The Halloween Effect: Trick or Treat?

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Abstract

Research documents higher stock returns in November through April than for the rest of the year. This anomaly is known as the "Halloween effect" and results in the following trading rule: Sell stocks in early May, invest in T-bills, and re-invest in stocks on Halloween. In contrast to recent studies, we show that the Halloween effect is robust to consideration of outliers and the "January effect." Additionally, we show that investing in a "Halloween portfolio" provides risk-adjusted returns in excess of buy and hold equity returns even after consideration of transaction costs.

JEL codes: G10, G14

Keywords: anomalies, market efficiency, calendar

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1. Introduction

The "Halloween effect," identified by Bouman and Jacobsen (2002), is an equity return anomaly in which the months of November through April provide superior returns with lower volatility than the remaining months of the year. This effect, if real, is perhaps of greater interest to investors than most other anomalies because the trading rule is simple to implement with low transactions costs, making exploitation of this anomaly potentially profitable. More recent studies posit that this anomaly might be driven by outliers or is simply the "January effect" in disguise. In this study, we examine the robustness of the Halloween effect to consideration of outliers and the January effect. We also construct mean-variance efficient portfolios to determine whether investing in a Halloween portfolio can result in risk-adjusted returns superior to those of a buy-and hold market portfolio. Finally, we examine the impact of transaction costs on the returns to investing in a Halloween portfolio.

2. Literature Review

In their seminal paper, Bouman and Jacobsen (2002) analyze stock returns across 37 countries from January 1970 through August 1998 and find a Halloween effect in 36 of these markets. This finding is remarkable in light of the adage "sell in May and go away" having appeared numerous times in the financial press before and during their sample period. Most return anomalies disappear after discovery, presumably as opportunistic traders exploit them. The effect is particularly strong in European countries and is not the result of risk differences between the May-October and November-April timeframes that delineate the Halloween effect. Bouman and

Jacobsen also demonstrate the economic significance of Halloween-based investment, even when transaction costs are considered.

Bouman and Jacobsen’s results for U.S. stock returns are more marginal. When the January effect is not considered, the Halloween effect attains statistical significance at the 5 percent level. After incorporating the January effect, significance falls just short of the 10 percent level they employ as a cutoff. However, the November-April period has a slightly smaller return standard deviation than the May-October period, adding to its attractiveness. Jacobsen and Visaltanachoti (2009) examine differences in the Halloween effect among U.S. stock market sectors and show that the effect is strongest for production sectors and weakest for defensive consumer oriented sectors.

Maberly and Pierce (2004) examine monthly U.S. stock returns over the same 1970 to 1998 period as Bouman and Jacobsen. By treating the October 1987 (-22.55 percent) and August 1998 (-15.81 percent) returns as outliers, the authors purport to show the dependence of the Halloween effect on these two extreme returns. The effect is diminished and not statistically significant at any conventional level in an alternative specification that controls for these two observations. The authors do not provide an objective basis for identifying exactly two outliers and do not investigate the impact of considering additional outliers. Maberly and Pierce (2003) also examine the impact of outliers on the Halloween effect in Japanese equity markets.

Galai, Kedar-Levy, and Schreiber (2008) also posit a relation between the Halloween effect and outliers. In contrast to the results of Maberly and Pierce (2004), Galai et al. (2008) find that, in daily S&P 500 returns, the Halloween effect is significant only after controlling for outliers. This difference in findings might be due to analyzing daily returns versus monthly, the different time period analyzed (1980–2002 versus 1970–1998), or even the dropping of return observations from the sample. “Returns on non-consecutive days, other than weekend returns, are excluded, as they are not daily returns” (Galai et al. (2008), p. 786-787).

Outliers are an important aspect researchers have investigated as a possible source of the Halloween effect. In this study, we utilize a more formal set of econometric techniques known as robust regression to determine the size and significance of the Halloween effect after controlling for extreme returns. The advantage of this approach is that it does not require any ad hoc specification of the number of outliers or the number of standard deviations from the mean an observation must be before it is considered an outlier. Rather, robust regression reduces the influence extreme returns have on the ordinary least squares (OLS) estimates in rough proportion to the departure of the observation from the regression fit. Our approach eliminates the possibility of data mining in the determination of the number of outliers for which to control.

Lucey and Zhao (2008) examine U.S. stock data from 1926 to 2002 to determine the robustness of the Halloween effect to consideration of the January effect, first identified by Wachtel (1942) and reinforced by Rozeff and Kinney (1976), in which equity returns are significantly higher in January than in other months. They find no evidence of a Halloween effect in their full sample. Using sub-period analysis, they show that neither the Halloween effect nor the January effect are consistently significant for value weighted returns, and that only the January effect is consistently significant for equal weighted returns. The authors contend that the Halloween effect, when it does appear, might simply be the January effect in disguise.

