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Sell in May and Go Away: Still good advice for investors?[☆]

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ABSTRACT

This study examines whether the "Sell in May and Go Away" (or Halloween) trading strategy still offers an opportunity to earn abnormal returns. In contrast to prior studies, we consider sample periods during which adequate investment instruments were available for an effective implementation of the Halloween strategy. In addition, we account for when the first study confirming the Halloween effect was published in a top academic journal. To use the limited data in the most efficient way, and to avoid possible data-snooping biases, we implement a bootstrap simulation approach. We find that the Halloween effect strongly weakened or even disappeared in recent years. Our results are robust across different markets and against various parameter variations. Overall, our findings support the theory of efficient capital markets.

1. Introduction

The old, somewhat simplistic, investment strategy "Sell in May and Go Away" (also known as the "Halloween" strategy), has enjoyed unbroken popularity in the academic literature as well as in actual investment practice. It posits that holding stocks from November through April, and then switching to cash from May through October, provides higher returns and lower risk than a buy-and-hold strategy.

In their seminal study, Bouman and Jacobsen (2002) support the widespread hypothesis that the Halloween strategy offers opportunities for earning abnormal returns. More recent studies confirm that the effect is still alive and provides profitable investment opportunities (Andrade, Chhaochharia, & Fuerst, 2013; Jacobsen & Zhang, 2012; Swinkels & van Vliet, 2012). However, if stock markets are informationally efficient, no such "anomaly" should exist over extended periods of time. As Fama (1970, 1991) and Jensen (1978) emphasize, in a semi-strong efficient market, it should be impossible to profit from publicly available information. And, if such abnormal returns net of all costs are nevertheless possible, these investment opportunities should diminish quickly as the underlying strategy becomes more transparent.

It is usually assumed that the first publication of an anomaly in the academic literature is of great relevance for the dissemination of research (Jacobsen & Visaltanachoti, 2009; Marquering, Nisser, & Valla, 2006; McLean & Pontiff, 2014; Schwert, 2003). Academic research draws attention to anomalies, and knowledge about an anomaly is more widespread after publication.[1] In particular, if publication generates the attention of sophisticated investors who learn about mispricing and these investors start trading against the mispricing, then one would expect an anomaly to disappear or at least diminish after the paper is published.[2] Therefore, two issues are crucial for tests of the success of any trading strategy: i) the availability of

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[1] "Anomalies" could be the outcome of a rational asset pricing model, statistical biases, or mispricing. While our analysis addresses the latter two explanations (by looking at post-publication performance and using a bootstrap simulation methodology), we do not account for a rational asset pricing explanation. Cochrane (1999) argues that if predictability entirely reflects rational expectations, then publication will not convey information that causes the average rational investor to behave differently, and an anomaly reflects risk that will persist.

[2] McLean and Pontiff (2014) study the post-publication return predictability of 95 predictor variables that have been shown to explain cross-sectional stock returns. They conclude that a large part of the post-publication decline in predictability is attributable to investors learning about mispricing from publications. Supporting this contention, post-publication declines are greater for stocks with larger in-sample returns. In addition, statistical biases contribute to the post-publication decline. Out-of-sample time series predictability is examined in Campbell and Thompson (2008) and Welch and Goyal (2008).

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adequate investment instruments, which make it possible to effectively implement a strategy, and ii) the date when a strategy has become publicly known and accepted in the investment community. As the Halloween strategy is based on a simple monthly seasonality, there should be hardly any impediments that prevent private and institutional investors from learning and then fully eliminating mispricing (Lucey & Zhao, 2008).[3] Therefore, the question is whether the Halloween strategy can really continue to offer potential for outperformance, as reported in a series of recent studies (Andrade et al., 2013; Jacobsen & Zhang, 2012; Swinkels & van Vliet, 2012; Zhang & Jacobsen, 2012). In contrast, Dichtl and Drobetz (2014) were not able to confirm that the Halloween strategy outperformed a buy-and-hold benchmark or any other monthly seasonality-based strategy.

We use a bootstrap-based simulation framework to test whether the Halloween strategy remains good advice for investors. In contrast to Dichtl and Drobetz (2014), we follow the methodological approach of prior studies, and compare the Halloween strategy with only a buy-and-hold benchmark rather than with all other monthly seasonality-based strategies. In addition to analyzing the time period during which adequate investment vehicles have been available to effectively implement the strategy, we also consider the period when the effect was first documented in a top academic journal (Bouman & Jacobsen, 2002). With respect to methodology, our simulation approach enables us to exploit small datasets in the most efficient way possible and to mitigate potential data snooping problems. In existing studies, the investment horizon is determined by the length of the available dataset (which results in unrealistically long investment horizons). We set the investment horizon to one year, because even long-term investors tend to evaluate their portfolios on a yearly basis due to myopic loss aversion (Barberis, Huang, & Santos, 2001; Benartzi & Thaler, 1995; among others). Furthermore, we implement hypothesis tests which enable us to derive conclusions about the statistical significance of the Halloween effect. Our hypothesis tests, which are also based on bootstrap simulations, do not require any distributional assumptions for the return and risk measures.

As Jones and Lundstrum (2009) note, to ensure backtests are realistic, it is important to use only historical data that was available at the time a strategy was implemented. Backtesting further requires that instruments with sufficient market liquidity are available during the entire sample period (e.g., index funds or exchange-traded funds). Therefore, in contrast to Bouman and Jacobsen's (2002) study, and more recent studies such as Jacobsen and Zhang (2012) and Andrade et al. (2013), we do not use the standard MSCI stock market indices (which begin in 1970 for most developed stock markets). Instead, we work with return data from stock market indices that were easy to invest in and featured low transaction costs during our sample period. For example, the German stock market index DAX consists of only thirty liquid blue-chip stocks, enabling full replication at low cost through efficient basket trades. A passive DAX index fund has been available since 1992, and a liquid DAX futures contract has been traded since November 1990. The MSCI Germany stock market index, on the other hand, is comprised of fifty-two constituents. To the best of our knowledge, no index fund or futures contract with a long enough history is available. Furthermore, in contrast to other studies that focus solely on the U.S. market (Jones & Lundstrum, 2009; Maberly & Pierce, 2004; Swinkels & van Vliet, 2012; Witte, 2010), we follow Bouman and Jacobsen (2002) and implement our analyses in an international context.

Our study thus differs from prior research along several important dimensions. First, we focus on markets and time periods that allow an effective implementation of the Halloween strategy. Second, we consider the date when the strategy was first published in a top academic journal (as a representation of public knowledge). Third, as our approach relies on relatively short return series, we implement a bootstrap simulation approach to mitigate potential data-snooping problems (Lo & MacKinlay, 1990; Sullivan, Timmermann, & White, 2001). Fourth, to incorporate the myopic loss aversion property of most investors, we evaluate strategy outcomes on a yearly basis. Fifth, our setup enables us to conduct statistical hypothesis tests. Sixth, and finally, we perform all analyses in an international context.

Our results are twofold. First, in line with prior studies, we confirm the existence of a Halloween anomaly in our regression analysis, the method of choice in most related studies, when we use the maximum history of available index data. Second, when we account for the availability of adequate investment instruments and the publication date of the Bouman and Jacobsen (2002) study, we find that the Halloween effect became weaker and in some markets even disappeared. These general findings show up both in a regression framework and in our simulation approach. While our results are in contrast to other recent studies, they are in line with the theory of market efficiency (Fama, 1970, 1991; Jensen, 1978).

The remainder is structured as follows. Section 2 contains a literature overview, while Section 3 describes our data. Section 4 discusses the results of our regression analyses. Section 5 introduces the design of our bootstrap-based simulation and discusses the results. Section 6 concludes and discusses implications for private and institutional investors.

