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Research Article

Effect of Ap-Index of Geomagnetic Activity on S&P 500 Stock Market Return

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Geomagnetic activity with global influence is an essential object of space weather research and is a significant link in the section of the solar wind-magnetospheric coupling process. Research so far provides strong evidence that geomagnetic activity affects stock investment decisions by influencing human health, mood, and human behaviours. Therefore, this research investigates the empirical association between geomagnetic activity and stock market return. Overall, we find that geomagnetic activity exerts a negative influence on the return of the US stock market. Further, market liquidity effectively magnifies the effect of geomagnetic activity. Inconsistent with previous literature, this effect is not mainly caused by the semiannual variation of geomagnetic activity. Our research contributes to the introduction of geomagnetic indices to financial economics studies on the impact of geomagnetic activity influence on stock market return.

1. Introduction

The geomagnetic field is formed by the superposition of different magnetic fields from various sources. When the corresponding disturbance of the geomagnetic field occurs, the geomagnetic activities form. These disturbances vary in length and intensity and significantly affect human activities in terms of economics. Since the 1960s, people have been aware of the critical influence of cosmic activity, especially geomagnetic activities, on human behaviour. Friedman et al. (1963) initially explored the relationship between human health and geomagnetic activity parameters [1]. We summarize the research progress on the correlation between geomagnetic activity and the stock market into three ways: geomagnetic activity and human behaviours; human behaviours and the stock market; geomagnetic activity and the stock market.

First, geophysics research has provided evidence of a relationship between geomagnetic activity and human behaviours. These human behaviours can be concluded into three aspects: the influence of geomagnetic activity on the body's mood and nervous system; geomagnetic activity on human diseases; and geomagnetic activity on birth or death rate. The occurrence of geomagnetic activity affects the body's emotional and nervous system [2–4]. Zakharov (2001) found that the effect is most marked during the recovery phase of geomagnetic storms and accompanied by the inhibition in the central nervous system [5]. According to Tarquini (1998), through influencing the activity of the pineal gland, geomagnetic activities cause imbalances and disruptions of the circadian rhythm of melatonin production [6], a factor that plays an important role in mood disturbances. Stoilova and Dimitrova (2008) examined blood pressure, heart rate, and electrocardiograms during perturbed and quiet days according to the Ap index; in particular, there was a clear tendency for changes in blood pressure during increased geomagnetic activity [7]. Mendoza (2010) studied that at middle and low latitudes there are biological consequences to the solar/geomagnetic activity coinciding [4], finding that geomagnetic perturbations cause gender differences, age differences, and myocardial infarctions (death or occurrence) influences.

Second, Economics and Psychology research also builds the relationship between human behaviours and the stock market, especially the correlation between mood and abnormal returns. Lerner et al. (2015) showed that mood affects economic decision making through a variety of pathways [8]. Shu (2010) showed that both equity and bill prices correlate positively with investor mood [9], with higher asset prices associated with better mood, and conversely, expected asset returns correlate negatively with investor mood. These findings suggested that investor mood is a vital factor in equilibrium asset prices and returns. Moreover, the relationship between human behaviours and the stock market also exists in other aspects, like physical health [10].

Based on the above literature, it is ready to connect the geomagnetic activity with the stock market indirectly. Instead, some research also builds the direct relationship between geomagnetic activity and the stock market. Krivelyova & Robotti (2003) demonstrated lower stock market returns during periods of high geomagnetic activity and provided an explanation with investment mood as a medicated variable [11]. Belkin (2013) also found the strong direct connection between long stagflation waves in the USA and super solar cycles, and the strong inverse connection between seasonal geomagnetic storms and economic cycles in the US and Russian economics [10]. Besides, some research focused on the effect of weather on the stock market, using geomagnetic storms as one of the variables [9, 12–14]. However, these papers focus on the effect of extreme or irregular geomagnetic activities. To explore the day-to-day counterpart, instead of dealing with extreme and rare events such as geomagnetic storms, this research explores causality between geomagnetic activity and the stock market by using monthly US stock market indices and monthly levels of geomagnetic indices, Ap. SAD (Seasonal Affective Disorder) for the potential semiannual variation will be used in order to test whether the semiannual variation is one underlying cause for the causality.

