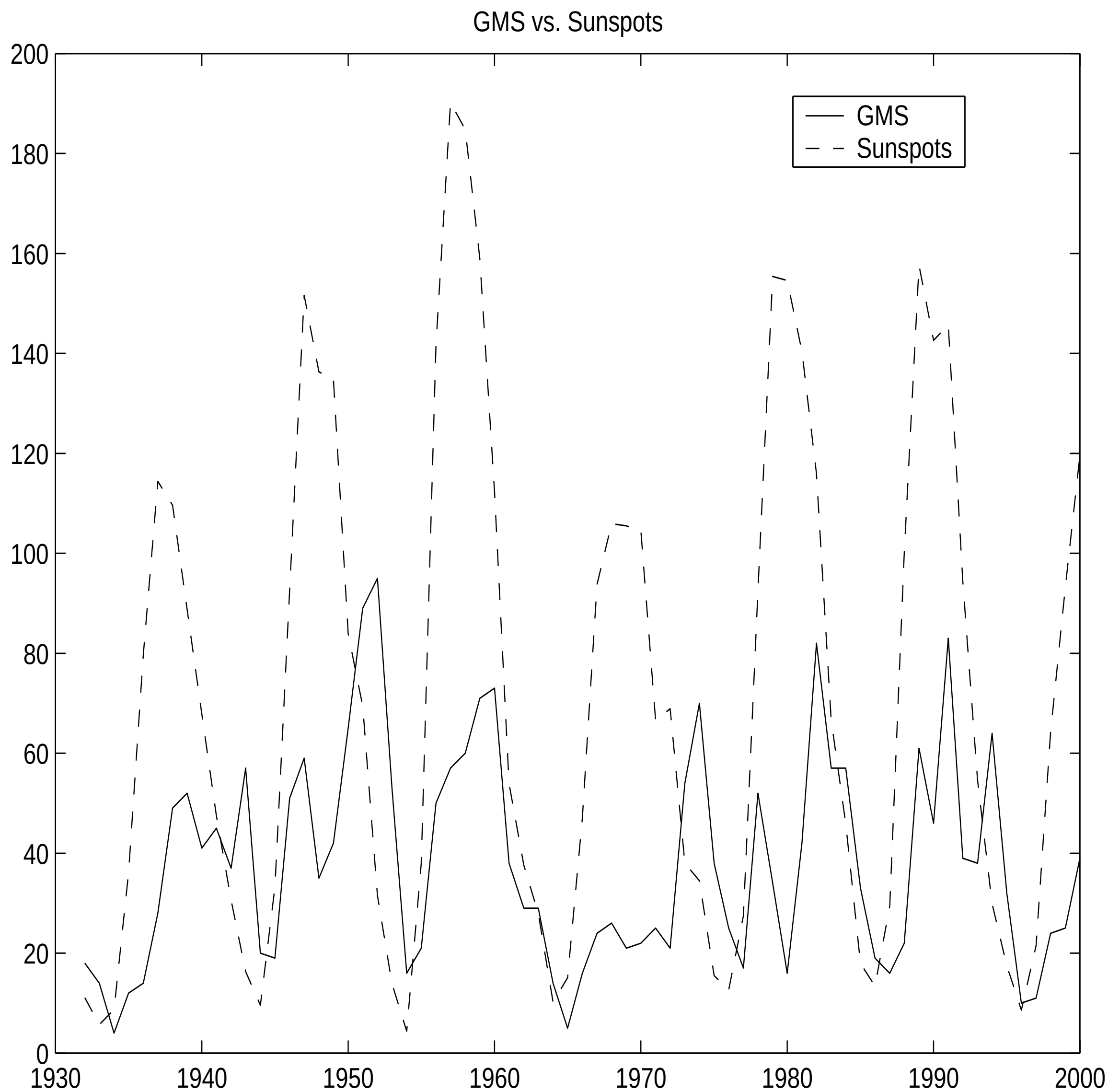

Figure I. Geomagnetic Storms vs. Sunspots. The figure displays the line graph of the average number of sunspots and geomagnetic storms (vertical axis) per year. Geomagnetic data can be downloaded from the following web site:
ftp : //ftp.ngdc.noaa.gov/STP/GEOMAGNETIC_DATA/INDICES/.

