Seasonality in Stock and Bond ETFs (2001–2014): *The Months Are Getting Mixed Up but Santa Delivers on Time*

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"October. This is one of the peculiarly dangerous months to speculate in stocks. The others are July, January, September, April, November, May, March, June, December, August, and February."

—Mark Twain, Pudd'nhead Wilson, 1894

This article seeks to explore whether broad market exchange-traded funds (ETFs) continue to exhibit seasonality in returns consistent with extant literature and recent trends in global capital markets. The second thrust of the article is to extend "seasonality analysis" beyond the oft seen traditional stock market framework to include bonds, real estate, and gold bullion via a set of highly liquid ETFs. The study researches seasonality in U.S. stocks, foreign stocks, bonds, real estate, and gold. These asset classes also have been utilized as constituents of a multiple-asset class portfolio (Agrrawal [2013]) with low market correlation and superior absolute and relative return performance, compared with a diversified but equity-only portfolio.

Specifically, we look at four different classifications of return seasonality: the January effect (small caps outperforming large caps in January), the Halloween effect (popularly known as "Sell in May and Go Away"), the Mark Twain effect (negative October returns), and the Santa Claus rally (positive December returns). The article also produces reference exhibits that include probabilities and averages for each month and for each seasonality effect, as well as their statistical significance given the limited return histories on ETFs. These exhibits could be utilized by a trader as inputs to the asset allocation decision process or as a tactical overlay on top of a longer-term strategic allocation.

The results are mixed. Some seasonality effects seem to have weakened, whereas others remain intact. This might be the result of improved market efficiency, arbitrage activity, or high frequency trading (HFT), between now and when such studies were performed in the past. The persistence of these effects is somewhat puzzling against the backdrop of Fama's [1970] efficient market hypothesis, which finds no conclusive evidence against either weakform efficiency (current prices reflecting past prices) or semi-strong form efficiency (current prices reflecting all public information). The implication of Fama's research is that traders have little opportunity to turn public information into abnormal profit (adjusted for systematic risk), and any opportunity to do so cannot be persistent. However, the persistence, or lack thereof, could be rationalized via differential investor sentiment responses (Waggle and Agrrawal [2015]). Whatever the case, the fact remains that traders do exist and do seek to exploit seasonal anomalies. Thus, this article looks at the current state of seasonality in returns, both in equity and nonequity assets.

BACKGROUND

In their study of seasonality on the New York Stock Exchange, Rozeff and Kinney [1976] find that January returns are significantly higher than returns for other months. Keim [1983] and Reinganum [1983] both determine that this outsized January effect is largely attributable to small firms. Tinic and West [1984] find that most returns on higher beta stocks occur in the month of January, to which Thaler [1987] remarks that "the CAPM [capital asset pricing model] is exclusively a January phenomenon" (p. 199).

Cadsby [1989], on the other hand, finds no evidence of a January effect in his study of the CAPM using daily Canadian stock returns. Instead, he finds turn-of-the-year, turn-of-the-month, and month-of-the-year effects. Cadsby [1989] finds evidence of a Mark Twain effect, defined as October returns being significantly lower than other months. Notably, in Balaban's [1995] study of seasonal anomalies in emerging markets, specifically Turkey, he finds evidence of a January effect, but no Mark Twain effect.

Bouman and Jacobsen [2002] find evidence of a Halloween effect in 17 countries. Their findings, reinforced by Witte [2010] and Swinkels and Vliet [2012], show that stock returns during the November–April period are significantly higher than the May–October period, even after accounting for any possible January effect.

There also exists the concept of a Santa Claus rally. This effect is broadly interpreted to mean positive returns for the month of December, coinciding with the holidays. However, Hirsch [2014], whose father first coined the term, reiterates that the Santa Claus rally involves just the last five trading days of the year and the first two trading days of the New Year. Empirical evidence compiled by Hirsch shows that, from 1994 to 2014, this seven-day period produced a negative return just four times. According to Hirsch [2014], the average return over this seven-day period has been 1.5%.

Agrawal and Tandon [1994] study seasonality effects in 18 countries, and Chan and Wu [1993] find evidence of seasonality in bonds. Friday and Peterson [1997] find evidence of a January effect in real estate investment trust (REIT) common stocks, but Tschoegl [1987] finds no evidence of a January effect in the gold market. Our analysis extends beyond the traditional stock market framework to also include bond, real estate, and gold assets, in a unified setting and with ETFs only.

METHODOLOGY AND DATA

We chose to examine ETF returns rather than index returns. To our knowledge, this is a new approach within seasonality literature. ETFs are directly investable assets with continuous daily pricing, whereas indexes are not. ETFs also have embedded expenses, which indexes do not have. For these and other reasons (such as taxation, bid-ask spreads, and slippage), ETFs and indexes, despite their similarities, exhibit nonidentical returns. In our view, ETF returns are more relevant to investors in practice, because they are actual investable assets. The interested reader can find a comprehensive long-term index return–based analysis of various calendar effects in Swinkels and Vliet [2012] for the period 1963–2008. Our study utilizes ETFs only, with an objective to provide investors with easily implementable investment options. However, that does present us with shorter return histories because most ETFs were launched only after 2000.[1] Each ETF was chosen for its representativeness, tradability, and ease-of-use in portfolio construction. Funds A, E, G, H, I, and J (Exhibit 1; TLT, SPY, EFA, EEM, IYR, and GLD, respectively) have been shown to improve the efficient frontier versus an all-equity portfolio when used in a 1/N combination or via a mean-variance optimized mechanism (Agrrawal [2013]). Funds B, C, D, and F (SHY, TIP, RSP, and IWM, respectively) were added to the asset set to draw additional comparisons with prior seasonality literature. To maintain maximum overlap of pricing data, the study period is 2005–2014, with an extended period of 2001–2014 for SPY and IWM (denoted in the exhibits as SPY* and IWM*); for the SPY ETF, we also tested for the overlap with S&P 500 returns and extended the returns back to 1980 (the same was done for IWM and the Russell 2000; please see the Appendix). Following the techniques of Agrrawal [2009], the data are drawn from several Internet-based sources, including Morningstar and the CSI data that are provided for web applications such as Yahoo! Finance and Google Finance. Coverage of all the asset classes was also accomplished using the Bloomberg Professional platform, CRSP data, and WRDS resources. Exhibit 1 lists the

Exhibit 1
ETFs Examined in the Study

	Fund Name	Ticker	Underlying Index	Total Fund Assets	Average Daily Volume (3-month avg.)
A	iShares 20+ Year Treasury	TLT	Barclays U.S. 20+ Year Treasury Bond Index	$4.56B	9.7M
B	iShares 1–3 Year Treasury	SHY	Barclays U.S. 1–3 Year Treasury Bond Index	$8.92B	1.6M
C	iShares TIPS Bond	TIP	Barclays U.S. TIPS Index	$13.75B	0.9M
D	Guggenheim S&P 500 Equal Weight	RSP	S&P 500 Equal Weight Index	$11.07B	1.1M
E	SPDR S&P 500 Index	SPY	S&P 500 Index	$170.51B	104.3M
F	iShares Russell 2000 Index	IWM	Russell 2000 Index	$29.69B	39.4M
G	iShares MSCI EAFE Index	EFA	MSCI EAFE Index	$60.94B	17.9M
H	iShares MSCI Emerging Markets Index	EEM	MSCI Emerging Markets Index	$29.58B	46.1M
I	iShares Dow Jones U.S. Real Estate	IYR	Dow Jones U.S. Real Estate Index	$4.22B	9.8M
J	SPDR Gold Trust	GLD	Gold Bullion*	$26.77B	5.1M

Notes: These values are as of June 30, 2015. These ETFs represent diverse asset classes and are among the most liquid in their respective asset type (Agrrawal, et al. [2014]).

