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Playing the Field: Geomagnetic Storms and International Stock Markets

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Abstract: This paper documents the impact of geomagnetic storms (GMS) on international stock market returns. For most of the countries in our sample we find that the previous week's unusually high levels of geomagnetic activity have a negative and statistically and economically significant impact on today's stock returns. Our results are consistent with changes in risk-taking behavior caused by depressive disorders, since GMS have been found to substantially increase the incidence of depression and other psychological disturbances among people.

JEL classification: G1

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

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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, major 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 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 major geomagnetic storms on human 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 and anxiety and unusually high levels of geomagnetic activity. Depressive disorders have been found to be linked to lower risk-taking behavior, including decisions of a financial nature. Through the links between geomagnetic storms[1] (GMS) and depression and depression and risk aversion, above average levels of geomagnetic activity can potentially affect stock market returns. Seminal papers by 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 show that the market clears at prices where marginal buyers are willing to exchange with marginal sellers. According to

[1]Geomagnetic storms are worldwide disturbances of the earth's magnetic field, distinct from regular diurnal variations. The intensity of the magnetic field at the earth's surface is approximately 0.32 gauss at the equator and 0.62 gauss at the north pole.

this principle, market participants directly affected by GMS can influence overall market returns. Reduced risk taking behavior translates into a relatively high demand for riskless assets, causing the price of risky assets 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.[2] The previous week's unusually high levels of geomagnetic activity have a negative and statistically significant effect on today's stock returns for seven out of nine countries and for ten out of twelve 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. Our results complement recent findings of a seasonal affective disorders (SAD) effect on international stock returns [Kamstra, Kramer, and Levi (2003)].

In an interesting 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 periods of high geomagnetic activity as compared with normal periods.[3] 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.[4] For example, on heliomagnetic (solar) exposures, pilots with a high level of anxiety operate at a new, even more intensive homeostatic level[5] which is accompanied by a decreased functional activity

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

[3]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.

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

[5]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

of the central nervous system. The latter leads to a sharp decline in flying skills.[6] 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 rows show that at least 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

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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.

[6] See Usenko (1992).

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.[7] While the relationship between depression and geomagnetic storms seems to be supported by the several studies in clinical sciences mentioned above, there is no convincing evidence of a link between lunar phases and depressive disorders. For example, in a review of empirical studies on the lunar effect, Campbell and Beets (1978) conclude that lunar phases have no effect on psychiatric hospital admissions, suicides, or homicides. Hence, several studies that examine the effect of lunar phases on stock returns can not establish a link between lunar cycles and depression.[8]

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

[7]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).

[8]See, for example, Yuan, Zheng, & Zhu (2001), Rotton and Kelly (1985a, 1985b), Rotton and Rosenberg (1984), and Dichev and Janes (2001). Yuan, Zheng, & Zhu (2001) and Dichev and Janes (2001) document a lunar cycle effect in stock returns, but they can not rely on a clear and testable hypothesis from psychology.

magnetic storms and their effects on human beings are not purely seasonal phenomena.[9] 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 winter depression, unusually high levels of geomagnetic activity seem to negatively affect people's mood all year long. Moreover, the response of human beings to a singularly intense geomagnetic storm may continue long after the perturbation has ceased. In summary, there seems to be a direct causal relationship between geomagnetic storms and common depressive disorders. Moreover, 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 depression brought on by GMS leads to relatively lower returns the days following severe levels of geomagnetic activity. Medical sciences do not allow us to identify a precise lag structure linking geomagnetic storms to depressive disorders, but make it clear that the effects of unusual 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 k free to vary.

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

[9]Notice that 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), and about the Halloween effect documented by Bouman and Jacobsen (2001).

conduct three robustness checks: i) We investigate the robustness of our results to the introduction of SAD and other environmental variables; ii) We consider different estimation techniques; and iii) We examine alternative ways of measuring the GMS effect. We conclude in section VI.

I. Geomagnetic Storms, Depression and Risk Aversion

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.[10] The vast majority of plasma "bubbles" miss earth, and many that do reach the earth are too weak to produce a significant storm.[11] 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 three 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 I).

Geomagnetic storms have been found to have brief but pervasive effects on human health. GMS are related to various forms of major depressive disorders and are connected to melatonin dysregulation in the brain through the activity of the pineal

[10]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.

[11]This is the reason why the association between the GMS index and the sunspots index is not strong, the correlation being 0.11 over the 1932-2002 period.

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 depression and reduced risk-taking behavior. [12] For example, Zuckerman (1984, 1994) shows that, when the willingness to take risk is related to measured levels of anxiety or depression, there is a clear tendency for greater anxiety or depression to be associated with reduced "sensation seeking" and reduced general willingness to take risk, even in decisions of a financial nature.[13] In summary, depressive disorders appear to correlate with risk aversion in decisions of a non-financial as well as of a financial nature.

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. Reduced risk taking behavior translates into a relatively high demand for riskless assets, causing the price of risky assets 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 depression during the recovery phase of geomagnetic storms. Based on previous considerations, we

[12]See Kamstra, Kramer and Levi (2003) for a brief summary of these studies.

[13]For example, Wong and Carducci (1991), Horvath and Zuckerman (1993), and Tokunaga (1993), among others, show that "sensation-seeking" propensity is a reliable measure of risk-taking tendency not only in gambling, but in more general financial decision-making settings.

expect to see a GMS effect on stock returns, if any, within a week from the origination of a strong geomagnetic storm.[14]

II. Data

A. Stock Market Returns and Calendar Variables

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.

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, the Amex, and the NYSE. 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).[15] Our longest time series is the US S&P500 which spans approximately 70 years. The longest spanning index we could obtain for South Africa is the Datastream Global Index of 70 large-cap stocks in that country, which spans approximately 30 years. Table I displays summary statistics for the raw stock market data used in this study. The sample sizes range from under 3,000 daily observations

[14]On the contrary, behavioral research documenting a direct link between SAD and stock returns suffers from the lack of a lag identification structure, which does not allow the authors to differentiate their findings from potentially more general mean reversion in stock returns.

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

for New Zealand to over 18,000 for the US S&P500 index. All of the returns series are strongly skewed to negative returns and exhibit high kurtosis. Conventional tests of normality (not reported) strongly reject the null hypothesis that any of these returns are normally distributed.

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.[16] 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.

B. Additional Control Variables

We 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) Millimiters 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, respectively. Cao and Wei (2001) find a link between temperature and stock market

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

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 control for additional calendar and behavioral variables. Specifically, we also include in our empirical specification a fall dummy, and the SAD variable. Fall is defined as September 21 to December 20 in the Northern Hemisphere and March 21 to June 20 in the Southern Hemisphere. Hence, the fall dummy equals 1 for trading days in the Fall and 0 otherwise.

Kamstra, Kramer and Levi (2003) (pp. 9-10) 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) (pp. 9-10) 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

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

"$arccos$" is the arc cosine and λ_t 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 depression 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.

Values of the Ap and Kp indices with corresponding geomagnetic field conditions are reported in the table below:

Geomagnetic Activity Indices

Kp Index	Ap Index	Geomagnetic Field Conditions
0	0-2	Very Quiet
1	3-5	Quiet
2	6-9	Quiet
3	12-18	Semi-Quiet
4	22-32	Unsettled
5	39-56	MINOR Storm
6	**67-94**	**MAJOR Storm**
7	**111-154**	**SEVERE Storm**
8	**179-236**	**SEVERE Storm**
9	**300-400**	**EXTREMELY SEVERE**

We choose the Ap index as a proxy for geomagnetic activity.[17] The Ap index series provides us with 8 daily values of the geomagnetic conditions, recorded at three hour intervals. For each day, we choose the maximum of these 8 values. [18] 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 67 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 decide to focus on major, severe and extremely severe environmental magnetic storms.

[17]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/.

[18]Results are virtually unchanged when we consider the arithmetic average of the eight daily values.

Accordingly, we construct a GMS dummy variable as follows:

$$D_{t-k}^{GMS} = \begin{cases} 1 & \text{for GMS} \geq 67 \\ 0 & \text{for GMS} < 67 \end{cases} \tag{1}$$

where GMS $= max(\text{Ap})$ at time $t-k$.

Ap index data start on January 1, 1932. Days of major, severe, and extremely severe geomagnetic storms represent, on average, 10-12% percent of our sample. Roughly speaking, two or 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 three. We see in Figure I that geomagnetic storms are not a purely seasonal phenomenon. Even if there are peaks in March and April, and September and October, geomagnetic activity seems to follow a smooth sinusoidal pattern across all months of the calendar year.

