Will Stock Rise on Valentine's Day?

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Abstract

This study is a pioneer in academic literature to investigate the relationship between Valentine's Day and stock market returns of major economies around the world. The findings indicate that stock returns are higher on the days when Valentine's Day is approaching than on other days for most cases, showing "the Valentine Effect" in the stock market. Specific control variables for Valentine's Day are also introduced to eliminate the potential influence of other effects. Unlike other holiday effects in previous literature, the Valentine's Day Effect cannot be explained by many conventional theories, such as tax-loss selling and the inventory adjustment hypothesis.

Keywords: Valentine Effect; Tax-loss Selling Hypothesis; Inventory Adjustment Hypothesis.

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1 Introduction

The belief that Valentine's Day is associated with emotion fluctuation has prevailed anecdotally and empirically in the literature of psychology and business marketing. Valentine's Day was named after a Christian martyr and dates back to the 5^{th} century. It is celebrated on February 14 each year and is recognized as a significant cultural and commercial celebration of love and romance. It is also found that this occasion is associated with extreme emotions, and commercialism contributes to people's strong feelings and experiences, thus generating love or hate, which might be exhibited in stock markets (Morse and Neuberg 2004; Close and Zinkhan 2006).

To date, there has been considerable quantities of empirical research identifying different kinds of calendar effects in stock markets. A well-known calendar anomaly is the holiday effect, which concerns abnormal returns on the day preceding a holiday. Such anomalies appear to be in conflict with the weak-form efficient market hypothesis (EMH), in which historical prices or return sequences cannot be used as the basis of marginally profitable trading rules (Fama 1970). As such, the existence of the holiday effect has significant theoretical implications. In addition, if the holiday effect exists, investors may make profits by constructing specialized trading strategies based on this effect.

This study is inspired by a psychological hypothesis. In this paper, the Valentine Effect is assumed to be a subset of the larger category of calendar and seasonal effects that depict abnormal stock returns and volatility during the week, month, or year. However, this assumption has been deemed to be at odds with previous research on other calendar anomalies, including the holiday closings (*public holiday effect*) (Ariel 1990), seasonal affective disorder (*week 44 effect*) (Levy and Yagil 2012), and window dressing (*month of the year effect*) (Rozeff and Kinney Jr 1976; Lakonishok and Smidt 1988). Since Valentine's Day is not recognized as a public holiday in any country, and stock markets are not closed. Conventional explanations for holiday effects, such as tax-loss selling and the inventory adjustment hypothesis, are hence not applicable to this special occasion. The psychological aspects of investors' behavior tend to offer the most promising explanation for this effect, which is against the main assumption of *rational behavior* in traditional economics. Substantial research evidence suggests that there is a relationship between psychological aspects and behavioral decisions in individual economies. For example, Gardner (1985) found that moods play a significant role in retail consumer behavior. For stock markets, empirical evidence on the Moon effect show how investors' moods and the extent of their aggressiveness differ during the moon phase and influence their stock market performance (Brahmana et al. 2014). In behavioral finance, some documented evidence also discussed the relationship between moods and investment decisions (See inter alia, Coval and Shumway 2005; Ben-David and Hirshleifer 2012). Valentine's Day, the day when love is in the air, is likely to have a significant impact on the sentiment of investors, suggesting that investors' behavior might be affected such that capital is invested in or withdrawn from a certain stock, which could generate a noteworthy impact on the whole equity market.

To investigate the relation between Valentine's Day and stock returns, this study first examines the largest stock market in the world, the US stock market, by using the Dow Jones Industrial Average. In this paper, an econometric model combining an autoregressive moving average (ARMA) model and a generalized autoregressive conditional heteroscedasticity (GARCH) model is estimated to test the abnormal pattern of the Valentine Effect. Dummy variables for Valentine's Day are introduced to the model, and different control variables are added in sequence in order to avoid other calendar-related anomalies. The findings indicate that the US stock returns are significantly higher when Valentine's Day is approaching (three days before Valentine's Day and on Valentine's Day). To control for other anomalies, the regression is run with different dummy variables, such as those corresponding to the Monday effect, the Full-moon effect, and the holiday effect. The Valentine Effect persists after controlling for these calendar effects. For robustness tests, this study replaces the Dow Jones Industrial Average with another important US stock market index, Standard & Poor's 500 Index. The estimated coefficient of the Valentine Effect still remains statistically significant.

To further confirm whether this Valentine Effect is a global phenomenon, the same analysis is performed on other global stock markets, which include major stock indices in the world (the UK, Germany, France, Japan, Hong Kong, and China). A similar Valentine Effect is found in the UK, France, and China. It is noteworthy that China exhibits the most profound effect (0.72), which is followed by France (0.18) and the UK (0.14). Given the unexpected performance of China's stock market returns, additional examinations are administered by introducing specific dummy variables and separating the Valentine dummy variable. The estimated Valentine Effect still shows similar movement after eliminating different potential effects.

This paper examines whether Valentine's Day, which is a stimulus of investor behavior, has an effect on stock markets and how it influences market returns. This study distinguishes itself from previous literature in three ways. Firstly, unlike prior research on extensive holiday effects, this study focuses specifically on a single celebration, Valentine's Day, which is not a public holiday in any country. Secondly, while many other studies which generally use the classic econometric model, such as the ordinary least squares (OLS) method (Geweke and Porter-Hudak 1983), this study, however, applies the ARMA-GARCH model (Bollerslev 1986), using different samples from 1 January 1990 to 1 March 2019. Such a model can deal with autocorrelation and time-varying variance in the sample data, which appears to be a better tool in this research. Thirdly, this study introduces control variables to eliminate the potential inference of other calendar effects, such as the *Monday effect* (Jaffe et al. 1989) and the *Full-moon effect* (Yuan et al. 2006).

The remaining research is organized as follows. Section 2 provides a review of the literature. The data and the econometric model used in this study are introduced in Section 3 and Section 4 respectively. Results are shown in Section 5. Finally, Section 6 concludes the paper.

2 Literature Review

Numerous studies have been conducted to explore the abnormal patterns in stock returns, which appear to challenge the weak form efficient market hypothesis. Early literature put forward the definition of the "holiday effect", which refers to irregular positive stock returns reported on days preceding exchange holidays (Fields 1934). The results of that investigation, which measures the extent of the preholiday-covering movement, afford a reasonable basis for generalization about short selling for the period before 1931. According to daily stock returns on the Dow Jones Industrial Average (DJIA) from 1897 to 1965, the average returns for the US stock market on pre-holidays were approximately 23 times higher than those on other trading days (Lakonishok and Smidt 1988).[2] Ariel (1990) found large positive returns accruing to stocks on pre-holiday trading days in the US stock market and further examined the hourly returns and the closing bids to confirm the time point. The study covers eight holidays, namely New Year's Day, President's Day, Good Friday, Memorial Day, Fourth of July, Labor Day, Thanksgiving and Christmas.

The holiday effect has been shown to be robust across international markets. Kim and Park (1994) examined the pre-holiday effect in several markets, finding evidence of this effect in the stock markets of the US, the UK and Japan. Their work indicates that the holiday effect is not driven by institutional arrangements, since the effect remains persistent across countries.

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[2] Lakonishok and Smidt classify days as preholiday, postholiday, or regular (neither) without regard to the day of the week. The empirical result shows that the average preholiday rate of return is 0.220 percent for the whole sample, compared with the regular daily rate of return of 0.0094 percent per day.

Institutional factors such as trading methods, clearing mechanisms and bid-ask spreads cannot explain the existence of such an effect because these factors vary across countries. Some perspectives from the behavior of the Israeli (Lauterbach and Ungar 1992) suggest the existence of significantly higher post-holiday returns but only slightly higher pre-holiday returns in the Tel Aviv Stock Exchange. Chong et al. (2005) argued that pre-holiday effects have declined in the major international markets of the US, the UK, and Hong Kong, and it is only statistically significant for the US until the late 1990s.

In addition to the holiday effect, there is substantial evidence showing daily, weekly, and monthly return patterns in academic literature. Empirical studies have documented the existence of different stock returns processes on different week- days, and the Monday effect is the most frequently mentioned one among these studies. Using the Standard and Poor's Composite Stock Index, Cross (1973) found that the mean returns on Mondays are lower than those on other weekdays in the US markets. Smirlock and Starks (1986) examined the day-of-the-week effect and intraday effects using hourly data of stock returns for the Dow Jones Industrial Average. In their study, the sample period is divided into several subperiods, and the return from the Friday close to the Monday open was positive from 1963 to 1968, while it turned to be negative over the period from 1968 to 1974; and for the post-1974 period, the non-trading weekend effect characterized by abnormal returns from the Friday close to the Monday open disappeared. It indicates that the intraday effect may not be stable.

As for weekly frequency, Levy and Yagil (2012) examined the weekly rates of return from the stock indices of 20 countries, including America, Europe, Asia, Africa, and Australia. The result shows that Week 44 was positive in 19 out of the 20 countries in the sample; and among which 18 of them are statistically significant at least at the 10% level.[3] In contrast to Week 44, Week 43 was negative at the 10% significance level in 19 out of 20 countries.

Comparing different monthly rates of return on the New York Stock Exchange from 1904 to 1974, the study reports that the January stock returns have a significantly higher performance relative to other months of the year (Rozeff and Kinney Jr 1976). The May-to-October effect is classified into monthly anomalies. It indicates that stock returns are significantly lower during the May-October period than during the rest of the year and shows that most investors sell in May in 36 of the 37 countries in their sample, especially in European countries (Bouman and Jacobsen 2002; Jacobsen and Marquering 2008). There is also another turn-of-the-month effect, the October effect. Cadsby (1989) finds that average returns in October are significantly lower than those in other months for an equally weighted index of the New York Stock Exchange from 1963 to 1985. However, recent studies have found that the effect disappears gradually. For example, Szakmary and Kiefer (2004) examined the S&P 500 Index and their results suggest that there are no abnormal movements for these monthly effects.

A range of explanations have been proposed for these calendar anomalies. The day-of-the-week effect is attributed to time zones in Condoyanni (1987)'s paper, which examines the US stock market and six other national capital markets, namely Sydney, Toronto, London, Tokyo, Paris, and Singapore. They concluded that time zones set boundaries to the speed of reaction, at least as reflected in changes in general stock indices. The "week 44 effect" mentioned above is

[3] Here, the 44^{th} week specifically refers to the period from October 29 to November 4.

traced to investors' moods, in particular, the seasonal affective disorder (SAD), a condition where shorter hours of daylight have a negative impact on investors' sentiment, which induces further variation in their investment decisions (Kamstra et al. 2003). Tax-loss selling (Branch 1977) and institutional investor window dressing (Lakonishok and Smidt 1988) are two main explanations of the January effect.

