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Abstract: Explaining movements in daily stock prices is one of the most difficult tasks in modern finance. This paper contributes to the existing literature by documenting the impact of geomagnetic storms on daily stock market returns. A large body of psychological research has shown 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. 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 geomagnetic storms may be more inclined to sell stocks on stormy days because they incorrectly attribute their bad mood to negative economic prospects rather than bad environmental conditions. 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. The authors find strong empirical support in favor of a geomagnetic-storm effect in stock returns after controlling for market seasonals and other environmental and behavioral factors. Unusually high levels of geomagnetic activity have a negative, statistically and economically significant effect on the following week's stock returns for all U.S. stock market indices. Finally, this paper provides evidence of substantially higher returns around the world during periods of quiet geomagnetic activity.

JEL classification: G1

Key words: stock returns, geomagnetic storms, seasonal affective disorders, misattribution of mood, behavioral finance

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Playing the Field: Geomagnetic Storms and the Stock Market

Abstract

Explaining movements in daily stock prices is one of the most difficult tasks in modern finance. This paper contributes to the existing literature by documenting the impact of geomagnetic storms on daily stock market returns. A large body of psychological research has shown 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. 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 geomagnetic storms may be more inclined to sell stocks on stormy days because they incorrectly attribute their bad mood to negative economic prospects rather than bad environmental conditions. 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. We find strong empirical support in favor of a geomagnetic–storm effect in stock returns after controlling for market seasonals and other environmental and behavioral factors. Unusually high levels of geomagnetic activity have a negative, statistically and economically significant effect on the following week's stock returns for all US stock market indices. Finally, this paper provides evidence of substantially higher returns around the world during periods of quiet geomagnetic activity.

Introduction

While it is the geomagnetic storms (GMS) that give rise to the beautiful Northern lights, occasionally 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, 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 and altered moods and altered moods and misattribution, above average levels and intensity of geomagnetic activity can potentially affect stock market returns. If people are more pessimistic during periods 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 neg-

[1] See, for example, Wong and Carducci (1991) and Loewenstein, Weber, Hsee, and Welch (2001).
[2] See, for example, Schwarz (1986) and Schwarz and Clore (1983).

ative economic prospects rather than environmental conditions. Seminal papers[3] in economics 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.[4] The previous week's unusually high levels of geomagnetic activity have a negative and statistically significant effect on today's stock returns for all US indices in our sample. We also provide evidence of substantially lower returns around the world during periods of intense geomagnetic activity. Furthermore, we find that the GMS effect in stock returns is related to stock size, small capitalization stocks being affected by GMS more than large capitalization stocks. This latter result is consistent with the empirical finding that institutional ownership is positively correlated with stock capitalization, small cap stocks being held mostly by individuals [Gompers and Metrick (2001)]. 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, the GMS effect should be more pronounced in the pricing of smaller cap stocks. The GMS effect on stock market returns 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

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

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

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), Goetzmann and Zhu (2003)] on international stock returns at the aggregate level.

The remainder of the paper is organized as follows. In section I, we discuss geomagnetic storms and misattribution of mood theories. In section II, we briefly describe US and international stock returns and other behavioral and environmental variables. In section III, we explain the construction of the variables intended to capture the influence of GMS on the stock market. In section IV, we document the statistical and economic significance of the GMS effect on US stock returns, discuss the GMS effect on NYSE–AMEX–NASDAQ returns of large capitalization vs. small capitalization stocks, analyze the international evidence, and identify the excess returns that would arise from trading strategies based on the GMS effect in World stock returns. 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 explore the possibility of a seasonal GMS effect in stock returns and control for stock market downturns. We conclude in section VI.

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

Geomagnetic storms are worldwide disturbances of the earth's magnetic field, distinct from regular diurnal variations.[5] The sun continuously emits a "solar wind" (often called by specialists the solar wind plasma) in all directions. It is very fast and highly

[5]We thank Ron Zwickl, Deputy Director at NASA's Space Environment Center in Boulder, Colorado, for helpful discussions on geomagnetic storms data.

variable, both in speed and in density. This wind blows radially away from the sun and always contains a magnetic field which is also highly variable in magnitude and direction. Because the sun rotates completely around in about 27 days, as seen from the earth, the average magnetic field contained within the solar wind forms a spiral pattern. When the magnetic field direction within the solar wind is directed opposite to the earth's magnetic field, then large geomagnetic storms can occur. Specifically, the sun, from time to time, emits "bubbles" (or coronal mass ejections) which are faster, often more dense than normal and contain higher magnetic fields. These bubbles travel away from the sun at about 2 million miles per hour. If "bubbles" leave the right place on the sun to reach earth, they travel the 93-million-mile distance in about 40 hours. Coronal mass ejections occur more often when the sun is more active, and sunspots are more numerous during such times. 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. On the contrary, the daily correlation between GMS and sunspots is only 0.1 over the same period.[6] 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 perfectly 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 classically divided

[6] 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 variables and for the exact reference to the web site where all geomagnetic data can be found.

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. 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. Geomagnetic variations have been correlated with enhanced anxiety, sleep disturbances, altered moods, and greater incidences of psychiatric admissions [Persinger (1987, page 92)]. In a study on GMS and depression, 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. A phase advance in the circadian rhythm of melatonin production was found to be the main cause of the higher depression rates.[7] 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. Usenko (1992) finds that, 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 func-

[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.

[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

tional activity of the central nervous system. The latter leads to a sharp decline in flying skills. Kuleshova et al. (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 et al. (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 75% of geomagnetic storms caused increase in hospitalization of patients with the above-mentioned diseases by 30-80% on 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". Using a sample of healthy people, Stoilova and Zdravev (2000) and Shumilov, Kasatkina, and Raspopov (1998) reach similar conclusions. 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. Abnormal melatonin patterns have been closely linked to a

by the 20th-century American physiologist Walter B. Cannon, who refined and extended the concept of self-regulating mechanisms in living systems.

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, Paparrigopoulos, and Stefanis (1996). 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". Even if geomagnetic activity is more intense during spring and fall (see Figure II), leading to increased susceptibility for desynchronization of circadian rhythms, geomagnetic 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 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.

Experimental research in psychology has documented a direct link between mood

[9] 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 (2003), or about the lunar effect documented by Yuan, Zheng, , and Zhu (2001), Rotton and Kelly (1985a), Rotton and Kelly (1985b), Rotton and Rosenberg (1984), and Dichev and Janes (2001).

disorders and decision making. 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.[10] Bad moods also lead to a more detailed and more critical analytical activity [Schwarz (1986), 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.[11] Frijda (1988), Schwarz (1986), Clore and Parrott (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. 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 [see, for example, Zakharov and Tyrnov (2001), Halberg et al. (2000), and Belisheva et al. (1995)]. Hence, we use daily data

[10]See, for example, Clore, Schwarz, and Conway (1994), Forgas (1995), and Schwarz and Bless (1991).

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

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. 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. 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.

II. Data

A. Stock Market Returns

We consider the same US stock market indices used by Kamstra, Kramer, and Levi (2003). The four US indices that we consider are the NASDAQ, the S&P500,[12] the Amex, and the NYSE. All of the indices are value-weighted and do not include dividends. For the US, we also considered CRSP indices of returns including dividends and we found qualitatively identical results in all cases. US stock market indices are obtained from CRSP. To analyze the effect of geomagnetic storms on small capitalization vs. large capitalization stocks, we focus on the NASDAQ and the NYSE–AMEX–NASDAQ size deciles from CRSP.

When focusing on international stock markets, we consider the world market index as well as the indices from eight other countries at different latitudes in different hemispheres. The 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). As Kamstra, Kramer, and Levi (2003) do, we choose the lat-

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

ter eight indices based on the following three criteria: 1) absence of hyper-inflation; 2) sufficiently long time series; 3) representation of a broad range of sectors. The international indices and the world index are from Datastream.[13]

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 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.[14] 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

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

[14]The tax year starts on January 1 in 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. See Ernst & Young International, Ltd. *1999 Worldwide Executive Tax Guide*, 1998. 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.

