Can We Profit from the Holiday Effect? A Test for Its Existence and a Corresponding Trading Strategy

Cai Wu, Eric Huang, Navein Suresh, Ankit Raparthi

1. Abstract

This paper investigates the potential presence of holiday effects on several sector indices of the US stock market over 2012-2018 by a regression model. The results indicate that different holidays selectively exert different effects on different industries, but individual holidays remain consistent throughout the period. Utilizing the resulting analysis, the study constructs a trading strategy using only holiday effects and also identifies the strategy's shortcomings and provides potential ideas to improve the strategy's efficiency and profitability.

2. Introduction

Holiday effect has been a renowned anomaly in stock markets of numerous countries, which refers to the tendency of the stock market to experience abnormal returns in the days leading up to and immediately following a holiday when the market is close. It is regarded as either seasonal patterns or calendar effect, which can be a nice fundamental to construct relevant trading strategies.

There has been numerous research conducted on holiday effect, thus different interpretations of this phenomenon in the meantime. However, most explanatory factors are behavioral. A main interpretation is that investors tend to close their positions prior to holidays to lower risk. A widespread shorting behavior can lead to decreasing liquidity and the emergence of price "vacuum", creating potential profit opportunities afterwards. Another reason is high tensions during holidays and positive attitudes toward future stock market trends among the general public. Various factors jointly result in a higher probability of positive market movement in general.

The remainder of the paper is organized as follows. Section 3 provides a brief review on individual relevant literature. Section 4 presents the dataset for testing the holiday effect and backtesting the constructed strategy. Section 5 gives the regression model, its identification results and a trading strategy based on our identification. Section 6 analyzes the backtest results. Section 7 concludes.

3. Review of existing literature

As a typical representative of the calendar effect, the holiday effect has been extensively studied in finance literature. Hansen et al. (2005) systematically studied tests of calendar effects in equity returns. They implemented the test with bootstrap to indices from several European countries, several East Asian countries and the US, which showed a significant calendar effect for returns in most markets.

Specifically targeting the holiday effect, different studies have investigated it in various stock markets of different countries, including the US (Tsiakas, 2010), New Zealand (Cao et al., 2009), Spain (Meneu and Pardo, 2004), Australia (Marrett and Worthington, 2007), South Africa (Bhana, 1994), pan-European countries (Carchano and Tornero, 2015) and so on.

It is worth mentioning that Cao et al. (2009) discussed that the holiday effect is inversely related to firm size and Meneu and Pardo (2004) concluded that pre-holiday effect might be due to the reluctance of small investors to long risky assets. Regarding behavioral interpretations of the holiday effect, Hirschleifer et al. (2020) analyzed a model based on differential sensitivity of stocks to investor mood and concluded that market performance during positive mood periods tends to persist in periods with congruent mood and eventually reverse in periods with non-congruent mood.

4. Dataset

Following the idea of Marrett and Worthington (2007), we used ten ETF products of different stock indices to test for the holiday effect in the US stock market. The index series we used to examine the holiday effect run from 9 January 2012 to 5 January 2018, and the series we used to backtest our strategy run from 8 January 2018 to 6 January 2023. Because the indices from different sectors were launched at different times, the corresponding ETF products were also introduced at different times. In order to ensure that there are an equal number of samples available for testing for each holiday, this is already the longest time series we can obtain.

The industries we chose to test for holiday effect are: banking, insurance, transportation, retailing, telecommunications, energy, materials, software & services and healthcare. These are the sectors that are intuitively more likely to generate holiday effects.

The ETFs we chose to represent the industries above are: SPDR S&P Bank ETF (KBE), SPDR S&P Insurance ETF (KIE), SPDR S&P Transportation ETF (XTN), SPDR S&P Retail ETF (XRT), SPDR S&P Telecom ETF (XTL), Energy Select Sector SPDR Fund (XLE), Materials Select Sector SPDR Fund (XLB), SPDR S&P Software & Services ETF (XSW), SPDR S&P Health Care Equipment ETF (XHE) and SPDR S&P Health Care Services ETF (XHS). It is worth mentioning that XHE and XHS contains different types of companies within the healthcare industry, hence we combined them with equal weights to construct a new price series (denoted by XHSE in our iPython notebook) representing the overall price trend of the whole healthcare industry.

Regarding data processing, we have taken the adjusted close price of each ETF from the downloaded dataframe as our key indicator (ETF always trades at the latest close price). We computed the percentage of the natural log of the daily relative price to construct a new dataframe consisting of series of continuously compounded daily returns of all ETFs. Here is a summary table of descriptive statistics of the daily returns, which reports the sample and annualized (assuming that there are 250 trade days per year) means, medians, standard deviations, skewnesses, kurtoses and Jarque-Bera statistics.