However, the existence of the holiday effect is still hardly explained. For instance, one of the rational explanations, the inventory adjustment hypothesis, cannot be backed up in advanced emerging markets because they lack institutional ownership (Pettengill 1989), and it is not applicable to non-public holidays, like the Valentine's Day in this study. Therefore, some studies argue that such holiday effects can be due to mood behavior. Specifically, Fabozzi et al. (1994) indicated that the effect of cheered investor mood around holidays has a positive impact on future market returns in light of higher trading volumes around exchange-open holidays. The extensive literature proposes multiple explanations for various calendar effects in stock markets;

a single specific holiday, especially celebrations that are not public holidays in any countries.

Furthermore, most of the studies generally use the OLS method, which is widely used to estimate the parameters of a linear regression model but requires strict assumptions about data characteristics, such as homoscedasticity and no autocorrelation. In reality, particularly for financial returns, there are some stylized facts (Cont 2001) that the OLS model is not able to capture, specifically leptokurtosis and volatility clustering. As such, running an OLS regression may give a spurious result. In view of this, we adopt a GARCH type model to examine the Valentine Effect in stock markets, as GARCH models are able to model stock returns displaying volatility clustering.

Given the extensive documentation of the correlation between holiday effects and investor behaviors, the hypothesis in this study is that investors may value financial assets *higher* during Valentine's Day than other trading days.

This paper is the first to link Valentine's Day alone to stock returns. Gilbert and Karahalios (2010) derived a quantitative measure of aggregate anxiety and worry from weblogs in the US, which is named as the Anxiety Index. They found that the Anxiety Index has a blip coinciding with Valentine's Day. Some more recent studies have quantified sentiments by using data from different social media platforms, like Facebook and Twitter, and examined the relation between such sentiment indices and the stock market performance (Siganos et al. 2017). Most of them give a rather sketchy depiction of Valentine's Day. All in all, their studies are concurrent with and independent of this study. The findings of this paper may provide a more detailed discussion about the Valentine Effect, and their findings complement this study in terms of persuasive explanations.

3 Data

This research uses eight stock market indices to examine the stock returns and volatility behaviors around the time of Valentine's Day. The daily stock prices of these stock market indices, denominated in local currencies, are obtained from *Yahoo Finance* using *Python*. These indices are the Dow Jones Industrial Average (US), FTSE 100 Index (UK), DAX Performance Index (Germany), CAC 40 Index (France), Nikkei 225 Index (Japan), Hang Seng Index (Hong Kong), and Shanghai Composite Index (China). For robustness purposes, another important index, S&P 500 Index, is employed to investigate the US stock market. The current study tends to examine *returns* rather than *prices*, and the prices used in this study are *adjusted closing prices*, which are often used when examining historical returns.[4] The stock market returns in this study are calculated as the natural logarithm of the adjusted closing price relative to successive closing price.[5] This paper covers a more recent sample period, which is from 1 January 1990 to 1 March 2019. During this period, the stock return experienced 30 Valentine's Days, providing stronger empirical evidence.

To ensure that the data is usable, this paper first employs the augmented Dickey-Fuller (ADF) tests with intercept and with intercept and trend (Dickey and Fuller 1979) for these eight stock return series. The augmented Dickey-Fuller statistic tests the stationarity of the time series, which is a negative number. More

[4] As *Investopedia* defined, adjusted closing price amends a stock's closing price to accurately reflect that stock's value after accounting for any corporate actions. See more details about adjusted closing price in $https://www.investopedia.com/terms/a/adjusted_closing_price.asp$

[5] $R_t = (lnP_t - lnP_{t-1}) \times 100$

specifically, the more negative it is, the more likely the null hypothesis will be rejected. The results are reported in Table 1, including the t-statistics and p-values. From the table, it is found that the null hypothesis of a unit root is rejected at the 1% significance level for all cases. In other words, all the data used in this study are stationary.

Table 1: Unit Root Test

	ADF T-stat (with intercept)	ADF T-stat (with intercept and trend)
US	-64.516	-64.5126
	(0.0001)***	(0.0000)***
UK	-63.6356	-63.6354
	(0.0001)***	(0.0000)***
Germany	-62.5978	-62.5937
	(0.0001)***	(0.0000)***
France	-62.7309	-62.728
	(0.0001)***	(0.0000)***
Japan	-62.7809	-62.8185
	(0.0001)***	(0.0000)***
Hong Kong	-60.2409	-60.2506
	(0.0001)***	(0.0000)***
China	-55.8228	-55.8561
	(0.0001)***	(0.0000)***
S&P 500	-64.5683	-64.5649
	(0.0001)***	(0.0000)***

Robust standard errors in parentheses:
*** represents $p<0.01$, ** represents $p<0.05$, * represents $p<0.1$

Table 2 summarizes the descriptive statistics for the daily returns for these stock market indexes. It covers the mean, standard deviation, skewness, and kurtosis for each of the return series. Moreover, Jarque-Bera statistics and the ARCH-LM test statistics are also provided. As can be seen in Table 2, except for Japan, all markets had positive mean returns during the period. Among these indexes, China had the highest mean returns (0.04%), followed by the US (0.030%), whereas Japan had the lowest mean returns (−0.008%) during this sample period.

Of these return series, the standard deviation is found to be the highest in China (2.2838%), and the lowest one is the US (1.0588%). Apart from China, the skewness of all daily returns is negative, indicating that there is a greater possibility for a decrease than increase in these stock markets. The kurtosis for all return series is more than three, which suggests fat-tailed distributions. The Jarque-Bera test (Dickey and Fuller 1979) is a goodness-of-fit test determining whether the sample time series have skewness and kurtosis matching that of a normal distribution.[6] The reported results in Table 2 are smaller than the 1% level of significance for all return series, in other words, they all reject the null hypothesis of normal distribution. This result is consistent with the Q-Q (quantile-quantile) plots in Figure 3 (see Appendix).

Table 2: Descriptive Statistics

	Observations	Mean(%)	Std.Dev.(%)	Skewness	Kurtosis	Jarque-Bera	ARCH-LM test
US	7333	0.0303	1.0593	-0.1858	8.1541	20325.7205	1967.8452
						(0.0000)****	(0.0000)***
UK	7355	0.0145	1.092	-0.1241	6.0670	11280.9639	1928.5476
						(0.0000)***	(0.0000)***
Germany	7369	0.0252	1.4044	-0.1223	4.6939	6771.7521	1418.8805
						(0.0000)***	(0.0000)***
France	7334	0.0143	1.3660	-0.0694	4.6870	6707.2935	1334.3136
						(0.0000)***	(0.0000)***
Japan	7166	-0.0081	1.5102	-0.1477	5.4132	8760.5557	1308.1543
						(0.0000)***	(0.0000)***
Hong Kong	7197	0.0322	1.5689	-0.0235	9.6119	27662.4105	1557.5931
						(0.0000)***	(0.0000)***
China	6939	0.0490	2.2838	5.3180	156.054	7063462.3726	41.6445
						(0.0000)***	(0.0000)***
S&P500	7341	0.0302	1.0588	-0.1858	8.1663	20409.0303	1970.6156
						(0.0000)***	(0.0000)***

Robust standard errors in parentheses: *** represents p<0.01, ** represents p<0.05, * represents p<0.1

[6] The Jarque–Bera test statistic (JB) is defined as: $JB = \frac{n-k+1}{6}\left(S^2 + \frac{1}{4}(C-3)^2\right)$, where n is the number of observations; S is the sample skewness; C is the sample kurtosis; and k is the number of regressors.

Therefore, the data used in this study cannot be approximated well by a normal distribution, which violates the requirement of the OLS model in classical linear regression models. Additionally, the last column in Table 2 depicts the result of the ARCH-LM test, which is a standard test to detect autoregressive conditional heteroscedasticity (Engle 1982). These statistics indicate that all of these daily return series reject the null hypothesis of no heteroscedasticity. Alternatively speaking, the variance of the daily returns in these stock markets is not constant but varies across time. As mentioned before, financial time series always exhibit volatility clustering, which can be seen in Figure 1 in the Appendix. The outcomes of these tables and figures sheds light upon a suitable econometric model for this study in the next step.

4 Methodology

As discussed before, most previous literature used the *OLS* regression, which is a statistical method that estimates the relationship between independent variables and a dependent variable, to study the daily stock returns around holiday periods. The OLS model can be formulated as below:

$$R_t = c + \beta D_{day} + \epsilon_t \tag{1}$$

, where R_t is the daily return at time t; c is an intercept term; and D_{day} represents a dummy variable which is equal to one for some specific calendar days, such as Monday or a whole month, and zero otherwise. In the equation, ϵ_t is the error term. After computing the regression, if the coefficient β of the dummy variable is significantly positive, it suggests that the stock returns on calendar days included in the study is significantly higher or lower than those on other trading days, which can directly confirm the existence of calendar anomalies in the stock market. In particular, the significant β coefficient for the holiday dummy will confirm a holiday effect for the stock return series.

Nevertheless, the OLS method might not be applicable to examining the abnormal movement in stock markets due to its empirically strict but invalid assumptions, for example, the error terms of the sample data must be normally distributed and homoscedastic. Thus, the results of studies employing the OLS regression model in preceding literature may be misleading.

As presented in Table 1 and Table 2, the return series in this study fail to follow a normal distribution and have the problems of autocorrelation and time-varying variance, which do not satisfy the assumptions of the OLS method. Besides, volatility clustering shown in Figure 1 indicates that these stock return series contradict a simple random walk model, violating another OLS assumption of random sampling. In light of these findings, an alternative model which does not require distributional assumptions for residuals is explored to examine seasonal anomalies.