The subperiod findings of Lucey and Zhao (2008) are likely the result of the relatively short subperiods they examine, as we demonstrate in this study. Over three subperiods since 1946, their average estimate of the Halloween effect for the CRSP value-weighted index is a large 1.02 percent per month. However, because the sampling subperiods are small, the tests have reduced power and statistical significance is only found in the 1946-1965 period. We update the CRSP returns through 2008 and, with larger subperiods, find a Halloween effect over the most recent 55 years that it is significant and independent of the January effect. Over the time period 1926-1953, we find no evidence of a Halloween effect. Thus, there is no Halloween effect that appears as a January effect ‘in disguise’ over this period. However, over both the 1954-1980 and the 1981-2008 sub-periods, our evidence suggests a sizable Halloween effect that is independent of the January effect. This might explain the timing of the earliest reference to “sell in May and go away” which appears in a 1964 issue of the *Financial Times*.

In this study, we examine the robustness of the Halloween effect to outliers and the January effect over the period from 1926 to 2008. We also investigate how investment in a “Halloween portfolio,” which holds equities from November to April and Treasury bills the remainder of the year, might improve upon the Sharpe (1966) ratio attainable using a buy-and-hold investment strategy.

3. Sample and Method

We use monthly value weighted and equal weighted stock returns from the Center for Research in Security Prices (CRSP) over the period 1926–2008. We use the following regression model, identical to that of Lucey and Zhao (2008), in our examination:

$$R_t = \alpha + \beta_1 W_t + \beta_2 J_t + \varepsilon_t \tag{1}$$

where R_t is the return on the index, W_t is the Halloween indicator, which has a value of “1” in the months from November to April and “0” otherwise, and J_t is the January indicator, which has a value of “1” in January and “0” otherwise. In addition to using OLS regression, which is sensitive to outliers, we use the *M-estimation* techniques of Huber (1964) and Hampel (1974), which are more robust in the presence of outliers than OLS. We perform these regressions for the entire sample period and for the subperiods of 1926–1953, 1954–1980, and 1981–2008. To further demonstrate the impact of outliers on the Halloween effect, we use a deletion diagnostic method (Belsley, 1980) to calculate the sensitivity of the estimated regression coefficient for the Halloween indicator to extreme observations.

Finally, we form mean-variance efficient portfolios using the method of Britten-Jones (1999). We consider investment in a market fund which holds all CRSP stocks, a Halloween fund which holds equities during November through April (except January) and Treasury bills otherwise, and a January fund which holds equities during January and Treasury bills otherwise. We perform this exercise to examine the economic importance of the Halloween effect relative to the January effect and to demonstrate any potential improvements in risk-adjusted returns that might be achieved by holding a Halloween portfolio. To explore the potential profitability of the Halloween strategy, we repeat this exercise including transaction costs of 20 basis points for each time a fund shifts from equities to Treasury bills or from Treasury bills to equities.

4. Results

We begin our investigation of the Halloween effect by examining the monthly returns on the CRSP value weighted portfolio, which we use as a proxy for the market portfolio. Figure 1 shows these returns alongside the CRSP equal weighted returns for the period 1954–2008. If the Halloween effect is real, monthly returns for November through April should be higher than monthly returns for May through October. The value weighted returns displayed in Figure 1 are consistent with the Halloween effect return pattern. The equal weighted returns are also consistent with this pattern, but the return for January towers above the returns for other months in this series. Keim (1983) documents higher returns for small firms than for large firms and reports that approximately 50 percent of this size effect occurs in January. Given that small firms receive greater weighting under an equal weighting scheme than under a value weighting scheme, it is not surprising to see a strong January effect in the equal weighted returns. However, the same effect is not apparent in the value weighted returns.

Next, we examine monthly returns by subperiod. Figure 2 displays value weighted returns for the 1954-2008 subperiod, as well as the subperiods of 1954-1980 and 1981-2008. The Halloween effect is visible in all three periods, but the return patterns are not entirely consistent between subperiods. For example, July returns are positive and large in magnitude in the 1954-1980 subperiod, but are negative in the 1981-2008 subperiod. Note that January value weighted returns are similar in magnitude to November and December returns in all three periods.

We use OLS regression for a more scientific examination of returns over the larger 1926-2008 period. Table 1 presents the results of regressions performed using Model (1). β_1 is the estimated coefficient on the Halloween indicator and β_2 is the estimated coefficient on the January indicator. In Column 1, we exclude the January indicator from the model. In Column 2, we include both the Halloween indicator and the January indicator. We perform these regressions using both value weighted and equal weighted CRSP returns.