This paper also explores how the effect of geomagnetic varies considering variations under two conditions. On one hand, when considering the variations of geomagnetic activities, semiannual variation was one of the earliest recognized patterns in geomagnetic activity [15, 16]. The semiannual variation in geomagnetic activity appears as spring and fall maximums in long-term averages of the various indices of geomagnetic activity. Kamstra et al. (2003) suggested that, in the process of the earth's seasonal alternation, the daily light time in a particular region will be different, and the length of the day and night changes will affect the internal rhythm of the human body [17], thus affecting the trading behaviour of investors. Therefore, we explore whether the targeted causality also has a semiannual effect similar to the geomagnetic activity itself.

On the other hand, motivated by Lanfear et al. (2018), abnormal illiquidity is only able to account for a small fraction of the observed abnormal returns caused by extreme weather events [18]. We then explore whether, during day-to-day counterparts, liquidity can still have a significant influence on the correlation between geomagnetic activities and the stock market indices. We find that market liquidity is positively related to the geomagnetic effect on the stock market. This finding is consistent with Krivelyova & Robotti (2003); the geomagnetic storm's effect is more significantly stronger in markets in worldwide important and open economies [11].

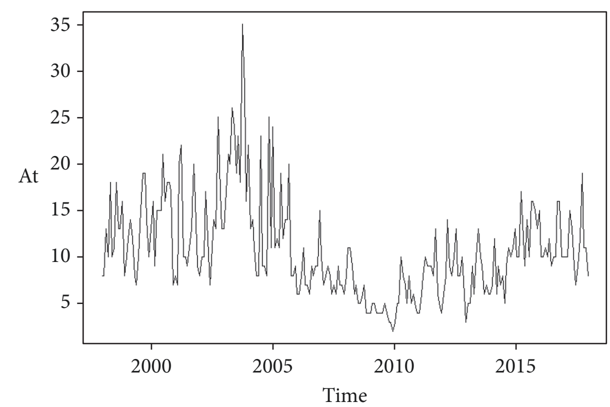

Figure 1: Overview of monthly DGD (1998-2017).

Our research implicates in two ways. First, by focusing on the liquidity and periodic output, this paper provides support for the two conditions. Second, we introduce a geomagnetic relationship to the financial economics literature. The rest of the paper is organized as follows. The data description and the methodology used for research questions are reported in Section 2. In Section 3, we present the results related to causality between geomagnetic activity and the stock market. In Section 4, we present the findings related to semiannual and liquidity variation. We conclude the whole paper in Section 5.

2. Materials and Methods

We use an empirical study for this research. The vast majority of empirical studies on daily geomagnetic data (DGD) use either the Ap or the Kp index to capture the intensity of the environmental magnetic field. In this paper, we choose the monthly Ap index as a proxy for DGD, named as DGD_t. The chosen period is from January 1998 to December 2017. Geomagnetic data for the Earth were obtained from the Space Weather Prediction Center, which is a part of the National Oceanic & Atmospheric Administration (NOAA). Figure 1 shows an overview of monthly DGD. Figure 2 shows an annual variation of the Ap index. As discussed above, there are significantly spring and fall maximums in long-term averages of this index.

We use S&P 500 as the index to describe the US stock market, named as SMI_t. The S&P 500 Index (formerly Standard & Poor's 500 Index) is a market-capitalization-weighted index of the 500 largest US publicly traded companies by market value. The index is widely regarded as the best single gauge of large-cap US equities. Monthly S&P 500 are obtained from Yahoo Finance. Figure 3 shows an overview of the monthly S&P 500. Figure 4 shows annually variation of S&P 500. Intuitively, the trend and seasonal changes of SMI_t and DGD_t are different.