Properties of these financial time series have led to the use of the *GARCH* model. This study augments the *GARCH* model by integrating an *ARMA* model to examine seven selected international stock market indexes (US, UK, Germany, France, Japan, Hong Kong, and China). The *ARMA(p,q)-GARCH(m,n)* model can overcome the main weakness of the OLS method in examining the stock returns. The superiority of this model is twofold. First, the *ARMA(p,q)* part can handle the autocorrelation problem in the data; Secondly, the *GARCH(m,n)* portion can help to capture the heteroskedastic characteristic of the data.

$$R_t = c + \sum_{i=1}^{p} \varphi_i R_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \tag{2}$$

, where $\varepsilon_t^2 | \Omega_{t-i}$ □ $N(0,\sigma_t^2)$; here, Ω_{t-i} represents the information set at time t− i:

$$\sigma_t^2 = \mu + \sum_{i=1}^{m} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{n} \beta_j \sigma_{t-j}^2 \tag{3}$$

In Equation (2), R_t represents the daily return at time t, which depends on its past values R_{t-i}, the error term ε_t, its past shocks ε_{t-j}. It should be noted that the error term here is no longer a white noise process but a GARCH process. In the GARCH component, σ2 (conditional variance) is one period ahead of the forecast variance based on this historical data. μ is a constant term; ε_{t-i}^2 (the ARCH term) is news about volatility from the previous period measured as a lag of squared residuals from the mean equation, while the estimated coefficients, α_i and β_j, capture the presence of heteroscedasticity in the data. In this study, after different p, q, m, and n are selected for this model, it is found that the AIC values obtained by ARMA(1,1)-GARCH(1,1) are relatively small.[7] Therefore, the model, selected for this research, is the ARMA(1,1)-GARCH(1,1) model as shown below :

$$R_t = c + \varphi_1 R_{t-1} + \varepsilon_t + \theta_1 \epsilon_{t-1} \tag{4}$$

, where $s_t^2 | \Omega_{t-1} \sim N(0, \sigma_t^2)$; here, Ω_{t-1} represents the information set at time t−1:

$$\sigma_t^2 = \mu + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{5}$$

[7] The selection process can be found in Appendices.

To examine the Valentine's Day effect in the stock market, Equation (4) is augmented with two additional dummy variables, representing the days right before Valentine's Day and the days after this special day:

$$R_t = c + \phi_1 R_{t-1} + \epsilon_t + \theta_1 \varepsilon_{t-1} + \lambda_{isV} D_{isV} + \lambda_{postV} D_{postV} \qquad (6)$$

, where the dummy variable D_{isV} will be equal to one if the observation falls within three trading days prior to Valentine's Day and on Valentine's Day, and zero otherwise. D_{postV} is another dummy variable that will take a value of one for three trading days after Valentine's Day and zero otherwise. The significance of the coefficients for these two dummy variables will indicate the existence of a is- or post-Valentine effect on stock returns. Specifically, the is-Valentine effect denotes abnormal stock market return performance three trading days before and on Valentine's Day, while the post Valentine effect refer to the unusual behavior three trading days after Valentine's Day in stock markets.

Furthermore, in case other anomalies interfere with the results of this model, we need to introduce control variables to eliminate the variance error. But there are numerous calendar effects, and it is not feasible to address all effects that have an impact on the Valentine Effect. For this reason, the focus is on the anomalies which are, arguably, the most possible ones that can affect daily stock returns, as revealed in the literature of financial economics. The most significant calendar effect on a daily basis is the Monday effect, as considerable research has confirmed its negative return throughout over 100 years of trading activity (Pettengill 2003). Therefore, the dummy variable M_t is introduced, which will take a value of 1 if day *t* is a Monday, and zero otherwise. The significance of the coefficient for the dummy variable M_t suggests the presence of Monday effect in stock returns.

$$R_t = c + \phi_1 R_{t-1} + \epsilon_t + \theta_1 \varepsilon_{t-1} + \lambda_{isV} D_{isV} + \lambda_{postV} D_{postV} + \gamma_M M_t \quad (7)$$

Since Valentine's Day is on February 14, the calendar day in question might coincide with the full moon period in the lunar calendar, which suggests that the *Full Moon Effect* is a potential factor interfering with the results of this study. Therefore, this paper introduces a Full-Moon dummy (F_t) as a control variable. When $F_t = 1$, day t is around the full moon period of a month, and $F_t = 0$ for the remaining days in that month: [8]

$$R_t = c + \phi_1 R_{t-1} + \epsilon_t + \theta_1 \varepsilon_{t-1} + \lambda_{isV} D_{isV} + \lambda_{postV} D_{postV} + \gamma_M M_t + \rho_F F_t \quad (8)$$

Similarly, the significance of the estimated coefficient of F_t indicates the influence of full moon periods on stock returns.

5 Results

5.1 The Valentine Effect in the US stock market

The first result in this paper is to give a portrayal of the Valentine Effect in the US stock market, and the selected ticker is the Dow Jones Industrial Average (DJIA)[9], which is one of the oldest stock indices in the world, as well as the most

[8] A full moon period can be defined as spanning from N days before the full moon day to the full moon day and N days after the full moon day (N = 3 or 7) (Yuan et al. 2006). In this paper, a full moon period is defined as the period between the 13^{th} and the 15^{th} days in alunar calendar.

[9] The Dow Jones Industrial Average (DJIA) is a market index composed of 30 large companies, and its timely computation for its constituent companies makes it an extremely useful indicator for representing short-term market movements (Rudd 1979). Thus, the DJIA is an apt proxy particularly for this study.

cited and widely recognized one. Table 3 presents the estimation result of the ARMA(1,1)-GARCH (1,1) model in the US stock market. The estimates show that except for the dummy variables, all coefficients in the mean and variance models are statistically significant, and the values of the estimated parameters μ, α and β, satisfy the requirement of GARCH stability. Panel A depicts the estimates of the mean equation, which uses an ARMA process to model the daily market returns with the is- and post- Valentine's Day dummy variables. Panel B displays the estimates of the conditional variance equation. In addition, the AIC values show the goodness of fit of the models.

Estimates in panel A reveal the results after examining the Valentine Effect with the is- and post- Valentine's Day dummy variables. The estimated coefficients of the is-Valentine dummy (λ_{isV}) are statistically significant at the 1% level. More specifically, the positive value (0.1914) of the estimated coefficient (λ_{isV}) suggests that stock returns are 19.14% higher when Valentine's Day is approaching, compared to the returns on other trading days. All estimates in Panel B are statistically significant, meaning that the GARCH part of the model fits the data well.

Then, two control variables, the Monday dummy and the Full-Moon dummy, are introduced to Model 2 and Model 3 respectively. Although control variables are included, the estimated coefficient of the is-Valentine dummy variable (λ_{isV}) is still positive and statistically significant. Note that the values of the estimated coefficient (λ_{isV}) are 0.1418 and 0.1925 respectively in Model 2 and Model 3, which seem to be affected by the newly introduced control variables. On the contrary, it is found that post-Valentine' Day effect is not significant for all models from Table 3. The estimated value of the post-Valentine dummy variable is about 0.09, while the *p-values* indicate that the estimates are statistically insignificant, all of which are over the 10% significance level. As for control variables, the Monday dummy is found to be positive and significant at the 5% level, and the estimated coefficient remains about 0.051, while the Full Moon effect is found to be weak in the US stock market. Despite this, the significant is-Valentine effect is still consistent with the result of the first model without adding any control variables. The result in Panel A suggests that there exists a significant Valentine Effect in the US stock market for these three models, which is consistent with the hypothesis that stock returns are affected by this romantic day.

On the other hand, in Panel B, the estimated coefficients of both lagged squared residuals and lagged conditional variance in the Variance Equation are statistically significant at the 1% level, which suggests that using the ARMA(1,1)-GARCH(1,1) model to describe the volatility of the R_t series is appropriate.

Furthermore, the sum of the ARCH and GARCH ($\alpha_1 + \beta_1$) coefficients of the US stock market index is close to a unit root, which indicates that shocks to volatility have a persistent effect on the conditional variance.

Table 3: The Valentine Effect in the US Stock Market

	(1) Model 1	(2) Model 2	(3) Model 3
Panel A: Mean equation			
c	0.0567***	0.0469***	0.0512***
	(0.0000)***	(0.0000)***	(0.0000)***
ϕ*(AR(1))*	0.9584***	0.9582***	0.9581***
	(0.0000)***	(0.0000)***	(0.0000)***
θ*(MA(1))*	-0.9714***	-0.9712***	-0.9711***
	(0.0000)***	(0.0000)***	(0.0000)***
λ_{isV}	0.1914***	0.1418**	0.1925***
	(0.0012)***	(0.0182)**	(0.0012)***
λ_{postV}	0.0854	0.0947	0.0943
	(0.4147)	(0.3662)	(0.3623)
γ_M		0.0512**	0.0513**
		(0.0356)**	(0.0352)**
ρ_F			-0.0413
			(0.1485)
Panel B: Variance equation			
μ	0.0160***	0.0159***	0.0160***
	(0.0028)***	(0.0022)***	(0.0018)***
α	0.0942***	0.0942***	0.0948***
	(0.0000)***	(0.0000)***	(0.0000)***
β	0.8908***	0.8909***	0.8903***
	(0.0000)***	(0.0000)***	(0.0000)***
Goodness of fit statistics			
AIC	2.5859	2.5829	2.5829

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

For a robustness check, this paper also examines the Valentine Effect by using another important index in the US stock market, the S&P 500 Index, which is an American stock market index based on the market capitalizations of 500 large companies having common stock listed on the NYSE, NASDAQ, or the Cboe BZX Exchange. The sample period remains the same as in Table 3, and Table 4 presents the results.

Table 4: Robustness Tests for the US Stock Market (S&P 500)

	(1) Model 1	(2) Model 2	(3) Model 3
Panel A: Mean equation			
C	0.0555***	0.0503***	0.0538***
	(0.0000)***	(0.0000)***	(0.0000)***
ϕ*(AR(1))*	0.9011	0.9013***	0.8998***
	(0.0000)***	(0.0000)***	(0.0000)***
θ*(MA(1))*	-0.9250	-0.9251***	-0.9237***
	(0.0000)***	(0.0000)***	(0.0000)***
λ_{isV}	0.1773***	0.1760***	0.1782***
	(0.0054)***	(0.0055)***	(0.0048)***
λ_{postV}	0.0325	0.0369	0.0356
	(0.7949)	(0.7683)	(0.7744)
γ_M		0.0273	0.0272
		(0.2607)	(0.2626)
ρ_F			-0.0340
			(0.2262)
Panel B: Variance equation			
μ	0.0149***	0.0149***	0.0149***
	(0.0000)***	(0.0000)***	(0.0000)***
A	0.0917***	0.0918***	0.0922***
	(0.0000)***	(0.0000)***	(0.0000)***
B	0.8951***	0.8951***	0.8946***
	(0.0000)***	(0.0000)***	(0.0000)***
Goodness of fit statistics			
AIC	2.6247	2.6248	2.6249

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The estimated coefficient for (λ_{isV}) is about 0.17 and is significant at the 1% level for all models. It is consistent with the results shown by the Dow Jones Industrial Average Index. This suggests that the Valentine Effect is still robust after changing the assessment index and controlling for other anomalies.

To conclude, all results in this section suggest that the is-Valentine effect (three trading days before and on February 14) is present in the US stock market, but no traces of the post-Valentine effect have been found. Based on the findings in Table 3 and Table 4, one may argue that abnormal performance on days near Valentine's Day might be universal in other stock markets. To confirm the existence of Valentine Effect, this paper further investigates the daily stock returns of major global stock market indices.