2. Literature review

Bouman and Jacobsen (2002) was the first paper published in a major academic journal that analyzed the Halloween effect. The authors document the Sell in May effect for thirty-six of thirty-seven sample countries. Their study uses ordinary least squares regression models with dummy variables, but it also tests trading strategies. They find that the Halloween trading strategy provided lower returns than the buy-and-hold strategy for only two out of eighteen countries. However, in terms of volatility, the Halloween strategy dominated the buy-and-hold benchmark in all cases.

Maberly and Pierce (2004) argue that Bouman and Jacobsen's (2002) regression results may be caused by data outliers. They compare the Halloween strategy based on S&P 500 futures contracts with a buy-and-hold strategy, and reject the hypothesis that the Halloween effect offers a profitable trading rule. However, Witte (2010) questions Maberly and Pierce's (2004) regression setup. He shows that if data outliers are handled using a robust regression methodology, instead of simply eliminating single outliers, Maberly and Pierce's (2004) conclusions cannot be confirmed.

Lucey and Zhao (2008) examine the Halloween effect in the U.S. stock market using monthly CRSP stock file capitalization decile indices. As stock-level return data has not been previously used to investigate the Halloween effect, their approach mitigates the problem of data mining. In addition, Lucey and Zhao (2008) emphasize that it is important to examine the profitability of a trading strategy based on the Halloween effect. In their simulations, they find pronounced instability in the attractiveness of the Sell in May strategy compared to the buy-and-hold benchmark. Their results further indicate that the Halloween strategy has become less attractive during the recent years. Overall, they conclude that evidence for the Halloween effect is weak, and attribute it mostly to the January effect.

[3] For example, McLean and Pontiff (2014) report that the post-publication returns are lower for predictors that can be constructed with only price and trading data and for predictors that are less costly to arbitrage (e.g., for predictors concentrated in stocks with low idiosyncratic risk and high liquidity).

Similarly, Jones and Lundstrum (2009) claim that a test based on trading strategies is more appropriate than a mere statistical analysis (e.g., estimation of regression models). In particular, they note it is important to focus on stock markets and time periods with liquid ETFs and futures contracts. They also find that the Halloween trading strategy is not superior when based on the Vanguard S&P 500 index fund. Jacobsen and Visaltanachoti (2009) test the Halloween effect for U.S. sector indexes. They observe the effect for more than two-thirds of the sectors and industries studied, and find it can be exploited to improve an investor's risk-return trade-off in a sector rotation strategy.

Dzhabarov and Ziemba (2010) also include the Halloween effect in their comprehensive study of seasonal anomalies in the U.S. stock market (based on Russell 2000 and S&P 500 futures). In contrast to their findings for most other seasonal anomalies, they conclude that the Halloween effect continues to exist. Zhang and Jacobsen (2012) also find a Halloween effect in their long-run data, but they emphasize that it fluctuates over time (as do other seasonal effects), and varies strongly depending on sample size. Swinkels and van Vliet (2012) test the interactions of various well-known calendar effects. They conclude that the "turn of the month" effect and the Halloween effect are the strongest. In their backtests, a Halloween strategy dominates the passive stock investment in all cases in terms of return, volatility, and Sharpe ratio.

Andrade et al. (2013) implement an out-of-sample update of Bouman and Jacobsen's (2002) study using several international MSCI stock market indices. They confirm Bouman and Jacobsen's (2002) earlier regression results. However, their trading strategy is based solely on the S&P 500 index, and the Halloween strategy generally provides higher returns than a passive S&P 500 investment. In all cases (with and without leverage), the Halloween strategy dominates the buy-and-hold strategy in terms of the Sharpe ratio. Furthermore, all tested Halloween strategies provide a lower beta and a statistically significant alpha against a passive S&P 500 investment. Andrade et al. (2013) conclude that "the adage Sell in May and Go Away remains good investment advice."

Jacobsen and Zhang (2012) use all available stock market data for the 108 countries that have a stock market. They conclude that investors who exploit the Halloween effect achieved higher risk-adjusted returns than buy-and-hold investors even after the publication of Bouman and Jacobsen's (2002) study. They classify the Halloween effect as "a strong market anomaly that has strengthened rather than weakened in the recent years." Jacobsen and Zhang (2012) also use price index data and argue that dividend payments do not affect their results if there is no clustering in a specific month.[4] While this argument applies in a regression framework, however, it no longer holds when investment strategies are implemented. A buy-and-hold investor receives dividends for all twelve months, while an investor applying the Halloween strategy would only receive dividends for six months from November through April. This effect is correctly captured when simulations are based on performance indices, but is ignored in simulations with price indices. In fact, the use of price indices implies that the buy-and-hold investment strategy is at a disadvantage against the Halloween strategy. Zhang and Jacobsen (2012) omit transaction costs in their simulations, which also adversely affects the buy-and-hold benchmark performance compared to the Halloween strategy.

In summary, all of the above-mentioned studies suffer from some or all of the following shortcomings: 1) they focus only on the U.S. stock market, 2) they do not simulate a realistic enough Halloween investment strategy, 3) they provide no statistical inference, 4) they use all available index data regardless of whether adequate investment instruments are available, and 5) they fail to consider when the Halloween effect was first published in a major academic journal. We believe our simulation setup addresses all these issues appropriately.

3. Data description

To ensure our analysis is relevant for practical investing, we use monthly return data of liquid stock markets that are investable with low transaction costs. As we noted above, in comparison to a buy-and-hold strategy, no dividends are received under the Halloween strategy from May through October. By using total return indices (with dividend payments reinvested), we adequately incorporate this effect into our analysis.

In contrast to Bouman and Jacobsen (2002), Andrade et al. (2013), and Jacobsen and Zhang (2012), we do not use MSCI stock market indices (with one exception). Jones and Lundstrum (2009) emphasize that investors are unlikely to use MSCI indexes in their asset allocation strategy even today, and they were certainly unable to do so in 1970 (which is the starting date of Bouman and Jacobsen's (2002) sample). They argue that trading strategy results based on MSCI indexes are of limited practical relevance. Therefore, we use popular stock market indices for which liquid investment instruments were available: the S&P 500 TR index for the U.S., the DAX 30 TR index for Germany, the FTSE 100 TR index for the U.K., and the CAC 40 TR index for France.[5] We also include the EuroStoxx 50 NR index and the MSCI Emerging Markets TR index. The latter MSCI index is the most established and frequently used index for broad stock investments in emerging markets. Total return indices are used in all cases (except the EuroStoxx 50 Net Return; see Exhibit 1).

In contrast to most prior studies, we explicitly consider when an investment in a given stock market index became possible for both institutional and private investors. Because futures investments are not always allowed for private or institutional investors (e.g., due to regulatory restrictions), we focus primarily on the availability of passive mutual index funds or Exchange Traded Funds (ETFs).[6] For example, in 1992, the bank Sal. Oppenheim jr. & Cie. KGaA launched a passively managed index fund for the DAX, the German stock market index (Ebertz & Ristau, 1992). Liquid futures contracts have been available on the DAX since November 1990. Therefore, we can assume that DAX investments have been available for almost all institutional and private investors since 1993. In the U.S., the Vanguard S&P 500 Index fund has been available since 1976 (i.e., much longer than the total return version of the S&P 500 index, which began trading on December 31, 1987).[7] For all other countries or regions, we similarly identify the date on which investment instruments that would effectively allow the implementation of a Halloween strategy became available, not only to institutional investors but also for most private investors (see Exhibit 1).

Following existing studies, we use a one-month interest rate as the risk-free asset (Jacobsen & Visaltanachoti, 2009; Swinkels & van Vliet, 2012). The corresponding cash market indices are listed in

[4] See Jacobsen and Zhang (2012, p. 9, footnote 3). The same argument is presented in Gultekin and Gultekin (1983), Bouman and Jacobsen (2002), and Zhang and Jacobsen (2012).

[5] In contrast to Jones and Lundstrum (2009), we work with index data rather than real funds data. Jacobsen and Visaltanachoti (2009) also use index data and note that using real funds data has several shortcomings compared to index data (see the arguments in their footnote 18).