IV. Influence of the Geomagnetic Storms Effect

A. Estimation

We run separate time series regressions for the nine countries in our dataset. Returns are regressed on a constant, up to two lagged returns (where necessary to control for residual autocorrelation), a Monday dummy, a dummy variable for a tax-loss selling effect, and the GMS dummy:

$$r_t \;=\; \alpha + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{GMS} D_{t-5,t-6}^{GMS} + \epsilon_t. \tag{2}$$

Variables are defined as follows: r_t is the period t return for a given country's index; r_{t-1} and r_{t-2} are lagged dependent variables; 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; and $D_{t-5,t-6}^{GMS}$ is a dummy variable which equals 1 if a major, severe, or extremely severe storm occurred on day $t-5$ or $t-6$ and 0 otherwise. This choice of the lags of the GMS variable is dictated by the empirical findings in Table II, which document 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. 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, we decide to present regression results using lag 5 and 6 of the GMS variable.[19] In separate 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 $D^{GMS}_{t-5,t-6}$ for each of the twelve indices are reported in panels A, B, and C of Table III. We use OLS to estimate equation (2) and we account for heteroskedasticity by reporting robust standard errors. In cases where a particular parameter was not estimated (ρ_1 and/or ρ_2 for some indices), a dot appears.[20] The parameter estimates on the GMS variable have the right sign and are statistically significant for almost all of the indices we consider. For seven out of nine countries in our sample, we find a negative and statistically significant relationship between r_t and $D^{GMS}_{t-5,t-6}$.[21] The only two exceptions are represented by Germany and South Africa.

[19]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.

[20]We only used as many lagged dependent variables as it was required to eliminate residual autocorrelation up to the 1% level of significance.

[21]As a robustness check, we controlled for the October 1987 stock market crash. We dummied out the whole month of October 1987 and found no substantial changes in the magnitude and in the

The GMS estimated coefficient for Germany is negative and insignificant, while the one for South Africa is approximately zero and insignificant.[22]

Overall, this is consistent with a GMS-induced pattern in returns as depressed and risk averse investors increase their demand for riskless assets, causing the price of risky assets to rise less quickly than otherwise.

The empirical evidence we provide is consistent with recent findings in psychology. Strong geomagnetic storms not only appear to cause depressive disorders during their recovery phase but also seem to affect international stock returns a few days after reaching unusually high levels. Regarding other aspects of the estimation, we find that the Monday dummy and to some extent the tax-loss dummy are significant for several countries.

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

Table IV shows the average annual percentage return due to GMS and the entire unconditional annual percentage return. The return due to GMS, when significant, is negative in all countries, ranging from -1.7 percent to -4.7 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 142.5 dollars instead of 96.8 dollars for each 1000 dollars invested in the British index.

Figure II displays, for each stock market index, the average daily returns during 'bad' days and 'good' days. We define the six calendar days following a major, severe, or extremely severe geomagnetic storm as 'bad' days. We define the remaining calendar days as 'good' days. As an example, consider the situation where a storm

precision of the coefficient estimates.

[22]These findings complement recent evidence provided by Kamstra, Kramer, and Levi (2003) of a weak SAD effect for Germany and South Africa.

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 differences in means are striking for most of the indices in our sample. Consistent with Table III and Table IV, we do not find evidence of a GMS effect for Germany and South Africa. The reason why returns in 'good' days are not substantially different from returns in 'bad' days for Japan can be understood by looking at Table II. Table II shows that, in the case of Japan, only the sixth lag of the GMS variable affects today's stock returns, the other lags being statistically insignificant.

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.

B. 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. We perform this exercise for two reasons. First, 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.[23] Since investment decisions of individual investors are more likely to be affected by sentiments 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 small cap stocks. Second, given the link we established between geomagnetic storms and depression and depression and risk aversion, we expect small cap stocks, being riskier than large cap stocks, to be more affected by the negative influence of geomagnetic storms.

Given data availability, we focus on US stock market indices. We form ten stock

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

portfolios based on market capitalization for stocks traded on NASDAQ, NYSE and AMEX, and NYSE, AMEX, and NASDAQ.[24] The sample period ranges from July 5, 1962 to December 29, 2000 for NYSE/AMEX and NYSE/AMEX/NASDAQ, and from December 18, 1972 to December 29, 2000 for NASDAQ.

Table V reports the results from estimating equation (2) for each decile portfolio. The GMS effect is more pronounced for small cap stocks than for 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 0.023, while the GMS coefficient estimate for the tenth NASDAQ decile portfolio is equal to -0.08 with standard error of 0.04.[25] Moreover, the GMS coefficient on the tenth decile turns out to be the largest across deciles, while the GMS coefficient on the first decile turns out to be the smallest across deciles. Finally, the magnitude of the regression coefficients increases almost monotonically going from the first to the tenth decile. The precision of the GMS coefficient estimates also increases as we go from large cap to small cap stocks. Figure III shows the difference between returns during 'good' days and returns during 'bad' days. The differences in returns increase as we move from large capitalization stocks to small capitalization stocks. Moreover, these differences are statistically significant at least at the 10% level for the eight, ninth, and tenth NASDAQ and NYSE/AMEX deciles. The differences in returns are statistically significant at the 10% level for the ninth, and tenth NYSE/AMEX/NASDAQ deciles.

In summary, our evidence suggests that the GMS effect is stronger for stocks that

[24]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.

[25]Similarly, regression results indicate that the GMS coefficient estimate for the first NYSE/AMEX decile portfolio is equal to -0.02 with standard error of 0.024, while the GMS coefficient estimate for the tenth NYSE/AMEX decile portfolio is equal to -0.06 with standard error of 0.028. The results for NYSE/AMEX/NASDAQ are qualitatively similar.

are held mostly by individual investors.

C. Trading Strategies

Figure II shows that returns during 'good 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 Figure II to build exploitable trading strategies. At a first glance, the answer to this question is no. Specifically, we examined two straightforward strategies: i) Strategy I. We test the hypothesis that the mean annualized return on a portfolio, 100% long in the market during 'good days' and 100% long in T-bills during 'bad' days, exceeds the mean annualized return on a portfolio which is 100% long in the market. We do not find evidence of profitable trading on the geomagnetic storms effect. Even if the cost of trading stock indices is relatively low in many markets, the transaction costs of this trading strategy would be non negligible given the frequent rebalancing of our active portfolio; ii) Strategy II. We exploit the seasonal patterns exhibited by geomagnetic storms and test the hypothesis that the mean annualized return on a portfolio, 100% short in the market and 100% long in T-bills during March-April and September-October, and 100% long in the market the remaining eight months, exceeds the mean annualized return on a portfolio which is 100% long in the market. Even if the transaction costs associated with this trading strategy are very moderate (trade would occur, on average, four times a year), it turns out that trading against the GMS effect is profitable only for holders of the Canadian stock market index. Notice that these results are also robust to changes in the composition of the benchmark portfolio.

In forming trading strategies based on the GMS effect, we face several problems. First, even if geomagnetic storms are predictable, their frequency, intensity, and persistence varies over time. Second, stock returns are substantially lower during 'bad' days, but remain mostly positive on average. Finally, any strategy based on the GMS effect in stock returns would carry non negligible transaction costs.[26]

However, our failure to identify implementable trading strategies does not rule out the possibility of finding more effective ways of taking advantage of the GMS effect in stock returns. Future work might consider the use of derivative securities as a hedging device. Trading against incoming storms by buying put options on stock market indices might turn out to be a valid strategy. Alternatively, it might also be appropriate to implement the GMS strategy using index futures. Transaction costs would also be lower. For instance, Solnik (1993) estimates round-trip transaction costs of 0.1% on future contracts.

V. Robustness Checks

In this section, we provide three types of robustness checks. First, we analyze the robustness of our regression results to the introduction of SAD, Fall, and other environmental variables used by Kamstra, Kramer, and Levi (2003). Second, we jointly model the mean and the variance of stock returns via Maximum likelihood. Third, we look at the sensitivity of our results to alternative ways of defining the geomagnetic storms variable.

A. Controlling for SAD, Fall, and Other Environmental 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, up to two lagged returns (where necessary to control for residual

[26]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.

autocorrelation), a Monday dummy, a dummy variable for a tax-loss selling effect, the GMS dummy, the SAD measure, a fall dummy, cloud cover, precipitation, and temperature:

$$\begin{aligned} r_t \;\; = \;\; & \alpha + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} \\ & + \beta_{GMS} D_{t-5,t-6}^{GMS} + \beta_{Fall} D_t^{Fall} + \beta_{SAD} SAD_t + \beta_{Cloud} Cloud_t \\ & + \beta_{Precipitation} Precipitation_t + \beta_{Temperature} Temperature_t + \epsilon_t \,. \end{aligned} \tag{3}$$

With the exception of the following new variables, all variables in this equation are defined as in equation (2). D_t^{Fall} is a dummy variable which equals 1 for a given country when period t is in the fall and equals 0 otherwise. 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 ($Cloud_t$), millimiters of precipitation ($Precipitation_t$), and temperature in degrees Celsius ($Temperature_t$).

The regression results are reported in panels A, B, and C of Table VI. 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. 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 modify 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 and Fall effects documented by Kamstra, Kramer, and Levi (2003) appear to be robust for most of the countries in our sample. Specifically, the SAD coefficient estimate is positive in all countries and is significant at least at the 10% level in all countries except one. The fall dummy coefficient is negative in all countries except one and is significant at least at the 10% level in all cases except three. The Monday dummy and the tax-loss dummy are signicant for several countries in our sample.