**SPDR Gold Trust holds gold bullion directly as its sole asset, with the exception of transactional cash from time to time.*

ETFs examined throughout the study. These ETFs are also among the most liquid in their respective asset classes (Agrrawal et al. [2014]).

For each ETF, we analyzed monthly total return data, including dividends (Agrrawal and Borgman [2010]), for the 10-year period starting January 2005 and ending December 2014. We chose January 2005 as our start date, because it was the earliest date for which full calendar-year data were available for all funds in the study. The study period includes one full bear market (2007–2009) and two partial bull markets (2005–2007 and 2009–2014), helping to insulate the study from business cycle or market phase bias. As previously mentioned, we also looked at the period from January 2001–December 2014 for SPY and IWM. This period corresponds with the earliest date for which full-year data were available for IWM, and it partially covers the 2000–2003 bear market. The ETF asset size and trading volume is as of June 30, 2015.

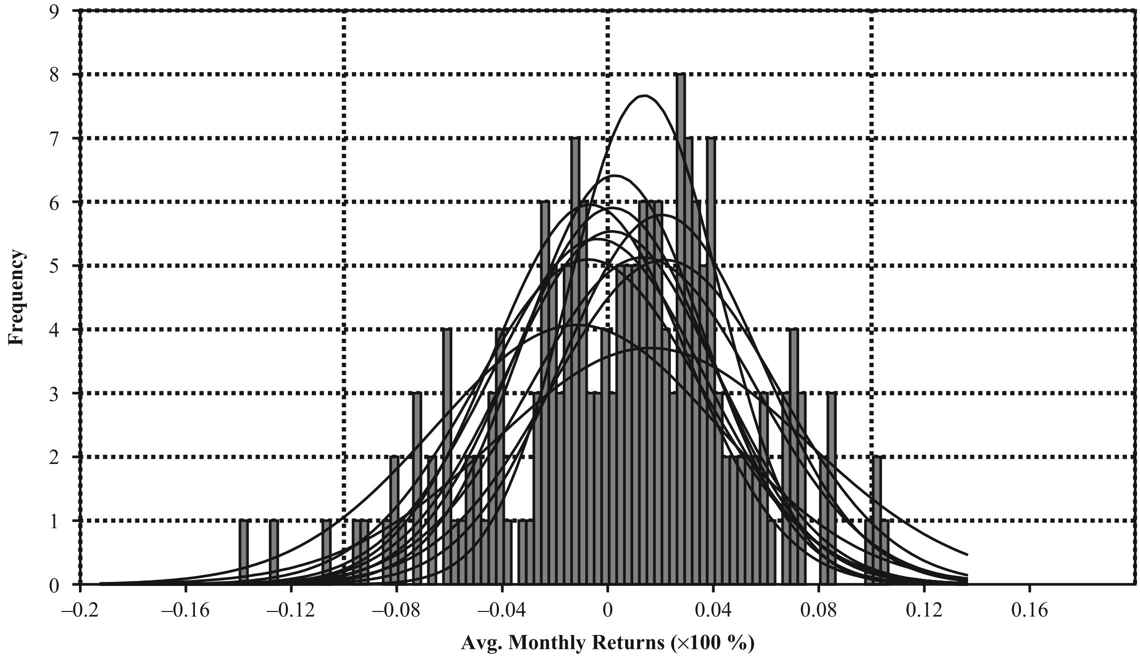
In Exhibit 2, the distribution of SPY monthly returns is shown, calculated from January 2001 to December 2014. Most months are either slightly positive or slightly negative. The histogram is slightly leptokurtic, indicating the existence of fat tails (please see Exhibit 3 for the associated excess kurtosis values).

Exhibit 3 provides summary statistics for each ETF based on the 120 monthly total return observations over the study period (168 observations for SPY and IWM). With the exception of GLD, fund return distributions exhibit excess kurtosis (leptokurtic), consistent with each fund's potential for infrequent, but large, positive and negative returns (fat tails). It is interesting to note that SHY and TIP, two low-volatility fixed-income ETFs, have the highest monthly probabilities of positive returns (72.50% and 65.83%, respectively). The monthly probabilities (last column) are significant at the 99% or higher level of significance ($P < 0.01$) and are calculated using the Altman-Wald test for proportions (Altman [1991]).[2]

To identify seasonality effects, we calculated average monthly returns, month-by-month, for each of the ETFs. We then calculated, month-by-month, the probability that any given ETF would generate a return greater than zero. These results are summarized in Exhibits 4 and 5, respectively, and will be referenced throughout. This table represents 25,920 points of pricing information on a diversified set of assets. For SPY we also tested for the overlap with S&P 500 returns and extended the returns back to 1980 at the suggestion of an anonymous referee. We found that the S&P 500 probability of a monthly positive return over the 1980–2014 period is 61.905% ($P < 0.0001$, $N = 420$). This compares well with the 61.31% probability ($P < 0.0003$) over the 2001–2014 period. One may notice the virtually monotonic association between downside deviation and median monthly returns. In fact, the correlation is 0.78, indicating a positive risk-return association, especially at the diversified portfolio level.

In Exhibit 4, we show the matrix of average monthly returns and calendar month, for each of the

EXHIBIT 2
Monthly Distribution of Returns (SPY, 2001–2014)



Note: Histograms for other assets are not shown to preserve space but can be provided upon request.