2.1. Augmented Dickey-Fuller Test. Testing time series data for stationarity is a prerequisite for moving forward since the presence of unit roots would lead to the regression

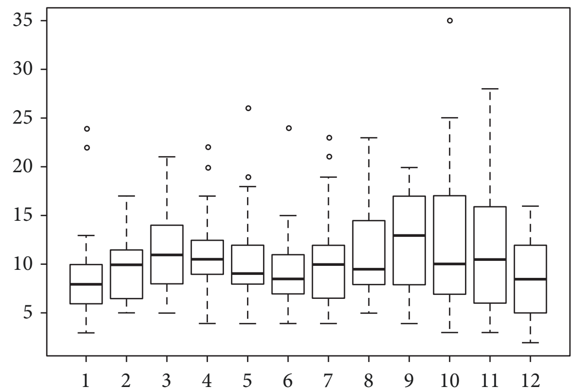

Figure 2: Annual variation of monthly DGD (1998-2017).

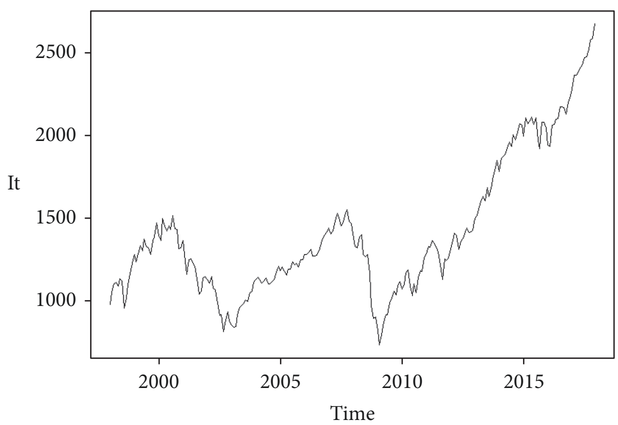

Figure 3: Overview of the monthly S&P 500 (1998-2017).

being spurious unless there is the existence of at least one cointegrating relationship. In order to check the stationarity of the variables that are considered in this study, we use the Augmented Dickey-Fuller (ADF) stationarity test to detect the possible existence of unit roots in the data set. The variables should ideally be stationary at either I(0) or their first difference forms, I(1). Once the variables are found to be stationary, the cointegration test is to be followed.

2.2. Engle-Granger Test. The most well-known test for cointegration, suggested by Engle and Granger (1987), is to run a static regression [19] (after first having verified that y_t and x_t both are I(1)) of $y_t = \theta x_t + e_t$ and $\hat{e}_t = y_t - \hat{\theta} x_t$, where x_t is one- or higher-dimensional. The asymptotic distribution of θ is not standard, but the test suggested by Engle and Granger was to estimate $\hat{\theta}$ by OLS and the test for unit roots in $\hat{e}_t$.

2.3. Granger Causality Test. According to cointegration analysis, when two variables are cointegrated, then there exists at least one direction of causality. Granger causality [20], introduced by Granger (1969), is one of the important matters that have been much studied in empirical macroeconomics and empirical finance. Only when the variables are cointegrated, it is possible to deduce that a long-run relationship exists

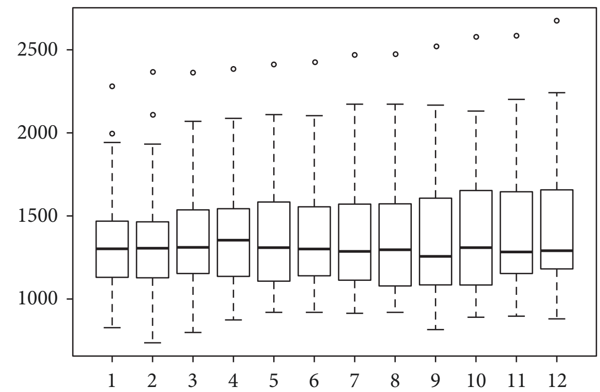

Figure 4: Annual variation of monthly S&P 500 (1998-2017).