In Column 1 for value weighted returns, the coefficient on the Halloween indicator is positive and significant at the 10 percent level. Returns are 58.7 basis points higher in the months from November to April than over the rest of the year, consistent with a Halloween effect. However, once we include the January indicator in Column 2, the coefficient on the Halloween indicator remains positive but loses significance. The coefficient on the January indicator is not significant for this regression. For equal weighted returns, we find a positive and significant coefficient on the Halloween indicator in Column 1, which loses significance after the introduction of the January indicator. In the case of equal weighted returns, the January indicator coefficient is positive and significant in Column 2. The results in Table 1 are, at first glance, consistent with the notion that the Halloween effect in the U.S. is driven by the January effect.

Bouman and Jacobsen (2002) first identify the Halloween effect in the period 1970–1998. Lucey and Zhao (2008) study the persistence of the Halloween effect over time and find the effect is independently significant of the January effect in only the 1946-1965 subperiod. The differences between the findings of these two studies are suggestive of time variation in the Halloween effect, as well as the reduced power of statistical tests in smaller subperiods. As Sauer, Brajer, Ferris, and Marr (1988) point out, “Splitting one large sample into many small samples makes for a less powerful test.” (p. 207) To study these issues, we break our sample into three subperiods: 1926–1953, 1954–1980, and 1981–2008. The fact that we have six more years of return data and break the whole sample into three subperiods rather than the four in Lucey and Zhao (2008) both positively impact the power of our tests. Table 2 presents OLS regressions of Model (1) over these three subperiods. Columns 1 and 2 in this table are identical to Columns 1 and 2 in Table 1, with the January indicator included only in Column 2.

For the subperiod 1926–1953, we find no significant Halloween effect or January effect in the value weighted returns. Using equal weighted returns, we find no Halloween effect for this subperiod, but we do document a positive and significant January effect, consistent with the role that small stocks play in the January effect. For the subperiod 1954–1980, we find a positive and significant Halloween effect for value weighted returns, which does not lose significance once the January indicator is included. For these returns, the Halloween effect is significant but the January effect is not, in contrast to the findings of Lucey and Zhao (2008). In the equal weighted returns regressions, the Halloween effect is positive and significant, remaining so after the inclusion of the January indicator. As expected for equal weighted returns, the coefficient on the January indicator is also positive and significant for this subperiod. For the subperiod 1981–2008, we find a similar pattern to the 1954-1980 subperiod. The Halloween effect is positive and significant in both value weighted return regressions, but the January effect does not attain significance. When we examine this period using equal weighted returns, we obtain positive and significant results for the Halloween effect in both models, indicative of a significant January effect that does not subsume the Halloween effect. Thus, the Halloween effect is present in both the 1954–1980 and 1981–2008 subperiods, and is not subsumed by the January effect as posited by Lucey and Zhao (2008). The results in Table 2 suggest that a significant Halloween effect has persisted in the U.S. over the past 55 years independent of the January effect.

Next, we turn our attention to the impact of outliers on the Halloween effect. Maberly and Pierce (2004) contend that the Halloween effect disappears after controlling for the two biggest outliers in value weighted returns. For both value and equal weighted returns over the 1954-2008 period, we compute an OLS influence vector for the observations. An influence vector measures the influence of an observation by calculating OLS coefficient estimates with that observation omitted. The observation omissions which most impact the estimates (relative to the estimates with the observation included) are deemed “influential observations” or outliers. The influence vector we compute measures the change in the coefficient estimate on the Halloween indicator in regressions of Model (1).

In Table 3 we report the ten most influential return outliers in descending order of their influence on the coefficient estimate on the Halloween indicator in regressions of Model (1). For value weighted returns we identify the biggest outlier, like Maberly and Pierce (2004), as

October 1987 at -22.55 percent. Omitting this observation would reduce the Halloween coefficient by 6.96 basis points from its original value of 105.39 basis points for this sample period. The second greatest outlier is October 2008, which has a return of -18.42 percent. Omitting this outlier reduces the Halloween coefficient by 5.71 basis points. The final column in Table 3 shows the cumulative effect of omitting the outliers. Omitting the first two outliers reduces the Halloween coefficient by 12.72 basis points. However, the next two largest outliers impact the Halloween coefficient in a positive way. If we discard the return of -12.13 percent in November 1973, the Halloween coefficient increases by 4.94 basis points. If we also discard the return of 16.58 percent in October 1974, the Halloween coefficient increases by another 4.93 basis points, bringing the cumulative change in the Halloween coefficient to just -2.85 basis points. The impact of omitting outliers 5–10 actually causes the Halloween coefficient to become greater than its original value. A similar pattern emerges for the equal weighted returns, where the cumulative effect of omitting outliers bounces back and forth from being negative to being positive. Table 3 shows that the impact of outliers is fairly neutral in equal weighted returns. In value weighted returns, while the two biggest outliers add to the Halloween effect, the impact of outliers more broadly is to reduce the Halloween effect.