[6] In most cases, futures contracts were available before the first index funds were launched. For example, futures on the DAX have been available since November 1990. However, buying and selling futures contracts was not or not easily possible for most private investors in Germany. Additionally, regulatory restrictions or statutes allowed many institutional investors to buy or sell futures only for hedging purposes, but not for active trading.

[7] Because our analysis is based on index data instead of real funds data, for the U.S. we use 1988 as our beginning year.

Exhibit 1
Availability of index data and investment instruments.

Country/region	Index	Availability	Availability of stock market fund
United States	S&P 500 TR	1988	1976 (Vanguard 500 Index)
	1-month T-Bills (CRSP)	1927	
Europe	EuroStoxx 50 NR	1987	2001 (iShares EuroStoxx 50)
	Euribor/Fibor 1 M	1991	
Germany	DAX 30 Performance	1965	1993 (Oppenheim DAX-Werte-Fonds)
	Euribor/Fibor 1 M	1991	
France	CAC 40 TR	1988	2001 (Lyxor ETF CAC 40)
	PIBOR 1 M	1988	
United Kingdom	FTSE 100 TR	1986	2001 (iShares FTSE 100)
	Libor 1 M	1986	
Emerging markets	MSCI EM TR	1988	2004 (iShares MSCI EM ETF)
	1-month T-Bills (CRSP)	1927	

The table summarizes the availability of index data and investment instruments. Index funds were launched in the year prior to the date listed in the table. All indices are on a total return basis. An exception is the EuroStoxx 50 Net Return, which became available in January 1987, while the total return version of this index was only introduced in February 2001. The Euribor 1 M rate is available since 1999, thus we use the Fibor 1 M rate for the earlier sample years.

Exhibit 1. To ensure that we have exactly the same number of months ranging from May through October and from November through April, we begin all index data in January (and end in December). Therefore, we work with full years of data, with exactly six months invested in the stock market, and six months in cash.

4. Linear regression analysis

4.1. Main regression results

In this section, we implement Bouman and Jacobsen's (2002) regression analysis (which has been replicated in many follow-up studies). All regressions are estimated using continuously compounded monthly returns of the stock market indices shown in Exhibit 1. In particular, we estimate the following model using a standard OLS technique:

$$R_t = \mu + \alpha_1 \times S_t + \varepsilon_t, \tag{1}$$

where R_t denotes the stock market return at time t, and S_t is a dummy variable that is equal to 1 if month t falls within the time interval from November to April, and 0 otherwise. μ is the regression intercept, and ε_t is an error term. To consider a possible January effect, we also estimate the following extended regression model:

$$R_t = \mu + \alpha_1 \times S_t^{adj} + \alpha_2 \times J_t + \varepsilon_t, \tag{2}$$

where the dummy variable S_t^{adj} is equal to 1 if month t falls within the time interval from November to April (January is the only exception). In January, S_t^{adj} is equal to 0. S_t^{adj} is also equal to 0 in all months from May to October. The dummy variable J_t controls for a possible January effect; this variable is equal to 1 in January, and 0 otherwise.

In a first step, we estimate the models in Eqs. (1) and (2) using all available index data. All index return data end in December 2012, and have an index-specific start date (see Exhibit 1). The results are summarized in panel A of Exhibit 2 (period I). In a second step, we divide the full sample into two subsamples. Subsample 1 captures the availability of suitable investment instruments. The regression results are shown in panel B of Exhibit 2 (period II). Subsample 2 captures the publication date of Bouman and Jacobsen's (2002) study, thus panel C presents the regression results when all index data begin as late as January 2003 (period III).[8] The sample period ends in December 2012 in all models.

All regressions in Exhibit 2 are run separately for each country or region. Pooled regressions are reported as a robustness test in Section 4.2 below. In general, we correct the t-statistics for heteroscedasticity using White's (1980) method. In the presence of autocorrelated residuals, however, we use Newey and West's (1987) method instead.

Using all available index data (period I) in regression model 1, we find a positive and statistically significant α_1 estimate for all markets in panel A of Exhibit 2. Accordingly, the monthly returns from November through April are significantly higher than the returns from May through October, which is generally interpreted as evidence for the Halloween effect. Controlling for a potential January effect in model 2, our results remain unchanged. The estimated α_1 is positive and statistically significant in all countries or regions. Overall, these results confirm the existence of the Halloween effect when all available index data is used.

As panel B shows, however, our results become much weaker when we consider the availability of adequate investment instruments (period II). Based on a 5% significance level, we find a significant Halloween effect in only two of six regressions based on model 1 (the S&P 500 and the DAX 30).[9] In model 2, the estimated α_1 also becomes significant for the FTSE 100. As indicated by the negative α_2 coefficient (which is close to being significant), this latter observation is attributable to a reverse January effect. We observe no significant Halloween effect for the EuroStoxx 50, the CAC 40, or the MSCI Emerging Markets in either regression model specification.

Finally, when we account for the publication date of Bouman and Jacobsen (2002) and begin our sample period as late as January 2003 (going through December 2012; period III), the estimates in panel C show that all statistically significant α_1 coefficients disappear in both model specifications (except for the FTSE 100 in model 2, where the coefficient remains significant at the low 10% level). Accordingly, the Halloween effect is no longer observable during this latest subperiod.

4.2. Robustness tests

To verify the robustness of our results, we follow Jacobsen and Zhang (2012) and repeat our regressions by modeling the residuals as a GARCH (1,1) process. In particular, we specify the residuals in Eqs. (1) and (2) as follows:

$$\varepsilon_t|\Phi_{t-1} \sim N\left(0;\sigma_t^2\right) \text{ and } \sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\sigma_{t-1}^2. \tag{3}$$

[8] Jacobsen and Visaltanachoti (2009) assume April 15, 1998 as the publication date, when the first draft of Bouman and Jacobsen's (2002) study was distributed through the SSRN network. Although any choice of publication date is unlikely to be associated with abrupt changes, we believe this study received public attention when it was published in the *American Economic Review* later in 2002. Most articles in practical investment journals and newspapers cite that version of the study.

[9] In contrast to all other stock markets, the U.S. market did have an adequate investment instrument available before the total return version of the S&P 500 was introduced. Note that, because we use index data rather than real funds data (Jacobsen & Visaltanachoti, 2009), both models in panels A and B show identical results for the S&P 500. A similar argument applies for the results of the MSCI Emerging Markets model in panels B and C.

Exhibit 2
Standard dummy variables regression approach.