between the nonstationary time series. When we take y and x as the variables of interest, then the Granger causality test (Granger (1969)) determines whether past values of y add to the explanation of current values of x as provided by the information in past values of x itself. If previous changes in y do not help explain current changes in x, then y does not Granger cause x. The equations are as follows:

$$y_t = \alpha + \sum_{i=1}^{t} \beta_i y_{t-i} + \varepsilon_{t,1} \tag{1}$$

$$y_t = \alpha + \sum_{i=1}^{t} \beta_i y_{t-i} + \sum_{j=1}^{t} \gamma_i x_{t-j} + \varepsilon_{t,2} \tag{2}$$

Similarly, we can examine if x Granger causes y to just be interchanging them and carrying out this process again. There could be four probable outcomes: (i) x Granger causes y; (ii) y Granger causes x; (iii) both x and y Granger cause the other; (iv) neither of the variables Granger causes the other. We consider the above set of equations for all possible pairs of (SMI_t, DGD_t) series in the group.

2.4. Regression. As shown in Table 1, there are some other variables which would be used in the following empirical tests. Specifically, ILLIQ is the measure of liquidity of the stock market. The bigger the ILLIQ is, the smaller the stock market liquidity is.

After Granger causality test, we use linear regression as a robust test for the relationship between geomagnetic activity and the stock market, as shown in (3). We predict that β_1 is significantly negative:

$$SMI_t = \beta_0 + \beta_1 DGD_t + \varepsilon_t \tag{3}$$

$$SMI_t = \beta_0 + \beta_1 DGD_t + YEAR + \varepsilon_t \tag{4}$$

To test seasonal variations in the targeted relationship, we consider the *SAD* index to represent this variation. In (5), *SAD* captures the effect of *DGD* varying semiannually, and e_t

Table 1: Variable Specifications.

Measure	Description
DGD	Monthly Geomagnetic activity index (Ap). The data source is Space Weather Prediction Center, a part of NOAA. Data period is Jan. 1998 – Dec. 2017.
SMI	Monthly S&P 500, popular US stock market indices. The data source is Yahoo Finance. Data period is Jan. 1998 – Dec. 2017.
SAD	Seasonal Affective Disorder index. Dummy variable. Variable equals to 1 if the set of indexes occurs in Jan., Feb., Mar., Nov. or Dec., and zero otherwise.
p_H	The monthly highest price in S&P 500.
p_L	The monthly lowest price in S&P 500.
VOLD	The stock trade-off volume among the 500 largest US publicly traded companies per month.
ILLIQ	The market illiquidity among the 500 largest US publicly traded companies per month. Compute the stocks' illiquidity as the ratio of dollar volume to the price difference. $\mathrm{ILLIQ}_t = (p_{H,t} - p_{L,t})/\mathrm{VOLD}_t * 10^{10}$.
YEAR	Period Dummy variable for years 1998 to 2017. For example, macroeconomic environment changes would happen year by year, and this index could control this kind of effect.

captures the remaining part. We predict that β_1 is significantly negative:

$$DGD_t = \alpha_0 + \alpha_1 SAD_t + e_t \tag{5}$$

$$SMI_t = \beta_0 + \beta_1 SAD_t + \beta_2 e_t + YEAR + \varepsilon_t \tag{6}$$

During a hurricane, assets with higher liquidity suffer more loss than assets with lower liquidity, such as gold [18]. Motivated by Amihud (2002), we consider the illiquidity index to represent this variation [21]. Note that ILLIQ represents the market illiquidity level per month. Therefore, for the third question, here we predict an adverse effect of this variable on the relationship between the geomagnetic index and stock market indices which is presented by (7). Some economic shocks may differentially affect the stock market with different degrees of reliance on geomagnetic activities. Therefore, interactions between *DGD* and *ILLIQ* on *SMI* variables are included to help control for any preexisting noises. β_3 is the coefficient of the interaction. We predict that this coefficient is significantly negative. To keep the comparability of β_1 in (3) and (7), motivated by Balli, Sørensen (2013), we further modify the model as (8), where $\overline{DGD_t}$, $\overline{ILLIQ_t}$ are the average value of the corresponding variables [22]:

$$\begin{aligned} SMI_t = {} & \beta_0 + \beta_1 DGD_t + \beta_2 ILLIQ_t \\ & + \beta_3 DGD_t * ILLIQ_t + YEAR + \varepsilon_t \end{aligned} \tag{7}$$

$$\begin{aligned} SMI_t = {} & \beta_0 + \beta_1 DGD_t + \beta_2 ILLIQ_t \\ & + \beta_3 \left(DGD_t - \overline{DGD_t} \right) \\ & * \left(ILLIQ_t - \overline{ILLIQ_t} \right) + YEAR + \varepsilon_t \end{aligned} \tag{8}$$

Table 2 shows the statistical summary of these variables used in the above equations. Table 3 shows the correlation matrix. The result shows a significantly negative relation between geomagnetic activity index and stock market indices as predicted. Also, we find a robust negative correlation which means that the market illiquidity varies with time. One explanation is that this variable is measured as monthly data. However, we further test the correlation between *ILLIQ* and month dummies and find no strong correlation (correlation = 0.01, p-value = 0.87). Then we rule out this possibility. Another explanation is the variance of the macroeconomic environment. For example, the promulgation of regulations and laws would have implications for the present and future years.

3. Causality between Geomagnetic Activity and the Stock Market

3.1. Main Test. The first question is whether geomagnetic activity is negatively related to the US stock market. For this problem, we use the Granger Causality Test to testify the causality between geomagnetic activity and the stock market and use linear regression as robustness for the magnitude of the effect.

Results from the ADF test are provided in Table 4. The results for the ADF unit root tests for variables at the primary level (non-first-order difference). As shown in the first two rows in Table 4, results are not stable. Then we further test whether SMI and DGD are cointegrated. The cointegration result of the primary level, as shown in the third row in Table 4, rejects the null hypothesis at 1% significant level. So, we can show that this regression is not spurious. The results from the ADF test confirm that both of the variables are stationary at their first differenced forms, and our following tests use the first-differenced data.

As two time-series variables are stationary and cointegrated, we continue the Granger Causality Test augmented with a lagged error correction term if the series are cointegrated. We use AIC and SC information law to choose the optimal lag length which equals 1. The p-value on the lagged explanatory variables of error correction indicates the significance of the short-run causal effects. Beginning with the short-run effects, we find that there are unidirectional causalities from DGD to SMI; in other words, SMI does not Granger cause DGD, but DGD Granger causes SMI. Additionally, we do the test in the case where lag order equals 2 and find a similar conclusion. This unidirectional

Table 2: Summary of Statistics.

	Mean	Std.Dev	Maximum	Minimum	Observations
DGD	10.76	5.23	35.00	2.00	240
SMI	1414.73	417.95	2673.61	735.09	240
p_H	1452.19	413.33	2694.97	832.98	240
p_L	1360.93	414.20	2605.52	666.79	240
VOLD($*10^{-10}$)	5.90	3.21	16.20	1.15	240
ILLIQ	22.63	20.49	109.15	4.2	240

Table 3: Correlation Matrix.

	DGD	SMI	SAD	ILLIQ	YEAR
DGD	1.00				
SMI	-0.13**	1.00			
SAD	-0.04	0.06	1.00		
ILLIQ	0.08*	-0.11	-0.01	1.00	
YEAR	-0.01	0.04	0.00	-0.71***	1.00

Note: ***, **, and * denote statistically significant at 1%, 5%, and 10% levels, respectively. See Table 1 for variable definitions.