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, 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. The geomagnetic data can be downloaded from the National Geophysical Data Center, which is a part of the National Oceanic & Atmospheric Administration (NOAA).[15]

Values of the Ap index with corresponding geomagnetic field conditions are reported in the table below:[16]

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: Ap $= AM(\text{ap})$, where AM denotes the arithmetic mean. 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. We then construct two GMS proxies in the following way:

[15] ftp : //ftp.ngdc.noaa.gov/STP/GEOMAGNETIC_DATA/INDICES/KP_AP/.

[16] Only extremely severe geomagnetic storms (usually storms characterized by an Ap index above 100) can affect satellite operation, power transmission, and oil pipeline durability. Storms of such strength are rare events and represent a negligible fraction of our sample.

1. The first GMS proxy is simply given by the realizations of the continuous GMS variable, i.e., the Ap index itself;

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

   Accordingly, we construct a GMS dummy variable as follows:

$$D^{GMS} = \begin{cases} 1 & \text{for Ap} > 29 \\ 0 & \text{for Ap} \leq 29 \end{cases} \tag{1}$$

In the analysis of the statistical significance of the GMS effect on stock returns, we will present results using both proxies for geomagnetic activity. Our GMS measures have 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. Given the on-line trading boom of the past decade, it is unlikely that the trading decisions of investors living in different parts of the country will be based on the weather in New York city.

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 Ap as well as the D^{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[17], 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 returns on the US indices 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.[18] 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. In terms of annualized percentage returns, the differences in means appear to be substantial. The difference in means for the NASDAQ is 14%, for the S&P500 and the AMEX is 7%, and for the NYSE is 8.7%.

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. Statistical Analysis

A..1 Controlling for GMS

In designing our regression setup, we rely on findings in physiology and psychology according to which the effect of GMS on human health is strongest during the recovery phase of geomagnetic storms. According to these independent findings, the effect of GMS on people does not seem to be contemporaneous and to extend beyond the first week. We tested this hypothesis on US stock return data and found no evidence

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

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

of a contemporaneous effect of GMS on stock returns and of a GMS effect beyond the first week.[19] These findings left us with a six day window to consider, in which lags one to six of the continuous and discrete GMS proxies could potentially affect stock market returns. Given the strong serial correlation in the geomagnetic–storm proxies, including all six lags of the GMS variables in an Ordinary Least Squares (OLS) regression of returns on GMS results in imprecisely estimated coefficients. As a remedy to near multi–collinearity, we use the method of Principal Components to create the continuous-based and discrete-based GMS indices used in the statistical analysis. Based on eigenvalues inspection, we extract the first principal component from the matrix of the six lags of the Ap and D^{GMS} proxies and call the corresponding indices $PC_{c,t}^{GMS}$ and $PC_{d,t}^{GMS}$. The two indices summarize the information contained in six-lag window of the corresponding GMS proxies.

In Table II, we run separate time series OLS regressions for the four US indices in our dataset to capture the effect of the GMS indices on returns at time t. Returns are regressed on a constant and $PC_{d,t}^{GMS}$

$$r_t \;\; = \;\; \alpha + \beta_{GMS} PC_{d,t}^{GMS} + \epsilon_t \qquad (2)$$

In Table II we also report results from regressing returns on a constant and $PC_{c,t}^{GMS}$. Variables are defined as follows: r_t is the period t return for a given US index; $PC_{d,t}^{GMS}$ is the principal-component GMS index that uses the first principal component extracted from lags one to six of D^{GMS}. Table II documents a widespread GMS effect across indices the week following relatively high recorded levels of geomagnetic activity. We report, in parenthesis, one-sided heteroskedasticity-robust White (1980) standard errors. All the stock market returns in our sample are negatively affected by GMS and the estimated GMS coefficients are strongly statistically significant.

Following Hirshleifer and Shumway (2003), we also examine whether the sign of an index return on a particular day is associated with past levels of geomagnetic

[19] We considered lags of the GMS proxies ranging from 0 up to 14. Lags equal to 0 or greater than 6 always delivered statistically insignificant results for all indices. Results are available from the authors on request.

activity. For each index, we estimate separate logit models, where the dependent variable equals zero if r_t is negative and equals one if r_t is positive. We estimate the logit models using $PC_{d,t}^{GMS}$ as well as $PC_{c,t}^{GMS}$ as independent variables. The results are consistent with our OLS findings and indicate a negative association between lagged values of GMS and the sign of an index return. This negative association is also significant at conventional confidence levels for all US indices in our sample. Finally, in Panel B of Table II, we report pooled time–series cross–section OLS and logit, and index specific fixed effects least squares and fixed effects linear probability model[20] results. Once again, the estimated coefficients are negative and strongly statistically significant.[21]

Our results are robust to the use of the continuous as well as the discrete proxies for GMS. Hence, in the rest of the paper, we drop the emphasis on the continuous GMS index and report results using $PC_{d,t}^{GMS}$ only.

A..2 Controlling for GMS and Calendar Effects

As in the previous subsection, we run separate OLS time series regressions for the four indices in our dataset. Returns are regressed on a constant, a Monday dummy, a dummy variable for a tax-loss selling effect, and the GMS Index $PC_{d,t}^{GMS}$

$$r_t \;=\; \alpha + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{GMS} PC_{d,t}^{GMS} + \epsilon_t \qquad (3)$$

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 index when period

[20] Instead of estimating a fixed effects linear probability model, it would be more appropriate to run a conditional (fixed effects) logit. However, given the length of the time series dimension of our data, we could not achieve convergence of the conditional logit in a reasonable amount of time. We did estimate conditional logit for sub-samples of the data and achieved results that are qualitatively similar to those obtained from the fixed effects linear probability model.

[21] In the pooled analysis, we include the NYSE, the AMEX and the NASDAQ.

t is in the last trading day or first five trading days of the tax year and equals 0 otherwise. As in the previous subsection, in addition to separate OLS and logit, we run pooled time–series cross–section OLS and logit, and fixed effects least squares and fixed effects linear probability models. We report one-sided heteroskedasticity-robust White (1980) standard errors.

Table III 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 strongly statistically significant for the indices in our sample.

In summary, the empirical results of this section document a statistically significant GMS effect in US stock returns.

B. Economic Significance

In this section, we analyze the economic significance of the GMS effect in stock returns. We run separate regressions of returns on day t on D_{t-k}^{GMS} $(k = 1, ..., 6)$.[22] For each trading day, we determine the value of the GMS dummy variable and multiply it by that index's GMS variable estimate. Then we adjust the value to obtain an annualized percentage return. Table IV shows the average annual percentage return due to GMS and the entire unconditional annual percentage return. In the case of the annualized return due to the GMS variable, significance is based on robust standard errors associated with the underlying parameter estimates. In the case of the average return, significance is based on standard errors for a mean daily return different from zero.

The return due to GMS is negative for all indices, ranging from -0.84 percent to -2.1 percent for the S&P500, from -1.11 percent to -2.40 percent for the AMEX, from -1.60 percent to -2.51 percent for the NASDAQ and from -1.2 percent to -1.76 percent

[22]Notice that D_{t-k}^{GMS} is a dummy variable which is equal to 1 if there was a storm on day $t-k$, and 0 otherwise.

for the NYSE. As a robustness check, we pooled the NYSE, AMEX and NASDAQ returns together. Then we run pooled time-series cross-section OLS of returns at time t on a GMS dummy variable that equals 1 if a storm happened any day of the previous week and 0 otherwise. The magnitude of this weekly effect is very similar to the magnitude of the daily effect documented above: the average annual percentage return due to GMS is -1.57% and this effect is significant at the 5% level using robust standard errors.