Country/region	Regression model 1 (without January effect)		Regression model 2 (with January effect)		
	μ t-value/prob.	α_1 t-value/prob.	μ t-value/prob.	α_1 t-value/prob.	α_2 t-value/prob.
Panel A: period I (availability of stock market index data — 12/2012)					
S&P 500	0.0034	0.0086	0.0034	0.0099	0.0021
	0.90/0.37	1.93/0.05	0.90/0.37	2.13/0.03	0.24/0.81
EuroStoxx 50	−0.0019	0.0150	−0.0019	0.0175	0.0027
	−0.37/0.71	2.53/0.01	−0.37/0.71	2.94/0.00	0.24/0.80
DAX 30	−0.0020	0.0135	−0.0020	0.0130	0.0161
	−0.52/0.60	2.98/0.00	−0.52/0.60	2.77/0.01	1.78/0.08
CAC 40	−0.0004	0.0145	−0.0004	0.0171	0.0013
	−0.07/0.94	2.38/0.02	−0.07/0.94	2.74/0.01	0.10/0.92
FTSE 100	0.0014	0.0124	0.0014	0.0150	−0.0001
	0.34/0.73	2.64/0.01	0.34/0.73	3.22/0.00	−0.01/0.99
MSCI EM	−0.0013	0.0023	−0.0013	0.0239	0.0161
	−0.18/0.86	2.62/0.01	−0.18/0.86	2.72/0.01	1.01/0.31
Panel B: period II (availability of stock market funds — 12/2012)					
S&P 500	0.0034	0.0086	0.0034	0.0099	0.0021
	0.90/0.37	1.93/0.05	0.90/0.37	2.13/0.03	0.24/0.81
EuroStoxx 50	−0.0067	0.0097	−0.0067	0.0136	−0.0101
	−0.78/0.43	1.01/0.32	−0.78/0.44	1.45/0.15	−0.53/0.59
DAX 30	−0.0024	0.0182	−0.0024	0.0212	0.0031
	−0.38/0.71	2.18/0.03	−0.36/0.72	2.57/0.01	0.21/0.84
CAC 40	−0.0055	0.0100	−0.0055	0.0131	−0.0058
	−0.67/0.50	1.07/0.29	−0.67/0.50	1.44/0.15	−0.32/0.75
FTSE 100	−0.0022	0.0094	−0.0022	0.0154	−0.0203
	−0.33/0.74	1.28/0.20	−0.33/0.74	2.14/0.03	−1.50/0.14
MSCI EM	0.0020	0.0167	0.0020	0.0213	−0.0067
	0.13/0.89	1.06/0.29	0.13/0.89	1.38/0.17	−0.22/0.82
Panel C: period III (01/2003–12/2012)					
S&P 500	0.0022	0.0071	0.0022	0.0112	−0.0133
	0.31/0.75	0.95/0.34	0.31/0.75	1.53/0.13	−0.96/0.34
EuroStoxx 50	0.0018	0.0030	0.0018	0.0073	−0.0186
	0.23/0.82	0.33/0.74	0.23/0.82	0.85/0.39	−0.86/0.39
DAX 30	0.0039	0.0083	0.0039	0.0141	−0.0203
	0.48/0.63	0.88/0.38	0.48/0.63	1.60/0.11	−0.84/0.40
CAC 40	0.0028	0.0033	0.0028	0.0067	−0.0141
	0.36/0.72	0.37/0.71	0.36/0.72	0.81/0.42	−0.69/0.49
FTSE 100	0.0039	0.0051	0.0039	0.0123	−0.0311
	0.60/0.55	0.69/0.49	0.60/0.55	1.73/0.09	−2.07/0.04
MSCI EM	0.0020	0.0167	0.0020	0.0213	−0.0067
	0.13/0.89	1.06/0.29	0.13/0.89	1.38/0.17	−0.22/0.82

The table reports the results from the standard dummy variables regressions approach. The two models are described in Eqs. (1) and (2) in Section 4 and estimated separately for each country or region. μ denotes the estimated intercept term, α_1 the coefficient that indicates the Halloween effect, and α_2 the coefficient on the dummy variable that controls for the January effect. All available index data are used in Panel A. Panel B accounts for the availability of suitable investment instruments, and Panel C captures the publication date of Bouman and Jacobsen's (2002) study. The first line reports the estimated coefficient. The second line contains the t-value (left) and the corresponding p-value (right). In general, t-statistics are corrected for heteroscedasticity using White's (1980) method. In the presence of autocorrelated residuals, we use Newey and West's (1987) method instead.

Exhibit 3 shows our results for the regressions with GARCH (1,1) residuals. Except for the S&P 500 index, we observe a significant Halloween effect in all stock markets when the full history of index data is used (panel A). When we incorporate the availability of index funds, we continue to observe the Halloween effect on the German market during this shorter sample period (panel B). For the FTSE 100 index, we observe a significant Halloween effect only in model 2 (at a 10% level), which controls for a potential January effect.

Most importantly, the results in panel C of Exhibit 3 are qualitatively the same as in panel C of Exhibit 2. As with the OLS estimation, the regression specification using GARCH (1,1) residuals indicates that the Halloween effect vanished during the most recent 2003–2012 sample period after Bouman and Jacobsen (2002) was published.

To analyze the influence of return outliers, we repeat our analysis by running median regressions. The mean value in a traditional OLS estimation minimizes the sum of squared residuals; the median value minimizes the sum of absolute residuals (Koenker & Hallock, 2001a,b). As a result, median regressions should be more robust against the influence of outliers. Exhibit 4 summarizes our median regression results. Even when we use all available index data (panel A), we observe that the Halloween effect is now much less pronounced than for the OLS estimation. This result holds for the S&P 500, the DAX 30, and the MSCI EM, where the estimated α_1 coefficient is no longer statistically significant. As expected, we find no significant Halloween coefficients for the shorter subsamples in panels B and C (with two exceptions when model 2 is applied). These findings confirm Maberly and Pierce's (2004) conjecture that the Halloween effect is (at least partly) driven by some extreme monthly return observations.

A final caveat is that the sample size declines over the three subperiods (from period I to period III in Tables 2–4). The declining sample length could lead to spurious results for the individual countries or regions. Following Andrade et al. (2013), we attempt to mitigate the small-sample problem by pooling return data across markets. Exhibit 5 shows the results of pooled regressions for the three subperiods. For robustness, we report a number of different pooled estimates for the α_1 coefficient in Eqs. (1) and (2). Both model specifications are estimated using either OLS or Prais–Winsten feasible generalized least

Exhibit 3
Dummy variables regression approach with GARCH (1,1) residuals.

Country/region	Regression model 1 (without January effect)		Regression model 2 (with January effect)		
	μ t-value/prob.	α_1 t-value/prob.	μ t-value/prob.	α_1 t-value/prob.	α_2 t-value/prob.
Panel A: Period I (availability of stock market index data – 12/2012)					
S&P 500	0.0067	0.0049	0.0067	0.0049	0.0049
	2.10/0.04	1.16/0.25	2.10/0.04	1.07/0.29	0.71/0.48
EuroStoxx 50	0.0006	0.0150	0.0006	0.0164	0.0073
	0.14/0.89	2.24/0.03	0.14/0.89	2.24/0.03	0.74/0.46
DAX 30	−0.0004	0.0120	−0.0005	0.0103	0.0200
	−0.14/0.89	2.65/0.01	−0.17/0.87	2.08/0.04	2.68/0.01
CAC 40	0.0030	0.0127	0.0030	0.0139	0.0072
	0.70/0.48	1.95/0.05	0.68/0.49	1.98/0.05	0.74/0.46
FTSE 100	0.0035	0.0098	0.0035	0.0124	−0.0039
	1.20/0.23	2.10/0.04	1.22/0.22	2.38/0.02	−0.50/0.62
MSCI EM	0.0029	0.0200	0.0029	0.0194	0.0201
	0.52/0.60	2.46/0.01	0.52/0.61	2.38/0.02	1.38/0.17
Panel B: period II (availability of stock market funds — 12/2012)					
S&P 500	0.0067	0.0049	0.0067	0.0049	0.0049
	2.10/0.04	1.16/0.25	2.10/0.04	1.07/0.29	0.71/0.48
EuroStoxx 50	0.0030	0.0060	0.0033	0.0094	−0.0119
	0.38/0.70	0.56/0.57	0.44/0.66	0.89/0.37	−0.70/0.49
DAX 30	0.0029	0.0150	0.0029	0.0173	0.0038
	0.61/0.54	2.28/0.02	0.47/0.64	1.83/0.07	0.30/0.76
CAC 40	0.0043	0.0088	0.0041	0.0107	−0.0036
	0.62/0.54	0.95/0.34	0.58/0.56	1.16/0.25	−0.25/0.80
FTSE 100	0.0036	0.0077	0.0042	0.0112	−0.0148
	0.79/0.43	1.07/0.28	0.97/0.33	1.64/0.10	−1.35/0.18
MSCI EM	0.0132	0.0078	0.0140	0.0119	−0.0165
	1.42/0.16	0.59/0.55	1.55/0.12	0.86/0.39	−0.82/0.41
Panel C: Period III (01/2003–12/2012)					
S&P 500	0.0053	0.0061	0.0054	0.0076	−0.0022
	1.13/0.26	1.00/0.32	1.15/0.25	1.19/0.23	−0.20/0.84
EuroStoxx 50	0.0065	0.0032	0.0067	0.0072	−0.0145
	0.85/0.39	0.31/0.76	0.87/0.38	0.67/0.50	−0.88/0.38
DAX 30	0.0060	0.0099	0.0063	0.0150	−0.0147
	0.70/0.49	0.90/0.37	0.72/0.47	1.14/0.25	−1.03/0.30
CAC 40	0.0069	0.0069	0.0067	0.0089	−0.0047
	1.00/0.32	0.74/0.46	0.96/0.34	0.95/0.34	−0.34/0.74
FTSE 100	0.0062	0.0060	0.0066	0.0095	−0.0172
	1.39/0.17	0.87/0.38	1.57/0.12	1.44/0.15	−1.68/0.09
MSCI EM	0.0132	0.0078	0.0140	0.0119	−0.0165
	1.42/0.16	0.59/0.55	1.55/0.12	0.86/0.39	−0.82/0.41