EXHIBIT 3
Summary Statistics (2005–2014; 2001–2014 for SPY* and IWM*)

	Ticker	Minimum Monthly Return	Maximum Monthly Return	Mean Monthly Return	Median Monthly Return	Standard Deviation	Downside Deviation	Skewness	Excess Kurtosis	Probability of Positive Monthly Return/*P*-value
A	TLT	–13.07%	14.34%	0.69%	0.68%	3.94%	2.22%	0.58	2.71	55.00%/*P = 0.1367*
B	SHY	–0.84%	1.79%	0.20%	0.16%	0.40%	0.14%	1.08	3.31	72.50%/*P < 0.0001*†
C	TIP	–8.09%	6.50%	0.36%§	0.32%§	1.84%	1.21%	–0.53§	4.41	65.83%/*P < 0.0004*†
D	RSP	–20.91%	18.69%	0.85%	1.41%	5.09%	3.46%	–0.56	3.29	64.17%/*P < 0.0010*†
E	*SPY**	*–16.52%*	*10.91%*	*0.52%*	*1.13%*	*4.36%*	*3.10%*	*–0.65*	*1.17*	*61.31%/P < 0.0003*†
F	*IWM**	*–20.96%*	*15.39%*	*0.82%*	*1.67%*	*5.71%*	*3.92%*	*–0.54*	*0.86*	*60.71%/P < 0.0025*†
G	EFA	–20.83%	13.19%	0.49%	0.63%	5.43%	3.87%	–0.67	1.72	56.67%/*P < 0.0721*
H	EEM	–25.58%	16.86%	0.87%	0.91%	7.08%	4.71%	–0.35	1.13	54.17%/*P < 0.1807*
I	IYR	–31.32%	29.62%	0.80%	1.79%	7.10%	5.11%	–0.74	5.56	63.33%/*P < 0.0017*†
J	GLD	–16.14%	12.79%	0.95%	1.03%	5.49%	3.39%	–0.11	0.15	55.00%/*P < 0.1367*

Notes: The values in the table are based on monthly returns from January 2005 to December 2014. Downside deviation accounts only for monthly returns less than zero, whereas standard deviation accounts for both positive and negative returns. The probability of positive monthly return is the likelihood that an ETF will provide a positive return in any given month. The shaded cells highlight numbers cited throughout the text.

**To include additional available history, we also looked at SPY and IWM from January 2001 to December 2014. This period corresponds with the earliest full-year data for IWM and covers 168 monthly observations.*

†These probabilities are significant at the 99% or higher level of significance (P < 0.01) and are calculated using the Altman-Wald test for proportions (Altman [1991]). N, the number of individual months for SPY and IWM, is 168 and is 120 for others.

§For TIP, the mean is greater than the median, which would normally be associated with positive skew. However, calculated skewness is negative. This is the result of a single large, negative outlier in the dataset resulting in a long, negative tail. In the absence of this outlier, TIP's calculated skewness would be positive.

EXHIBIT 4
Average Monthly Returns by ETF (2005–2014; 2001–2014 for SPY* and IWM*)

	TLT	SHY	TIP	RSP	*SPY**	*IWM**	EFA	EEM	IYR	GLD
January	–0.73%	0.27%	0.92%§	–0.13%	–0.33%	0.28%	–1.55%	–1.40%	0.49%	3.19%
February	0.15%	0.14%	0.01%	0.63%	*–0.51%*	*–0.51%*	0.50%	0.64%	–0.71%	1.87%
March	–0.65%	0.08%	0.42%	2.53%†	*1.36%*	*2.24%†*	1.84%	2.68%	2.47%	–1.00%
April	0.99%	0.13%	0.72%	3.36%§	*2.44%†*	*2.36%*	3.13%†	3.66%†	6.05%†	1.54%
May	0.80%	0.11%	0.21%	0.38%	*0.47%*	*0.88%*	–1.39%	–0.87%	–0.89%	–1.07%
June	0.40%	0.13%§	0.07%	–1.43%	*–1.31%*	*–0.08%*	–0.71%	–0.39%	–1.74%	–0.55%
July	0.80%	0.25%†	0.70%	1.51%	*0.52%*	*–0.47%*	2.03%	2.88%§	2.63%	1.30%
August	3.34%†	0.42%†	0.78%†	0.38%	*–0.12%*	*–0.09%*	–0.51%	–1.55%	0.96%	2.04%
September	0.92%	0.18%§	–0.03%	0.49%	*–0.78%*	*–0.98%*	0.74%	1.34%	0.20%	1.10%
October	–0.86%	0.25%†	–0.08%	0.07%	*1.41%*	*1.77%*	–0.10%	0.80%	–0.35%	–0.16%
November	2.56%§	0.44%†	0.73%	0.44%	*1.94%§*	*2.09%*	–0.43%	–0.29%	–2.20%	3.37%
December	0.56%	–0.01%	–0.13%	1.99%†	*1.20%*	*2.34%†*	2.37%§	2.92%§	2.74%	–0.27%
November to April	**0.48%**	**0.18%**	**0.45%**	**1.47%†**	***1.01%†***	***1.47%†***	**0.98%†**	**1.37%§**	**1.47%§**	**1.45%†**
May to October	**0.90%**	**0.22%§**	**0.27%**	**0.23%**	***0.03%***	***0.17%***	**0.01%**	**0.37%**	**0.13%**	**0.44%**
Overall Average	**0.69%**	**0.20%**	**0.36%**	**0.85%**	***0.52%***	***0.82%***	**0.49%**	**0.87%**	**0.80%**	**0.95%**

Notes: Results are based on monthly returns from January 2005 to December 2014. The shaded cells highlight broad market equity returns for the months of January and December, as well as other numbers cited throughout the text.

**To draw additional comparisons, we also looked at SPY and IWM from January 2001 to December 2014. This period corresponds with the earliest full-year data for IWM. Furthermore, at the suggestion of an anonymous referee, we utilized the S&P 500 index as a proxy, to look at its returns over the 1980–2014 period, since the SPY and S&P 500 returns are significantly similar (correlation is 0.998 and significant at P < 0.01). The Russell 2000 shows a similar differential. For the 1980–2000 period the average January return for the Russell 2000 was 2.7% (P = 0.0112), and 2.14% (P = 0.0191) for the S&P 500, both of which are over twice the average monthly returns for that period (see the Appendix). This contrasts with the January numbers in the table above but supports our finding that the January effect seems to have weakened in the post-2000 period.*

†These monthly returns are significant at the 95% or higher level of significance (P < 0.05). §These monthly returns are significant at the 90% or higher level of significance (P < 0.10); the full table can be supplied to the interested reader. January equity returns are lower than the December returns across the board. October returns for U.S. equity indexes are mostly higher than the overall average for the period. For ease of reference, the bottom rows contain aggregated information pertaining to the "Sell in May" effect. Two of the three bond assets perform better than overall averages during the May–October period.

10 ETFs in the study. The average monthly return over the November–April period on the S&P 500 (1980–2014) was 1.199%, versus 0.403% over the May–October period ($P < 0.01$, $N = 420$). This is similar to the within-year differential that we show in Exhibit 4 and is indicative of the presence and persistence of the "Sell in May" (Halloween) effect, over a longer time period.

In Exhibit 5, we show the monthly probability of positive returns for the set of ten ETFs and test for significance using the Altman-Wald test for proportions (Altman [1991]). Furthermore, we looked at a longer time period at the suggestion of an anonymous referee; for the S&P 500 (proxied by SPY), we find that probability of a monthly positive return over the entire 1980–2014 period is 61.905% ($P < 0.0001$, $N = 420$), which compares reasonably with 61% ($P < 0.004$) for the SPY over the 2001–2014 period (last row in Exhibit 5). The probabilities for other ETFs and months can be seen in Exhibit 5.