The size of the GMS effect appears to be similar across indices, and the return due to GMS never exceeds the entire unconditional annual return. As an example, consider an investor able to obtain an average annual return of 125 dollars for each 1000 US dollars invested in the NASDAQ. If five days ago was a day of quiet geomagnetic activity, she would have earned an average annual return of 150 dollars instead of 125 dollars for each 1000 dollars invested in the US index.

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 US stock returns within a week from hitting the atmosphere.

C. 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.[23] 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

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

be more pronounced in the pricing of smaller cap stocks.

In the subsequent analysis, 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.[24] The sample period ranges from July 3, 1962 to December 29, 2000 for NYSE/AMEX/NASDAQ, and from December 15, 1972 to December 29, 2000 for NASDAQ.

Table V reports the separate OLS and logit results from estimating the specification with the GMS, Monday, and Tax variables 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 OLS GMS coefficient estimate for the first NASDAQ decile portfolio is equal to -0.007 with standard error of 0.010, while the GMS coefficient estimate for the tenth NASDAQ decile portfolio is equal to -0.05 with standard error of 0.016. The results for NYSE–AMEX–NASDAQ are qualitatively similar. The OLS GMS coefficient on the first decile turns out to be the smallest across deciles. The magnitude of the OLS regression coefficients increases, almsot monotonically, going from the first to the tenth decile. logit results qualitatively confirm the OLS findings. The precision of the GMS coefficient estimates is low for the first decile, and it increases as we move towards smaller cap stocks. Figure IV 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.

[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.

D. International Evidence

We run separate OLS time series regressions for the World index (World) and for the eight country indices[25] in our dataset using equation (3). Returns are regressed on a constant, a Monday dummy, a dummy variable for a tax-loss selling effect, and the GMS Index $PC_{d,t}^{GMS}$. In addition to OLS, we also run separate logistic regressions for each country index in our dataset. Finally, we run pooled time–series cross–section OLS and logit, and fixed effects least squares and linear probability models with and without the US indices. For all specifications, we report one-sided heteroskedasticity-robust White (1980) standard errors.

Panel A of Table VI and Figure V show a widespread GMS effect in stock returns around the world. Unusually high levels of geomagnetic activity have a negative and statistically significant effect on the following week's stock returns for the World, Canadian, German, British, Australian and New Zealander indices. On the contrary, the South African, Swedish and Japanese stock market indices do not seem to be affected by GMS.

The generally weaker results for the international indices compared to the results for the US might be due to several factors among others: i) shorter time series; ii) more noisy stock market indices; and iii) limited representation of a broad range of sectors. Hence, as Hirshleifer and Shumway (2003) do, we pull the international indices together to deal with these issues. Panels B and C of Table VI show that, by pulling the indices together, the effect of GMS on stock returns around the world is negative and strongly statistically significant.

Regarding other aspects of the estimation, we find that the Monday dummy and the tax-loss dummy are strongly statistically significant for most of the indices in our sample.

In summary, the empirical results of this section document a statistically and economically significant GMS effect in US and world stock returns.

[25]The foreign countries we consider are Canada (CAN), Germany (GER), United Kingdom (UK), Australia (AUS), New Zealand (NZ), South Africa (SA), Sweden (SWE) and Japan (JAP).

E. Trading Strategies

Figures III to V 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 to V 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[26] 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.[27] 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

[26]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.

[27]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.

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.[28] 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 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 for the US 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 US stock returns via Maximum likelihood. Finally, we allow for the possibility of a seasonal GMS effect in US stock returns, and we control for the October 1987 stock market crash and for major downturns in US market returns.

[28] 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.

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 calendar as well as behavioral and environmental variables. As in Table II and III, we run separate time series OLS regressions for the four US indices 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

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

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 New York city, 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 II and 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 wipe out the effect of the GMS variable on US stock market returns. Logistic regression results confirm our OLS findings.

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 the indices in our sample. Specifically, the SAD coefficient estimate is positive for all indices and, in some cases, also statistically significant. The Monday dummy and the tax-loss dummy continue to be highly statistically significant for all the US indices 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

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

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.

Table VIII displays our results. With the exception of some minor quantitative changes, the Maximum Likelihood results are very similar to the results reported above.[29] Log-likelihood values are reported at the bottom of the table. The coeffi-

[29]Results available from the authors show that the precision of the coefficient estimates increases

cients on the GMS variable remain strongly statistically significant. In summary, we still see largely significant effects due to GMS.

C. 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 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 variable, as measured by the Ap index. We found evidence of a weaker but non negligible GMS seasonal effect in US stock returns.[30]

Second, we controlled for the October 1987 stock market crash. For each US index, 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 US index, 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 non negligible GMS effect on stock market returns in the United States, even after controlling for the influence of other environmental

when we allow for a GARCH term in the mean equation. The magnitude of the coefficient estimates is virtually unchanged. Hence, after adjusting for risk in a CAPM framework, the GMS factor continues to be priced.

[30]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.

factors and well-known market seasonals. The World and several international stock market indices also 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. For the US, the GMS effect is similar across indices, ranging from -0.84 to -2.51 percent 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, while small cap stocks are 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 more pronounced for small cap stocks.[31]

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.

[31]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

In panel A, we report summary statistics of daily (continuously compounded) returns on the four US indices: NASDAQ, S&P 500, NYSE, and AMEX. In panel B, we report summary statistics of the returns on the NASDAQ (12/15/1972 – 12/29/2000) and NYSE–AMEX–NASDAQ (07/03/1962 – 12/29/00) size deciles. In panel C, we report summary statistics of the returns on the world index and on the eight international country indices. Indices are value-weighted. All returns are in percentage points per day and are denominated in local currency.

Panel A: US Indices

Country Period	Mean	Standard Deviation	Min	Max	Skewness	Kurtosis
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

Panel B: US Size Deciles (NASDAQ and NYSE–AMEX–NASDAQ)

Indices	Mean	Standard Deviation	Min	Max	Skewness	Kurtosis
NASDAQ-1	0.075	0.759	-8.320	6.750	-0.396	12.616
NYSE–AMEX–NASDAQ-1	0.073	0.768	-8.180	7.290	-0.284	12.330
NASDAQ-2	0.052	0.684	-8.330	3.860	-1.251	16.021
NYSE–AMEX–NASDAQ-2	0.057	0.737	-9.050	6.250	-0.867	14.198
NASDAQ-3	0.049	0.707	-8.860	5.910	-1.622	18.712
NYSE–AMEX–NASDAQ-3	0.048	0.754	-10.560	6.330	-1.215	17.927
NASDAQ-4	0.045	0.742	-10.010	6.250	-1.803	23.120
NYSE–AMEX–NASDAQ-4	0.050	0.758	-10.530	6.330	-1.298	18.241
NASDAQ-5	0.044	0.754	-9.890	7.760	-1.808	22.736
NYSE–AMEX–NASDAQ-5	0.048	0.779	-11.430	7.620	-1.266	19.877
NASDAQ-6	0.050	0.802	-10.290	7.520	-1.672	21.394
NYSE–AMEX–NASDAQ-6	0.050	0.790	-10.890	6.960	-1.169	17.351
NASDAQ-7	0.045	0.832	-10.280	6.480	-1.562	19.248
NYSE–AMEX–NASDAQ-7	0.050	0.804	-11.490	8.010	-1.064	17.534
NASDAQ-8	0.046	0.899	-10.140	7.850	-1.231	17.720
NYSE–AMEX–NASDAQ-8	0.051	0.796	-11.750	7.760	-0.983	16.748
NASDAQ-9	0.049	0.993	-10.900	9.660	-0.937	18.585
NYSE–AMEX–NASDAQ-9	0.051	0.810	-13.250	8.240	-0.945	18.612
NASDAQ-10	0.056	1.205	-12.050	11.580	-0.278	13.288
NYSE–AMEX–NASDAQ-10	0.048	0.884	-18.280	8.850	-0.961	27.268

Panel C: International Indices

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
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 1973/01/02 - 2001/12/12 (7283 obs.)	0.031	1.157	-13.710	7.288	-0.649	11.543

Table II
Controlling for GMS

For each index in our sample and for each GMS index, we report separate OLS and logistic regressions in Panel A. In panel B, we report pooled time-series cross-section OLS and logit, fixed effects least squares and linear probability model regression results. NYSE$_d$, NASDAQ$_d$, AMEX$_d$ and S&P500$_d$ refer to the regression of the NYSE, NASDAQ, AMEX and S&P500 return indices on a constant and the $PC_{d,t}^{GMS}$ respectively, while NYSE$_c$, NASDAQ$_c$, AMEX$_c$ and S&P500$_c$ refer to the regression of the NYSE, NASDAQ, AMEX and S&P500 return indices on a constant and the $PC_{c,t}^{GMS}$ respectively. 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.