The alternating results of omitting outliers demonstrated in Table 3 raises a question: How many outliers are appropriate to omit? Surely any answer to this question would be subjective. A more rigorous analytical approach would include all of the data, but limit the ability of outliers to unduly influence the results. In Table 4, we use two such robust regression methods to investigate the Halloween effect. First, we use the Huber (1964) *M-estimation* technique, the most common general method of robust regression, and then apply the redescending estimator of Hampel (1974). Both of these techniques limit the influence of outliers on regression results without arbitrarily selecting outliers ex ante for omission.

Table 4 presents the results of OLS, Huber, and Hampel regressions of Model (1) for both value and equal weighted returns over the 1954-2008 period, as well as the subperiods of 1954-1980 and 1981-2008. For value weighted returns over 1954–2008, the Halloween effect is positive and significant in all three types of regression. Using the coefficient from the Huber regression, returns in the months November through April (excluding January) are, on average, 96.7 basis points higher than the returns of from May through October. Over this period, the Halloween effect is robust to consideration of outliers and to the January effect, which does not achieve significance in any of these regressions. Equal weighted returns over the same period display a significant Halloween effect, but also display a significant January effect. Once again, this is due to the greater weight placed on small stocks in equal weighted returns. An identical pattern of significance occurs for the subperiod 1954-1980, and a similar pattern exists over the subperiod 1981-2008. The only difference between the 1954–1980 results and the 1981–2008 results is the lack of significance of the Halloween coefficient in the Hampel regression of equal weighted returns. The results presented in Table 4 reinforce the robustness of the Halloween effect to both outliers and the January effect over the 1954-2008 time period.

We perform, but do not report in a table, robust regressions of Model (1) over the entire 1926-2008 sample period. Using Huber regression, the Halloween effect is significant at the 10 percent level for value weighted returns and significant at the 5 percent level for equal weighted returns. The Hampel regression results are qualitatively similar. These results are the robust regression analogue of the OLS full sample results reported in Column 2 of Table 1. There, when we control for the January effect but not for outliers, the Halloween effect is not significant. This contrast between the OLS and robust regression results suggests that, over the entire sample period, outliers have the net effect of obscuring the Halloween effect. Outliers appear to be the primary reason for the lack of significance in our full sample OLS results as well as those reported by Lucey and Zhao (2008) for their full 1926-2002 sample period. This does not imply, however, the Halloween effect is pervasive over the entire sample. Our subperiod analysis, as well as that of Lucey and Zhao, strongly indicates that the Halloween effect is not present in the earliest part of the sample.

In our final exercise of the study, we attempt to determine whether the Halloween effect can be exploited for profit and whether the January effect might subsume such profit. We form mean-variance efficient portfolios using the regression-based method of Britten-Jones (1999). The attractive features of the Britten-Jones framework are that the scaled coefficient estimates represent the portfolio weightings which create the most efficient (highest Sharpe ratio) portfolios possible and the *t*-statistics on the coefficient estimates allow us to infer whether the weightings are significantly different from zero.

We consider three investment options. One option is a market fund which continuously holds all CRSP stocks. This represents a buy-and-hold investment strategy. The second option is a Halloween fund which holds equities during November through April (except January) and Treasury bills otherwise. The third option is a January fund which holds equities during January and Treasury bills otherwise. We perform this exercise to examine the economic significance of the Halloween effect relative to the January effect and to demonstrate any potential improvements in risk-adjusted returns that might be earned by investing in the Halloween fund.

Table 5 presents the results. Column 1 represents investment of the entire portfolio in the market fund (represented by the value weighted returns on all CRSP stocks). Column 2 represents potential investment in two funds, the market fund and the Halloween fund. Column 3 represents potential investment in three funds; the market fund, the Halloween fund, and the January fund. To explore the potential profitability of the Halloween strategy, we repeat the Column 3 exercise including transaction costs of 20 basis points for each time a fund shifts from equities to Treasury bills or from Treasury bills to equities and present the results in Column 4.

For each column of Table 5, we calculate the optimal portfolio weights given the fund choices available, the excess return of the portfolio, the standard deviation of the return, and the Sharpe ratio. Using value weighted returns, the market fund has excess returns of 0.51 percent per month and standard deviation of 4.34 percent, resulting in a Sharpe ratio of 0.117. The mean-variance efficient portfolio composed of the market fund and the Halloween fund would invest 11 percent of the portfolio in the market fund and 89 percent in the Halloween fund. The resulting portfolio would have an excess return of 0.43 percent per month, which is less than the return on the market portfolio. However, the standard deviation of such a portfolio would drop to 2.58 percent, raising the Sharpe ratio to 0.168 – a material improvement over holding only the market fund.