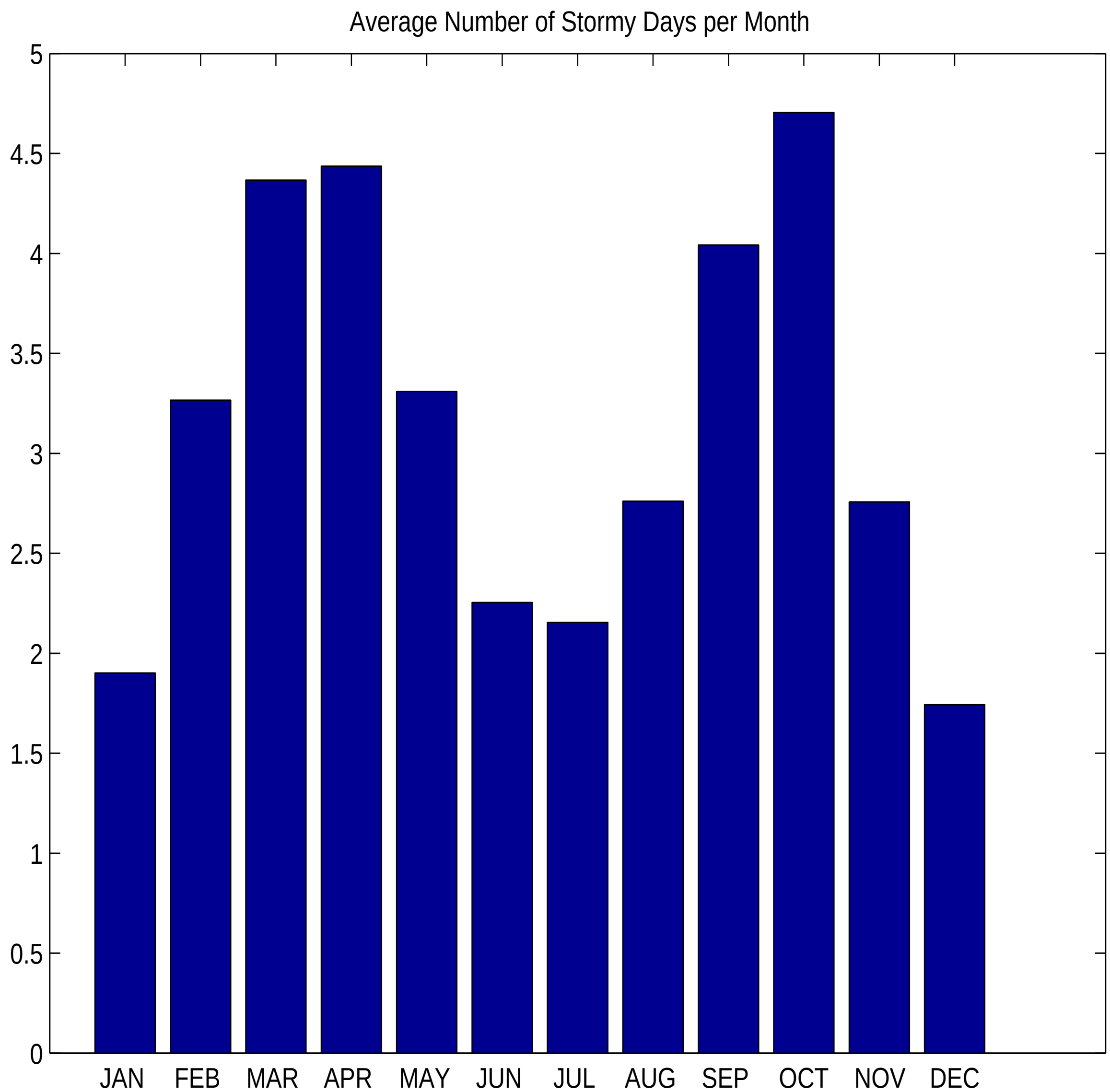

Figure II. Number of Storms per Month. The figure displays the bar graph of the average number of stormy days (vertical axis) per month using the Ap index. Daily Ap index data can be downloaded from the following web site:
ftp : //ftp.ngdc.noaa.gov/STP/GEOMAGNETIC_DATA/INDICES/KP_AP/.