Panel A: NYSE, NASDAQ, AMEX and S&P500

Index	NYSE$_d$	NYSE$_c$	NASDAQ$_d$	NASDAQ$_c$	AMEX$_d$	AMEX$_c$	S&P500$_d$	S&P500$_c$
OLS Results								
Intercept	0.035^{***} (0.008)	0.035^{***} (0.014)	0.008^{***} (0.013)	0.047^{***} (0.013)	0.032^{***} (0.008)	0.032^{***} (0.008)	0.030^{***} (0.008)	0.030^{***} (0.008)
Slope	-0.033^{***} (0.011)	-0.023^{***} (0.009)	-0.047^{***} (0.016)	-0.037^{***} (0.015)	-0.040^{***} (0.011)	-0.028^{***} (0.009)	-0.018^{**} (0.009)	-0.010 (0.008)
Logit Results								
Intercept	0.129^{***} (0.020)	0.129^{***} (0.020)	0.264^{***} (0.024)	0.264^{***} (0.024)	0.209^{***} (0.020)	0.209^{***} (0.020)	0.156^{***} (0.015)	0.156^{***} (0.015)
Slope	-0.069^{***} (0.027)	-0.067^{***} (0.024)	-0.069^{**} (0.031)	-0.058^{**} (0.028)	-0.105^{***} (0.027)	-0.078^{***} (0.024)	-0.027^{*} (0.019)	-0.023^{*} (0.017)

Panel B: NYSE, AMEX and NASDAQ

Pooled Time-Series Cross-Section OLS		
Using $PC_{d,t}^{GMS}$		Using $PC_{c,t}^{GMS}$
Intercept	0.037^{***} (0.006)	0.037^{***} (0.006)
Slope	-0.039^{***} (0.007)	-0.028^{***} (0.006)
Pooled Time-Series Cross-Section Logit		
Using $PC_{d,t}^{GMS}$		Using $PC_{c,t}^{GMS}$
Intercept	0.194^{***} (0.012)	0.194^{***} (0.012)
Slope	-0.080^{***} (0.016)	-0.066^{***} (0.014)
Fixed Effects Least Squares		
Using $PC_{d,t}^{GMS}$		Using $PC_{c,t}^{GMS}$
Intercept	0.037^{***} (0.006)	0.037^{***} (0.006)
Slope	-0.039^{***} (0.007)	-0.029^{***} (0.006)
Fixed Effects Linear Probability Model		
Using $PC_{d,t}^{GMS}$		Using $PC_{c,t}^{GMS}$
Intercept	0.548^{***} (0.003)	0.548^{***} (0.003)
Slope	-0.020^{***} (0.004)	-0.017^{***} (0.003)

Table III

Controlling for GMS and Calendar Effects

For each index in our sample, we report separate OLS and logistic regressions in Panel A. In panel B, we report pooled time-series cross-section OLS and logit, fixed effects least squares and linear probability model regression results. 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.

Panel A: NYSE, NASDAQ, AMEX and S&P500

Index	NYSE	NASDAQ	AMEX	S&P500
OLS Results				
Intercept	0.057*** (0.009)	0.090*** (0.014)	0.072*** (0.009)	0.064*** (0.009)
Monday	−0.115*** (0.024)	−0.235*** (0.034)	−0.235*** (0.023)	−0.181*** (0.022)
Tax	0.083 (0.066)	0.231*** (0.088)	0.361*** (0.067)	0.092** (0.051)
GMS	−0.033*** (0.011)	−0.048*** (0.015)	−0.040*** (0.011)	−0.018** (0.009)
Logit Results				
Intercept	0.171*** (0.023)	0.372*** (0.027)	0.310*** (0.023)	0.219*** (0.017)
Monday	−0.229*** (0.050)	−0.559*** (0.059)	−0.544*** (0.051)	−0.330*** (0.037)
Tax	0.253** (0.136)	0.430*** (0.166)	0.615*** (0.145)	0.142** (0.101)
GMS	−0.069*** (0.027)	−0.071** (0.031)	−0.107*** (0.031)	−0.027* (0.019)

Panel B: NYSE, AMEX and NASDAQ

Pooled Time-Series Cross-Section OLS	
Intercept	0.072^{***} (0.006)
Monday	-0.191^{***} (0.015)
Tax	0.224^{***} (0.042)
GMS	-0.039^{***} (0.007)
Pooled Time-Series Cross-Section Logit	
Intercept	0.275^{***} (0.014)
Monday	-0.432^{***} (0.031)
Tax	0.427^{***} (0.085)
GMS	-0.081^{***} (0.016)
Fixed Effects Least Squares	
Intercept	0.072^{***} (0.006)
Monday	-0.191^{***} (0.015)
Tax	0.224^{***} (0.042)
GMS	-0.040^{***} (0.007)
Fixed Effects Linear Probability Model	
Intercept	0.568^{***} (0.003)
Monday	-0.107^{***} (0.008)
Tax	-0.101^{***} (0.019)
GMS	-0.021^{***} (0.004)

Table IV

Economic Significance of the GMS Effect Based on Regression Results

This Table displays the average annual percentage return (last row) and the annual percentage return due to the different lags of D^{GMS} (rows 1 to 6) for each index. For each trading day, we determine the value of the GMS dummy variable and multiply it by that index's GMS variable estimate. Then we adjust the value to obtain an annualized percentage return. In the case of the rows for the annualized return due to the GMS variable, significance is based on robust standard errors associated with the underlying parameter estimates (not reported in the Table). In the case of the average return row, significance is based on standard errors for a mean daily return different from zero. One, two, and three asterisks denote significance at the 10 percent, 5 percent, and 1 percent levels respectively.

GMS Lags	NYSE	NASDAQ	AMEX	S&P500
D_{t-1}^{GMS}	$-1.20^{\star\star}$	$-1.67^{\star}$	$-1.53^{\star\star}$	$-2.10^{\star\star\star}$
D_{t-2}^{GMS}	$-1.24^{\star\star}$	-0.99	$-1.11^{\star}$	-0.58
D_{t-3}^{GMS}	-0.68	$-1.86^{\star\star}$	$-1.16^{\star\star}$	-0.42
D_{t-4}^{GMS}	-0.77	$-2.07^{\star\star}$	-0.70	-0.13
D_{t-5}^{GMS}	$-1.76^{\star\star\star}$	$-2.51^{\star\star}$	$-2.04^{\star\star\star}$	-0.76
D_{t-6}^{GMS}	$-1.40^{\star\star\star}$	$-1.60^{\star}$	$-2.40^{\star\star\star}$	$-0.84^{\star}$
Average Annual % Return	$9.19^{\star\star\star}$	$12.47^{\star\star\star}$	$8.40^{\star\star\star}$	$7.83^{\star\star\star}$

Table V

Returns on Large Cap vs. Small Cap Stocks

The table displays the OLS and logit GMS coefficient estimates for NASDAQ, and NYSE, AMEX and NASDAQ size deciles (1=large,...,10=small). In the regressions, we account for week-end and tax effects in stock returns. 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.