If we add the January fund as an investment option, the optimal portfolio would actually short the market fund by holding -1 percent, and hold 58 percent of the portfolio in the Halloween fund and 44 percent of the portfolio in the January fund. Rounding error prevents all figures from adding to 100 percent. Note that, if the Halloween effect were merely the January effect in disguise, the portfolio would invest primarily in the January fund and not in the Halloween fund. The excess return on such a portfolio would drop again, to 0.28 percent per month, but the standard deviation would drop even more, to 1.56 percent, resulting in a Sharpe ratio of 0.181.

Finally, we include transaction costs for the Halloween fund and January fund of 20 basis points per transaction to determine the robustness of our results to transaction costs. Doing so increases the attractiveness of the market fund, which bears no transaction costs since it is a buy-and-hold fund. Such a portfolio would invest six percent in the market fund, 55 percent in the Halloween fund, and 39 percent in the January fund. Excess returns of such a portfolio would be 0.27 percent per month with a standard deviation of 1.70 percent. The resulting Sharpe ratio is 0.157, which is 34.19 percent greater than the Sharpe ratio for the market fund. Note that for all portfolios which allow for investment in a Halloween fund, the positive portfolio weightings on the Halloween fund are highly significant.

The results for the equal weighted returns are similar. As one would expect, the January fund is more heavily weighted under equal weighted returns due to the inordinate contribution of small stocks to the January effect. Small stocks receive greater weight under an equal weighting scheme. However, the January fund does not totally dominate the Halloween fund, which still accounts for 38 percent of the portfolio after consideration of transaction costs. The Sharpe ratio of the Column 4 portfolio exceeds the Sharpe ratio of the market fund by 17.32 percent using equal weighted returns. As is the case for value weighted returns, Halloween fund weightings are highly significant for equal weighted returns.

The exercise illustrated in Table 5 demonstrates that investing in the Halloween effect (and the January effect) can produce risk-adjusted returns in excess of the market, even after consideration of transaction costs. Although the Column 4 portfolios have lower returns than the market, their returns could be raised to the level of the market through the use of leverage without raising the volatility of those returns to the market level. From an investment strategy perspective, the value weighted results presented in Table 5 are more realistic for actual investors. Small firm stocks are not as liquid and might not be as available for immediate purchase or sale as compared to large firm stocks. Therefore, constructing an equal weighted portfolio might prove to be far more difficult than constructing a value weighted portfolio.

5. Conclusion

In this study, we show that the Halloween effect in U.S. returns is significant in the period 1954–2008, but not before. Anomalies usually are present only in older data, given that they can be exploited for profit by savvy investors once they are identified. This does not appear to be the case with the Halloween effect. We also show that the Halloween effect is robust to consideration of outliers, the January effect, and transactions costs. Some anomalies, such as those related to weather, would require many transactions per year and a touch of clairvoyance to exploit, making profitability from exploitation of these anomalies questionable. By contrast, the Halloween effect is an especially attractive anomaly for investors, given the low number of transactions required and the easily predictable dates of those transactions. The greater risk-adjusted returns available by investing in a Halloween portfolio are a challenge to the efficient markets hypothesis. Further research is needed to reconcile these results with rational human behavior.

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Figure 1. Value Weighted and Equal Weighted CRSP Returns in Percent by Month. Monthly Returns Data for 1954-2008.