The table reports the results from the standard dummy variables regressions approach using GARCH (1,1) residuals. The two models are described in Eqs. (1) and (2) in Section 4 and estimated separately for each country or region. The specification of the residuals is shown in Eq. (3). μ denotes the estimated intercept term, α_1 the coefficient that indicates the Halloween effect, and α_2 the coefficient on the dummy variable that controls for the January effect. All available index data are used in Panel A. Panel B accounts for the availability of suitable investment instruments, and Panel C captures the publication date of Bouman and Jacobsen's (2002) study. The first line reports the estimated coefficient. The second line contains the t-value (left) and the corresponding p-value (right).

squares (FGLS).[10] In addition, we report three types of robust standard errors in the OLS specifications: (i) panel-corrected standard errors (PCSEs), (ii) Newey–West standard errors with one lag, and (iii) Driscoll–Kraay standard errors with one lag.[11] The FGLS specifications use panel-corrected standard errors.

Using all available index data in model 1, we again observe a positive α_1 coefficient in panel A of Exhibit 5; all different Halloween estimates are statistically significant. As panel B reveals, our results become slightly weaker when we consider the availability of adequate investment instruments, but all estimates for the α_1 coefficient remain consistently significant in both models. In contrast, when we account for the publication of Bouman and Jacobsen's (2002) study and begin our sample period as late as January 2003 (going through December 2012), we observe the same pattern as in our country-level regressions: in most specifications, the α_1 coefficient is no longer statistically significant. Most important, using Driscoll–Kraay standard errors, which correct for both cross-sectional and time-series correlation of residuals, the Halloween effect is no longer observable during this latest subperiod.

In summary, our regression analyses corroborate the existence of the Halloween effect when all available index data are used. However, even for the longest sample periods, we find that, in some cases, the Halloween effect is driven by a few extreme return observations. In addition, when we account for the availability of adequate investment instruments and the publication date of Bouman and Jacobsen's (2002) study, the Halloween effect decayed or even disappeared over time. These findings are supported in pooled regressions

[10] For the sake of brevity, we do not report the results when we further include market fixed effects. In our setup, the monthly returns are highly correlated across countries or regions, thus the results are almost identical with and without market fixed effects (with the fixed effect coefficients never being statistically significant).

[11] In contrast to PCSE and Newey-West standard errors, Driscoll-Kraay standard errors correct for both cross-sectional correlation of residuals across countries and time-series correlation of residuals within each country. PCSE and Newey-West standard errors can over- or underestimate standard errors depending on the correlation structure of the residuals. Therefore, Andrade et al. (2013) use Driscoll-Kraay standard errors as their preferred choice.

Exhibit 4
Median regressions.

Country/region	Regression model 1 (without January effect)		Regression model 2 (with January effect)		
	μ t-value/prob.	α_1 t-value/prob.	μ t-value/prob.	α_1 t-value/prob.	α_2 t-value/prob.
Panel A: period I (availability of stock market index data — 12/2012)					
S&P 500	0.0067	0.0071	0.0067	0.0069	0.0115
	1.59/0.11	1.25/0.21	1.59/0.11	1.18/0.24	1.09/0.28
EuroStoxx 50	0.0073	0.0094	0.0073	0.0128	0.0051
	1.38/0.17	1.33/0.19	1.37/0.17	1.75/0.08	0.36/0.72
DAX 30	0.0029	0.0085	0.0029	0.0065	0.0143
	0.68/0.50	1.58/0.11	0.68/0.50	1.17/0.24	1.61/0.11
CAC 40	0.0091	0.0134	0.0091	0.0134	0.0134
	1.58/0.12	1.71/0.09	1.57/0.12	1.67/0.10	0.78/0.43
FTSE 100	0.0079	0.0096	0.0079	0.0109	0.0005
	1.87/0.06	1.78/0.08	1.87/0.06	1.96/0.05	0.05/0.96
MSCI EM	0.0091	0.0090	0.0091	0.0148	−0.0031
	1.52/0.13	1.04/0.30	1.52/0.13	1.63/0.10	−0.19/0.85
Panel B: period II (availability of stock market funds — 12/2012)					
S&P 500	0.0067	0.0071	0.0067	0.0069	0.0115
	1.59/0.11	1.25/0.21	1.59/0.11	1.18/0.24	1.09/0.28
EuroStoxx 50	0.0052	0.0072	0.0052	0.0139	−0.0033
	0.60/0.55	0.62/0.53	0.60/0.55	1.15/0.25	−0.13/0.90
DAX 30	0.0073	0.0140	0.0073	0.0140	0.0099
	1.07/0.29	1.53/0.13	1.07/0.29	1.47/0.14	0.59/0.56
CAC 40	0.0090	0.0031	0.0090	0.0060	0.0029
	1.04/0.30	0.27/0.79	1.04/0.30	0.51/0.61	0.13/0.90
FTSE 100	0.0031	0.0084	0.0031	0.0158	−0.0086
	0.46/0.65	1.01/0.32	0.46/0.64	1.84/0.07	−0.58/0.56
MSCI EM	0.0084	0.0044	0.0084	0.0305	−0.0188
	0.78/0.44	0.27/0.79	0.75/0.45	1.91/0.06	−0.57/0.57
Panel C: period III (01/2003–12/2012)					
S&P 500	0.0127	−0.0016	0.0127	−0.0016	0.0023
	2.05/0.04	−0.18/0.85	2.05/0.04	−0.18/0.86	0.12/0.90
EuroStoxx 50	0.0126	0.0025	0.0126	0.0065	−0.0001
	1.53/0.13	0.22/0.82	1.54/0.13	0.56/0.58	−0.01/1.00
DAX 30	0.0137	0.0085	0.0137	0.0085	0.0100
	1.65/0.10	0.75/0.46	1.65/0.10	0.73/0.47	0.40/0.69
CAC 40	0.0166	−0.0015	0.0166	−0.0015	−0.0046
	2.03/0.04	−0.14/0.89	2.03/0.04	−0.13/0.90	−0.18/0.86
FTSE 100	0.0096	0.0028	0.0096	0.0110	−0.0151
	1.53/0.13	0.35/0.73	1.52/0.13	1.31/0.19	−0.85/0.40
MSCI EM	0.0084	0.0044	0.0084	0.0305	−0.0188
	0.78/0.44	0.27/0.79	0.75/0.45	1.91/0.06	−0.57/0.57

The table reports the results from median regressions (rather than OLS) applied to the standard dummy variables model. The two models are described in Eqs. (1) and (2) in Section 4 and estimated separately for each country or region. Rather than estimating these models using OLS, the table shows median regression coefficients to control for potential outliers (least-absolute-deviations regression). μ denotes the estimated intercept term, α_1 the coefficient that indicates the Halloween effect, and α_2 the coefficient on the dummy variable that controls for the January effect. All available index data are used in Panel A. Panel B accounts for the availability of suitable investment instruments, and Panel C captures the publication date of Bouman and Jacobsen's (2002) study. The first line reports the estimated coefficient. The second line contains the t-value (left) and the corresponding p-value (right).

that mitigate potential small-sample problems in our country-level regressions.