THE JANUARY EFFECT

Primary Findings

In their study of monthly returns on the New York Stock Exchange from 1904–1974, Rozeff and Kinney [1976] find evidence that returns in the month of January typically exceed returns in other months. Notably, the study uses an equal-weighted stock index. This is important because equal-weighted indexes overweight small capitalization (cap) stocks and underweight large cap stocks, relative to cap-weighted indexes. Therefore, the study implies but falls short of demonstrating that outsized January returns might be a small cap phenomenon and not a phenomenon attributable to all stocks.

EXHIBIT 5

Monthly Probabilities of Positive Returns (2005–2014; 2001–2014 for SPY* and IWM*)

	TLT	SHY	TIP	RSP	*SPY**	*IWM**	EFA	EEM	IYR	GLD
January	40%	80%†	80%†	50%	*50%*	*43%*	50%	30%	70%	60%
February	50%	60%	50%	70%	*57%*	*57%*	50%	50%	60%	70%
March	40%	60%	50%	80%†	*71%†*	*71%†*	70%	60%	70%	30%
April	70%	80%†	70%	80%†	*71%†*	*64%*	70%	70%	90%†	60%
May	50%	70%	80%†	60%	*57%*	*64%*	40%	50%	60%	30%
June	50%	50%	70%	30%	*43%*	*50%*	30%	50%	40%	50%
July	60%	80%†	60%	50%	*50%*	*43%*	60%	70%	80%†	60%
August	80%†	90%†	80%†	60%	*64%*	*50%*	50%	50%	60%	80%†
September	60%	70%	60%	70%	*57%*	*57%*	70%	60%	60%	60%
October	40%	80%†	70%	60%	*71%†*	*71%†*	60%	60%	60%	50%
November	80%†	90%†	80%†	70%	*71%†*	*79%†*	60%	40%	40%	60%
December	40%	60%	40%	*90%†*	*71%†*	*79%†*	70%	60%	70%	50%
Grand Avg.	**55%**	**73%†**	**66%†**	**64%†**	***61%†***	***61%†***	**57%**	**54%**	**63%†**	**55%**

Notes: Results are based on monthly returns from January 2005 to December 2014. These ETFs are among the most liquid in their respective asset types and have the longest price histories. The shaded cells highlight numbers cited throughout the text.

**To draw additional comparisons, we also looked at SPY and IWM from January 2001 to December 2014. This period corresponds with the earliest full-year data for IWM, the ETF that tracks the Russell 2000 small cap index. The probability of a positive December is 76% ($P < 0.0001$) with an average return of 1.85% ($P = 0.0086$) over the 1980–2000 period (see Appendix) which compares well with the 71% positive probability (Exhibit 5) and a 1.2% return ($P = 0.056$) return for December (Exhibit 4), over the 2001–2014 period.*

†These probabilities are significant at the 93% or higher level of significance ($P < 0.07$) and are calculated using the Altman-Wald test for proportions (Altman [1991]); the full table can be supplied to the interested reader.

Banz [1981] presents evidence that small cap stocks generate significantly larger risk-adjusted returns than large cap stocks, and Keim [1983] and Reinganum [1983], in two separate studies, demonstrate that this small cap outperformance is largely concentrated in the month of January. Roughly one-half of small cap outperformance (versus large cap) occurs in the month of January, and roughly one-half of January small cap returns occur in the first five trading days of the month (Thaler [1987]). Ritter and Chopra [1989] pull together these earlier studies by analyzing cap-weighted, rather than equal-weighted, returns. They find that small cap stocks exhibit increased risk-return characteristics in the month of January, but, outside of small cap stocks, January returns are not statistically higher than returns in any other month. Therefore, the January effect is solely a small cap stock phenomenon. Furthermore, Ritter and Chopra [1989] find that small cap stocks outperform in both up and down markets.

With these prior studies as our backdrop, we define, for the purposes of this study, the January effect having two potential cases, a weak case and a strong case. In the weak case, small cap stocks outperform large cap stocks in the month of January. In the strong case, the weak case holds, and, additionally, about one-half of overall small cap outperformance is concentrated in January (Keim [1983]). With respect to both cases, we found no significant supporting evidence.

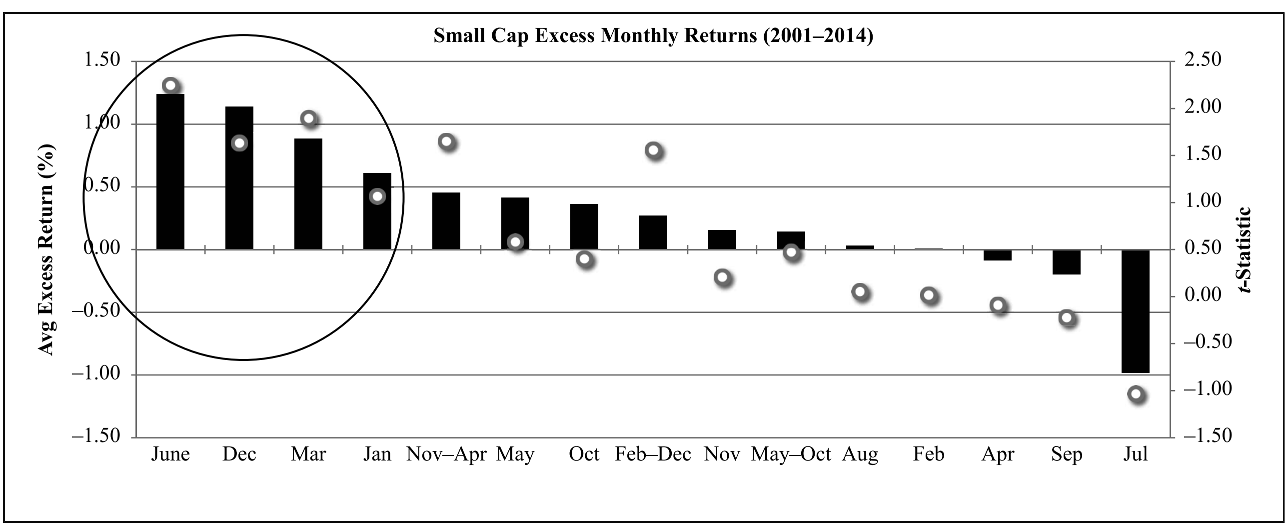
To test the January effect, we used ETFs to measure whether small cap stocks outperformed large cap stocks in the month of January over the study period. We subtracted January returns for SPY, which tracks the S&P 500 Index (a large cap index), from January returns for IWM, which tracks the Russell 2000 Index (a small cap index). In any given January, a positive result meant that small cap stocks generated excess return over large cap stocks; a negative result meant small cap stocks generated less return than large cap stocks. Over the study period (2001–2014), IWM generated an average excess return of 0.61% in the month of January. However, this result was not statistically significant (t-stat 1.07). Therefore, we cannot say with confidence that a weak case January effect is persistent within our data, despite some evidence that IWM generated excess returns on average.