5.2 International Evidence of Valentine Effect

In the case that Valentine Effect in the US stock market is an isolated case, the paper examines the Valentine Effect in global stock markets, including the European and Asian economies. Note that for the stock markets of the UK, France, Germany, Japan, Hong Kong, and China, this study takes FTSE 100, DAX, CAC 40, Nikkei 225, Hang Seng Index, and Shanghai Composite Index as the proxies, respectively.

Our findings from the other six stock markets are mixed. Table 5 is the result of the fitted model without the control variables, revealing that the Valentine Effect is present in only three stock markets, which are those of the UK, France, and China. The is-Valentine dummy variable (λ_{isV}) is positive and significant at the 5% level for the stock markets of the UK and France, and at the 1% level for the Chinese stock market. In contrast, the estimated coefficient for λ_{isV} in the mean equation is statistically insignificant for Germany, Japan, and Hong Kong, indicating that stock returns in these three stock markets are not affected by Valentine's Day. Additionally, it is interesting to note that, out of these stock markets, the most profound effect is exhibited in the Chinese market. The is- Valentine dummy variable (λ_{isV}) of 0.7261 indicates that stock returns in China are 72.61% higher on the period three days before the Valentine's Day and including that day, than returns on other trading days. The US has the second highest is-Valentine incremental returns (19.42%), followed by a country known for its romance, France (18.86%), and then the UK (14.03%). The findings are consistent with the expectation that stock returns in global stock markets are affected by Valentine Effect at different levels.

In the following parts, Table 6 and Table 7 separately present the empirical results after adding the Monday dummy and the Full-Moon dummy variables; the estimated coefficient (λ_{isV}) in Panel A remains statistically significant in the stock markets of the UK, France, and China, which is consistent with the estimated results of the model without control variables. To be more specific, the is-Valentine effect is stronger when the Monday dummy and the Full-Moon dummy are included with a lower significance level. The estimated coefficient of the Monday dummy is found to be significant in France and Japan and both of them are negative, at -0.0578 and -0.0788 respectively. It suggests that in France and Japan, stock returns exhibit a downward movement on Mondays. From Table 7, the Full Moon effect is less significant, with only France and Japan having a significant coefficient of F_t at the 10% significance level. On the other hand, it is found that for most cases in this study, the estimated coefficients for the dummy λ_{postV} are all statistically insignificant, except for the UK and China. The UK stock market has a positive post-Valentine dummy variable (0.2028) at the 10% significance level, while China shows a significant and negative post-Valentine dummy variable (-0.6483) at the 1% level. This implies that stock returns in these two markets tend to perform abnormally on days after Valentine'sDay.

Table 5: The Valentine's Day Effect in Global Stock Markets

	US	UK	Germany	France	Japan	Hong Kong	China
Panel A: Mean equation							
C	0.0567***	0.0342***	0.0629***	0.0440***	0.0369	0.0644***	0.0276*
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0001)***	(0.3846)	(0.0000)***	(0.0637)*
ϕ(*AR(1)*)	0.9584***	0.9520***	0.8857***	0.8556***	0.9320***	-0.2268	0.7659***
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.7067)	(0.0000)***
θ(*MA(1)*)	-0.9714***	-0.9655***	-0.8981***	-0.8780***	-0.9407***	0.2820	-0.7806***
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.6355)	(0.0000)***
λ_{isV}	0.1942***	0.1403**	0.1434	0.1886**	0.2256	0.1247	0.7261***
	(0.0012)**	(0.0201)**	(0.1280)	(0.0172)**	(0.1572)	(0.3513)	(0.0012)***
λ_{postV}	0.0854	0.2047**	0.1169	0.1436	0.2017	0.2213	-0.6485***
	(0.4147)	(0.0125)**	(0.2374)	(0.2170)	(0.1733)	(0.1508)	(0.0027)***
Panel B: Variance equation							
μ	0.0160***	0.0150***	0.0282***	0.0277***	0.0539***	0.0292***	0.0538***
	(0.0028)***	(0.0003)***	(0.0020)***	(0.0005)***	(0.0000)***	(0.0000)***	(0.0000)***
A	0.0942***	0.0913***	0.0828***	0.0903***	0.1120***	0.0768***	0.1482***
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
B	0.8908***	0.8954***	0.9015***	0.8954***	0.8669***	0.9103***	0.8507***
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
Goodness of fit statistics							
AIC	2.5833	2.6739	3.2000	3.1907	3.4365	3.3829	3.8583

Table 6: The Valentine Effect in Global Stock Market after Controlling for the Monday Effect

	US	UK	Germany	France	Japan	Hong Kong	China
Panel A: Mean equation							
C	0.0469***	0.0392***	0.0574***	0.0554***	0.0519***	0.0700***	0.0250
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0002)***	(0.0000)***	(0.1302)
$\phi(AR(1))$	0.9582***	0.9518***	0.8862***	0.8557***	0.9316***	-0.2526	0.7664***
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.5941)	(0.0000)***
$\theta(MA(1))$	-0.9712***	-0.9653***	-0.8985***	-0.8782***	-0.9404***	0.3074	-0.7811***
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.5103)	(0.0000)***
λ_{isV}	0.1914***	0.1418**	0.1419	0.1911**	0.2238	0.1252	0.7293***
	(0.0012)***	(0.0186)**	(0.1317)	(0.0164)**	(0.1607)	(0.3496)	(0.0012)***
λ_{postV}	0.0947	0.2036**	0.1189	0.1396	0.1986	0.2221	-0.6477***
	(0.3662)	(0.0136)**	(0.2292)	(0.2333)	(0.1815)	(0.1495)	(0.0029)***
γ_M	0.0512**	-0.0270	0.0274	-0.0578*	-0.0788**	-0.0282	0.0134
	(0.0356)**	(0.2616)	(0.4171)	(0.0682)*	(0.0276)**	(0.4045)	(0.7206)
Panel B: Variance equation							
μ	0.0159***	0.0151***	0.0282***	0.0278***	0.0536***	0.0292***	0.0539***
	(0.0022)***	(0.0002)***	(0.0011)***	(0.0006)***	(0.0000)***	(0.0000)***	(0.0000)***
A	0.0942***	0.0914***	0.0828***	0.0906***	0.1121***	0.0768***	0.1484***
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
B	0.8909***	0.8953***	0.9015***	0.8950***	0.8669***	0.9102***	0.8505***
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
Goodness of fit statistics							
AIC	2.5829	2.6740	3.2002	3.1905	3.4365	3.3831	3.8585

Table 7: The Valentine Effect in Global Stock Market after Controlling for the Monday Effect and the Full-Moon Effect

	US	UK	Germany	France	Japan	Hong Kong	China
Panel A: Mean equation							
C	0.0512***	0.0412***	0.0599***	0.0595***	0.0605***	0.0710***	0.0251
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0002)***	(0.0000)***	(0.1490)
$\phi(AR(1))$	0.9581***	0.9518***	0.8859***	0.8547***	0.9325***	-0.2536	0.7663***
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.5926)	(0.0000)***
$\theta(MA(1))$	-0.9711***	-0.9653***	-0.8982***	-0.8772***	-0.9411***	0.3083	-0.7811***
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.5091)	(0.0000)***
λ_{isV}	0.1925***	0.1418**	0.1417	0.1906**	0.2222	0.1250	0.7290***
	(0.0012)***	(0.0182)**	(0.1331)	(0.0169)**	(0.1642)	(0.3501)	(0.0013)***
λ_{postV}	0.0943	0.2028**	0.1188	0.1388	0.1942	0.2221	-0.6483***
	(0.3623)	(0.0141)**	(0.2297)	(0.2375)	(0.1917)	(0.1493)	(0.0031)***
γ_M	0.0513**	-0.0268	0.0277	-0.0576*	-0.0787**	-0.0282	0.0134
	(0.0352)**	(0.2645)	(0.4137)	(0.0694)*	(0.0279)**	(0.4048)	(0.7213)
ρ_F	-0.0413	-0.0202	-0.0237	-0.0402*	-0.0816*	-0.0092	-0.0008
	(0.1485)	(0.5339)	(0.5755)	(0.3323)*	(0.0750)*	(0.8402)	(0.9864)
Panel B: Variance equation							
μ	0.0160***	0.0151***	0.0283***	0.0279***	0.0537***	0.0292***	0.0539***
	(0.0018)***	(0.0002)***	(0.0011)***	(0.0006)***	(0.0000)***	(0.0000)***	(0.0000)***
A	0.0948***	0.0914***	0.0829***	0.0907***	0.1119***	0.0769***	0.1484***
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
B	0.8903***	0.8953***	0.9013***	0.8948***	0.8669***	0.9102***	0.8505***
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
Goodness of fit statistics							
AIC	2.5829	2.6742	3.2004	3.1906	3.4359	3.3834	3.8588

5.3 *The Presence of Valentine Effect in China*

Furthermore, it is noteworthy that the estimated coefficient for the post-Valentine's Day effect is significantly negative for China's stock market. The findings are consistent with the expectation that great differences between the period prior to and after Valentine's Day are associated with investor mood, which suggests that it is possible for investors to be in a positive mood before Valentine's Day, leading to changes in trading patterns, which in turn lead to changes in returns. Nevertheless, what cannot be ignored is that, in China's stock market, Valentine's Day is usually close to the Spring Festival and even falls within the period of public holidays. Thus, this seems to challenge the previous hypothesis that the abnormal performance of stock returns is solely caused by Valentine's Day. Accordingly, this study further delves into China's Valentine's Day. Firstly, this study scrutinizes the Lunar and the Gregorian calendars of 1990-2019 and finds that nearly half of all Valentine's Days fell into the Spring Festivalperiod, during which China's stock market is closed.[10] This suggests that the significant Valentine Effect present in Table 6 might sometimes be confused with the Spring Festival effect. In light of this, we introduce two Spring Festival dummy variables (Yuan and Gupta 2014), which are ξ_{preN}, taking a value of one for observations which are at least three trading days before the Spring Festival public holidays and zero otherwise, and ξ_{postN}, which assigns a value of one to observations which are three trading days after the Spring Festival public holidays and zero otherwise.[11] The mean equation of the model for

[10] Specific details for the Valentine's Day in the Lunar calendar can be found in Appendices.
[11] According to the regulations of the State Council, the Spring Festival public holidays start from the Lunar New Year's Eve to the 6^{th} day of the first month in Lunar calendar.