5. Bootstrap-based simulation of trading strategies

Our various regression results show that the monthly returns from November through April are significantly higher, on average, than the returns from May through October for the full sample period. A stronger test for seasonal anomalies is to analyze their potential to earn abnormal (risk-adjusted) returns compared to an adequate benchmark and net of transaction costs. Therefore, following Lucey and Zhao (2008) and Jones and Lundstrum (2009), we test the profitability of real-world trading strategies based on the Halloween effect to derive further conclusions about market efficiency. Our analysis of actual trading strategies is based on a bootstrap simulation approach. We first describe our methodology (Section 5.1), and then discuss the simulation setup used for statistical inference (Section 5.2). Finally, we show and discuss the results of our trading strategy simulations (Section 5.3) and implement a series of robustness tests (Section 5.4).

5.1. Simulation analysis design

All prior studies discussed in Section 2 used trading strategies based on the Halloween effect as historical backtests, implying that only one single return path was considered. To overcome this deficiency, and to use the data in the most efficient way, we use a bootstrap simulation approach. We divide all available monthly returns for a market into two subsets: Subset 1 contains the monthly stock and cash market returns from May through October, and subset 2 contains the returns from November through April. As in Barberis et al. (2001), we set the investment horizon to one year, recognizing that even long-term investors evaluate their portfolio performance on a yearly basis (Benartzi & Thaler, 1995).

To simulate the Halloween and buy-and-hold strategies, we draw (with replacement) six pairs of monthly stock and cash market returns from subset 1, and six pairs of monthly returns from subset 2. We use the first four monthly stock market returns from subset 2 as the returns for the Halloween strategy and the buy-and-hold strategies from January through April. The six monthly cash market

Exhibit 5
Pooled regressions.

Pooled sample	Regression model 1 (without January effect)		Regression model 2 (with January effect)		
	μ t-value/prob.	α_1 t-value/prob.	μ t-value/prob.	α_1 t-value/prob.	α_2 t-value/prob.
Panel A: period I (availability of stock market index data — 12/2012; 2112 observations)					
Coefficient	−0.0004	0.0143	−0.0004	0.0157	0.0075
Standard error					
PCSE	−0.11/0.92	2.95/0.00	−0.11/0.92	3.08/0.00	0.83/0.41
Newey–West	−0.19/0.85	5.91/0.00	−0.19/0.85	6.42/0.00	1.60/0.11
Driscoll–Kraay	−0.09/0.93	3.06/0.03	−0.09/0.93	3.32/0.02	0.85/0.43
Coefficient	−0.0021	0.0140	−0.0002	0.0153	0.0070
Prais–Winsten PCSE	−0.12/0.91	5.51/0.00	−0.09/0.93	5.81/0.00	1.55/0.12
Panel B: period II (availability of stock market funds — 12/2012; 1440 observations)					
Coefficient	−0.0007	0.0139	−0.0007	0.0166	0.0004
Standard error					
PCSE	−0.15/0.88	2.17/0.03	−0.15/0.88	2.58/0.01	0.03/0.97
Newey–West	−0.29/0.78	4.66/0.00	−0.29/0.78	5.57/0.00	0.07/0.95
Driscoll–Kraay	−0.12/0.91	2.16/0.08	−0.12/0.91	2.56/0.05	0.03/0.98
Coefficient	−0.0006	0.0138	−0.0006	0.0162	0.0005
Prais–Winsten PCSE	−0.29/0.77	4.41/0.00	−0.25/0.81	5.03/0.00	0.08/0.93
Panel C: period III (01/2003–12/2012; 714 observations)					
Coefficient	0.0036	0.0063	0.0036	0.0112	−0.0182
Standard error					
PCSE	0.71/0.48	0.59/0.56	0.59/0.55	1.22/0.22	−1.12/0.26
Newey–West	1.53/0.13	1.09/0.28	1.09/0.28	2.88/0.00	−0.18/0.03
Driscoll–Kraay	0.72/0.51	0.45/0.67	0.45/0.67	1.35/0.23	−0.96/0.38
Coefficient	0.0029	0.0075	0.0033	0.0117	−0.0175
Prais–Winsten PCSE	0.92/0.36	1.71/0.09	1.03/0.30	2.63/0.01	−2.37/0.02

The table reports the results from pooled regressions. The two models are described in Eqs. (1) and (2) in Section 4 and estimated for the full aggregated sample. μ denotes the estimated intercept term, α_1 the coefficient that indicates the Halloween effect, and α_2 the coefficient on the dummy variable that controls for the January effect. All available index data are used in Panel A. Panel B accounts for the availability of suitable investment instruments, and Panel C captures the publication date of Bouman and Jacobsen's (2002) study. The first line reports the estimated coefficient. The second line contains the t-value or z-value (left) and the corresponding p-value (right). The estimates are based on either OLS or Prais–Winsten AR(1) regressions. The standard errors of OLS regressions are panel corrected (PCSE; no autocorrelation), Newey–West with one lag (no cross-market correlations), or Driscoll–Kraay with one lag. The standard errors of Prais–Winsten FGLS regressions are panel-corrected.

returns from subset 1 are used for the Halloween strategy from May through October, and the corresponding stock market returns are used for the buy-and-hold strategy. Finally, we use the remaining two monthly stock market returns from subset 2 for both strategies for November and December. The shift from the stock market into the cash market in May, and the reverse shift at the end of October under the Halloween strategy are executed with transaction costs of 50 bps (DeMiguel, Garlappi, & Uppal, 2009).

This procedure is repeated 100,000 times, resulting in 100,000 yearly returns for the Halloween strategy and the buy-and-hold benchmark.[12] We transform all returns into excess returns by subtracting the risk-free rate.[13] For both strategies, we calculate the mean annual excess return, the volatility of annual excess returns, and the Sharpe ratio.[14] As in our regression analysis in Section 4, we again simulate our investment strategies using the full index history and the two shorter subsamples (accounting for the availability of adequate investment instruments and the publication date of Bouman and Jacobsen's (2002) study, respectively).

To further verify the robustness of our bootstrap simulation results, we modify the simulation design. Instead of dividing the available data into two subsamples, we generate twelve subsamples, one for each month. For example, subset 1 contains all return pairs for January, subset 2 contains all return pairs for February, and so on. For each month, we draw a pair of stock and cash market returns from the underlying subsample with replacement. For the Halloween strategy, we use the stock market returns from January through April and November and December, and the cash market returns from May through October. For the buy-and-hold strategy, we use the monthly stock market return for each of the twelve months. In comparison with our original bootstrap design, this alternative approach guarantees that the monthly structure of any given year is maintained, i.e., each year contains a January return, followed by a February return, and so on.

As an additional robustness check, we reduce the turnover-based round-trip transaction costs to 0.1% (Solnik, 1993) and then increase them to 1.0% (Pesaran & Timmermann, 1994). As proposed by Andrade et al. (2013), we also implement a "leveraged Halloween strategy," which, just as in the traditional Halloween strategy, holds cash from May through October. However, a 200% stock market allocation is accumulated from November through April, implying a 100% stock allocation over the entire year on average (similarly to the buy-and-hold benchmark strategy).

5.2. Statistical significance testing

Our simulation framework allows us to implement statistical significance tests for the performance differences between the Halloween and buy-and-hold strategies. Our starting points are the $N = 100,000$ yearly returns for the two strategies. To evaluate the profitability of the Halloween strategy, we focus on the differences between the mean excess returns, the volatilities of the excess returns, and the

[12] Repeated simulations indicate that our results are sufficiently stable with this number of runs.