	Sample Mean	Annualized Mean	Median	Standard Deviation	Skewness	Kurtosis	Jarque-Bera
Banking	0.0614	15.3419	0.0948	1.2070	-0.3702	2.6224	466.5380
Insurance	0.0666	16.6398	0.0943	0.8410	-0.3724	1.7799	233.9038
Transportation	0.0724	18.0892	0.1082	1.1713	-0.3638	1.1193	111.9770
Retailing	0.0420	10.4956	0.0819	1.0744	-0.2814	0.6054	42.9237
Telecommunications	0.0390	9.7585	0.0000	1.0327	-0.3297	1.3403	140.2041
Energy	0.0134	3.3558	0.0227	1.2270	-0.1998	2.1131	290.6036
Materials	0.0475	11.8627	0.0795	0.9889	-0.2842	1.3144	128.8425
Software & Services	0.0670	16.7551	0.0886	1.0407	-0.5921	2.1523	379.1828
Healthcare	0.0655	16.3786	0.1183	0.9116	-0.6134	2.1838	394.2324

All the series show a significant negative skewness, which is common for financial time series. In the meantime, all the series also present significant large kurtosis, which indicating the possibility of frequent extreme observations. Though not shown, all p-values of Jarque-Bera statistics are smaller than 0.01, which means all the series are significantly non-normal.

In addition to the aforementioned data, we also downloaded the price of SPDR S&P 500 ETF Trust (SPY) as a benchmark for us to assess the strategy later and also 1 month treasury rate (^IRX) to modify our strategy. The two series run from 8 January 2018 to 6 January 2023. All data is sourced from YahooFinance.

5. Methods of Modeling

5.1 Test for holiday effect

We proposed the following regression model to test for the existence of holiday effects:

$$\begin{aligned} r_t = \beta_0 &+ \beta_1 MLK\_PRE + \beta_2 MLK\_POST + \beta_3 PRESD\_PRE + \beta_4 PRESD\_POST \\ &+ \beta_5 EASTER\_PRE + \beta_6 EASTER\_POST + \beta_7 MEMOR\_PRE \\ &+ \beta_8 MEMOR\_POST + \beta_9 INDEP\_PRE + \beta_{10} INDEP\_POST + \beta_{11} LABOR\_PRE \\ &+ \beta_{12} LABOR\_POST + \beta_{13} THXG\_PRE + \beta_{14} THXG\_POST + \beta_{15} XMAS\_PRE \\ &+ \beta_{16} XMAS\_POST + \beta_{17} NEWY\_PRE + \beta_{18} NEWY\_POST + \epsilon_t, \end{aligned}$$

where $r_t = log\frac{p_t}{p_{t-1}} \times 100$ is the daily return at day t, XXX_PRE are dummy variables representing the last trading day before a holiday and XXX_POST are dummy variables representing the first trading day after a holiday, and XXX is one of the following holidays: Martin Luther King Jr. Day, Presidents' Day, Easter, Memorial Day, Independence Day, Labor Day, Thanksgiving, Christmas and New Year's Day. ϵ_t is a random error term, and all the β representing the daily return exactly one day before/after a holiday are coefficients to be estimated.

After corrected heteroskedasticity and higher-order serial correlation of the least square residuals following Newey-West estimator, the result of regression is as follows. Since there are many dummy variables in the regression model and also we have nine series, we only present those dates showing a significant ($p < 0.05$) positive (since to implement a negative effect we might have to add additional short ETFs to the portfolio, and there may not be corresponding products available) holiday effect.

KBEr:
It doesn't show any holiday effect!

KIEr:

	Coef.	Std.Err.	t	P>|t|	[0.025	0.975]
Presd_post	0.4614	0.1512	3.0507	0.0023	0.1647	0.758

XTNr:

	Coef.	Std.Err.	t	P>|t|	[0.025	0.975]
Indep_pre	0.6552	0.2552	2.5676	0.0103	0.1546	1.1557

XRTr:

	Coef.	Std.Err.	t	P>|t|	[0.025	0.975]
Thxg_pre	0.4723	0.2036	2.32	0.0205	0.073	0.8717

XTLr:

	Coef.	Std.Err.	t	P>|t|	[0.025	0.975]
Thxg_pre	0.6424	0.1217	5.2792	0.000	0.4037	0.8810
Thxg_post	0.4797	0.1906	2.5165	0.012	0.1058	0.8536

XLEr:

	Coef.	Std.Err.	t	P>|t|	[0.025	0.975]
Indep_pre	0.9167	0.3625	2.5292	0.0115	0.2058	1.6277

XLBr:
It doesn't show any holiday effect!