China's stock market is augmented as follows:

$$R_t = c + \phi_1 R_{t-1} + \epsilon_t + \theta_1 \varepsilon_{t-1} + \lambda_{isV} D_{isV} + \lambda_{postV} D_{postV} + \gamma_M M_t + \rho_F F_t + \xi_{preN} + \xi_{postN} \quad (9)$$

Table 8 presents the results after controlling for the Spring Festival effect, and the estimated coefficients of the is-Valentine and post-Valentine dummy variables are still significant at the 1% level. Although the value of the estimated coefficient of λ_{isV} has decreased substantially from 0.729 in Model 3 to 0.0065 in Model 4, it is still statistically significant at the 1% level. A similar change occurs in the estimated coefficient of λ_{postV}, with the size reducing from 0.6483 to -0.0056 at the 1% significance level. Such a result further indicates that the Valentine Effect still exists, though the effect is considerably weakened by the Spring Festival effect. For the Spring Festival dummy, the estimated coefficient is found to be positive (0.0059) and significant at the 1% level, suggesting that stock returns experience larger movements on days after the Spring Festival public holidays than on other trading days.

To better understand how Valentine's Day specifically affects China's stock market, this study sets separate dummy variables for pre-Valentine's Day and post-Valentine's Day periods.[12] Since the Monday effect and the Full Moon effect do not exert influence on China's stock market, as evidenced in Table 8, these two dummy variables are omitted in this process.

[12] The specific dummy variables are defined as follows. λ_{is_V} represents the Valentine's Day. $\lambda_{preV\,1}$, $\lambda_{preV\,2}$ and $\lambda_{preV\,3}$ are the three days before the Valentine's Day, whereas $\lambda_{postV\,1}$, $\lambda_{postV\,2}$ and $\lambda_{postV\,3}$ denote their counterparts for the post-Valentine's Day period.

Table 8: Adding Spring Festival Dummy Variables to the Estimation

	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
Panel A: Mean equation				
c	0.0276*	0.0250	0.0251	0.0002
	(0.0637)*	(0.1302)	(0.1490)	(0.2221)
$\phi(AR(1))$	0.7659***	0.7664***	0.7663***	0.7588***
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
$\theta(MA(1))$	-0.7806***	-0.7811***	-0.7811****	-0.7751***
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
λ_{isV}	0.7261***	0.7293***	0.7290***	0.0065***
	(0.0012)***	(0.0012)***	(0.0013)***	(0.0000)***
λ_{postV}	-0.6485***	-0.6477***	-0.6483***	-0.0056***
	(0.0027)***	(0.0029)***	(0.0031)***	(0.0045)***
γ_M		0.0134	0.0134	0.0002
		(0.7206)	(0.7213)	(0.5867)
ρ_F			-0.0008	0.0000
			(0.9864)	(0.9135)
ξ_{preN}				-0.0005
				(0.7707)
ξ_{postN}				0.0059***
				(0.0000)***
Panel B: Variance equation				
μ	0.0538***	0.0539***	0.0539***	0.0000
	(0.0000)***	(0.0000)***	(0.0000)***	(0.1396)
α	0.1482***	0.1484***	0.1484***	0.1469***
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β	0.8507***	0.8505***	0.8505***	0.8520***
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
Goodness of fit statistics				
AIC	2.6247	2.6248	2.6249	-5.3521

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

From Table 9, it can be seen that the estimated coefficient of the Valentine's Day dummy (λ_{is_V}) remains statistically significant, which is about 0.8425, indicating that this is not a negligible effect. The similar statistically significant results are also found for the coefficients of λpreV 2 and λpostV 3.

Specifically, the estimated value of λ_{preV2} is 0.68 at the 10% significance level, which is considerably impactful as well. The coefficient of λ_{postV3} is significant and negative, with a value of -1.20. The signs of the coefficients for the pre- and the post- Valentine's Day periods are still positive and negative respectively, which is consistent with the results in Table 6. Based on these findings, we can further confirm the existence of the Valentine Effect and locate the abnormal performances in China's stock market two days before and three days after Valentine's Day.

Table 9: Specific Dummies for Valentine Effect in China's Stock market

	Estimate	Std. Error	t value	Pr(>|t|)
Panel A: Mean equation				
C	0.0262	0.0149	1.7615	0.0781
ϕ*(AR(1))*	0.7619	0.1200	6.3497	0.0000
θ*(MA(1))*	-0.7770	0.1155	-6.7236	0.0000
λ_{isV}	0.8425	0.4089	2.0601	0.0393
λ_{preV1}	0.1954	0.3689	0.5296	0.5963
λ_{preV2}	0.6822	0.3624	1.8826	0.0597
λ_{preV3}	0.5595	0.3762	1.4871	0.1369
λ_{postV1}	-0.2636	0.4060	-0.6494	0.5160
λ_{postV2}	-0.2400	0.3285	-0.7304	0.4651
λ_{postV3}	-1.2033	0.2883	-4.1728	0.0000
ξ_{preN}	-0.0239	0.1828	-0.1312	0.8955
ξ_{postN}	0.4635	0.2134	2.1720	0.0298
Panel B: Variance equation				
μ	0.0516	0.0090	5.7031	0.0000
A	0.1474	0.0079	18.4414	0.0000
B	0.8515	0.0092	92.1363	0.0000
Goodness of fit statistics	AIC	BIC	SIC	HQIC
	3.8580	3.8728	3.8580	3.8631

Overall, this section reports the major findings of this paper. It aims to examine the existence of Valentine Effect in stock markets. Daily stock data was collected from the US, the UK, France, Germany, Japan, Hong Kong, and China, covering the period from 1 January 1990 to 1 March 2019. The estimated results from the ARMA (1,1)-GARCH (1,1) model confirm that the positive is-Valentine effect exists in major stock markets around the world, even after adding control variables. In response to the unusual performance of China's stock market, further investigations are conducted, and the result is unexpectedly consistent with the hypothesis. However, for the China's stock market, half of all Valentine's Days in the sample fell into public holiday periods, which makes the sample size smaller and the result less convincing. This is a relatively critical and unsolvable limitation because it was not until 1990 that China's stock market index was established. Future studies can look into the trend of the Valentine Effect to see if the effect is just a blip. In summary, stock returns before Valentine's Day are significantly higher than those on other trading days for most cases.

6 Conclusion

This paper examines the presence of the Valentine Effect in seven stock markets, including those of the US, the UK, France, Germany, Japan, Hong Kong, and China. Daily data was collected over the period from 1 January 1990 to 1 March 2019. There is evidence to support the presence of a significant is-Valentine effect in most stock markets, which is consistent with the hypothesis. The returns of the two most important US stock markets are shown to be significantly higher on the days when Valentine's Day is coming. When the study is extended to other international markets, the similar is-Valentine effect is found to be significant in other three stock markets, which are those of the UK, France, and China. Yet, the estimated coefficient of the post-Valentine dummy is only found to be statistically significant in France and China. Particularly, of these seven stock markets, China has both positive is- and negative post- Valentine effects and exhibits the most profound Valentine effect. Such great differences prior to and after Valentine's Day are deduced to be associated with investor mood. More importantly, the Valentine Effect remains similar after controlling for other calendar anomalies, such as the Monday effect, the Full-moon effect, and the Spring Festival holiday effect, which indicates that the Valentine Effect in this study is independent from other effects.

Valentine's Day is an annual celebration of romantic love, friendship, and admiration. Similar to most other major holidays, Valentine's Day evokes feelings of love and intimacy in some people but melancholy and the sense of loneliness in others. If Valentine's Day affects the mood of the general public, by extension, these feelings may affect investor behavior and thus stock market returns, which has been documented in the literature of behavioral finance (for instance, Ariel 1990; Hirshleifer and Shumway 2003). This might explain why Germany and Japan do not show significantly high stock returns when Valentine's Day is coming. Japanese and German cultures tend not to emphasize on the importance of Valentine's Day as much as other countries investigated in the study. Based on this, it is possible to deduce that they may often stay level-headed while investing and are less likely to be affected by individual emotions.

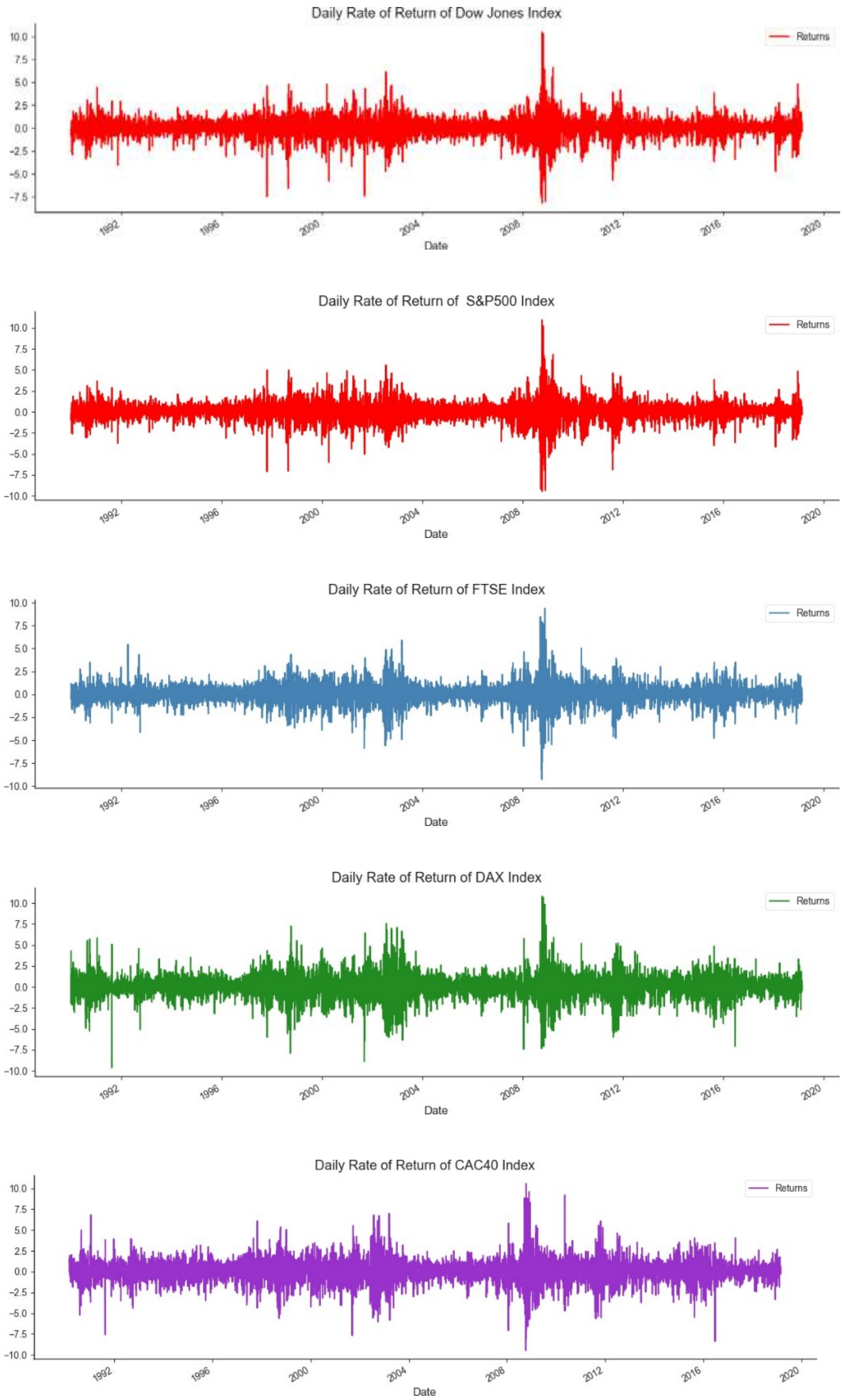
Moreover, the reason why China's Valentine Effect is distinct from other stock markets examined in this study might be attributed to behavioral finance as well. The Chinese stock market is dominated by retail investors who are generally irrational traders, and compared with institutional investors, individuals are more easily affected by 'high spirits' and 'holiday euphoria' or some rather motivation of a prosaic nature. However, the sample size in the study is too small to provide conclusive evidence for the existence of Valentine Effect.