We then repeated this process every month for each of the years in the study period (and for 1980–2000, with the S&P 500 and the Russell 2000 indexes, see the Appendix). This resulted in a matrix of excess returns across all months for all years, which we consolidated into the two-axis bar chart presented in Exhibit 6 (numerical table available upon request). Excess monthly returns (black bars) are charted on the primary y-axis, and the associated *t*-statistics (hollow dots) are charted on the secondary y-axis. In order for the strong case to hold, January excess returns would need to account for roughly one-half of overall excess returns. As can be seen in Exhibit 6, January's excess returns (0.61%), in addition to being statistically not significant, are only the fourth highest among all months, trailing June (1.24% with $t = 2.24$, statistically significant at the 95% level of significance), December (1.14%, marginally significant, $t = 1.63$), and March (0.88%, statistically significant, $t = 1.90$). As an additional test, we subdivided the year into three groups of continuous months (May–October, November–April, and February–December), but we found no persistent small cap outperformance over the full study period. We also looked at the differential of the Russell 2000 over the S&P 500 for the period 1980–2000; for January it was 0.56% (P = 0.02) and for December it was 1.01% (P = 0.006). These differentials are similar to the 2001–2014 period (see Exhibit 6 text note and the Appendix).

In short, while we did observe small cap outperformance in many months, we cannot say with statistical confidence that small caps consistently outperformed large caps over the study period. Furthermore, while we did observe small cap outperformance on average in the month January, this excess return was less than the one-half of total excess return identified by Keim [1983]. Therefore, we found no support for a strong case January effect in the data. The analysis was repeated by utilizing the equal-weighted approach of Rozeff and Kinney [1976], where we subtracted January returns for SPY from the January returns for RSP, which tracks the Guggenheim S&P 500 Equal Weight index; the results were similar.[1]

Data from Exhibits 3, 4, and 5 reinforce our findings. From 2005 to 2014, IWM and RSP outperformed SPY, on average, for the month of January: IWM returned 0.28% on average, RSP returned

EXHIBIT 6
Mixed Evidence for the January Effect



Notes: The January excess return is calculated as the monthly return on IWM minus the monthly return on SPY, and the monthly excess returns range from a maximum of 1.24% to a minimum of −0.98%. Only the months of June, December, and March have large enough t-stats to warrant significance (>1.63). Although we found evidence of positive excess return in the month of January, it is not the largest contributor to overall excess return, and the January result (0.61%) is not statistically significant (t-stat 1.07). Strong December returns (1.14%) imply that investors might be anticipating the January effect in the previous month (t-stat 1.63; see also Exhibit 4 for the returns in December). Results were similar when RSP (equal-weighted S&P 500) was used as the small cap proxy instead of IWM.

−0.13% on average, and SPY returned −0.33% on average (Exhibit 4).[3] This lends some support for a weak case January effect. However, average January returns for both IWM and RSP were measurably lower than each ETF's average monthly return across all months: IWM's average monthly return from 2001 to 2014 was 0.82%, and RSP's average monthly return was 0.85% (Exhibit 4). This is consistent with our earlier finding that little to no strong case January effect exists in the data. Unlike Keim's [1983] finding, we find that most of the small cap excess return is *not* being generated in January. We think this is an important change in how the January effect is generally understood and how it actually has manifested since 2001.

Furthermore, Exhibit 5 shows that positive returns for RSP and IWM are less likely in the month of January than in other months (50% and 43%, respectively). In fact, December appears to be the strongest month for small cap stocks (IWM), followed closely (in order) by November and March (79%, 79%, and 71% probabilities, respectively). Based on these results, we see disconfirming evidence in support of a strong case of January effect.

Implications for Other Asset Classes

The January effect has been observed in other countries beyond the United States. Agrawal and Tandon [1994] studied seasonality effects in 18 stock markets around the world and found evidence of the January effect in most of them. Seasonality effects have also been observed in asset classes other than stocks. Chan and Wu [1993] observed a January effect in high yield bonds, and they found that government and investment-grade corporate bonds outperform in the month of November during economic contractions. Friday and Peterson [1997] found evidence of a January effect in real estate investment trust (REIT) common stocks. However, this effect, as with non-REIT common stocks, remains a small cap phenomenon, and home prices do not explain the observed seasonality. Lastly, Tschoegl [1987] finds no evidence of a January effect in the gold market.

The results of an initial analysis of the January effect in international stocks, U.S. bonds, U.S. real estate, and gold, using ETFs as are shown in Exhibits 4 and 5. Initial results show that gold (as measured by GLD), TIPS (as measured by TIP), and short-term U.S. Treasuries (as measured by SHY) warrant further investigation and are a topic for further research. From January 2005 to December 2014, each of these ETFs exhibited higher-than-average January returns compared to other months. The probability of achieving a positive January return was also 50% or greater for each of these ETFs. By contrast, long-term U.S. Treasuries (TLT), U.S. small cap stocks (IWM), and emerging market international stocks (EEM) had less than a 50% chance of a positive January.

Our analysis of developed international market stocks (EFA) and emerging market stocks (EEM) indicates little to no January effect present within the data. The January–December return differential was about −4.5% for each of these two regions (Exhibit 4), indicating that December tends to be stronger than the following January. However, Ritter and Chopra [1989] indicated that capitalization-weighted indexes containing large cap stocks, a definition met by both EFA and EEM, may not be appropriate for studying the January effect. Hence, additional analysis that includes small cap international indexes would be prudent and a topic for further research.

THE HALLOWEEN EFFECT ("SELL IN MAY")

Primary Findings

Bouman and Jacobsen [2002] found that, from January 1970 to August 1998, a "Sell in May and Go Away" trading strategy outperformed a buy-and-hold market index strategy in 17 different countries, including the United States. This was on both an absolute basis and a risk-adjusted basis. Witte [2010] provided support for this conclusion, and Jacobsen and Visaltanachoti [2009] found evidence of a Sell in May effect in all U.S. stock market sectors and 48 of 49 U.S. industries. We also find support for this effect.

The Sell in May effect stems from the old European saying, "Sell in May and go away, but remember to come back in September." In their study, Bouman and Jacobsen [2002] adapted the saying to account for the Halloween indicator, which states that an investor should return to the market on October 31. It is this definition that we use in our own analysis. Therefore, consistent with Bouman and Jacobsen [2002], we define the Halloween effect as follows: each year, an investor exits the market from May through October, investing instead in a portfolio of short-term Treasuries. The investor then returns to the equity market from November through April.

EXHIBIT 7
Evidence of a Halloween Effect ("Sell in May")

	TLT	SHY	TIP	RSP	*SPY **	*IWM **	EFA	EEM	IYR	GLD
November–April										
Avg. Monthly Return	0.48%	0.18%	0.45%	1.47%	***1.01%***	***1.47%***	0.98%	1.37%	1.47%	1.45%
Avg. Cumulative Return	1.86%	1.04%	2.89%	9.61%	***5.32%***	***9.28%***	7.29%	10.06%	8.93%	8.72%†
Probability of Return >0	53.33%	71.67%	61.67%	73.33%	***65.48%***	***65.48%***	61.67%	51.67%	66.67%	55.00%
May–October										
Avg. Monthly Return	0.90%	0.22%	0.27%	0.23%	***0.03%***	***0.17%***	0.01%	0.37%	0.13%	0.44%
Avg. Cumulative Return	5.51%	1.35%	1.70%	1.60%	***0.45%***	***1.08%***	0.70%	3.41%	0.84%	2.46%†
Probability of Return >0	56.67%	73.33%	70.00%	55.00%	***57.14%***	***55.95%***	51.67%	56.67%	60.00%	55.00%
Halloween Effect	No	No	Yes	Yes	***Yes***	***Yes***	Yes	Yes	Yes	Yes
Safety in Summer Effect	Yes									

Notes: Average monthly returns are calculated from January 2005 to December 2014. Statistical significance of monthly returns is displayed in Exhibit 4. The probability of a positive return is the average probability, from January 2005 to December 2014, of achieving a positive return in any given month.