B. Maximum Likelihood Model

We previously addressed the issue of autocorrelation by introducing lags of the dependent variable, and we 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. Specifically, we estimate the following Asymmetric Component Model with GARCH in mean (GARCH-M):[27]

$$\begin{aligned} r_t &= \alpha + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \\ &\quad \beta_{GMS} D_{t-5,t-6}^{GMS} + \beta_{GARCH}\, \sigma_t^2 + \epsilon_t \end{aligned} \tag{4}$$

$$\sigma_t^2 - q_t = \delta(\epsilon_{t-1}^2 - q_{t-1}) + \eta(\epsilon_{t-1}^2 - q_{t-1})D_{t-1} + \nu(\sigma_{t-1}^2 - q_{t-1}) \tag{5}$$

$$q_t = \omega + \gamma(q_{t-1} - \omega) + \phi(\epsilon_{t-1}^2 - \sigma_{t-1}^2) \tag{6}$$

$$\epsilon_t \sim (0, \sigma_t^2)$$

$$D_{t-1} = \begin{cases} 1 & \text{if } \epsilon_{t-1} < 1 \\ 0 & \text{otherwise}. \end{cases}$$

Equation (4) represents the mean equation. Equations (5) and (6), 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. We estimate model (4)-(6) by adding, when statistically significant, a GARCH-M term.

[27]See Engle, Lilien, and Robins (1987) for a description of the GARCH-M model.

Panels A, B, and C of Table VII display our results. With the exception of some minor quantitative changes, the Maximum Likelihood results are very similar to the results reported above. Log-likelihood values, ARCH(10) p-values, 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 significant. In summary, we still see large and economically significant effects due to SAD.

C. Other Measures for Geomagnetic Storms

We analyzed some alternate measures of the geomagnetic storms variable. First, we considered the continuous counterpart of D_{t-k}^{GMS} and found weaker results, consistent with the clinical finding that only unusually high values of geomagnetic activity affect people's moods. Second, we used the Kp index in its discrete and continuous version as another proxy for geomagnetic storms. With a few minor changes in the lag structure, we found similar results to the ones obtained using the Ap index. Finally, we explored the possibility of a purely seasonal GMS effect in stock returns. Specifically, we interacted a dummy 0,1 variable (1 in March/April and September/October, 0 otherwise) with our continuous GMS measure. Again, we found evidence of a non negligible GMS seasonal effect in stock returns around the world.[28]

VI. Conclusions

This paper provides evidence of an economically 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. International stock returns appear to be negatively affected by severe geomagnetic storms during their recovery phase. This effect is statistically as well as economically significant. The size of the GMS

[28]The use of the interaction dummy drastically reduces the number of stormy days in our sample. As a consequence, magnitude and precision of the coefficient estimates are somewhat smaller.

effect is similar within and across countries, ranging from -1.7% to -4.7% of average annual returns.

We also document a more pronounced GMS effect in the pricing of small 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 sentiments and mood than those of institutional investors, we expect the GMS effect to be bigger for small cap, riskier stocks.

Overall, results support 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 risk aversion. By using the same underlying logic and similar medical arguments, our results complement recent findings by Kamstra, Kramer, and Levi (2003) of a significant SAD effect in stock market returns.

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Table I

Summary Statistics of International Stock Returns

We report summary statistics of daily (continuously compounded) returns on the equity indices of nine countries: Australia, Britain, Canada, Germany, Japan, New Zealand, South Africa, Sweden and United States. Indices do not include dividend distributions and 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
Australia 1980/01/03 - 2001/12/18 (5567 obs.)	0.033	1.004	-28.761	9.786	-4.890	134.367
Britain 1984/01/04 - 2001/12/06 (4530 obs.)	0.037	1.001	-13.029	7.597	-0.928	15.276
Canada 1969/01/03 - 2001/12/18 (8310 obs.)	0.023	0.853	-10.295	9.878	-0.752	16.957
Germany 1965/01/05 - 2001/12/12 (9312 obs.)	0.025	1.105	-13.710	8.872	-0.503	11.614
Japan 1950/04/04 - 2001/12/06 (12852 obs.)	0.037	1.119	-16.135	12.430	-0.339	13.817
New Zealand 1991/07/01 - 2001/12/18 (2639 obs.)	0.013	0.973	-13.307	9.475	-0.854	21.735
South Africa 1973/01/03 - 2001/12/06 (7405 obs.)	0.054	1.343	-14.528	13.574	-0.717	12.682
Sweden 1982/09/15 - 2001/12/18 (4831 obs.)	0.063	1.245	-8.986	9.777	-0.251	9.008
US: S&P500 1932/01/09 - 2000/12/29 (18209 obs.)	0.030	1.065	-20.467	15.366	-0.355	22.622
US: NYSE 1962/07/05 - 2000/12/29 (9693 obs.)	0.035	0.842	-18.359	8.791	-1.156	31.748
US: AMEX 1962/07/05 - 2000/12/29 (9693 obs.)	0.032	0.840	-12.746	10.559	-0.862	19.398
US: NASDAQ 1972/12/18 - 2000/12/29 (7084 obs.)	0.047	1.095	-11.350	10.573	-0.480	15.066

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:

$$r_t = \alpha + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{GMS} D_{t-k}^{GMS} + \epsilon_t$$

$(k = 1, ..., 6)$ 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
NASDAQ	$\surd$			$\surd$	$\surd$	$\surd$
S&P500	$\surd$				$\surd$	$\surd$
AMEX	$\surd$		$\surd$		$\surd$	$\surd$
NYSE	$\surd$	$\surd$			$\surd$	$\surd$
Canada	$\surd$				$\surd$	$\surd$
Sweden			$\surd$		$\surd$	$\surd$
UK		$\surd$			$\surd$	$\surd$
Japan						$\surd$
Australia		$\surd$	$\surd$			$\surd$
New Zealand	$\surd$				$\surd$	$\surd$
South Africa				$\surd$		
Germany						

Table III.A

Regression Results for Each of the US Indices

We report regression results for NASDAQ, S&P500, AMEX, and NYSE using the following equation:

$$r_t = \alpha + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{GMS} D_{t-5,t-6}^{GMS} + \epsilon_t \, .$$

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-tests with p-values are displayed at the bottom of the table.

Parameter	NASDAQ	S&P500	AMEX	NYSE
α	0.101*** (0.015)	0.071*** (0.009)	0.084*** (0.009)	0.062*** (0.010)
ρ_1	0.147*** (0.029)	0.072*** (0.017)	0.270*** (0.030)	0.151*** (0.025)
ρ_2	.	−0.033** (0.017)	.	.
β_{Monday}	−0.256*** (0.034)	−0.188*** (0.022)	−0.279*** (0.022)	−0.124*** (0.024)
β_{Tax}	0.191** (0.087)	0.085** (0.051)	0.260*** (0.064)	0.061 (0.065)
β_{GMS}	−0.077** (0.036)	−0.042** (0.021)	−0.058*** (0.024)	−0.055** (0.026)
R^2	0.031	0.011	0.090	0.027
F-stat	19.79 (0.00)	18.31 (0.00)	55.05 (0.00)	12.86 (0.00)

Table III.B

Regression Results for UK, Canada, Germany, and Sweden

We report regression results for UK, Canada, Germany, and Sweden using the following equation:

$$r_t = \alpha + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{GMS} D_{t-5,t-6}^{GMS} + \epsilon_t \, .$$

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-tests with p-values are displayed at the bottom of the table.

Parameter	UK	Canada	Germany	Sweden
α	0.073*** (0.018)	0.055*** (0.011)	0.051*** (0.013)	0.076*** (0.021)
ρ_1	0.062* (0.044)	0.154*** (0.032)	0.058*** (0.019)	0.111*** (0.028)
ρ_2	.	.	.	.
β_{Monday}	−0.115*** (0.039)	−0.131*** (0.024)	−0.149*** (0.031)	−0.037 (0.047)
β_{Tax}	0.138* (0.091)	0.121* (0.076)	0.243*** (0.093)	0.297** (0.151)
β_{GMS}	−0.119*** (0.045)	−0.070*** (0.027)	−0.014 (0.031)	−0.119*** (0.050)
R^2	0.008	0.029	0.007	0.016
F-stat	4.15 (0.00)	14.44 (0.00)	10.28 (0.00)	7.76 (0.00)

Table III.C

Regression Results for Australia, Japan, New Zealand, and South Africa

We report regression results for Australia, Japan, New Zealand, and South Africa using the following equation:

$$r_t = \alpha + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{GMS} D_{t-5,t-6}^{GMS} + \epsilon_t \, .$$

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-tests with p-values are displayed at the bottom of the table.