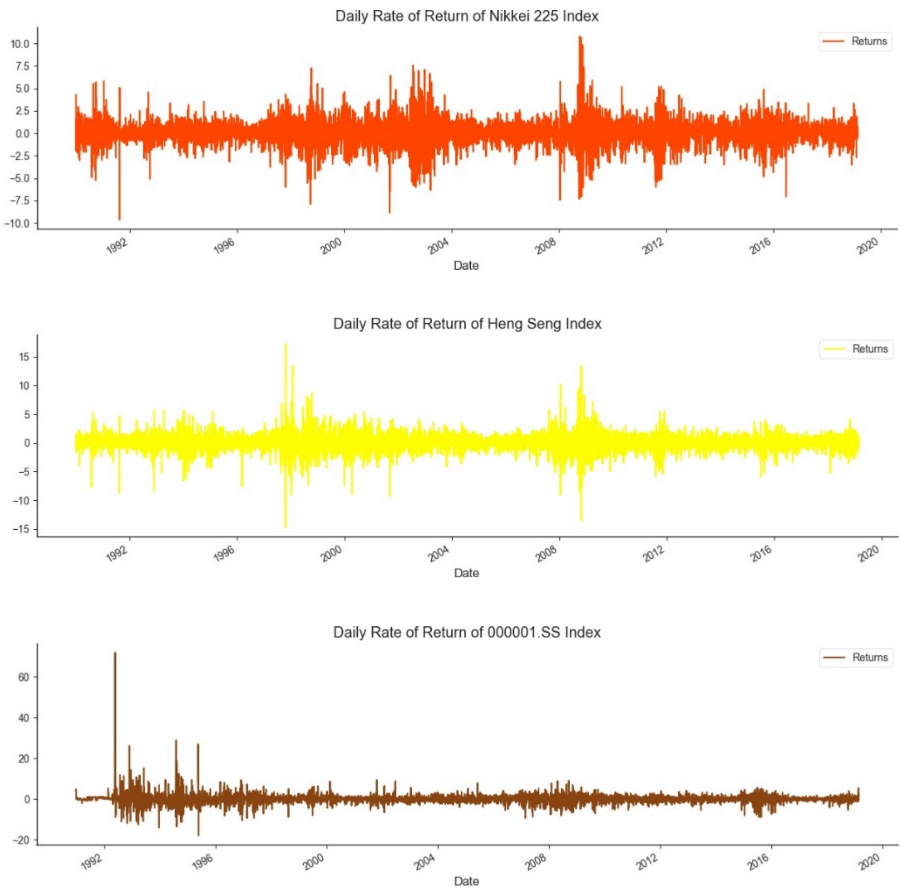
This study provides important implications for both theory and practice. The examination of such an anomaly is important, in light of evidence that conflicts with the classic financial theory of efficient market hypothesis. Compared with other anomalies which are designated as public holidays, the research concerning celebrations without a long trading break is scarce, and this study extends the previous holiday effects by focusing on a single celebration, Valentine's Day. Meanwhile, unlike most prior studies, this paper employs an ARMA(1,1)-GARCH(1,1) model with different control variables to examine the existence of Valentine Effect. From the perspective of practice, the result can provide a predictor of expected returns in those particular stock markets. In other words, it is possible for investors to acquire excess returns by using the implication of this paper to formulate a specific investment strategy.

While this study has demonstrated the robustness of the Valentine Effect, it has also shown that the existence of the anomalies in stock market performances is a perplexing puzzle, as the effect of such a celebration without public holidays cannot be explained by any of the theories propounded in previous literature, such as the inventory adjustment hypothesis. Hence, such effect seems to be explained only by behavioral finance and investor psychology. Nevertheless, the identification of the sources of the Valentine Effect is beyond the scope of this study. Future research can look into factors that lead to the Valentine Effect in stock markets. There is an emerging trend that big data from social networking sites have blazed a trail in quantifying public sentiment and transforming it into indicators (Rao and Srivastava 2014), for example, Bollen et al. (2011) collected mood states from *Twitter*. Thus, further work can make use of these intelligent systems to study how the mood of investors during Valentine's Day affect stock returns.

Appendices

Figure 1: Daily Rate of Returns of Global Stock Market Indices





Note:

Figure 1 suggests that the daily return series are not random walk processes, and that there exists significant volatility clustering, especially during the period of 2008-2009, when there was a global financial crisis, as well as around the year of 2015, when there was a violent shock in July. China’s abnormal performance is due to the fact that it was not until 1990 that the Shanghai Composite Index was launched.

Figure 2: Distribution of Global Stock Returns

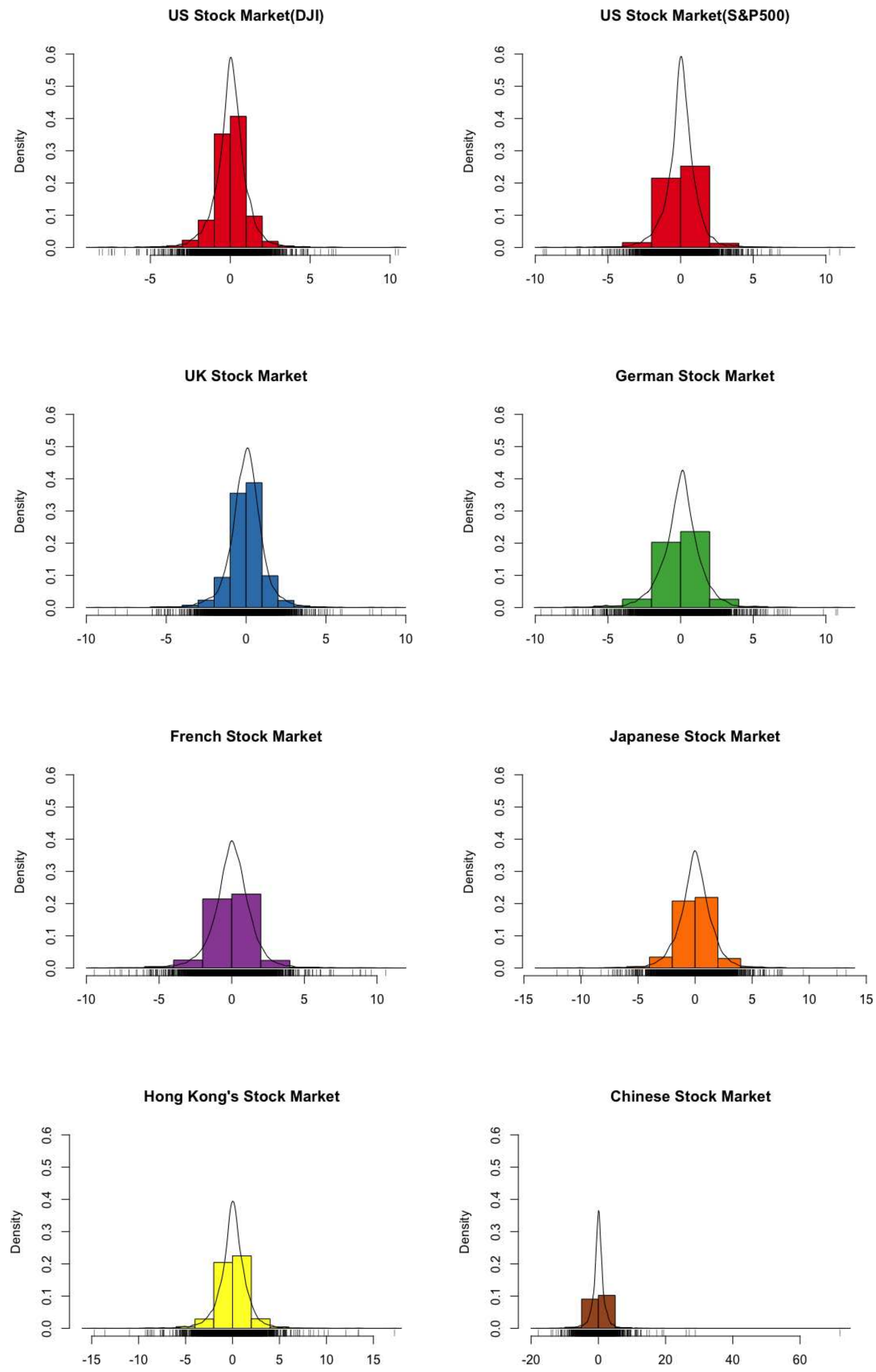
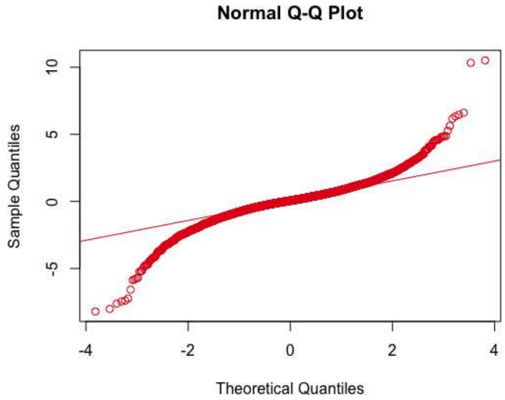
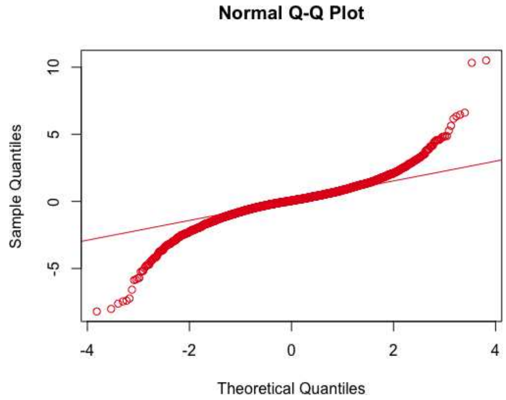