[13] Because we draw pairs of monthly stock and cash market returns, this transformation is straightforward.

[14] Following Sharpe (1994), we compute the Sharpe ratio as the ratio of the mean excess return to the volatility of the excess return.

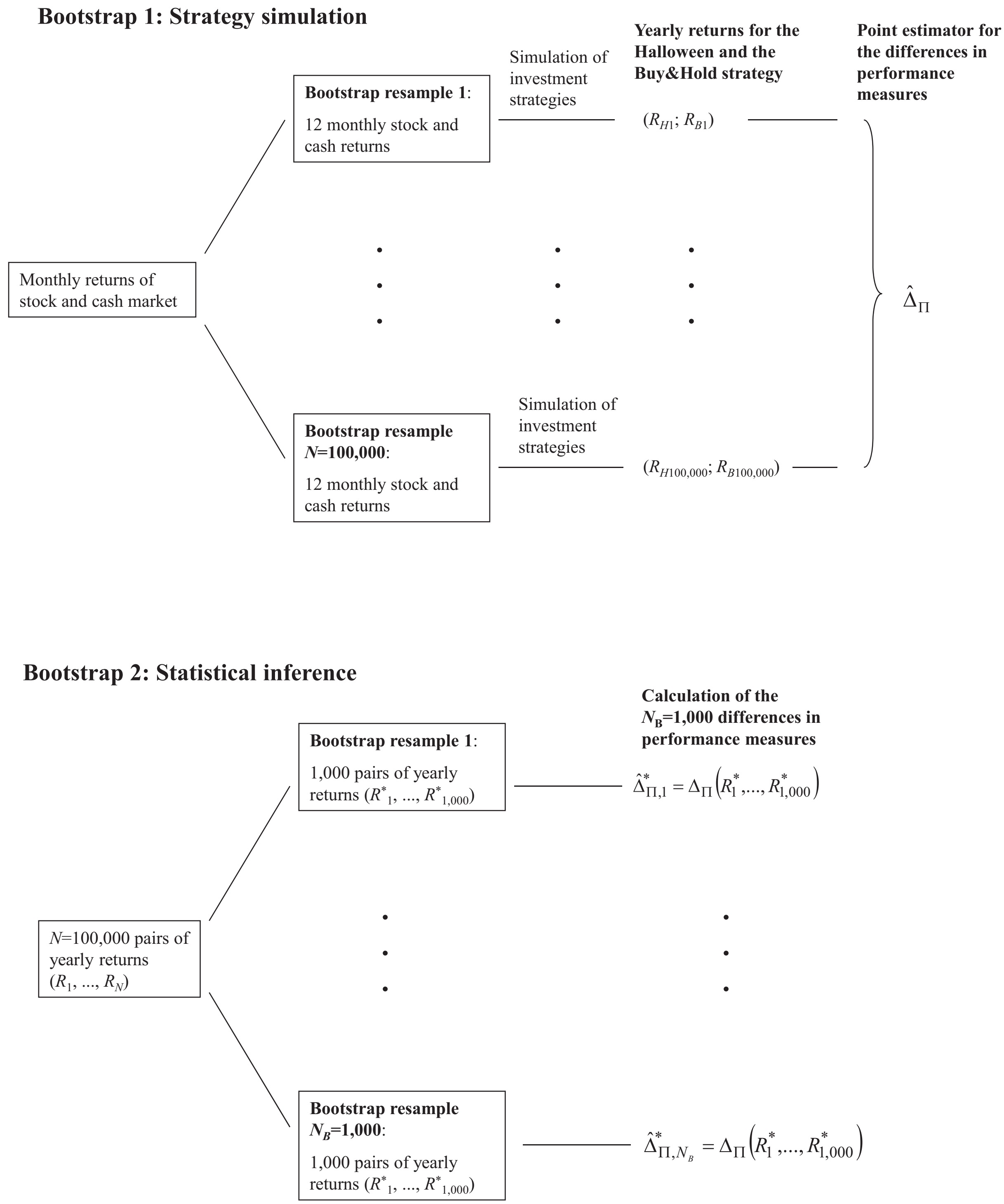

Exhibit 6. Bootstrap simulation environment.

Sharpe ratios of the Halloween strategy H and the buy-and-hold benchmark strategy B [15]:

$$\Delta_\Pi = \Pi_H - \Pi_B. \tag{4}$$

We analyze whether there is a statistically significant difference in the performance measure Π (mean excess return, volatility, or Sharpe ratio) of the two compared strategies (Π_H, Π_B). Formally, we test:

$$H_0 : \Delta_\Pi = 0 \quad \text{against} \quad H_1 : \Delta_\Pi \neq 0. \tag{5}$$

Given the $N = 100,000$ yearly returns for each strategy, an appropriate point estimator for the performance difference in Eq. (4) is:

$$\hat{\Delta}_\Pi = \widehat{\Pi}_H - \widehat{\Pi}_B. \tag{6}$$

[15] Zeisberger, Langer, and Trede (2007) implement a similar type of hypothesis testing based on a bootstrap approach.

In order to implement a statistical significance test, we require the distribution of the $\widehat{\Delta}_{\Pi}$ value. We thus run another bootstrap simulation based on the $N = 100{,}000$ yearly returns (i.e., the result of the preceding strategy simulation bootstrap). Within this second bootstrap, we create 1000 bootstrap resamples ($N_B = 1{,}000$), each consisting of 1,000 yearly returns.[16] We compute the $\widehat{\Delta}^*_{\Pi}$ value for each $N_B = 1{,}000$ bootstrap resamples in the same way as for the $\widehat{\Delta}_{\Pi}$ value. Let

$$\widehat{\Delta}^*_{\Pi[1]} \le \widehat{\Delta}^*_{\Pi[2]} \le \ldots \le \widehat{\Delta}^*_{\Pi[N_B]} \tag{7}$$

equal the ordered series of the differences in the performance measures. Based on this series, we can construct the following confidence interval as per Efron and Tibshirani (1998):

$$CI = \left[\xi^*_{low}, \xi^*_{high}\right] \tag{8}$$

where:

$$\xi^*_{low} = \widehat{\Delta}^*_{\Pi[\alpha/2 \cdot N_B]} \tag{9a}$$

and

$$\xi^*_{high} = \widehat{\Delta}^*_{\Pi[(1-\alpha/2) \cdot N_B]}. \tag{9b}$$

We can reject the null hypothesis H_0 at significance level α if $0 \notin CI$. We use Efron's (1979) standard bootstrap technique because our bootstrap sample consisting of 100,000 elements does not exhibit any significant serial dependencies. As described in Section 5.1, we obtain the 100,000 yearly returns of the Halloween strategy and the buy-and-hold benchmark by randomly drawing monthly returns.[17]

Exhibit 6 illustrates our simulation setup, which consists of the first-step bootstrap for the simulation of investment strategies, and the second-step bootstrap for the hypothesis tests. Let R_i be a pair of yearly returns of the Halloween strategy H and the buy-and-hold benchmark B: $R_i = (R_{Hi}; R_{Bi})$. The second-stage bootstrap uses the N pairs of annual returns (R_1, …, R_N) from the first-stage bootstrap, with point estimator $\widehat{\Delta}_{\Pi} = \Delta_{\Pi}(R_1, \ldots, R_N)$. Similarly, the $\widehat{\Delta}^*_{\Pi}$ values are $\widehat{\Delta}^*_{\Pi} = \Delta_{\Pi}\left(R^*_1, \ldots, R^*_{1{,}000}\right)$, where the R^*_i values refer to the results from the second-stage bootstrap (statistical inference bootstrap).