Parameter	Australia	Japan	New Zealand	South Africa
α	0.044*** (0.015)	0.054*** (0.011)	0.070*** (0.021)	0.074*** (0.019)
ρ_1	0.091** (0.044)	.	.	0.089*** (0.024)
ρ_2	.	.	.	.
β_{Monday}	−0.038 (0.033)	−0.039* (0.028)	−0.208*** (0.053)	−0.123*** (0.041)
β_{Tax}	0.131** (0.072)	0.095 (0.075)	0.141 (0.138)	0.012 (0.104)
β_{GMS}	−0.057* (0.042)	−0.066*** (0.027)	−0.120** (0.053)	0.003 (0.043)
R^2	0.010	0.001	0.010	0.010
F-stat	2.65 (0.03)	3.12 (0.02)	6.91 (0.00)	5.48 (0.00)

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
NASDAQ	−3.10** (0.036)	12.47*** (0.013)
S&P500	−1.67** (0.021)	7.79*** (0.008)
AMEX	−2.10*** (0.024)	8.33*** (0.009)
NYSE	−2.02** (0.026)	9.14*** (0.009)
Canada	−2.72*** (0.027)	5.92*** (0.009)
Sweden	−4.74*** (0.050)	17.05*** (0.018)
UK	−4.57*** (0.045)	9.68** (0.015)
Japan	−2.75*** (0.027)	9.69*** (0.001)
Australia	−2.35* (0.042)	8.60*** (0.013)
New Zealand	−4.41** (0.053)	3.30 (0.019)
South Africa	0.12 (0.043)	14.45*** (0.016)
Germany	−0.52 (0.031)	6.45** (0.011)

Table V

Returns on Large Cap vs. Small Cap Stocks

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

$$r_t \quad = \quad \alpha + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{GMS} D_{t-5,t-6}^{GMS} + \epsilon_t \,.$$

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	NYSE+AMEX+NASDAQ
1	−0.012 (0.023)	−0.026 (0.024)	−0.011 (0.019)
2	−0.025 (0.021)	−0.044** (0.022)	−0.030* (0.019)
3	−0.053*** (0.021)	−0.037** (0.022)	−0.018 (0.021)
4	−0.042** (0.022)	−0.038** (0.021)	−0.037** (0.020)
5	−0.049** (0.023)	−0.040** (0.022)	−0.030* (0.021)
6	−0.062*** (0.025)	−0.056*** (0.022)	−0.045** (0.022)
7	−0.066*** (0.026)	−0.050** (0.022)	−0.047** (0.023)
8	−0.072*** (0.029)	−0.043** (0.023)	−0.045** (0.023)
9	−0.070** (0.032)	−0.049** (0.024)	−0.052** (0.023)
10	−0.080** (0.040)	−0.059** (0.028)	−0.059** (0.028)

Table VI.A

Regression Results for Each of the US Indices Using Additional Controls

We report regression results for NASDAQ, S&P500, AMEX, and NYSE using the following equation:

$$
\begin{aligned}
r_t \;=\; & \alpha + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{GMS} D_{t-5,t-6}^{GMS} + \beta_{Fall} D_t^{Fall} + \beta_{SAD} SAD_t \\
& + \beta_{Cloud} Cloud_t + \beta_{Precipitation} Precipitation_t + \beta_{Temperature} Temperature_t + \epsilon_t \,.
\end{aligned}
$$

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. R^2 and F-tests with p-values are displayed at the bottom of the table.

Parameter	NASDAQ	S&P500	AMEX	NYSE
α	-0.000 (0.149)	-0.060 (0.107)	0.086* (0.057)	0.025 (0.116)
ρ_1	0.145*** (0.029)	0.071*** (0.017)	0.268*** (0.030)	0.151*** (0.025)
ρ_2	.	-0.034** (0.017)	.	.
β_{Monday}	-0.256*** (0.034)	-0.188*** (0.022)	-0.279*** (0.022)	-0.124*** (0.024)
β_{Tax}	0.068 (0.093)	0.050 (0.054)	0.184*** (0.067)	0.010 (0.068)
β_{GMS}	-0.065** (0.037)	-0.037** (0.021)	-0.052*** (0.024)	-0.051** (0.026)
β_{Fall}	-0.129*** (0.041)	-0.035* (0.025)	-0.081*** (0.026)	-0.037* (0.029)
β_{SAD}	0.067*** (0.024)	0.038*** (0.016)	0.033** (0.015)	0.023* (0.016)
β_{Cloud}	0.088 (0.220)	0.135 (0.157)	0.023 (0.162)	0.049 (0.171)
$\beta_{Precipitation}$	-0.003 (0.004)	-0.002 (-0.003)	-0.002 (0.003)	-0.001 (0.003)
$\beta_{Temperature}$	0.003 (0.002)	0.004** (0.002)	0.001 (0.002)	0.000 (0.002)
R^2	0.033	0.011	0.092	0.028
F-stat	10.52 (0.00)	10.36 (0.00)	26.74 (0.00)	6.93 (0.00)

Table VI.B

Regression Results for UK, Canada, Germany, and Sweden Using Additional Controls

We report regression results for UK, Canada, Germany, and Sweden using the following equation:

$$\begin{aligned} r_t &= \alpha + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{GMS} D_{t-5,t-6}^{GMS} + \beta_{Fall} D_t^{Fall} + \beta_{SAD} SAD_t \\ &\quad + \beta_{Cloud} Cloud_t + \beta_{Precipitation} Precipitation_t + \beta_{Temperature} Temperature_t + \epsilon_t \, . \end{aligned}$$

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. R^2 and F-tests with p-values are displayed at the bottom of the table.

Parameter	UK	Canada	Germany	Sweden
α	0.269** (0.170)	−0.057 (0.133)	0.099 (0.142)	0.297* (0.190)
ρ_1	0.060* (0.044)	0.152*** (0.032)	0.057*** (0.019)	0.109*** (0.028)
ρ_2	.	.	.	.
β_{Monday}	−0.116*** (0.039)	−0.131*** (0.024)	−0.149*** (0.031)	−0.035 (0.047)
β_{Tax}	0.154** (0.093)	0.034 (0.080)	0.162** (0.098)	0.135 (0.159)
β_{GMS}	−0.111*** (0.045)	−0.062** (0.027)	−0.008 (0.032)	−0.110** (0.050)
β_{Fall}	−0.029 (0.045)	−0.065** (0.032)	−0.069** (0.037)	−0.106** (0.056)
β_{SAD}	0.027** (0.015)	0.049*** (0.002)	0.025* (0.016)	0.025** (0.014)
β_{Cloud}	−0.296 (0.261)	0.177 (0.266)	−0.130 (0.244)	−0.382* (0.290)
$\beta_{Precipitation}$	−0.016* (0.010)	−0.003 (0.003)	0.001 (0.013)	0.001 (0.016)
$\beta_{Temperature}$	−0.002 (0.004)	0.001 (0.001)	0.001 (0.003)	−0.001 (0.003)
R^2	0.011	0.029	0.008	0.018
F-stat	2.99 (0.00)	9.76 (0.00)	5.18 (0.00)	4.70 (0.00)

Table VI.C

Regression Results for Australia, Japan, New Zealand, and South Africa Using Additional Controls

We report regression results for Australia, Japan, New Zealand, and South Africa using the following equation:

$$\begin{aligned} r_t &= \alpha + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{GMS} D_{t-5,t-6}^{GMS} + \beta_{Fall} D_t^{Fall} + \beta_{SAD} SAD_t \\ &\quad + \beta_{Cloud} Cloud_t + \beta_{Precipitation} Precipitation_t + \beta_{Temperature} Temperature_t + \epsilon_t\,. \end{aligned}$$

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. R^2 and F-tests with p-values are displayed at the bottom of the table.

Parameter	Australia	Japan	New Zealand	South Africa
α	0.109 (0.221)	0.020 (0.133)	−0.387 (0.542)	−0.277* (0.194)
ρ_1	0.090** (0.044)	.	.	0.088*** (0.024)
ρ_2	.	.	.	.
β_{Monday}	−0.038 (0.033)	−0.040* (0.028)	−0.207*** (0.053)	−0.123*** (0.041)
β_{Tax}	0.124* (0.078)	0.010 (0.080)	0.216* (0.144)	0.011 (0.105)
β_{GMS}	−0.054* (0.042)	−0.061** (0.027)	−0.111** (0.054)	0.008 (0.043)
β_{Fall}	0.011 (0.033)	−0.056** (0.031)	−0.010** (0.050)	−0.034 (0.038)
β_{SAD}	0.027 (0.032)	0.033* (0.024)	0.041* (0.028)	0.114* (0.070)
β_{Cloud}	−0.305 (0.320)	0.094 (0.162)	0.467 (0.779)	0.139 (0.223)
$\beta_{Precipitation}$	−0.005** (0.002)	−0.003 (0.003)	0.001 (0.003)	−0.001 (0.005)
$\beta_{Temperature}$	0.005 (0.007)	−0.001 (0.002)	0.010* (0.008)	0.016* (0.010)
R^2	0.010	0.002	0.011	0.010
F-stat	1.70 (0.08)	2.95 (0.00)	3.37 (0.00)	2.76 (0.00)

Table VII.A

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

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

$$
\begin{aligned}
r_t &= \alpha + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{GMS} D_{t-5,t-6}^{GMS} + \beta_{GARCH}\, \sigma_t^2 + \epsilon_t \\
\sigma_t^2 - q_t &= \delta(\epsilon_{t-1}^2 - q_{t-1}) + \eta(\epsilon_{t-1}^2 - q_{t-1}) D_{t-1} + \nu(\sigma_{t-1}^2 - q_{t-1}) \\
q_t &= \omega + \gamma(q_{t-1} - \omega) + \phi(\epsilon_{t-1}^2 - \sigma_{t-1}^2) \\
\epsilon_t &\sim (0, \sigma_t^2) \\
D_{t-1} &= \begin{cases} 1 & \text{if } \epsilon_{t-1} < 1 \\ 0 & \text{otherwise}. \end{cases}
\end{aligned}
$$