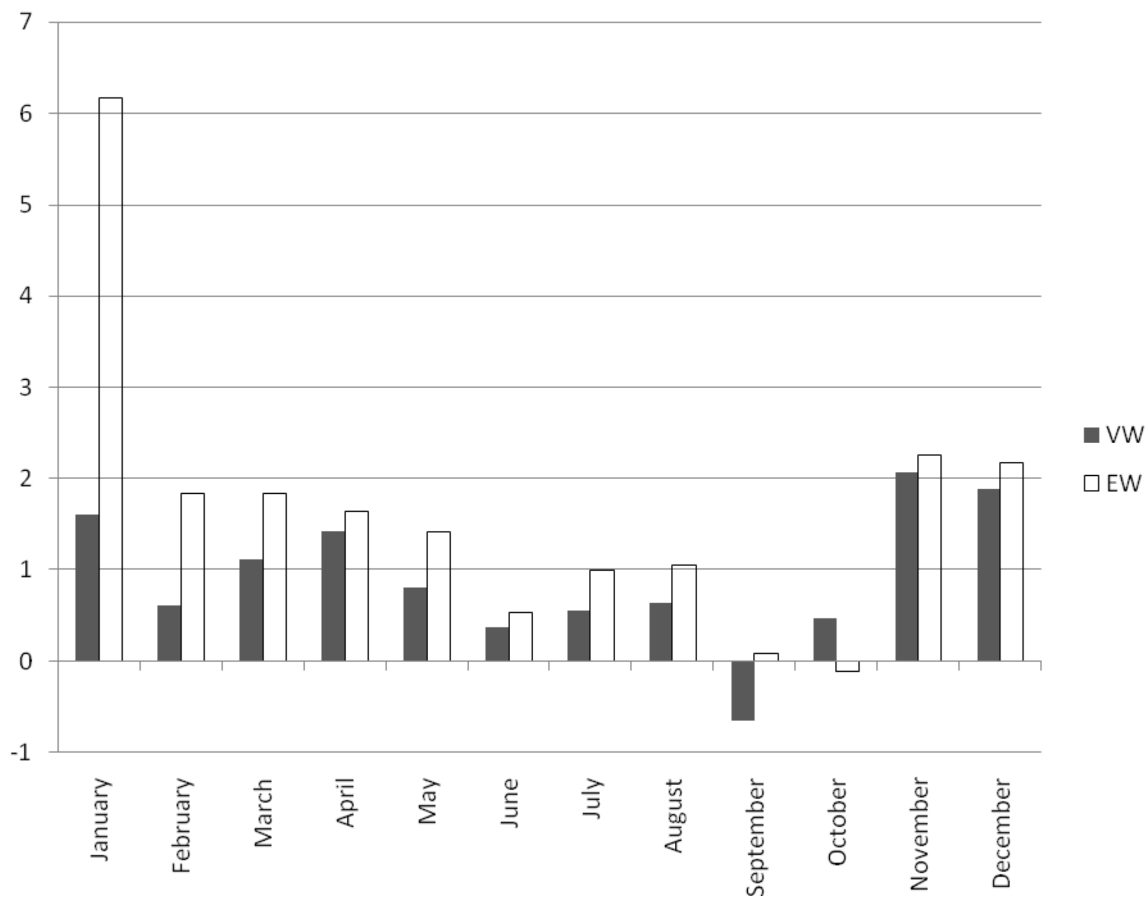

Figure 2. Value Weighted CRSP Returns in Percent by Month. Monthly Returns Data for 1954-2008, 1954-1980, and 1981-2008.

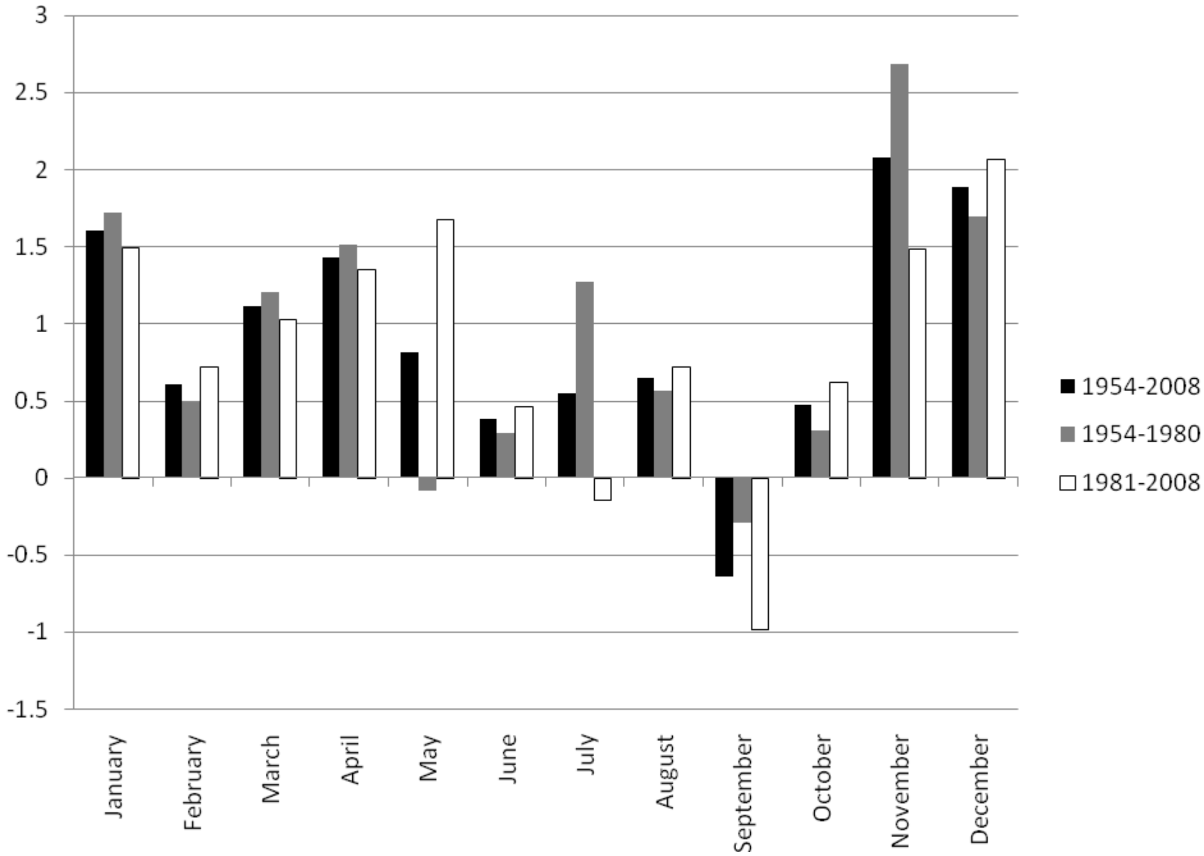

Table 1. Regressions of Monthly Returns on Indicators for the Halloween Effect (β_1) and the January effect (β_2), Monthly Returns Data for 1926-2008
(*t*-statistics in parentheses, returns in basis points)