**To draw additional comparisons, we also looked at SPY and IWM from January 2001 to December 2014. This period corresponds with the earliest full-year data for IWM. Furthermore, at the suggestion of an anonymous referee, we looked at the S&P 500 index returns over the 1980–2014 period, as the SPY ETF and S&P 500 returns are significantly similar (correlation is 0.998 and significant at $P < 0.01$). The average monthly return over the November–April period on the S&P 500 (1980–2014) was 1.199%, vs. 0.403% over the May–October period ($P < 0.01$, $N = 420/2$), with a similar spread (0.73%) over the subperiod of 1980–2000 (see the Appendix). This also reinforces the within-year differential that we show in the Exhibit 7 and is indicative of the presence and continuation of the "Sell in May" (Halloween) effect, over a longer time period.*

†Because GLD opened in November 2004, we began our cumulative return analysis for the fund in December 2004.

To test for this effect, we looked at average monthly returns over the study period. Exhibit 7 shows that, for each ETF except TLT (long-term U.S. Treasuries) and SHY (short-term U.S. Treasuries), the average monthly return from November to April exceeded the average monthly return from May to October. We also looked at the probability of monthly returns over the study period. For each ETF except TLT, SHY, and EEM, the average probability of generating a positive return from November to April was greater than or equal to the average probability from May to October. Specifically, over the 2001–2014 period, SPY returned 1.01% on average from November to April with a 65.48% probability of positive return, compared with a return of 0.03% on average from May to October with a 58.33% probability of positive return. The delta persists for all other non-bond-type assets and is indicative of a post-October outperformance period (Exhibit 7). This information could be potentially useful in a bond-stock switching mechanism and to limit downside risk.

To further look into the Halloween effect, we analyzed the cumulative returns over each six-month period from November to October. Exhibit 7 shows that, for each ETF except TLT and SHY (both of which are comprised of bonds), the average cumulative, six-month return from November to April was much higher than the average cumulative, six-month return from May to October. The average cumulative return was calculated as the grand average of periodic cumulative returns over the 10-year study period, where each periodic cumulative return is the six-month total return, from either November to April or May to October. This was done over the 2005–2014 period for all ETFs except for SPY and IWM, which were calculated from 2001 to 2014 (and furthermore for the S&P 500 index over the 1980–2014 period, where the November–April period outperforms the May–October period, with a monthly spread of 0.73%; please see text note in Exhibit 7 and the Appendix). For example, the cumulative return for the S&P 500 Index ETF (SPY) would be calculated as follows:

$$CRet = \frac{\left\langle \sum_{i=1}^{n} \left(\left[\prod_{j=Nov}^{Apr} (1 + r_j) \right] - 1 \right) \right\rangle}{n} \quad \forall \, \Theta \equiv \{ set\ of\ all\ ETFs \} \tag{1}$$

where n is the number of applicable years (2001–2014 or 2005–2014) for each ETF in Θ, $CRet$ is the cumulative return (reported in Exhibit 7), r is the monthly return, and i and j are time counters.

These findings support the idea that most of the ETFs in our study exhibit characteristics consistent with the Halloween effect. Interestingly, the only two ETFs not exhibiting such characteristics were TLT and SHY, the two U.S. Treasury ETFs (excluding TIPS) in the study. This actually makes sense from an investment standpoint. If, via the Halloween effect, there is an incentive for investors to leave risky markets, such as stocks, from May through October, then those investors must still be invested in the interim. The logical place to invest during that time, as illustrated by Bouman and Jacobsen [2002], would be Treasuries. Such asset-switching behavior should increase Treasury returns from May through October, essentially reversing the Halloween effect for these assets. We find evidence for this phenomenon in this study (including the 1980–2000 period for the S&P 500 and Russell 2000 indexes) and would like to think of it as the "Safety in Summer" effect.

A visual depiction of this effect can be seen in Exhibit 8 (Panel A), where the distribution of IWM monthly returns is calculated from January 2001 to December 2014 and then subgrouped into the May–October (black solid bars) and November–April (gray bars with white circles) periods. The post-Halloween period exhibits a higher average return and is associated with the highest frequency, at about a 3% monthly return.

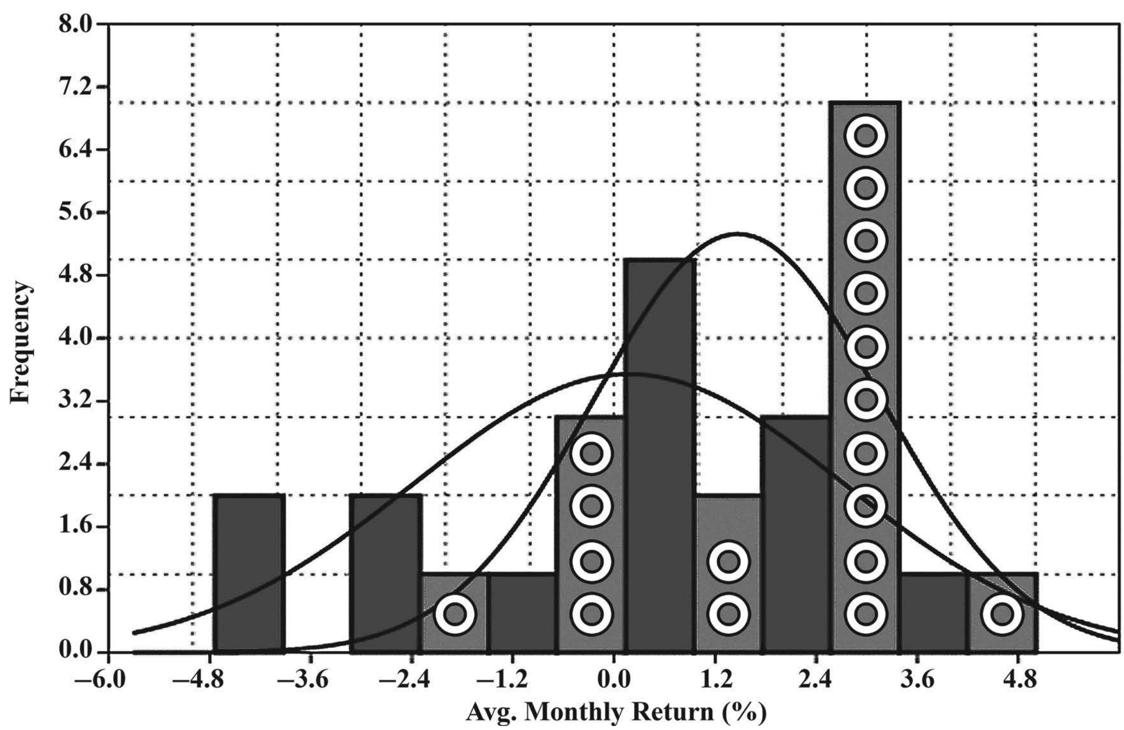
We tested for the statistical significance of this important result by utilizing the Friedman test. The Friedman test is a nonparametric test for equality of medians in univariate groups, and it can be seen as a variant of the repeated-measures version of the Kruskal-Wallis test. The test follows Bortz et al. [2000] and is computed as:

$$\chi^2 = \frac{12}{nk(k+1)} \sum_{j=1}^{k} T_j^2 - 3n(k+1) \tag{2a}$$

EXHIBIT 8

Comparing "May–Oct" and Nov–April" Returns (IWM, 2001–2014)

Panel A: Distribution of "Sell in May and Go Away" Returns (IWM, 2001–2014)



Note: Distribution of IWM monthly returns calculated from January 2001 to December 2014 and then sub-grouped into May to October (solid bars) and November to April (circular white bars) periods. The post-Halloween period exhibits a higher average return and has the highest frequency (at about 3% return).

EXHIBIT 8 *(Continued)*

Panel B: Friedman Test for the "Sell in May and Go Away" Effect (IWM, 2001–2014)

P-values	May–Oct Return	Nov–Apr Return	All Months Return	Feb–Dec Return	January Return
May–Oct Return	-	0.1353*	0.5016	0.5016	0.5016
Nov–Apr Return		-	0.01349†	0.01349†	0.0108†
All Months Return			-	0.8078	0.8078
Feb–Dec Return					0.8078
January Return					-

Note: We tested for the statistical significance of this result by utilizing the Friedman test, which is a nonparametric test for equality of medians in univariate groups. We find that the post-October period returns for IWM from November to April are significantly different from 'All Months' returns, 'Feb to Dec' returns, and even January returns. The same cannot be said for the 'May to October' period.

**Low significance at about 86% level, P = 0.1353.*

†Shaded cells significant at about 99% level, P < 0.015.

$$\chi^2_{tie} = \frac{\chi^2}{1 - \frac{1}{nk(k^2-1)}\sum_{i=1}^{m}(t_i^3 - t_i)} \tag{2b}$$

where n is the number of cases, k the variables, T_j the column sums, m the number of tie groups, and t_i the number of values in each group. We report the P-values associated with the Friedman statistic in Exhibit 8 (Panel B). We find that the post-October period returns for IWM from November to April are significantly different from "All Months" returns, "Feb–Dec" returns, and even the January returns. The same cannot be said for the "May–October" period. Results are near the 99% level of significance (P < 0.015).

THE MARK TWAIN EFFECT

Drawing from Cadsby [1989], we define the Mark Twain effect as persistent, negative returns in the month of October. Looking again at Exhibits 4 and 5, we find no support for this effect in our data. With the exception of TLT, all of the ETFs in our study demonstrated a 50% or higher probability of earning a positive return in October. The U.S. equity markets, as proxied by SPY and IWM, delivered 1.41%[4] and 1.77%, respectively, for the month of October and had a greater than 70% chance of being positive in that month. Average returns in October, however, were negative for TLT, TIP, EFA, IYR, and GLD. That said, with the exception of TLT, each of these funds experienced abnormal losses in October 2008 as a result of the financial crisis. If we were to adjust for the downward bias caused by this outlier event, then returns in October would have been positive for each of these funds. We find this interesting given the general belief that October is a particularly bad month for equity investors; there is no support for this belief in our data. In fact, to the contrary, both U.S. and emerging markets exhibited good returns in October. In short, our evidence (as well as S&P 500 returns over 1980–2000; see the Appendix) provides little support for the Mark Twain effect (Exhibits 4 and 5).

THE SANTA CLAUS RALLY

Hirsch [2014] has a seven-day definition of the Santa Claus rally. We examined the broader interpretation of this effect, defined as persistent, positive returns in the month of December. Here we found support for a Santa Claus rally (perhaps better termed as the December effect) among risk assets (equities primarily). Exhibit 4 shows that RSP, SPY, IWM, EFA, EEM, and IYR each returned strong monthly returns in December on average. Most equity ETFs posted December returns in excess of 2% (Exhibit 4), well above their annual averages. This could also be a result of the January effect being anticipated by the market, resulting in earlier buying. We discussed this in the preceding section on the January effect. Exhibit 5 reinforces this possibility, as each ETF had a 60% or higher average probability of achieving a positive return in that month.

The bond ETFs in our study (TLT, SHY, and TIP) demonstrated returns consistent with the idea that the Santa Claus rally primarily pertains to risk assets (equity). Exhibit 4 shows negative December returns, on average, for SHY and TIP. Although TLT shows a positive average return, we need to recall the outlier returns in 2008 as a result of the financial crisis. In December 2008, bonds rallied significantly as investors converged to the assumed safety of government securities. This had the effect of upwardly biasing returns for TLT, SHY, and TIP over the study period. If we were to adjust for this bias, then returns in December would have been negative for each of these funds. This makes sense, because returns for government bonds tend to be lowly, or even negatively, correlated with risk assets (Agrrawal [2013]). If risk assets are consistently positive in December, then one would expect government bonds to be less positive or even negative. The probability of a positive December is 76% with an average return of 1.85% over the 1980–2000 period (for the S&P 500), which compares well with the 71% positive probability and a 1.2% return for December over the 2001–2014 period for the SPY ETF (see Exhibit 5 text note and Appendix).

Our evidence, over the 2001–2014 period, shows that Santa Claus has been delivering (in December), and in fact, the returns have been rather fat (see Exhibits 4 and 5 and the Appendix).

FURTHER RESEARCH

We see some indication that a January effect might be present in nonstock asset classes, such as bonds and gold (Exhibits 4 and 5). One of our next steps will be to develop a means of testing for a January effect in these asset classes using the ETFs outlined in this article, namely SHY, TIP, and GLD. We also hope to examine the January effect using foreign small cap and foreign equal-weighted stock ETFs, if we can find appropriate ETFs with long enough price histories to study.

Additionally, ETF trading strategies and ETF portfolio allocations could be structured to take advantage of shifts in seasonality effects. Early results indicate that risk-adjusted returns might be improved by rotating into and out of certain ETFs, using the January effect or the Halloween effect as a signal. We plan to continue this research and integrate it with our prior work using ETFs in mean-variance optimized portfolios, to test whether seasonality effects might be a basis for alpha tilts in actively managed ETF products.