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	0.083^{***} (0.004)	0.061^{***} (0.007)	0.076^{***} (0.002)	0.043^{***} (0.006)
ρ_1	0.286^{***} (0.005)	0.145^{***} (0.007)	0.299^{***} (0.010)	0.179^{***} (0.010)
ρ_2	.	-0.037^{***} (0.007)	.	.
β_{Monday}	-0.253^{***} (0.009)	-0.155^{***} (0.011)	-0.220^{***} (0.011)	-0.110^{***} (0.007)
β_{Tax}	0.171^{***} (0.040)	0.041^{*} (0.029)	0.220^{***} (0.011)	0.064^{**} (0.029)
β_{GMS}	-0.022^{***} (0.004)	0.012 (0.013)	-0.036^{***} (0.015)	-0.022^{***} (0.005)
β_{GARCH}	0.044^{***} (0.010)	0.013^{*} (0.008)	0.040^{***} (0.002)	0.046^{***} (0.001)
δ	-0.006 (0.009)	-0.004 (0.004)	0.063^{***} (0.010)	-0.025^{***} (0.007)
η	0.161^{***} (0.012)	0.106^{***} (0.005)	0.086^{***} (0.011)	0.107^{***} (0.008)
ν	0.795^{***} (0.015)	0.856^{***} (0.007)	0.787^{***} (0.013)	0.857^{***} (0.015)
ω	0.586^{***} (0.080)	0.581^{***} (0.047)	0.464^{***} (0.047)	0.624^{***} (0.095)
γ	0.996^{***} (0.001)	0.997^{***} (0.000)	0.994^{***} (0.001)	0.996^{***} (0.001)
ϕ	0.028^{***} (0.003)	0.026^{***} (0.002)	0.034^{***} (0.004)	0.049^{***} (0.004)
Log Likelihood	-8332.384	-22249.14	-9529.277	-10482.910
ARCH(10) p-value	0.765	0.451	0.308	0.880
F-statistic p-value	0.000	0.000	0.000	0.000

Table VII.B

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

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

$$
\begin{aligned}
r_t &= \alpha + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{GMS} D_{t-5,t-6}^{GMS} + \beta_{GARCH}\, \sigma_t^2 + \epsilon_t \\
\sigma_t^2 - q_t &= \delta(\epsilon_{t-1}^2 - q_{t-1}) + \eta(\epsilon_{t-1}^2 - q_{t-1}) D_{t-1} + \nu(\sigma_{t-1}^2 - q_{t-1}) \\
q_t &= \omega + \gamma(q_{t-1} - \omega) + \phi(\epsilon_{t-1}^2 - \sigma_{t-1}^2) \\
\epsilon_t &\sim (0, \sigma_t^2) \\
D_{t-1} &= \begin{cases} 1 & \text{if } \epsilon_{t-1} < 1 \\ 0 & \text{otherwise}. \end{cases}
\end{aligned}
$$

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

Parameter	UK	Canada	Germany	Sweden
α	0.093*** (0.015)	0.057*** (0.008)	0.028*** (0.004)	0.061*** (0.009)
ρ_1	0.065*** (0.016)	0.249*** (0.009)	0.120*** (0.006)	0.165*** (0.015)
ρ_2	.	.	.	.
β_{Monday}	−0.139*** (0.031)	−0.126*** (0.014)	−0.173*** (0.018)	−0.113*** (0.029)
β_{Tax}	0.085 (0.089)	0.075** (0.035)	0.235*** (0.042)	0.510*** (0.066)
β_{GMS}	−0.090*** (0.034)	−0.011 (0.018)	0.009 (0.020)	−0.095*** (0.031)
β_{GARCH}	.	.	0.040*** (0.002)	0.048*** (0.008)
δ	−0.080*** (0.011)	0.111*** (0.009)	0.050*** (0.008)	0.068*** (0.012)
η	0.066*** (0.018)	0.007 (0.010)	0.097*** (0.010)	0.090*** (0.012)
ν	−0.054 (0.419)	0.736*** (0.016)	0.824*** (0.012)	0.809*** (0.014)
ω	1.058*** (0.093)	0.694*** (0.068)	1.228*** (0.337)	1.326*** (0.137)
γ	0.969*** (0.007)	0.994*** (0.001)	0.999*** (0.000)	0.994*** (0.001)
ϕ	0.099*** (0.009)	0.041*** (0.003)	0.017*** (0.002)	0.018*** (0.004)
Log Likelihood	−6000.339	−8721.858	−12709.130	−7129.709
ARCH(10) p-value	0.319	0.036	0.688	0.999
F-statistic p-value	0.000	0.000	0.011	0.000

Table VII.C

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

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

$$
\begin{aligned}
r_t &= \alpha + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{GMS} D_{t-5,t-6}^{GMS} + \beta_{GARCH}\, \sigma_t^2 + \epsilon_t \\
\sigma_t^2 - q_t &= \delta(\epsilon_{t-1}^2 - q_{t-1}) + \eta(\epsilon_{t-1}^2 - q_{t-1}) D_{t-1} + \nu(\sigma_{t-1}^2 - q_{t-1}) \\
q_t &= \omega + \gamma(q_{t-1} - \omega) + \phi(\epsilon_{t-1}^2 - \sigma_{t-1}^2) \\
\epsilon_t &\sim (0, \sigma_t^2) \\
D_{t-1} &= \begin{cases} 1 & \text{if } \epsilon_{t-1} < 1 \\ 0 & \text{otherwise}. \end{cases}
\end{aligned}
$$

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	0.049*** (0.013)	0.055*** (0.002)	0.021** (0.011)	0.031*** (0.007)
ρ_1	0.177*** (0.014)	.	.	0.138*** (0.010)
ρ_2	.	.	.	.
β_{Monday}	−0.032* (0.023)	0.021** (0.011)	−0.167*** (0.033)	−0.137*** (0.018)
β_{Tax}	0.105* (0.069)	0.169*** (0.038)	0.030 (0.102)	0.044 (0.096)
β_{GMS}	−0.049** (0.027)	−0.010*** (0.000)	−0.083** (0.040)	−0.117*** (0.016)
β_{GARCH}	.	0.027*** (0.008)	0.064** (0.027)	0.047*** (0.005)
δ	−0.024 (0.051)	0.117*** (0.006)	0.054* (0.037)	0.123*** (0.009)
η	0.087*** (0.015)	0.048*** (0.007)	0.057* (0.039)	0.066*** (0.013)
ν	0.767*** (0.059)	0.773*** (0.007)	0.194 (0.183)	0.665*** (0.015)
ω	0.756*** (0.021)	1.584*** (0.401)	0.916*** (0.064)	1.919*** (0.041)
γ	0.896*** (0.022)	0.999*** (0.000)	0.940*** (0.013)	0.993*** (0.001)
ϕ	0.117*** (0.044)	0.021*** (0.002)	0.117*** (0.017)	0.018*** (0.002)
Log Likelihood	−6967.456	−17417.320	−3404.732	−11879.370
ARCH(10) p-value	0.425	0.887	0.653	0.998
F-statistic p-value	0.394	0.000	0.000	0.050