OLS Results			**Logit Results**		
Decile	NASDAQ	NYSE+AMEX+NASDAQ	Decile	NASDAQ	NYSE+AMEX+NASDAQ
1	-0.007 (0.010)	$-0.012^{\star}$ (0.009)	1	$-0.041^{\star}$ (0.030)	-0.027 (0.027)
2	$-0.013^{\star}$ (0.010)	$-0.017^{\star\star}$ (0.009)	2	$-0.050^{\star\star}$ (0.030)	$-0.046^{\star\star}$ (0.027)
3	$-0.023^{\star\star\star}$ (0.010)	$-0.020^{\star\star}$ (0.009)	3	$-0.089^{\star\star\star}$ (0.030)	$-0.081^{\star\star\star}$ (0.027)
4	$-0.021^{\star\star}$ (0.010)	$-0.026^{\star\star\star}$ (0.010)	4	$-0.055^{\star\star}$ (0.030)	$-0.093^{\star\star\star}$ (0.028)
5	$-0.024^{\star\star}$ (0.010)	$-0.020^{\star\star}$ (0.010)	5	$-0.081^{\star\star\star}$ (0.030)	$-0.062^{\star\star}$ (0.027)
6	$-0.025^{\star\star}$ (0.011)	$-0.023^{\star\star}$ (0.010)	6	$-0.047^{\star}$ (0.030)	$-0.052^{\star\star}$ (0.027)
7	$-0.029^{\star\star\star}$ (0.012)	$-0.032^{\star\star\star}$ (0.011)	7	$-0.090^{\star\star\star}$ (0.030)	$-0.090^{\star\star\star}$ (0.027)
8	$-0.037^{\star\star\star}$ (0.013)	$-0.033^{\star\star\star}$ (0.011)	8	$-0.061^{\star\star}$ (0.030)	$-0.070^{\star\star\star}$ (0.027)
9	$-0.044^{\star\star\star}$ (0.014)	$-0.034^{\star\star\star}$ (0.010)	9	$-0.090^{\star\star\star}$ (0.030)	$-0.049^{\star\star}$ (0.027)
10	$-0.050^{\star\star\star}$ (0.016)	$-0.033^{\star\star\star}$ (0.011)	10	$-0.079^{\star\star\star}$ (0.030)	$-0.074^{\star\star\star}$ (0.027)

Table VI

International Evidence

For each index in our sample, we report separate OLS and logistic regressions in Panel A. In panel B, we report pooled time-series cross-section OLS and logit, fixed effects least squares and linear probability model regression results without the US markets. In panel C, we report pooled time-series cross-section OLS and logit, fixed effects least squares and linear probability model regression results with the US markets (NYSE, AMEX, and NASDAQ). 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.

Panel A: World and Country Indices

Index	World	CAN	GER	UK	AUS	NZ	SA	SWE	JAP
OLS Results									
Intercept	0.025^{***} (0.008)	0.045^{***} (0.010)	0.048^{***} (0.015)	0.056^{***} (0.017)	0.037^{***} (0.015)	0.052^{***} (0.020)	0.079^{***} (0.017)	0.060^{***} (0.019)	0.043^{***} (0.010)
Monday		-0.121^{***} (0.024)	-0.112^{***} (0.037)	-0.113^{***} (0.039)	-0.033 (0.034)	-0.206^{***} (0.053)	-0.123^{***} (0.041)	-0.027 (0.048)	-0.040^{*} (0.028)
Tax		0.155^{**} (0.076)	0.250^{**} (0.111)	0.142^{*} (0.092)	0.141^{**} (0.074)	0.140 (0.138)	0.009 (0.105)	0.352^{***} (0.150)	0.099 (0.075)
GMS	-0.025^{***} (0.010)	-0.026^{**} (0.015)	0.002 (0.016)	-0.029^{**} (0.017)	-0.034^{**} (0.015)	-0.023 (0.024)	0.001 (0.020)	-0.020 (0.022)	-0.008 (0.012)
Logit Results									
Intercept	0.114^{***} (0.023)	0.200^{***} (0.025)	0.148^{***} (0.027)	0.171^{***} (0.034)	0.154^{***} (0.030)	0.115^{***} (0.044)	0.163^{***} (0.026)	0.215^{***} (0.066)	0.115^{***} (0.020)
Monday		-0.274^{***} (0.054)	-0.204^{***} (0.058)	-0.192^{***} (0.074)	-0.103^{*} (0.067)	-0.318^{***} (0.097)	-0.041 (0.058)	-0.101^{*} (0.071)	0.022 (0.043)
Tax		0.420^{***} (0.150)	0.207^{*} (0.157)	-0.051 (0.197)	0.265^{*} (0.181)	0.031 (0.260)	0.145 (0.155)	0.711^{***} (0.209)	0.0375^{***} (0.119)
GMS	-0.048^{**} (0.029)	-0.053^{**} (0.031)	-0.053^{**} (0.031)	-0.096^{***} (0.039)	-0.104^{***} (0.035)	-0.065^{*} (0.050)	0.006 (0.030)	-0.035 (0.038)	0.008 (0.023)

Panel B: Pooled Regressions Without the US

Pooled Time-Series Cross-Section OLS	
Intercept	0.051*** (0.005)
Monday	−0.086*** (0.013)
Tax	0.149*** (0.036)
GMS	−0.014*** (0.006)
Pooled Time-Series Cross-Section Logit	
Intercept	0.157*** (0.010)
Monday	−0.122*** (0.021)
Tax	0.285*** (0.059)
GMS	−0.037*** (0.011)
Fixed Effects Least Squares	
Intercept	0.051*** (0.005)
Monday	−0.086*** (0.013)
Tax	0.149*** (0.036)
GMS	−0.014*** (0.006)
Fixed Effects Linear Probability Model	
Intercept	0.539*** (0.002)
Monday	−0.030*** (0.005)
Tax	0.070*** (0.014)
GMS	−0.009*** (0.003)

Panel C: Pooled Regressions With the US

Pooled Time-Series Cross-Section OLS	
Intercept	0.058*** (0.004)
Monday	−0.121*** (0.010)
Tax	0.173*** (0.028)
GMS	−0.022*** (0.005)
Pooled Time-Series Cross-Section Logit	
Intercept	0.196*** (0.008)
Monday	−0.224*** (0.017)
Tax	0.330*** (0.048)
GMS	−0.051*** (0.009)
Fixed Effects Least Squares	
Intercept	0.058*** (0.004)
Monday	−0.121*** (0.010)
Tax	0.173*** (0.028)
GMS	−0.022*** (0.005)
Fixed Effects Linear Probability Model	
Intercept	0.549*** (0.002)
Monday	−0.056*** (0.004)
Tax	0.080*** (0.011)
GMS	−0.013*** (0.002)

Table VII

Controlling for GMS, Calendar, Environmental and Behavioral Effects

Returns on the NASDAQ, S&P500, AMEX, and NYSE 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.