	Value Weighted Index		Equal Weighted Index	
	1	2	1	2
Intercept	60.1	60.1	141.7	141.7
	(2.466)	(2.466)	(4.111)	(4.161)
β_1	58.7	49.0	122.6	45.8
	(1.702)	(1.356)	(2.516)	(0.908)
β_2		57.8		460.6
		(0.885)		(5.042)
R^2	0.0029	0.0037	0.0063	0.0311
Adjusted R^2	0.0019	0.0017	0.0053	0.0292

β_1 is the estimated coefficient on the Halloween indicator, which has a value of "1" in the months from November to April, "0" otherwise. β_2 is the estimated coefficient on the January indicator, which has a value of "1" in January, "0" otherwise.

Table 2. Regressions of Monthly Returns on Indicators for the Halloween Effect (β_1) and the January effect (β_2), Monthly Returns Data for 1926-1953, 1954-1980, and 1981-2008.
(*t*-statistics in parentheses, returns in basis points)

	Value Weighted Index		Equal Weighted Index	
	1	2	1	2
A. Regressions for the subperiod 1926-1953				
Intercept	106.0	106.0	289.9	289.9
	(1.918)	(1.917)	(3.457)	(3.482)
β_1	-39.1	-61.7	-27.5	-117.1
	(-0.501)	(-0.754)	(-0.232)	(-0.948)
β_2		135.4		537.3
		(0.913)		(2.405)
R^2	0.0007	0.0032	0.0002	0.0172
Adjusted R^2	-0.0022	-0.0027	-0.0028	0.0113
B. Regressions for the subperiod 1954-1980				
Intercept	34.1	34.1	54.0	54.0
	(1.049)	(1.047)	(1.261)	(1.294)
β_1	120.9	117.6	205.2	125.5
	(2.629)	(2.434)	(3.391)	(2.030)
β_2		20.0		478.2
		(0.229)		(4.273)
R^2	0.0210	0.0212	0.0345	0.0864
Adjusted R^2	0.0180	0.0151	0.0315	0.0807
C. Regressions for the subperiod 1981-2008				
Intercept	39.3	39.3	78.0	78.0
	(1.144)	(1.047)	(1.926)	(1.957)
β_1	96.4	93.6	193.1	131.9
	(1.986)	(1.836)	(3.372)	(2.232)
β_2		16.8		367.1
		(0.182)		(3.433)
R^2	0.0117	0.0118	0.0329	0.0656
Adjusted R^2	0.0087	0.0058	0.0300	0.0604

β_1 is the estimated coefficient on the Halloween indicator, which has a value of "1" in the months from November to April, "0" otherwise. β_2 is the estimated coefficient on the January indicator, which has a value of "1" in January, "0" otherwise.

Table 3. The Impact of Outliers on the Halloween Effect. Change in β_1 Resulting from Omitting Outliers in Descending Order of Magnitude. Monthly Returns Data for 1954-2008.

				$\Delta\beta_1$	
	Month	Year	Outlier Return	Outlier Omitted	Cumulative
A. Value Weighted Index Returns. β_1 = 105.39 basis points in original regression over 1954-2008.					
1	October	1987	-22.55%	-6.96	-6.96
2	October	2008	-18.42%	-5.71	-12.72
3	November	1973	-12.13%	4.94	-7.77
4	October	1974	16.58%	4.93	-2.85
5	August	1998	-15.81%	-4.92	-7.84
6	March	1980	-12.04%	4.91	-2.89
7	April	1970	-10.54%	4.37	1.55
8	November	2000	-10.32%	4.28	5.93
9	February	2001	-9.95%	4.15	10.21
10	November	2008	-8.40%	3.58	13.95
B. Equal Weighted Index Returns. β_1 = 128.78 basis points in original regression over 1954-2008.					
1	October	1987	-25.20%	-7.86	-7.86
2	November	1973	-17.45%	7.08	-0.78
3	March	1980	-16.14%	6.60	5.87
4	April	1970	-16.00%	6.55	12.52
5	August	1998	-18.99%	-5.97	6.50
6	October	2008	-17.94%	-5.65	0.77
7	October	1978	-17.87%	-5.63	-4.97
8	November	2000	-11.46%	4.89	0.05
9	February	1991	15.05%	-4.78	-4.70
10	November	2008	-11.04%	4.74	0.20

β_1 is the estimated coefficient on the Halloween indicator from Model (1), which has a value of “1” in the months from November to April, “0” otherwise.