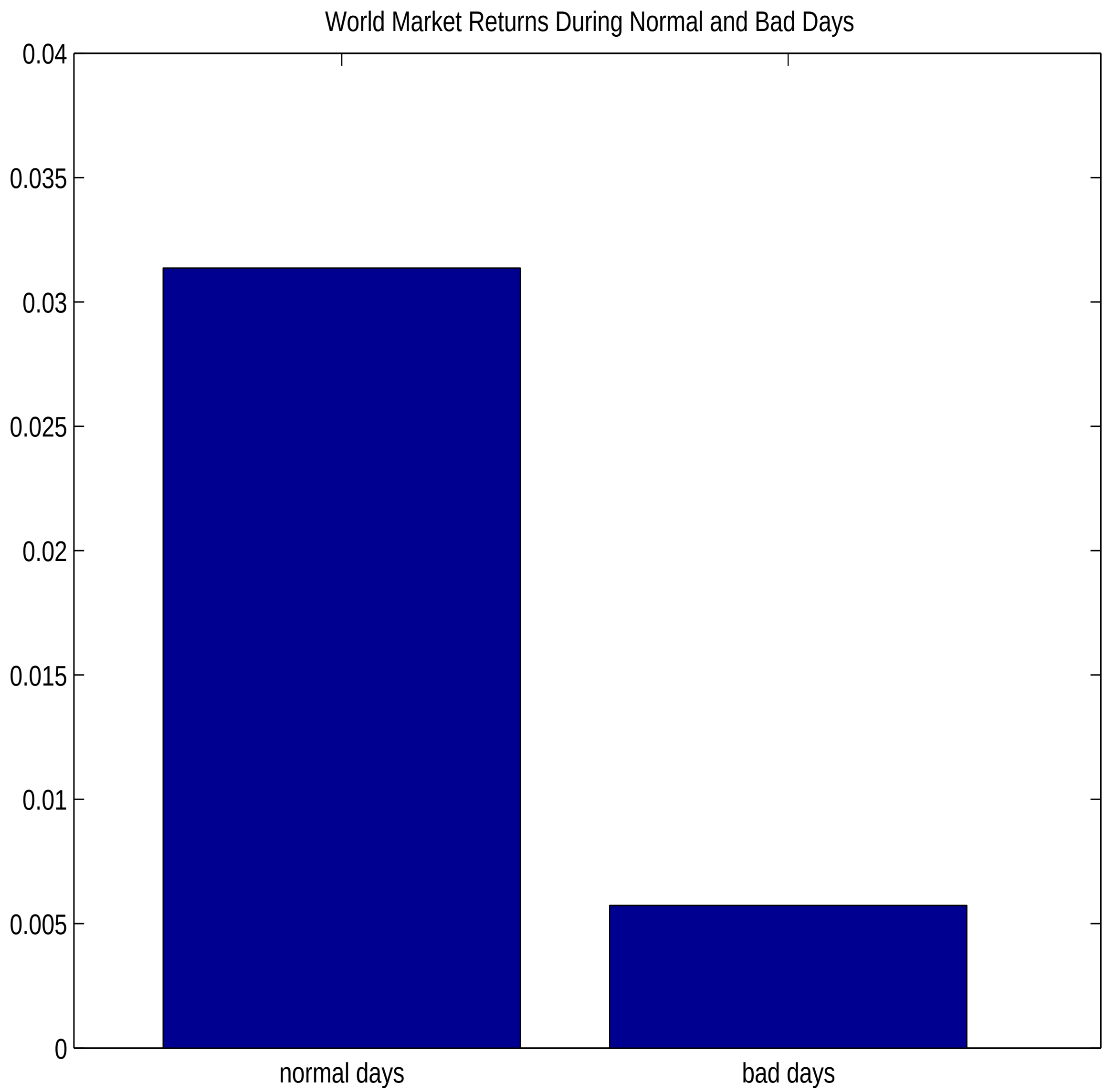

Figure III. World Stock Returns during Normal Days and Bad Days. The figure displays the bar graphs of the returns on the world stock market index during normal days and bad days. We define the six calendar days following a geomagnetic storm as bad days. We define the remaining calendar days as normal days.