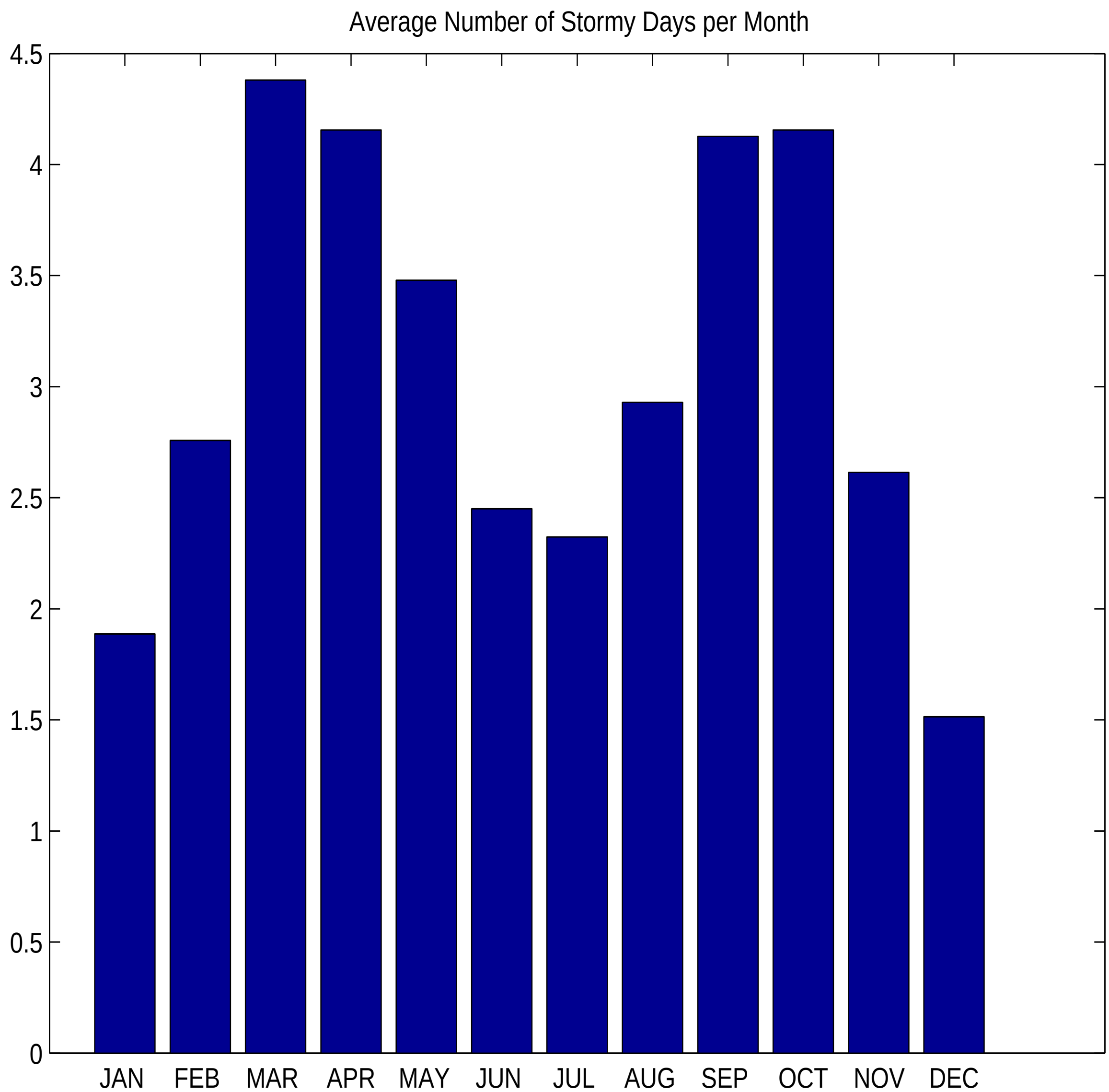

Figure 1. Number of Storms per Month. The figure displays the bar graph of the average number of stormy days (vertical axis) per month using the Ap index. Daily Ap index data can be downloaded from the following web site:

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

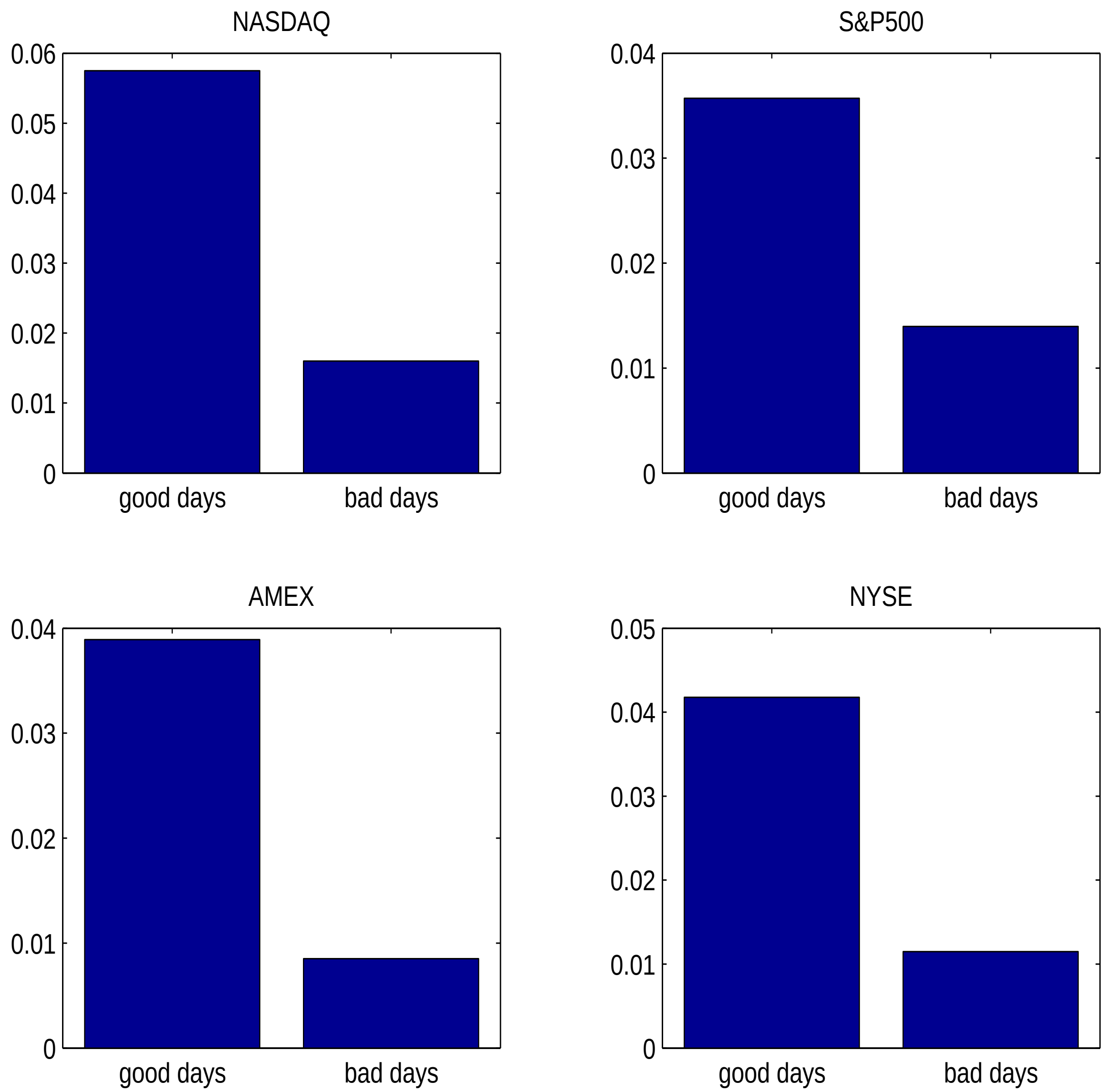

Figure 2. Returns during Good Days and Bad Days. The figure displays the bar graphs of the returns on the US stock market indices during 'good' days and 'bad' days. We define the six calendar days following a major, severe, or extremely severe geomagnetic storm as bad days. We define the remaining calendar days as good days.