Index	NYSE	NASDAQ	AMEX	S&P500
OLS Results				
Intercept	-0.002 (0.110)	-0.104 (0.145)	0.012 (0.106)	-0.095 (0.105)
Monday	-0.115^{***} (0.024)	-0.235^{***} (0.034)	-0.235^{***} (0.023)	-0.181^{***} (0.022)
Tax	0.052 (0.068)	0.187^{**} (0.092)	0.330^{***} (0.069)	0.079^{*} (0.052)
GMS	-0.032^{***} (0.011)	-0.046^{***} (0.016)	-0.040^{***} (0.011)	-0.016^{**} (0.009)
SAD	0.014 (0.016)	0.039^{**} (0.024)	0.012 (0.016)	0.031^{**} (0.015)
Cloud	0.108 (0.159)	0.299^{*} (0.209)	0.142 (0.154)	0.192 (0.152)
Prec	-0.001 (0.003)	-0.003 (0.004)	-0.003 (0.003)	-0.002 (0.003)
Temp	-0.000 (0.002)	0.002 (0.003)	-0.001^{**} (0.002)	0.003^{**} (0.002)
Logit Results				
Intercept	0.077 (0.244)	0.034 (0.279)	0.128 (0.246)	-0.019 (0.189)
Monday	-0.229^{***} (0.050)	-0.559^{***} (0.059)	-0.544^{***} (0.051)	-0.330^{***} (0.037)
Tax	0.187^{*} (0.141)	0.408^{***} (0.172)	0.519^{***} (0.150)	0.132 (0.105)
GMS	-0.067^{***} (0.027)	-0.072^{**} (0.031)	-0.110^{***} (0.027)	-0.024 (0.019)
SAD	0.034 (0.036)	0.038 (0.042)	0.020 (0.037)	0.047^{**} (0.027)
Cloud	0.190 (0.349)	0.650^{*} (0.399)	0.540^{*} (0.353)	0.315 (0.270)
Prec	-0.009^{*} (0.006)	-0.015^{**} (0.007)	-0.009^{*} (0.006)	-0.012^{**} (0.005)
Temp	-0.000 (0.004)	0.002 (0.005)	-0.006^{*} (0.004)	0.006^{**} (0.003)

Table VIII

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

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

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

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	0.111^{***} (0.009)	-0.014 (0.015)	0.099^{***} (0.007)	0.074^{***} (0.007)
β_{Monday}	-0.220^{***} (0.016)	-0.135^{***} (0.015)	-0.178^{***} (0.013)	-0.111^{***} (0.014)
β_{Tax}	0.264^{***} (0.043)	0.064^{**} (0.035)	0.313^{***} (0.032)	0.061^{**} (0.036)
β_{GMS}	-0.037^{***} (0.010)	-0.015^{**} (0.006)	-0.045^{***} (0.007)	-0.029^{***} (0.008)
δ	0.029^{***} (0.011)	-0.012^{*} (0.008)	0.132^{***} (0.020)	-0.024^{***} (0.007)
η	0.142^{***} (0.014)	0.107^{***} (0.016)	0.033^{*} (0.021)	0.110^{***} (0.008)
ν	0.739^{***} (0.018)	0.867^{***} (0.019)	0.255^{***} (0.050)	0.863^{***} (0.014)
ω	0.660^{***} (0.092)	0.715^{***} (0.128)	0.971^{***} (0.209)	0.722^{***} (0.141)
γ	0.996^{***} (0.001)	0.998^{***} (0.000)	0.991^{***} (0.002)	0.996^{***} (0.001)
ϕ	0.030^{***} (0.003)	0.030^{***} (0.003)	0.109^{***} (0.006)	0.048^{***} (0.004)
Log Likelihood	-8592.530	-22433.15	-9912.727	-10635.16

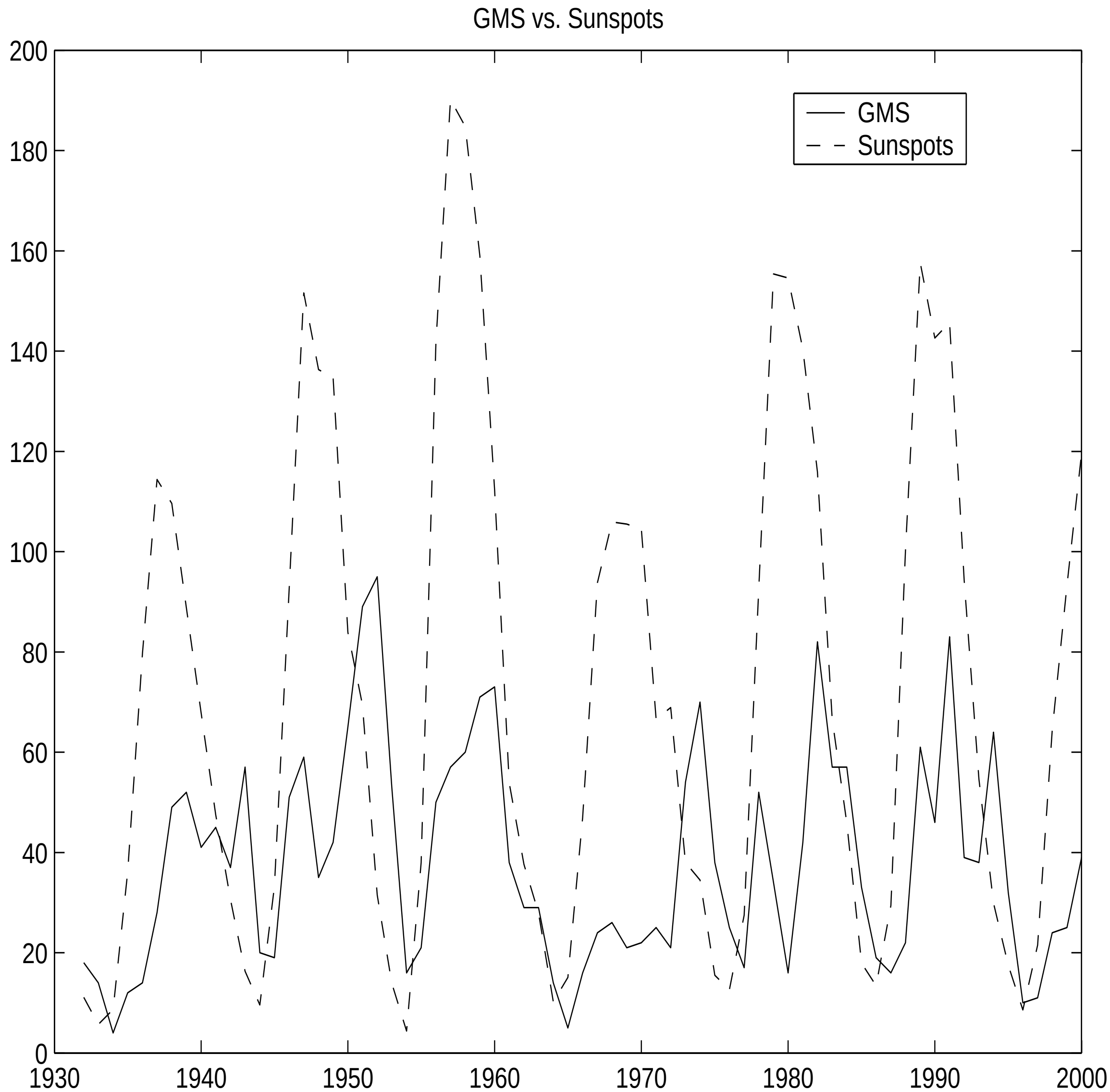

Figure I. Geomagnetic Storms vs. Sunspots. The figure displays the line graph of the average number of sunspots and geomagnetic storms (vertical axis) per year. Geomagnetic data can be downloaded from the following web site:
ftp : //ftp.ngdc.noaa.gov/STP/GEOMAGNETIC_DATA/INDICES/.