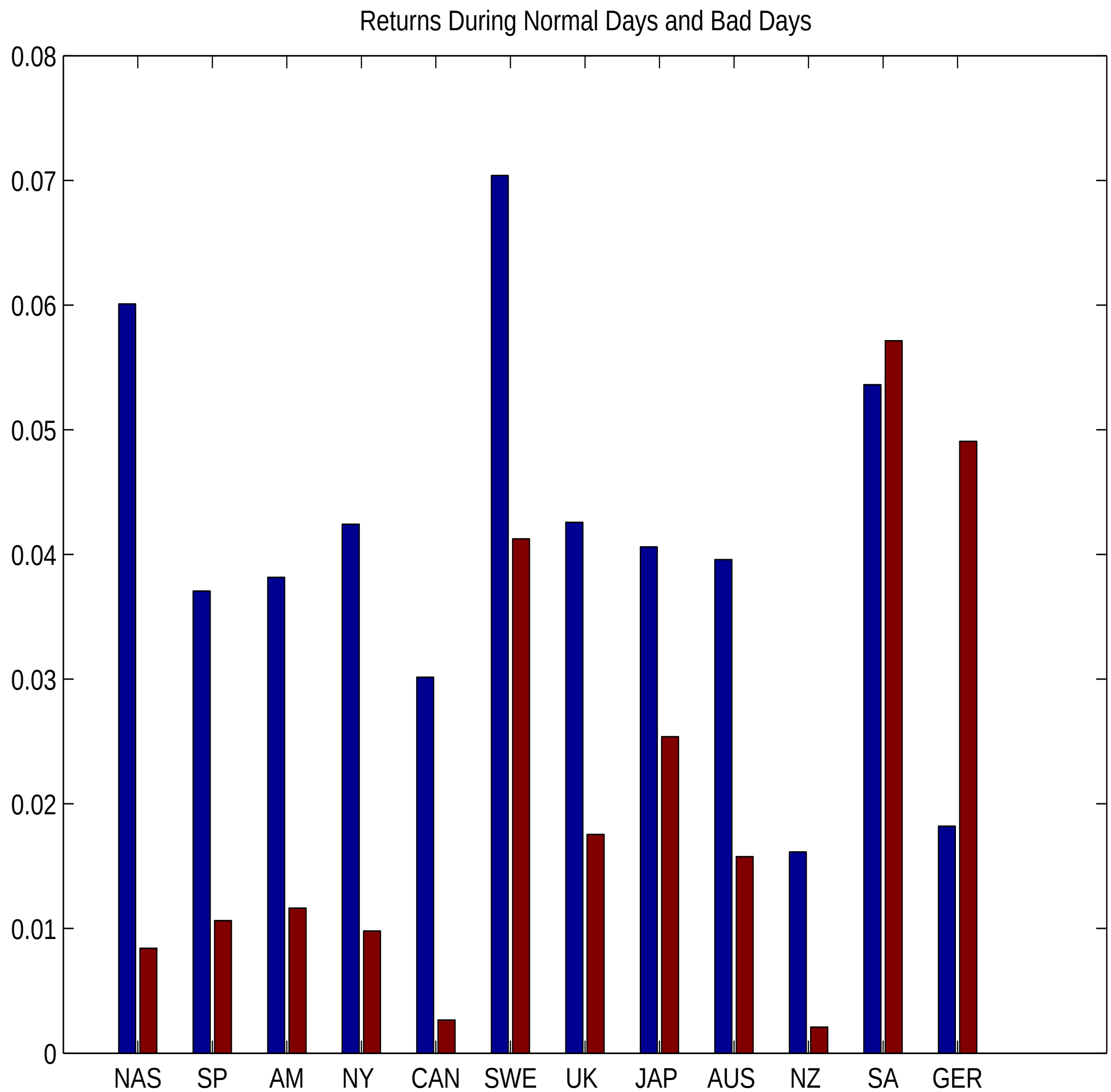

Figure IV. Returns during Normal Days and Bad Days. The figure displays the bar graphs of the returns on the NASDAQ (NAS), S&P500 (SP), AMEX (AM), NYSE (NY), Canadian (CAN), Swedish (SWE), British (UK), Japanese (JAP), Australian (AUS), New Zealander (NZ), South African (SA), and German (GER) stock market indices during normal days (left column) and bad days (right column). We define the six calendar days after a storm as bad days and the remaining calendar days as normal days.