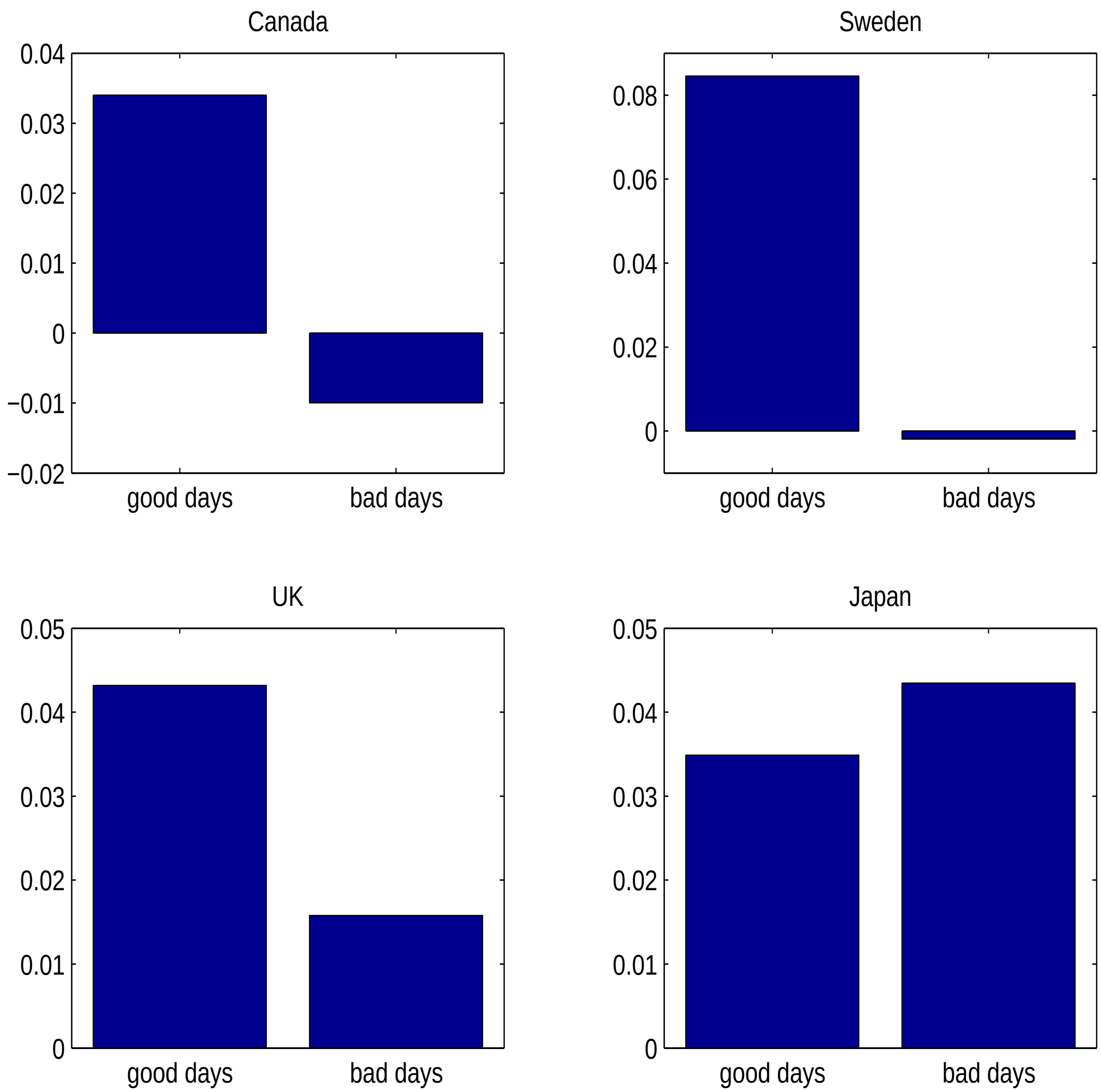

Figure 2 (cont'd). Returns during Good Days and Bad Days. The figure displays the bar graphs of the returns on the Canadian, Swedish, British, and Japanese stock market indices during 'good' days and 'bad' days. We define the six calendar days following a major, severe, or extremely severe geomagnetic storm as bad days. We define the remaining calendar days as good days.

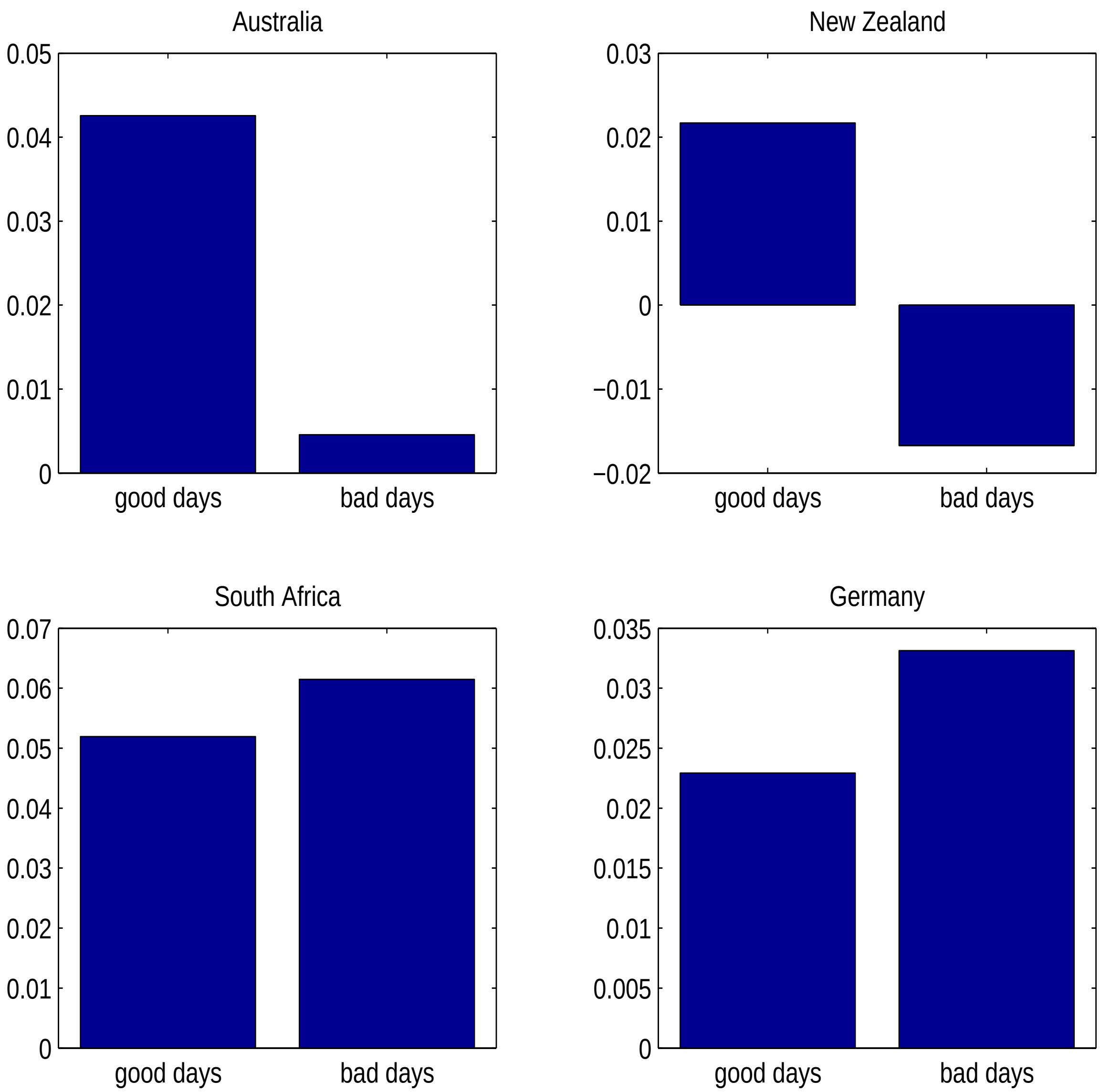

Figure 2 (cont'd). Returns during Good Days and Bad Days. The figure displays the bar graphs of the returns on the Australian, New Zealander, South African, and German stock market indices during 'good' days and 'bad' days. We define the six calendar days following a major, severe, or extremely severe geomagnetic storm as bad days. We define the remaining calendar days as good days.

NASDAQ

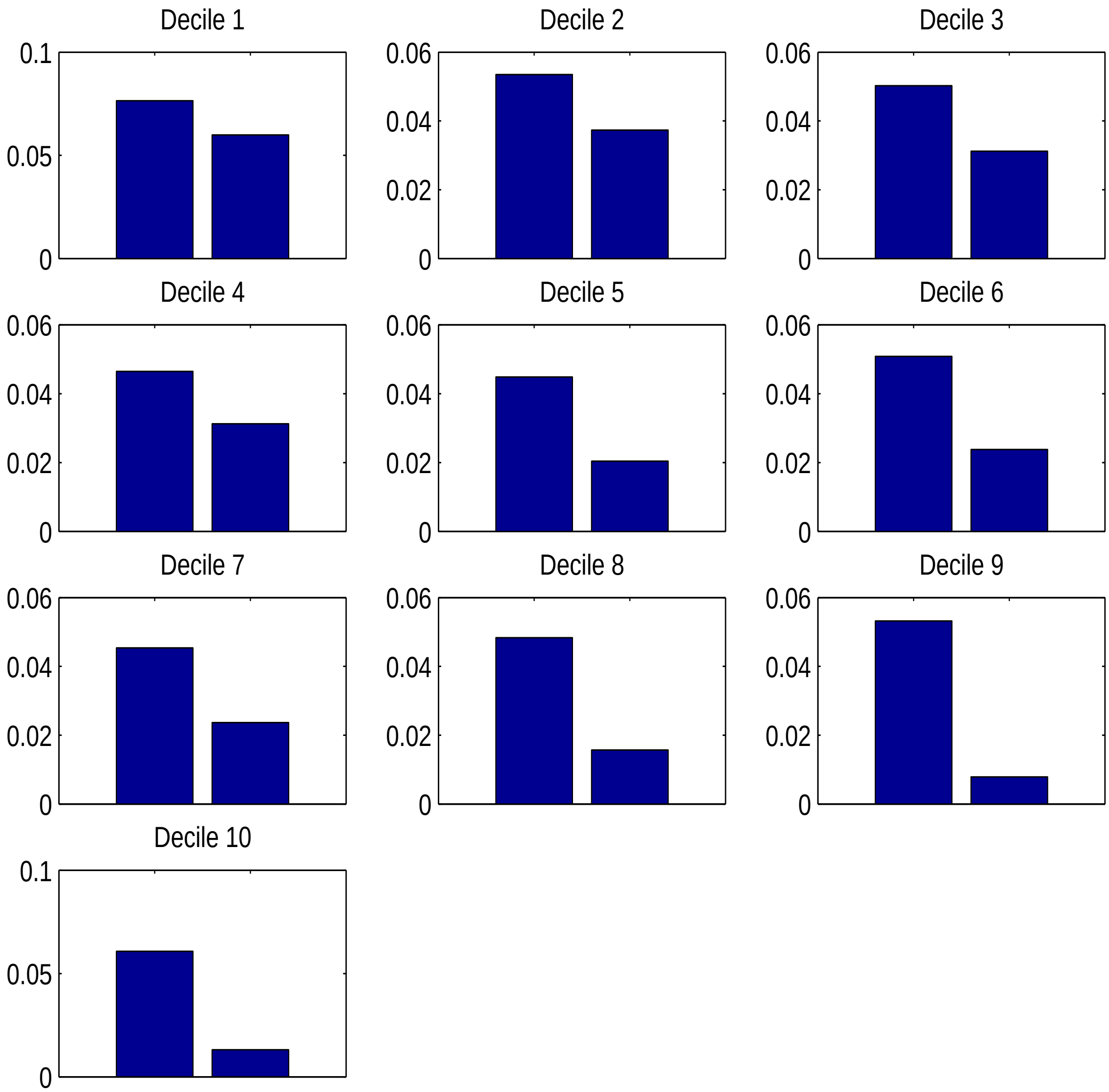

Figure 3. Returns during Good Days and Bad Days. The figure displays the bar graphs of the returns on the NASDAQ size deciles during 'good' days (left column) and 'bad' days (right column). We define the six calendar days following a major, severe, or extremely severe geomagnetic storm as bad days. We define the remaining calendar days as good days.