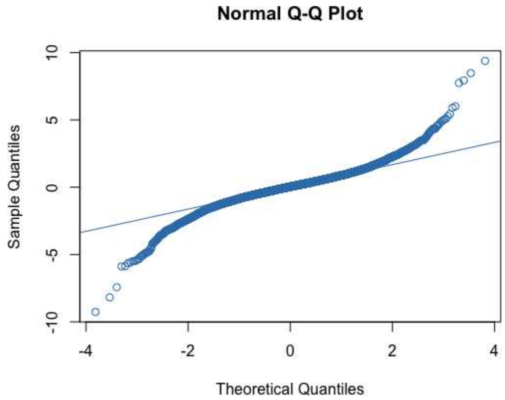
Figure 3: Q–Q (Quantile-Quantile) Plots for Global Stock Market Indices



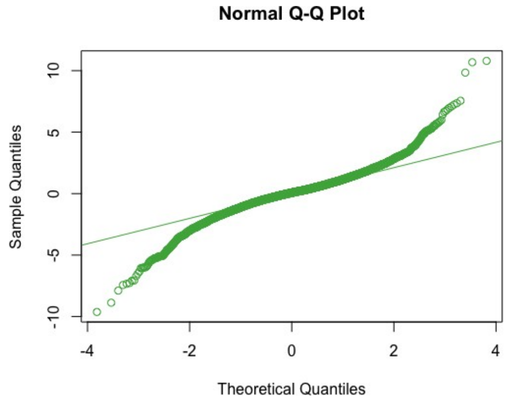
(a) US stock market(DJI)



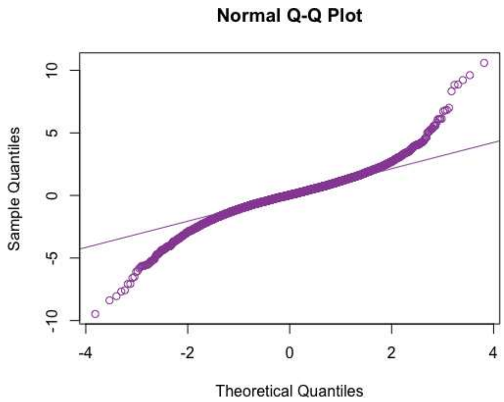
(b) US stock market(S&P500)



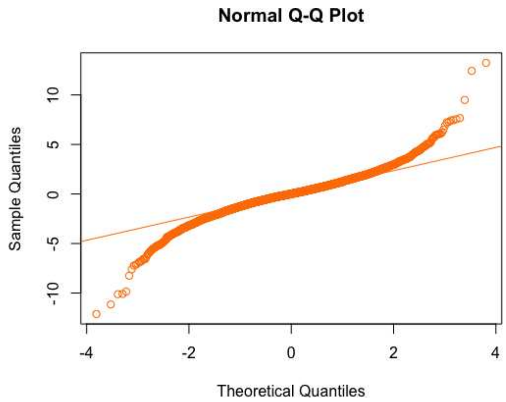
(c) UK stock market



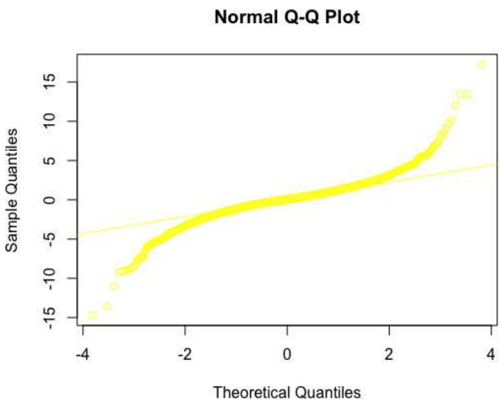
(d) German stock market



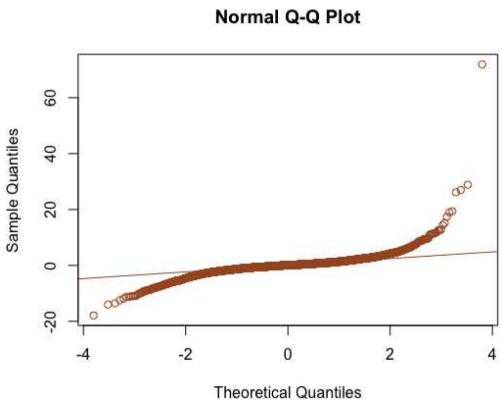
(e) French stock market



(f) Japanese stock market



(g) Hong Kong's stock market

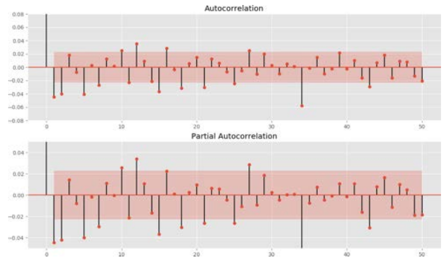


(h) Chinese stock market

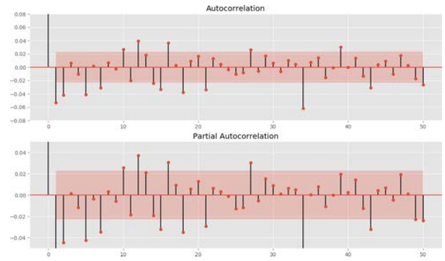
Table 10: Order Selection for the GRACH Model

	AIC	BIC	SIC	HQIC
GARCH(1,1)	2.6372	2.6421	2.6372	2.6388
GARCH(1,2)	2.6374	2.6432	2.6374	2.6394
GARCH(1,3)	2.6377	2.6443	2.6377	2.6399
GARCH(2,1)	2.6374	2.6432	2.6374	2.6394
GARCH(2,2)	2.6373	2.6439	2.6373	2.6396
GARCH(2,3)	2.6378	2.6453	2.6378	2.6404
GARCH(3,1)	2.6377	2.6443	2.6377	2.6400
GARCH(3,2)	2.6376	2.6450	2.6376	2.6401
GARCH(3,3)	2.6381	2.6463	2.6381	2.6409

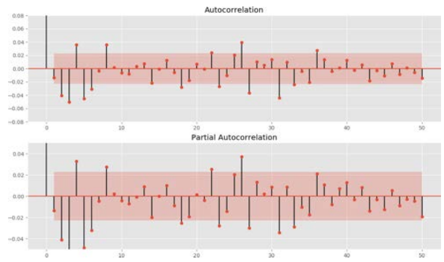
Figure 4: ACF and PACF of Stock Return Series



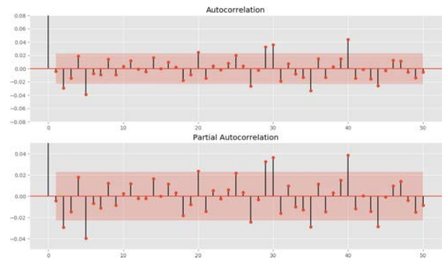
(a) US stock market(DJI)



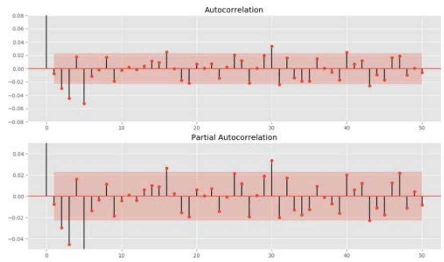
(b) US stock market(S&P500)