CONCLUSION

The article extends the seasonality analysis beyond the traditional stock market framework to include bonds and gold via a set of highly liquid ETFs. Our use of ETFs is a newer approach in the study of seasonality effects. ETF returns are more relevant to investors in practice, because they are actual investable assets and the fastest growing asset type over the past fifteen years (Agrrawal et al. [2014]). After analyzing returns for 10 different ETFs across multiple asset classes from January 2005 to December 2014 (and from January 2001 to December 2014, additionally, for SPY and IWM), we found mixed evidence of seasonal anomalies. The shorter return histories were an unavoidable consequence in this study, as most ETFs were launched only after 2000.[5] We deployed the Altman-Wald and Friedman test to determine statistical significance and also proxied the SPY with the S&P 500, and the IWM with the Russell 2000 indexes, to analyze the 1980–2014 period as well and confirm overlap with the 2001–2014 period. It seems that climate change has not spared time invariant seasonality in returns; in other words, the generally accepted seasonality effects seem to have somewhat changed over time.

First, we studied January returns and found no significant evidence of what we define as a weak case January effect in U.S. small cap and equal-weighted ETFs. We also found no evidence of what we define as a strong case January effect. With the exception of Cadsby [1989], our conclusions largely contradict findings by earlier studies, which look at longer time periods and document a strong January effect. If anything, we find that the month of December has a strong "January" effect. We also find that the months of December, March, and April (in that order) generated higher and more consistent total returns than the month of January.

We also present data for further study regarding nonstock asset classes, such as bonds, real estate, and gold. Of these, gold (GLD), short-term U.S. Treasuries (SHY), and TIPS (TIP) seem to have the most potential for exhibiting a January effect.

We found evidence of a robust Halloween effect (Sell in May) in all ETFs in our study, with the exception of TLT and SHY. This result is consistent with findings by earlier studies. We also found that the Santa Claus rally (better termed as the December effect) is intact in equity assets. However, we found no evidence of a Mark Twain effect. This is consistent with Balaban [1995], but inconsistent with Cadsby [1989]. Based on our research, October does not appear to be a "dangerous" month during which to invest.

APPENDIX

Index to ETF Comparison 1980–2014—Split Period

This table provides monthly probabilities, monthly returns, and monthly differentials for the Russell 2000 index and the S&P 500 index (Jan 1980–Dec 2000), and their associated ETFs viz. IWM and SPY (Jan 2001–Dec 2014). The shaded cells are some of the more interesting values.

	Probab. (Positive) Monthly Return		Monthly Return	
	SPY (2001–2014)	**S&P 500 (1980–2000)**	**SPY (2001–2014)**	**S&P 500 (1980–2000)**
Jan	50%	**71%**	–0.33%	**2.14%**
Feb	57%	67%	–0.51%	0.91%
Mar	**71%**	67%	1.36%	1.00%
Apr	**71%**	67%	**2.44%**	**1.29%**
May	57%	67%	0.47%	**1.43%**
Jun	43%	67%	–1.31%	**1.14%**
Jul	50%	38%	0.52%	0.81%
Aug	64%	57%	–0.12%	0.44%
Sep	57%	43%	–0.78%	–0.46%
Oct	71%	62%	1.41%	1.01%
Nov	71%	67%	**1.94%**	**1.56%**
Dec	71%	**76%**	1.20%	**1.85%**

	IWM (2001–2014)	**Russell 2000 (1980–2000)**	**IWM (2001–2014)**	**Russell 2000 (1980–2000)**
Jan	43%	62%	0.28%	**2.70%**
Feb	50%	67%	–0.51%	**2.56%**
Mar	**79%**	67%	**2.24%**	0.20%
Apr	57%	62%	2.36%	1.17%
May	64%	67%	0.88%	**1.86%**
Jun	57%	62%	–0.08%	0.77%
Jul	43%	48%	–0.47%	–0.47%
Aug	50%	62%	–0.09%	0.37%
Sep	57%	57%	–0.98%	–0.04%
Oct	**71%**	48%	1.77%	–1.08%
Nov	**71%**	57%	2.09%	1.38%
Dec	**79%**	**81%**	**2.34%**	**2.86%**

	Monthly Return	
	IWM minus SPY (2001–2014)	**Russell 2000 minus S&P 500 (1980–2000)**
Jan	**0.61%**	**0.56%**
Feb	0.00%	1.65%
Mar	0.88%	–0.80%
Apr	–0.08%	–0.12%
May	0.41%	0.43%
Jun	**1.23%**	–0.37%
Jul	**–0.99%**	–1.28%
Aug	0.03%	–0.07%
Sep	–0.20%	0.42%
Oct	**0.36%**	**–2.09%**
Nov	0.15%	–0.18%
Dec	**1.14%**	**1.01%**

*All values in **bold** are significant at $P = 0.1353$.*

To summarize, we find limited statistical significance in the January effect and the Mark Twain (October) effect, but a strong persistence of the "Sell in May and Go Away" effect as well as the December Santa Claus rally. We also introduce the bond-based "Safety in Summer" effect.

ENDNOTES

To conserve space, not all numerical tables are displayed but can be provided upon request. The index overlapping analysis was done at the suggestion of a referee, and the relevant numbers for the 1980–2000 period are mentioned in the text accompanying the exhibits or woven into the body of the article. The Appendix contains the data for the 1980–2000 and 2001–2014 periods.

[1]At the suggestion of an anonymous referee, we utilized the S&P 500 index as a proxy, to look at its returns over the 1980–2014 period, and found that the SPY and S&P 500 returns are significantly similar over the 2001–2014 period (correlation is 0.998, significant at $P < 0.01$). We also deployed the Altman-Wald test for proportions and the Friedman test to establish the significance of our results, given the relatively small observation periods (2001–2014 and 2005–2014). It may, however, be noted that in the case of ETF returns, the sample size approximates the ETF population size, due to their recency.

[2]Similar probabilities were calculated for the S&P 500 and the Russell 2000 over the 1980–2000 period and can be provided upon request (Appendix).

[3]For the 1980–2000 period, this contrasts with an average January return of 2.14% ($P = 0.0191$) for the S&P 500 and 2.7% ($P = 0.0112$) for the Russell 2000, both of which are over twice the average monthly returns for that period. It is possible that this phenomenon, seen over a 20-year period, has become a belief that has carried over into the new millennium but is not supported by readily available evidence (see the Appendix and Exhibit 4).

[4]The probability of a positive October is 62% with an average return of 1.01% over the 1980–2000 period (for the S&P 500); over the 2001–2014 period both these numbers have drifted upward, indicating that October may not be as pernicious as believed by some (see the Appendix).

[5]At the suggestion of an anonymous referee, we utilized the S&P 500 index as a proxy, to look at its returns over the 1980–2014 period (Appendix), and found that the SPY and S&P 500 returns are significantly similar over the 2001–2014 period (correlation is 0.998, significant at $P < 0.01$); we did a similar analysis for IWM and the Russell 2000. We also deployed the Altman-Wald test for proportions and the Friedman test to establish the significance of our results, given the relatively small observation periods (2001–2014 and 2005–2014). It may, however, be noted that in the case of ETF returns, the sample size approximates the population size.

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