NYSE/AMEX

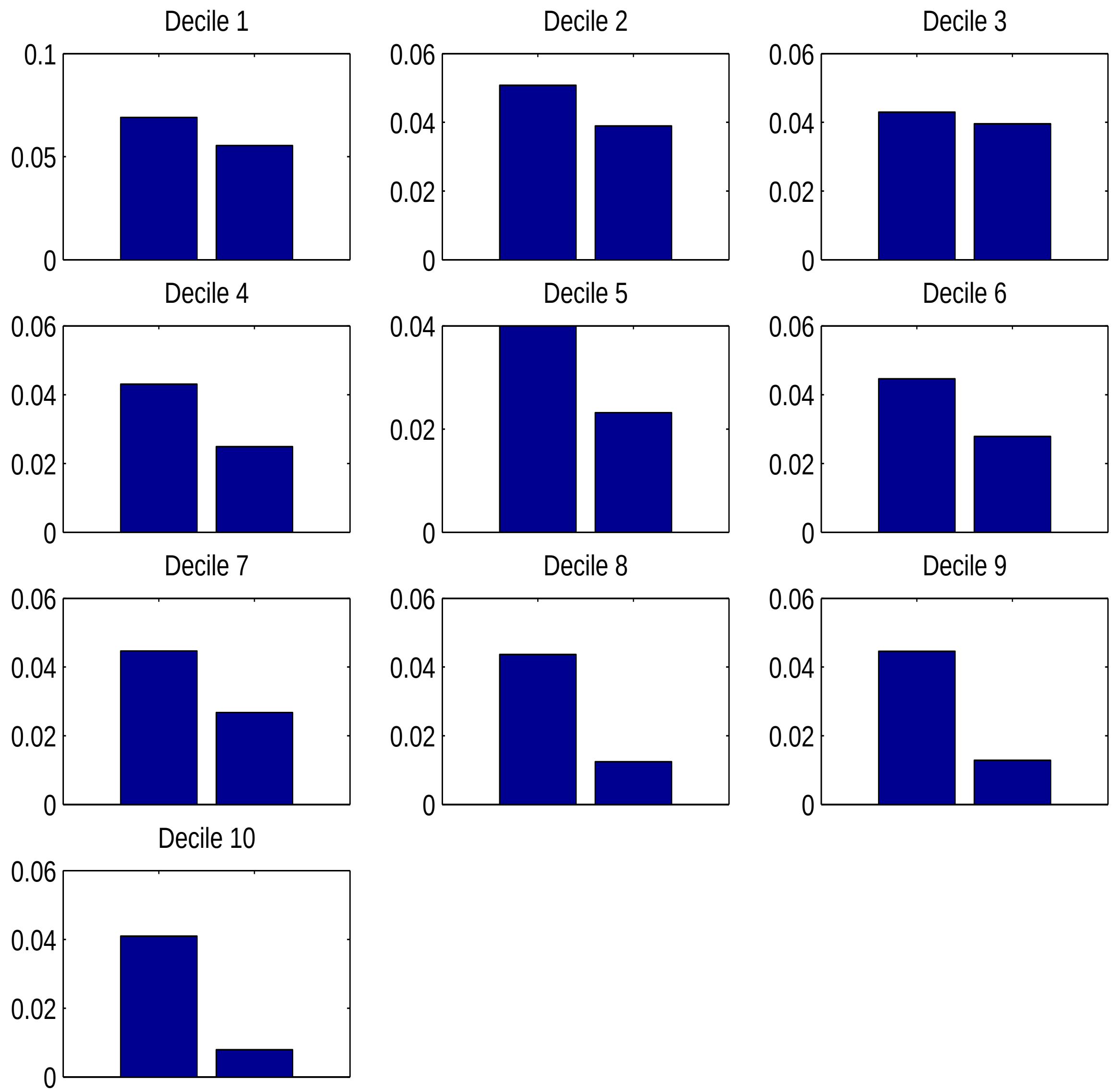

Figure 3 (cont'd). Returns during Good Days and Bad Days. The figure displays the bar graphs of the returns on the NYSE+AMEX size deciles during 'good' days (left column) and 'bad' days (right column). We define the six calendar days following a major, severe, or extremely severe geomagnetic storm as bad days. We define the remaining calendar days as good days.

NYSE/AMEX/NASDAQ

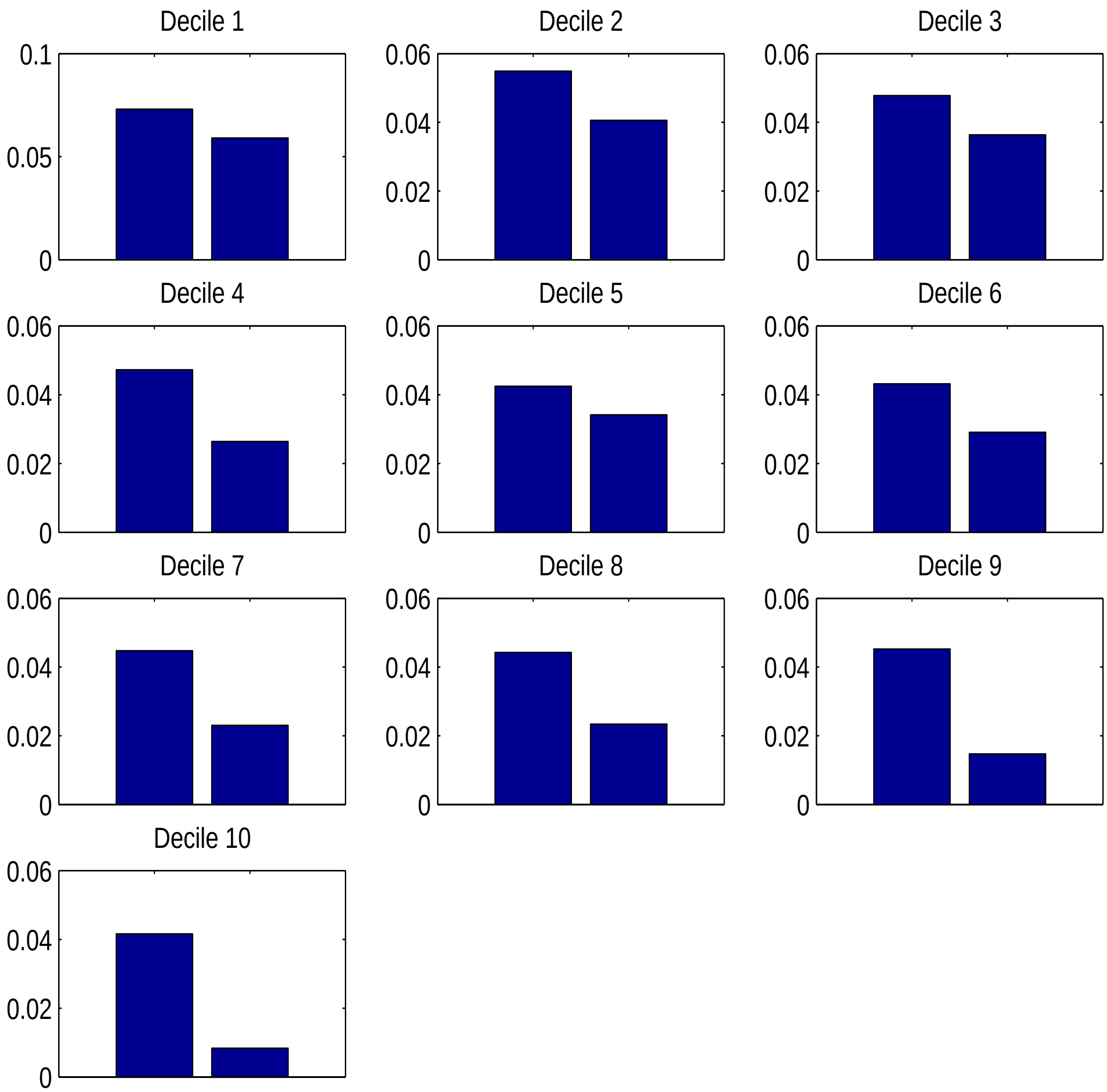

Figure 3 (cont'd). Returns during Good Days and Bad Days. The figure displays the bar graphs of the returns on the NYSE+AMEX+NASDAQ size deciles during 'good' days (left column) and 'bad' days (right column). We define the six calendar days following a major, severe, or extremely severe geomagnetic storm as bad days. We define the remaining calendar days as good days.