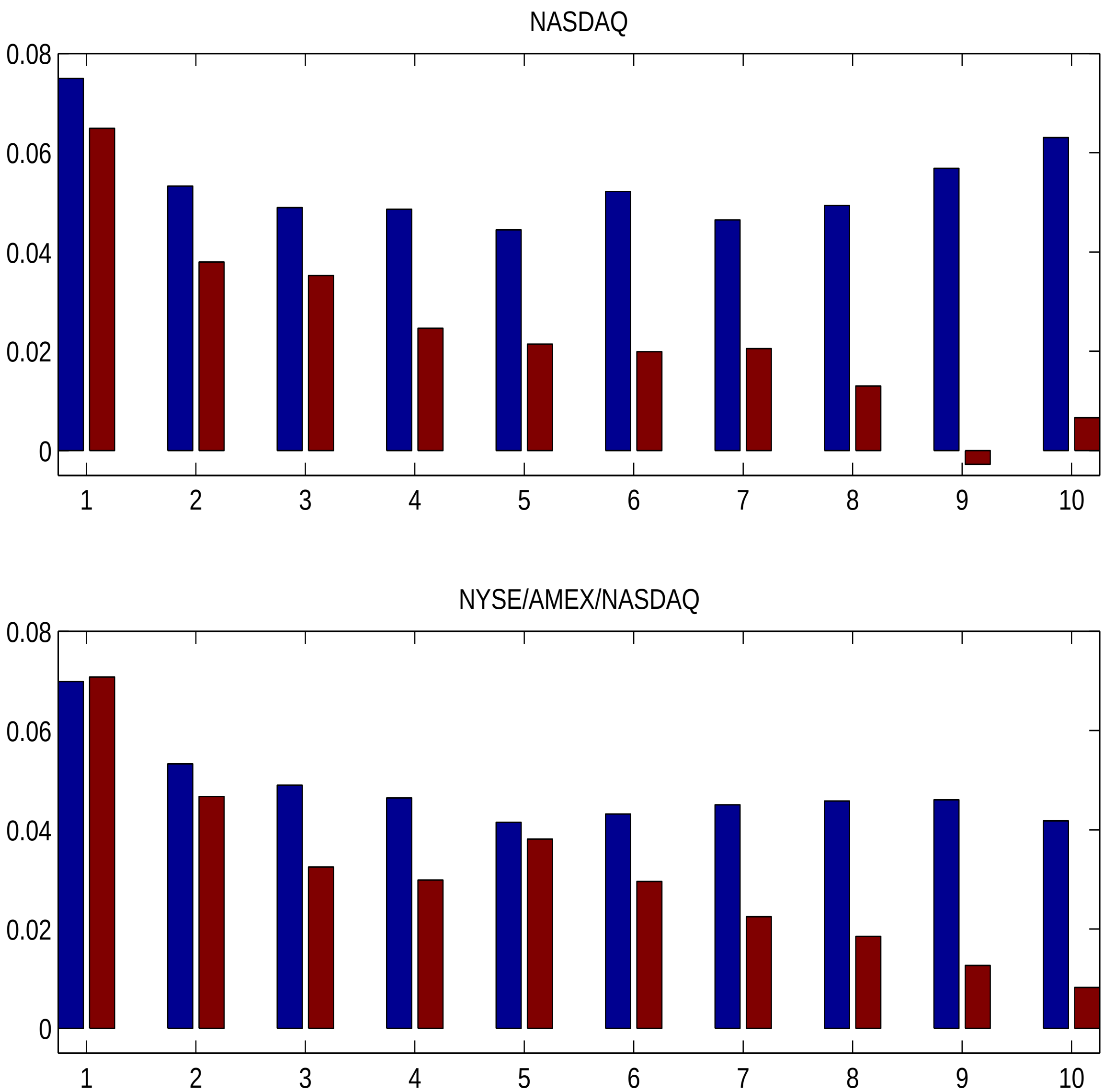

Figure V. Returns during Normal Days and Bad Days for Stock Deciles. The figure displays the bar graphs of the returns on the NASDAQ and NYSE/AMEX/NASDAQ size deciles during normal days (left column) and bad days (right column). We define the six calendar days following a geomagnetic storm as bad days. We define the remaining calendar days as normal days. Large Cap = 1,..., Micro Cap = 10.