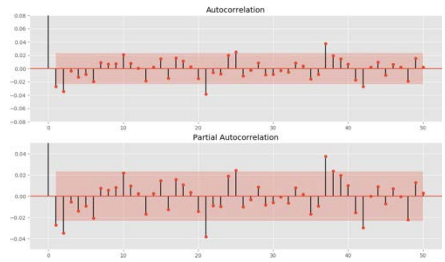
(c) UK stock market



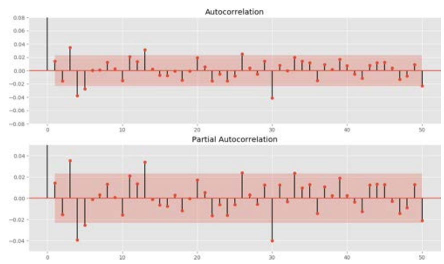
(d) German stock market



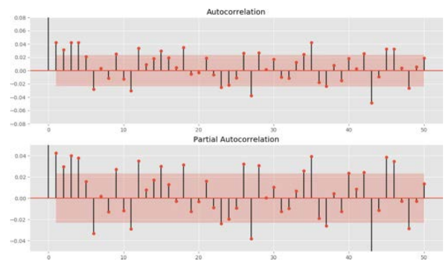
(e) French stock market



(f) Japanese stock market

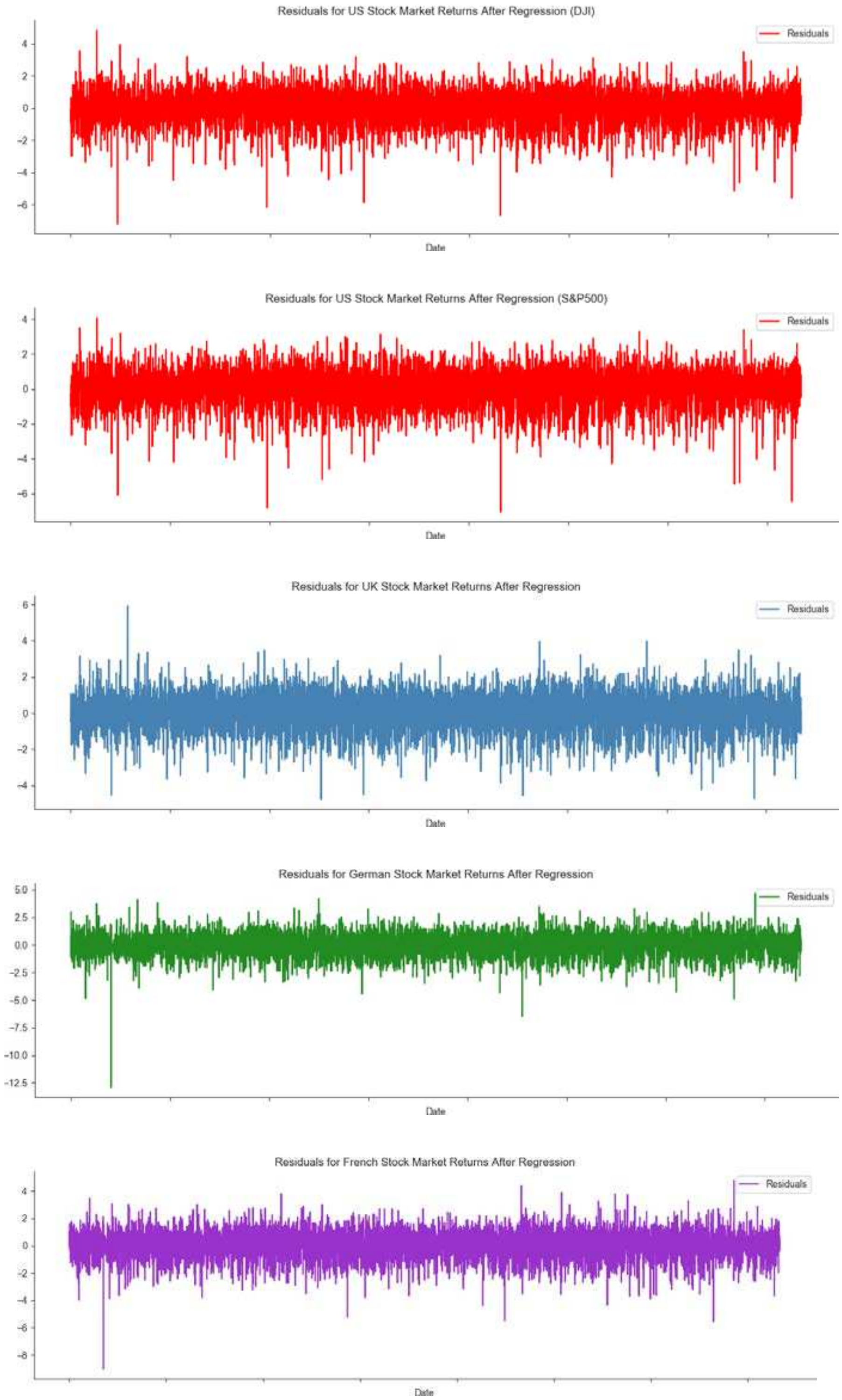


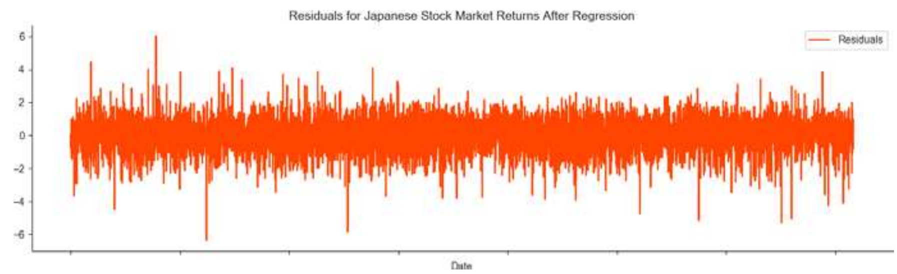
(g) Hong Kong's stock market

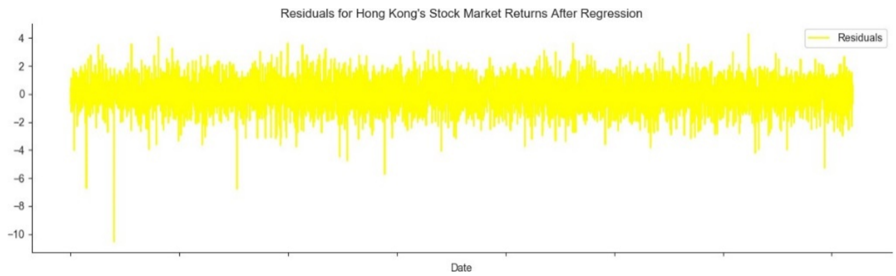


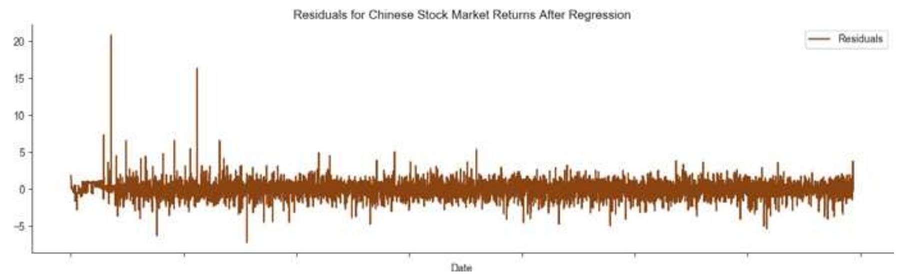
(h) Chinese stock market

Figure 5: Residuals after Fitting Models for Stock Returns





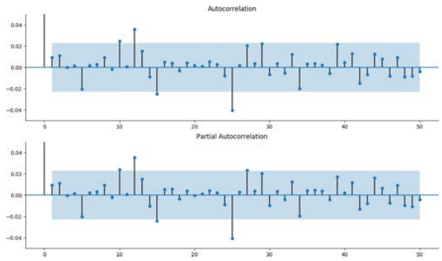




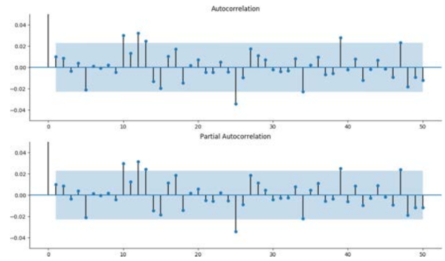
Note:

Residuals here are all from the ARMA(1,1)-GARCH(1,1)-V (V represents is-Valentine and post-Valentine dummy variables) model after controlling for the Monday effect and the Full-Moon effect for the eight stock market indices. It shows that there is no significant volatility clustering after fitting the model, which indicates that this model fits the data well and has overcome the weakness of the OLS model.

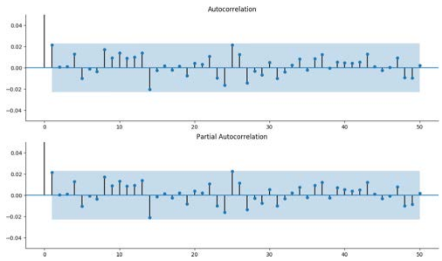
Figure 6: ACF and PACF for Residuals



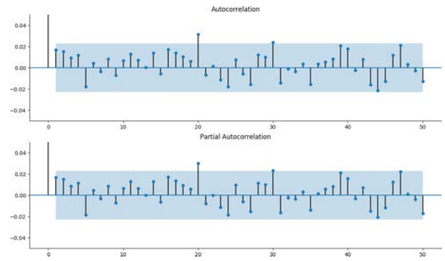
(a) US stock market(DJI)



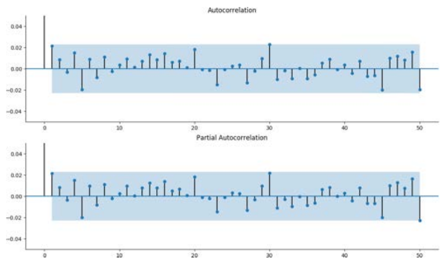
(b) US stock market(S&P500)



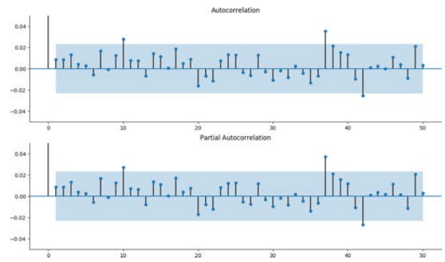
(c) UK stock market



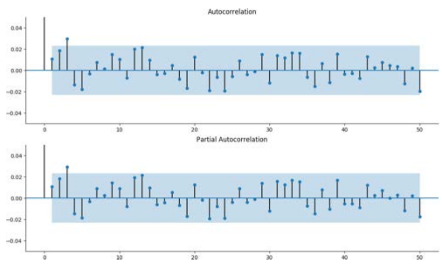
(d) German stock market



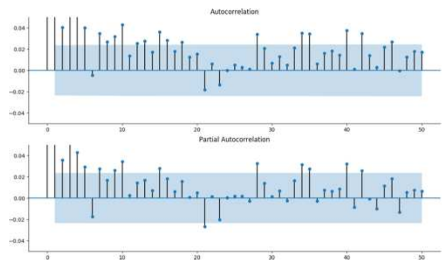
(e) French stock market



(f) Japanese stock market



(g) Hong Kong's stock market



(h) Chinese stock market

Table 11: Ljung-Box Test of Serial Correlation of up to 24^{th} Order

	Returns		**Standardized Residuals**	
	χ^2	*p-value*	χ^2	*p-value*
US	102.19	0.0000	27.331	0.2893
UK	96.906	0.0000	19.728	0.7121
Germany	38.37	0.0318	28.236	0.2502
France	61.521	0.0000	19.678	0.7149
Japan	46.808	0.0035	23.005	0.5195
Hong Kong	49.468	0.0017	32.916	0.1059
China	85.455	0.0000	188.07	0.0000
S&P 500	121.89	0.0000	34.62	0.0742

Note:

This table are the results of the Ljung-Box Q statistics with a χ^2 distribution. The null hypothesis is that no serial correlation exists in sample data. The Ljung-Box Q statistics, up to lag 24, for each return are both significant at the 1% critical value, which indicates that the null hypothesis of serial independence is rejected for return series; but after applying the ARMA(1,1) — GARCH(1,1) model, the test accepts this null hypothesis of no serial correlation for most cases. It indicates that the model used in this study can overcome the problem of autocorrelation.

Table 12: The Valentine's Day Sample in China's Stock Market

Date	isValentines	Date	isValentines
1991/2/14	1	1993/2/14	0
1992/2/14	1	1997/2/14	0
1994/2/14	1	1998/2/14	0
1995/2/14	1	1999/2/14	0
1996/2/14	1	2002/2/14	0
2000/2/14	1	2004/2/14	0
2001/2/14	1	2005/2/14	0
2003/2/14	1	2009/2/14	0
2006/2/14	1	2010/2/14	0
2007/2/14	1	2013/2/14	0
2008/2/14	1	2015/2/14	0
2011/2/14	1	2016/2/14	0
2012/2/14	1		
2014/2/14	1		
2017/2/14	1		
2018/2/14	1		
2019/2/14	1		

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