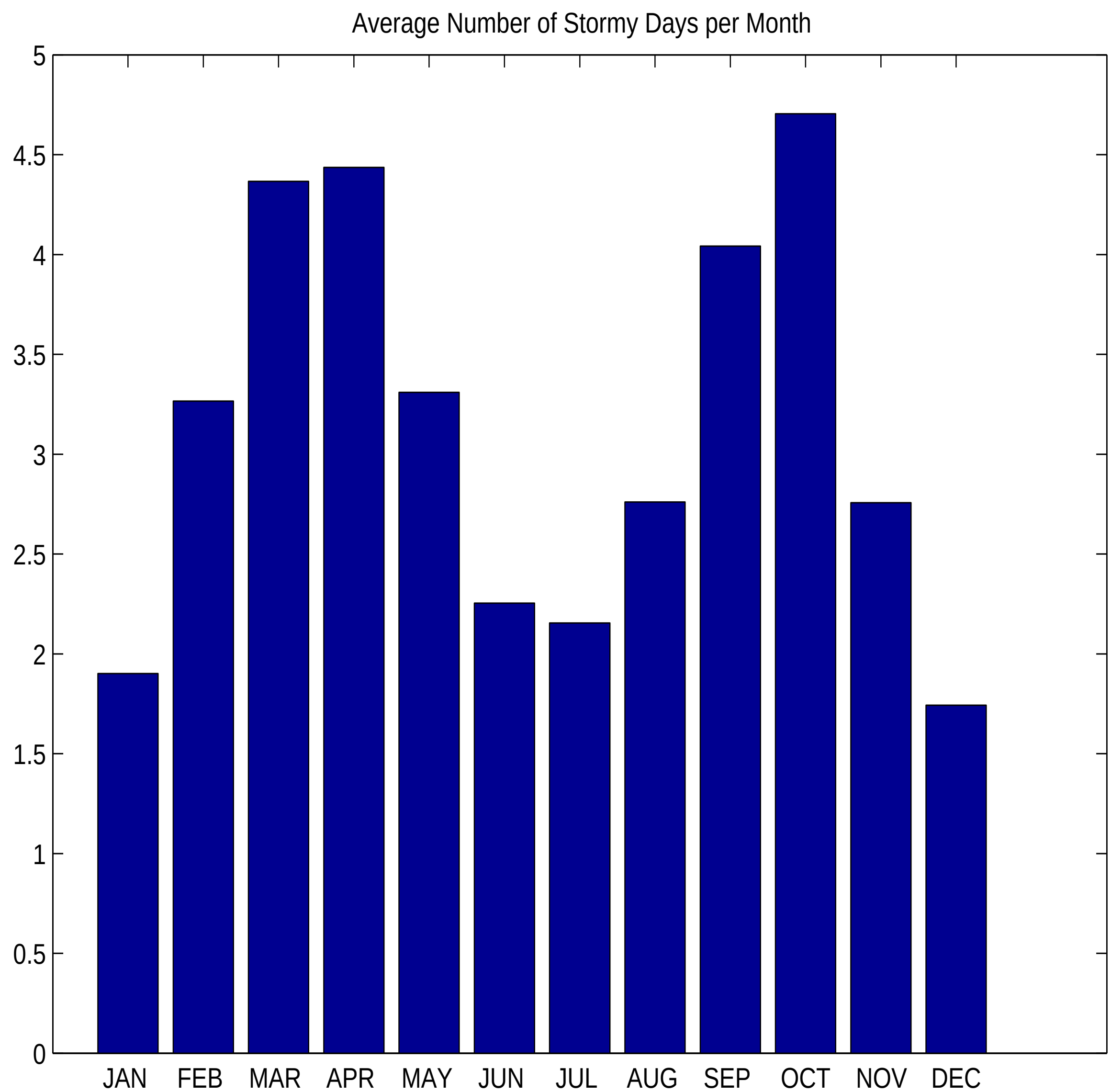

Figure II. Number of Storms per Month. The figure displays the bar graph of the average number of stormy days (vertical axis) per month using the Ap index. Daily Ap index data can be downloaded from the following web site:
ftp : //ftp.ngdc.noaa.gov/STP/GEOMAGNETIC_DATA/INDICES/KP_AP/.

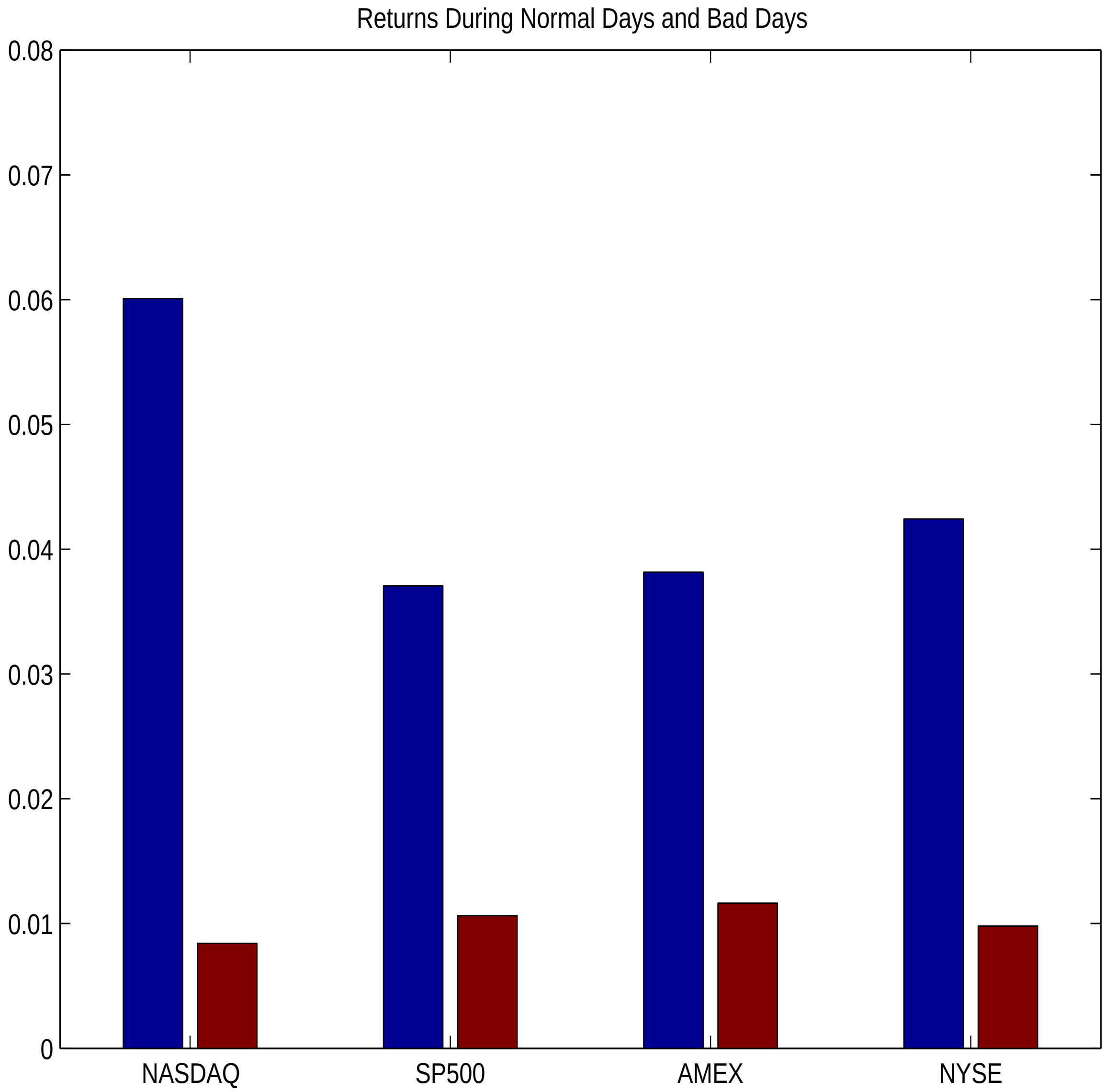

Figure III. US Stock Returns during Normal Days and Bad Days. The figure displays the bar graphs of the returns on the NASDAQ, S&P500, AMEX, and NYSE (NY) stock market indices during normal days (left column) and bad days (right column). We define the six calendar days after a storm as bad days and the remaining calendar days as normal days.