Table 4. Robust Regressions of Monthly Returns on Indicators for the Halloween Effect (β_1) and the January effect (β_2), Monthly Returns Data for 1954-2008, 1954-1980, and 1981-2008.

(*p*-values in parentheses, returns in basis points)

	Value Weighted Index			Equal Weighted Index		
	OLS	Huber	Hampel	OLS	Huber	Hampel
A. Regressions for the subperiod 1954-2008						
Intercept	36.7	57.2	91.7	66.2	92.6	131.9
	(0.1209)	(0.0096)	(0.0000)	(0.0217)	(0.0005)	(0.0000)
β_1	105.4	96.7	83.0	128.8	117.2	86.8
	(0.0028)	(0.0032)	(0.0079)	(0.0026)	(0.0031)	(0.0129)
β_2	18.4	-10.5	-0.2	421.6	349.1	309.2
	(0.7724)	(0.8594)	(0.9970)	(0.0000)	(0.0000)	(0.0000)
B. Regressions for the subperiod 1954-1980						
Intercept	34.1	46.2	88.6	54.0	69.3	93.1
	(0.2958)	(0.1317)	(0.0020)	(0.1965)	(0.0786)	(0.0042)
β_1	117.6	115.8	86.2	125.6	136.8	137.7
	(0.0155)	(0.0108)	(0.0426)	(0.0432)	(0.0193)	(0.0042)
β_2	20.0	-15.5	-13.8	478.2	359.5	260.9
	(0.8191)	(0.8504)	(0.8577)	(0.0000)	(0.0007)	(0.0028)
C. Regressions for the subperiod 1981-2008						
Intercept	39.3	67.5	95.0	78.0	113.5	165.0
	(0.2541)	(0.0328)	(0.0026)	(0.0512)	(0.0019)	(0.0000)
β_1	93.6	77.5	77.2	131.9	100.5	41.2
	(0.0673)	(0.0987)	(0.0981)	(0.0263)	(0.0634)	(0.4188)
β_2	16.8	-42.8	2.7	367.1	338.3	343.8
	(0.8557)	(0.9598)	(0.9749)	(0.0007)	(0.0006)	(0.0002)

β_1 is the estimated coefficient on the Halloween indicator, which has a value of "1" in the months from November to April, "0" otherwise. β_2 is the estimated coefficient on the January indicator, which has a value of "1" in January, "0" otherwise. Huber (1964) M-Estimation is performed with k = 1.5. Hampel (1974) estimation is performed with a = 1, b = 2 and c = 4.

Table 5. Maximum Sharpe Ratio Portfolios Composed of the Market Portfolio, the Halloween Effect Portfolio, and the January Effect Portfolio. Monthly Returns Data for 1954-2008.
(*t*-statistics in parentheses)

	1	2	3	4
A. Portfolio Weights. Value Weighted Index Returns.				
Market	1.00	0.11	-0.01	0.06
		(0.624)	(-0.139)	(0.449)
Halloween		0.89	0.58	0.55
		(3.081)	(3.423)	(2.606)
January			0.44	0.39
			(1.707)	(1.206)
Return	0.51%	0.43%	0.28%	0.27%
Std. Dev.	4.34%	2.58%	1.56%	1.70%
Sharpe Ratio	0.117	0.168	0.181	0.157
B. Portfolio Weights. Equal Weighted Index Returns.				
Market	1.00	0.49	0.08	0.13
		(3.557)	(0.932)	(1.413)
Halloween		0.51	0.42	0.38
		(2.193)	(3.368)	(2.724)
January			0.50	0.49
			(3.497)	(3.091)
Return	1.26%	0.94%	0.61%	0.61%
Std. Dev.	5.45%	3.82%	2.15%	2.27%
Sharpe Ratio	0.231	0.247	0.284	0.270

The Market Portfolio is composed of all stocks in CRSP. The Halloween Portfolio holds the Market Portfolio from November to April (excluding January) and 3-month T-bills at all other times. The January Portfolio holds the Market Portfolio during January and 3-month T-bills at all other times. Column 1 represents investing in the Market Portfolio continually. Column 2 represents the portfolio weights for the maximum Sharpe ratio portfolio when only the Market Portfolio and the Halloween Portfolio are available. Column 3 represents the portfolio weights for the maximum Sharpe ratio portfolio when the Market Portfolio, the Halloween Portfolio, and the January Portfolio are available. Column 4 is identical to Column 3, except for consideration transaction costs of 20 basis points (each way). Calculations follow Britten-Jones (1999).