XSWr:

	Coef.	Std.Err.	t	P>|t|	[0.025	0.975]
Presd_post	1.0749	0.3276	3.2808	0.0011	0.4322	1.7175
Labor_post	0.6972	0.3478	2.0047	0.0452	0.0150	1.3794
Thxg_pre	0.4563	0.1015	4.4959	0.0000	0.2572	0.6554

XHSEr:

	Coef.	Std.Err.	t	P>|t|	[0.025	0.975]
Presd_post	0.7379	0.3019	2.4445	0.0146	0.1458	1.3300
Thxg_pre	0.3322	0.1311	2.5329	0.0114	0.0749	0.5894
Thxg_post	0.4502	0.1300	3.4640	0.0005	0.1953	0.7051

We can conclude that for the testing period, insurance industry shows post-Presidents'-Day effect, transportation industry shows pre-Independence-Day effect, retailing industry shows pre-Thanksgiving-effect, telecommunications industry shows both pre- and post-Thanksgiving effect, energy industry shows pre-Independence-Day effect, software & services industry shows post-Presidents'-Day effect, post-Labor-Day effect and pre-Thanksgiving effect, and healthcare industry shows post-Presidents'-Day effect, pre- and post-Thanksgiving effect. Hence, we consider constructing a trading strategy based on the regression results above.

5.2 Strategy construction

We only test for "intraday" trading strategy in this project. We make the following assumptions for the market and trading system to implement our strategy:

(a) We do not incur any commission or transaction fees for our trades, and the profit and loss of our trades come solely from the price movements of the ETF itself;

(b) We long the corresponding ETFs at full position for every scheduled trading day, and also liquidate all holdings when we short the ETFs;

(c) When we are in a cash position, we assume that all assets are deposited in an ideal bank to earn interest with an interest rate equal to 1 month treasury rate. We make this assumption because our backtesting period is over 5 years, while the actual holding period of the ETF is very short, and most of the time is spent in a cash position without being influenced by the fluctuation of the stock market.

We construct our strategy as follows:

(a) long KIE, XLE, XSW and XHSE (1:2:3:2, weights crudely determined based on significance differences and coefficient differences in regression results) at the market closure on the last day before Presidents' Day and short at the closure on the first day after Presidents' Day;

(b) long XTN, XTL and XLE (3:2:5) at the market closure on the second-to-last day before Independence Day and short at the closure on the last day;

(c) long XSW at the market closure on the last day before Labor Day and short at the closure on the first day after Labor Day;

(d) long XTN, XRT, XTL, XSW and XHSE (1:2:2:2:2) at the market closure on the second-to-last day before Thanksgiving and short at the closure on the last day;

(e) long XTL and XHSE (1:1) with a full position at the market closure on the last day before Thanksgiving and short at the closure on the first day after Thanksgiving.

6. Results

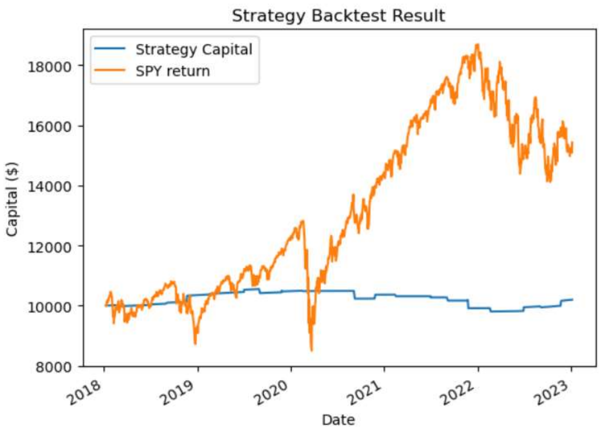
We start our backtest with initial capital $10,000, and we end with $10,195, with a total profit of 1.95%. The maximum capital is $10,551 and the minimum is $9,802. The maximum drawdown is -7.10% and Sharpe ratio is 0.18.

During the backtesting period (8 January 2018 - 6 January 2023), there are 24 trades in total, among which we profit for 13 trades and lose for 11 trades. The overall winning rate is 54.17%.

Compared to the benchmark, there are 16 trades that win the daily profit of SPY and 8 trades that lose. The winning rate is 66.67%, showing that constructing holiday-based strategy with industry ETFs has a significant advantage over the whole market.

However, we only outperformed SPY 15.25% of the whole backtesting period, even after we modified our strategy with non-risky asset assumption. Obviously, this is because we hold the ETFs for a relatively short period of time (one day for each trade), and the majority of the returns come from non-risky asset for most of the time.

A graph for both the strategy returns and SPY returns is as follows:



7. Conclusion

We examine the existence of holiday effects for specific sectors in the US stock market from 2012 to 2018. Our findings show that Thanksgiving exhibits a strong and wide pre/post-holiday effect, while Presidents' Day, Independence Day, and Labor Day exhibit a one-sided holiday effect for individual industries. We then construct a trading strategy based solely on holiday effects, which, while outperforming the whole market for individual trades, performs poorly overall. The strategy's shortcomings are due to its short holding period and low trading frequency, rather than its reliance on holiday signals for trades. To improve the strategy, we suggest extending the holding period after each purchase and setting sell signals that are not dependent on holidays, thus increasing efficiency and profitability.

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