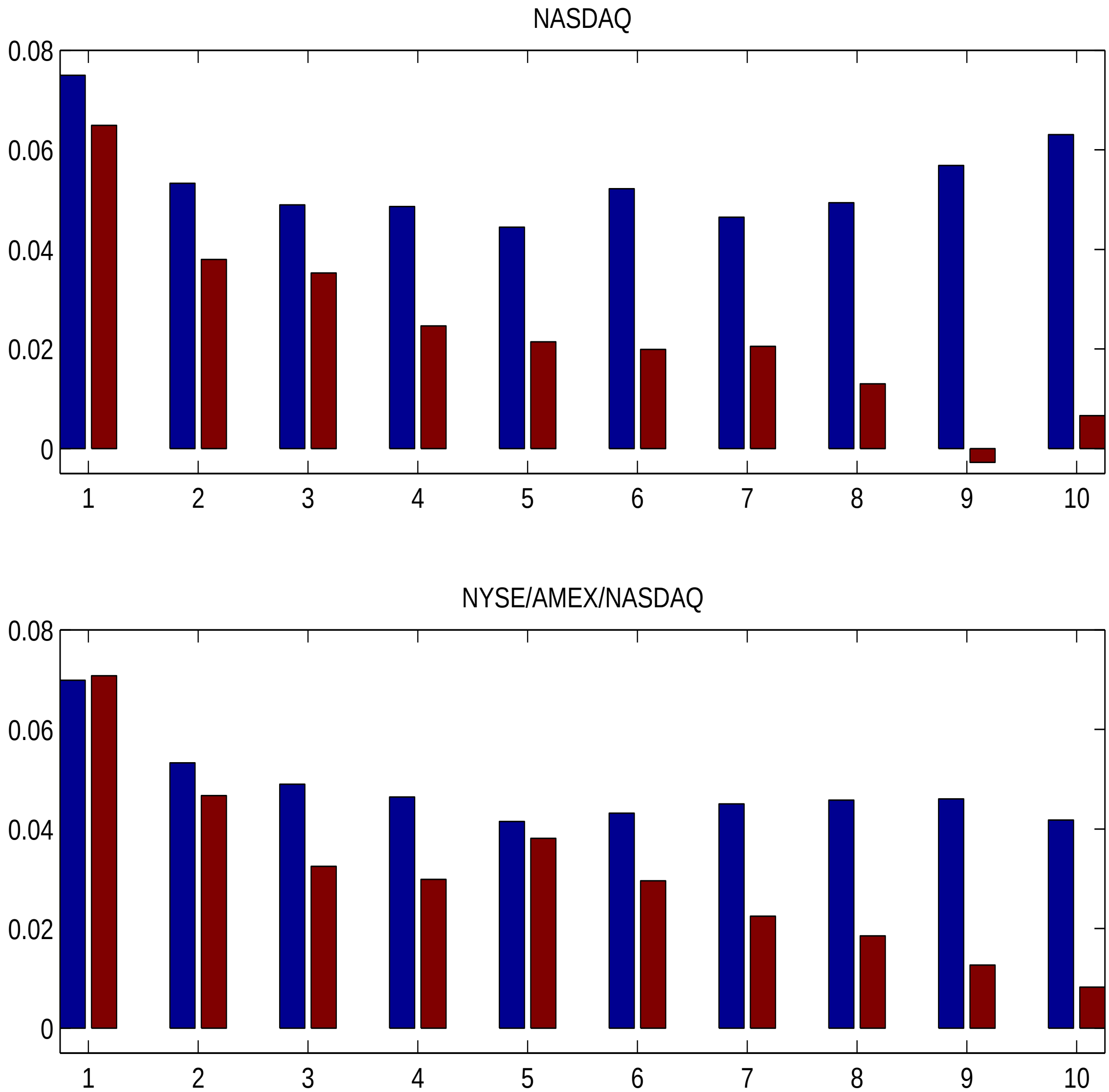

Figure IV. Returns during Normal Days and Bad Days for US Size Deciles. The figure displays the bar graphs of the returns on the NASDAQ and NYSE/AMEX/NASDAQ size deciles during normal days (left column) and bad days (right column). We define the six calendar days following a geomagnetic storm as bad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

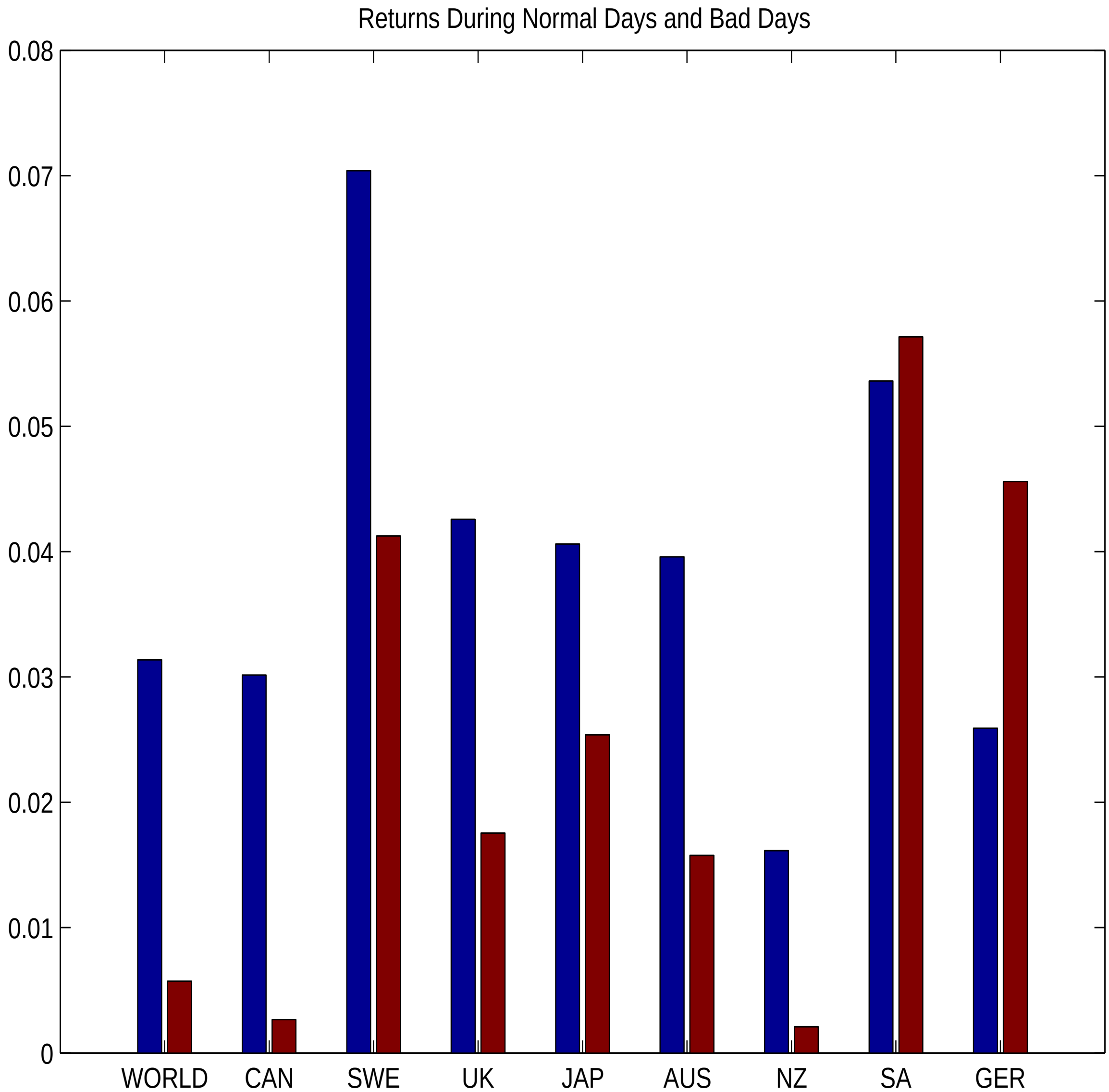

Figure V. International Stock Returns during Normal Days and Bad Days. The figure displays the bar graphs of the returns on the World, Canadian (CAN), Swedish (SWE), British (UK), Japanese (JAP), Australian (AUS), New Zealander (NZ), South African (SA), and German (GER) stock market indices during normal 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.