Table 4: Augmented Dickey-Fuller (ADF) Test Results.

	Variable	Dickey-Fuller	Lag	p-value	Conclusion
Unit root test for primary level	SMI	-0.66	6	0.9731	Not Stationary
	DGD	-2.75	6	0.2618	Not Stationary
Cointegration test		-5.55	6	<0.01	Stationary
Unit root test for 1st differenced	SMI	-7.84	6	<0.01	Stationary
	DGD	-5.57	6	<0.01	Stationary

causality result provides statistical support for our primary prediction that geomagnetic activity is negatively related to the US stock market. Furthermore, geomagnetic activity has a unidirectional effect on the stock market.

3.2. Robustness. To testify the magnitude and direction of the targeted relationship, we also test the relation between geomagnetic activity and the stock market by linear regression. Table 6 reports the regression results for (3). Column (3) is without control variable year dummy, while column (4) is for regression with controls. Consistent with the causality results reported in Table 5, results in Table 6 are both significantly negative, suggesting that there is indeed an inverse relationship between geomagnetic activity and U.S. stock market (p-value < 0.05). Further, it is indicated that the effect of geomagnetic activity on the stock market is economically significant. The predicted possibility of an inverted market signal is 1.2‰. Comparing the results in column (3) and column (4), the control variable YEAR does not have an evident influence on the conclusion.

4. Additional Tests

4.1. Variation in Semiannual Periods. Based on the above results, we hold a further question of whether the targeted causality also has a semiannual variation similar to the geomagnetic activity itself. We use Two-Stage Least Squares (2SLS) Regression. In the first stage, we regress SAD on DGD and decompose DGD into two parts. One represents the variations in winter and summer, and the other is the remaining part (4). In the second stage, we regress the two parts on SMI. As shown in Table 7, we do not find significant results to support our second prediction (5). We find that the significant effect of DGD on SMI is mainly due to the remaining part without seasonal variations, other than the semiannual variation effect as predicted. To some extent, this is also consistent with Dowling, M., & Lucey (2008) [13]. Although they prefer to use seasonal affective disorder to explain changes in investors' mood, most of them do not find significant results. We also use month dummy variable (data in January equals 1, in February equals 2, . . ., and in December equals 12) or half year dummy variable (data in January–June equals 1 and in July–December equals 0) for the similar test; however, we do not find expected results either.

One explanation is that monthly aggregate data remove some difference among daily or smaller-unit data and cause too much noise. Another potential explanation is that the trend of increasing geomagnetic activity which removed seasonality effect is the primary cause of the targeted causality. Our results support the second explanation.

4.2. Variation in Liquidity. Furthermore, we explore whether the relationship between geomagnetic activity and the US

Table 5: Granger Causality Test Results.

Null Hypothesis	Lag	p-value	Conclusion
DGD does not Granger cause of SMI	1	0.0505	Causality significant at 10% level
SMI does not Granger cause of DGD	1	0.2012	No Causality
DGD does not Granger cause of SMI	2	0.0233	Causality significant at 5% level
SMI does not Granger cause of DGD	2	0.5333	No Causality

Table 6: Regression Results for Equ. (3) and (4).

	SMI			
	(3)		(4)	
	Coefficient	p-value	Coefficient	p-value
Intercept	0.0000	1.000	-0.6509	0.5026
DGD	-0.0012	0.0480**	-0.0012	0.0489**
YEAR	No		Yes	
Adj. R-squared	0.0122		0.0099	
Obs.	240		240	

Table 7: Regression Results for Equ. (5), (6) and (8).

	DGD		SMI		SMI	
	(5)		(6)		(8)	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Intercept	0.1476	0.7020	-0.0023	0.5216	0.0035	0.3939
SAD	-0.3543	0.5530	0.0056	0.3263		
e			-0.0012	0.0523*		
DGD					-0.0007	0.1923
ILLIQ					-0.0001	0.3811
DGD*ILLIQ					-0.0001	0.0009***
Adj. R-squared	-0.0027		0.0115		0.0585	
Obs.	240		240		240	

stock market would be moderated by market liquidity. As mentioned before, ILLIQ is the inverse index for market liquidity; in other words, the bigger the ILLIQ is, the smaller the stock market liquidity is. Therefore, the coefficient of DGD*ILLIQ on SMI in Table 7 column (6) is negative which means that market liquidity is positively related to the geomagnetic effect on the stock market as predicted. This finding is also consistent with the findings in Lanfear et al. (2018) [18].

One potential explanation for the results about variation in market liquidity is that they are influenced by geomagnetic waves subconsciously or unconsciously; investors suffer bad moods which lead to a preference for more meaningful decisions and an increase in risk aversion [23, 24]. Meanwhile, market liquidity would magnify this kind of risk estimation which causes a higher premium on equity with higher liquidity.

What is more, it is evident that after adding the market illiquidity, R-squared has increased from 1.22% in Table 6 column (3) to 5.85% in Table 7 column (6) and the significance of regression results has been strengthened simultaneously. This change provides evidence for our prediction that monthly aggregate data covered up some variations in the daily level. However, the fact that with so much noise, the relationship between geomagnetic activity and the stock market is still found further verifies our primary assumption. Because of the high correlation between YEAR and ILLIQ, we also do robust tests to rule out the multicollinear problem (κ=370.25, VIF=2.03).

In conclusion, we explore our research questions by examining monthly geomagnetic data (DGD) Ap indices and S&P stock market indices from 1998 to 2017. Our primary analysis tests whether the geomagnetic activity is related to the stock market. There is an inverse connection between geomagnetic activity and the stock market in the US. This increase is economically significant. The predicted probability of issuing an adverse stock signal is 1.2‰. Furthermore, the relationship could be evolved into a causality. The Granger Causality Test is valid for both lag orders 1 and 2. Together, the results are consistent with previous research that geomagnetic activity and stock market are related indirectly or directly. One explanation for our findings is that annual or semiannual variations caused by geomagnetic activity affect investors' mood unconsciously or subconsciously, which leads to the waves in the stock market.

5. Conclusions

Using monthly-based geomagnetic indices and US stock market indices for the recent 20 years, we find compelling evidence supporting a causal relation between geomagnetic activity and stock return. First, supported by the results from the Granger Causality Test, geomagnetic activity is negatively related to the US stock market. Secondly, by regressing SAD on DGD and decomposing DGD, the seasonal variations of DGD on SMI are not directly supported, although the results represent the variations in winter and summer. At last, this research finds that market liquidity is positively related to the geomagnetic effect. To dig out more explanations for the influence of geomagnetic activity on the stock market, we view the potential relation between geomagnetic activity and behaviour finance as an avenue for future research.

This research offers several contributions. On the one hand, we introduce a geomagnetic relationship to the financial economics literature. Instead of dealing with extreme events such as geomagnetic storms, this research avoids the influence of virtual prediction on a strong result by exploring the causality effectiveness of monthly Ap index on the monthly US stock index. We view the potential relation between geomagnetic activity and behaviour finance as an avenue for future research. On the other hand, we contribute to existing research in financial economics examining whether geomagnetic activity pessimism impacts stock returns. Further, we explore how the effect of geomagnetic varies under two conditions which are (1) periodic effect of geomagnetic activities on the stock market and (2) liquidity effect on the correlation between Ap stock market indices. By focusing on the illiquidity and periodic output, this paper provides compelling support for the two conditions and reinforces existing studies.

This relationship and our findings should be of interest to the broader literature studying the geomagnetic activity on capital market effects of limited attention and also be of interest to study the geomagnetic activity effect on stock market behaviour. The geomagnetic effect on human investment behaviour will be discussed in future study.

Data Availability

The geomagnetic index data and US stock market index data used to support the findings of this study are included in the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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