5.3. Main simulation results

Exhibit 7 presents the results of our baseline bootstrap simulations, where we draw twelve monthly returns from the two subsets and assume transaction costs of 50 bps (see Section 5.1). Panel A of Exhibit 7 shows the results with all available index data (period I).[18] In five of the six markets, the Halloween strategy provides higher excess returns than the buy-and-hold strategy. In one case (the German DAX), the difference is even statistically significant at the 1% level. In contrast to buy-and-hold, the Halloween strategy is not fully invested in the stock market during the assumed investment horizon of one year. It therefore exhibits significantly lower excess return volatilities in all six countries or regions. Finally, based on the Sharpe ratio, the Halloween strategy generates significantly higher risk-adjusted excess returns than the buy-and-hold in all cases.

When we consider the availability of adequate investment instruments in panel B of Exhibit 7 (period II), we find similar results. The Halloween strategy provides lower excess returns than the buy-and-hold strategy for the S&P 500 and the MSCI Emerging Markets, but its excess returns are higher for the EuroStoxx 50, the DAX 30, the CAC 40, and the FTSE 100. Moreover, because of its lower volatility, the Halloween strategy dominates buy-and-hold in terms of the Sharpe ratio in all six countries (the differences are statistically significant).

Finally, panel C of Exhibit 7 shows the results for simulating the two strategies after the publication of Bouman and Jacobsen's (2002) study (i.e., the most recent 2003–2012 sample years; period III). We now observe that the Halloween strategy exhibits significantly lower excess returns than buy-and-hold in all six markets. Comparing Sharpe ratios, the Halloween strategy significantly dominates buy-and-hold only for the MSCI Emerging Markets index. In all other markets, either the buy-and-hold strategy dominates or the Sharpe ratio differences are no longer statistically significant. Overall, our simulation results do not support the hypothesis that the Halloween effect continues to offer a "free lunch" for investors.

5.4. Robustness tests

To check the robustness of our results, we repeat the bootstrap simulations using the modified simulation design as described in Section 5.1. Instead of drawing returns from two subsets of data, we draw the return pairs from the twelve different monthly subsets. The results shown in Exhibit 8 generally confirm our baseline simulation results. The Halloween strategy dominates buy-and-hold in terms of Sharpe ratios in panels A and B. However, the results in panel C are again markedly different. In terms of Sharpe ratios, the Halloween strategy significantly dominates the buy-and-hold benchmark only for the MSCI Emerging Markets index. In all other countries or regions, buy-and-hold either generates significantly higher Sharpe ratios, or the difference is lost in estimation errors.

In another robustness check, we examine the influence of different levels of transaction costs. Exhibit 9 shows our results with varying transaction costs for the last ten sample years (January 2003 through December 2012; period III).[19] The results for low transaction costs of 0.1% (round-trip) are summarized in panel A of Exhibit 9. As expected, lower transaction costs make the Halloween strategy more attractive than the buy-and-hold strategy. However, even with low transaction costs, the Halloween strategy provides significantly lower excess returns than buy-and-hold in all six countries or regions. The performance of the Halloween and buy-and-hold strategies for the EuroStoxx 50 is now similar in terms of Sharpe ratios. For the S&P 500, the FTSE 100, and the MSCI Emerging Markets index, the Halloween strategy exhibits a significantly higher Sharpe ratio. For the DAX 30, the Halloween strategy also becomes superior to buy-and-hold, albeit the difference is not statistically significant.

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[16] The results of our hypothesis tests are stable with this number of simulation runs.

[17] Note that overlapping blocks of data or even blocks of data from a rolling window approach would suffer from serial dependencies. Politis and Romano (1994) suggest a stationary block bootstrap approach that is appropriate even with weakly dependent data. As a robustness check, we implement their approach and use Patton, Politis, and White's (2009) methodology to determine the optimal (average) block length. We find that a block length of 1 – and thus the application of Efron's (1979) standard bootstrap approach – is appropriate in our context.

[18] In contrast to the regressions in Section 4, here the maximum length of available index data is determined not only by stock market data but also by cash market data. For example, monthly stock market data are available from 1965 for the German DAX. The regressions including all index data begin in January 1965 and end in December 2012. However, cash market data are only available from 1991, thus our trading strategy simulations using all available index data only begin in January 1991 (and end in December 2012).

[19] The results in Exhibit 9 are based on bootstrap simulations where we draw the monthly returns from the twelve data subsets. The results should therefore be compared with those in Exhibit 8.

Exhibit 7
Baseline bootstrap simulation results.

	Strategy	Mean excess return p.a.	Volatility p.a.	Sharpe ratio
Panel A: period I (availability of stock market index data — 12/2012)				
S&P 500	Halloween	5.26	10.49	0.501
	Buy-and-hold	7.30	16.25	0.449
	Δ/significance	−2.04/***	−5.76/***	0.052/*
EuroStoxx 50	Halloween	7.15	13.16	0.543
	Buy-and-hold	6.40	20.31	0.315
	Δ/significance	0.75/−	−7.15/***	0.228/***
DAX 30	Halloween	8.49	15.27	0.556
	Buy-and-hold	6.84	23.52	0.291
	Δ/significance	1.65/***	−8.25/***	0.265/***
CAC 40	Halloween	6.52	14.86	0.439
	Buy-and-hold	6.10	22.05	0.277
	Δ/significance	0.42/−	−7.19/***	0.162/***
FTSE 100	Halloween	5.03	10.71	0.470
	Buy-and-hold	4.57	17.38	0.263
	Δ/significance	0.46/−	−6.67/***	0.207/***
MSCI EM	Halloween	12.28	17.48	0.703
	Buy-and-hold	12.23	27.61	0.443
	Δ/significance	0.05/−	−10.13/***	0.26/***
Panel B: period II (availability of stock market funds — 12/2012)				
S&P 500	Halloween	5.26	10.49	0.501
	Buy-and-hold	7.30	16.25	0.449
	Δ/significance	−2.04/***	−5.76/***	0.052/*
EuroStoxx 50	Halloween	0.49	13.30	0.037
	Buy-and-hold	−2.56	20.06	-
	Δ/significance	3.05/***	−6.76/***	-
DAX 30	Halloween	8.44	15.66	0.539
	Buy-and-hold	7.88	24.36	0.323
	Δ/significance	0.56/−	−8.70/***	0.216/***
CAC 40	Halloween	1.22	12.69	0.096
	Buy-and-hold	−1.28	19.47	-
	Δ/significance	2.50/***	−6.78/***	-
FTSE 100	Halloween	2.19	9.44	0.232
	Buy-and-hold	0.85	15.33	0.055
	Δ/significance	1.34/***	−5.89/***	0.177/***
MSCI EM	Halloween	11.14	16.70	0.667
	Buy-and-hold	14.99	28.70	0.522
	Δ/significance	−3.85/***	−12.00/***	0.145/***
Panel C: period III (01/2003–12/2012)				
S&P 500	Halloween	4.32	9.87	0.438
	Buy-and-hold	6.59	15.87	0.415
	Δ/significance	−2.27/***	−6.00/***	0.023/−
EuroStoxx 50	Halloween	1.66	13.06	0.127
	Buy-and-hold	3.61	18.96	0.190
	Δ/significance	−1.95/***	−5.90/***	−0.063/***
DAX 30	Halloween	6.64	15.54	0.427
	Buy-and-hold	10.21	22.58	0.452
	Δ/significance	−3.57/***	−7.04/***	−0.025/−
CAC 40	Halloween	2.25	12.26	0.184
	Buy-and-hold	4.80	18.44	0.260
	Δ/significance	−2.55/***	−6.18/***	−0.076/***
FTSE 100	Halloween	3.32	9.41	0.353
	Buy-and-hold	5.83	15.01	0.388
	Δ/significance	−2.51/***	−5.60/***	−0.035/−
MSCI EM	Halloween	11.14	16.70	0.667
	Buy-and-hold	14.99	28.70	0.522
	Δ/significance	−3.85/***	−12.00/***	0.145/***

The table reports the results from the baseline bootstrap simulations and shows the mean annual excess return, the volatility of excess returns, and the Sharpe ratio of the simulated Halloween strategy and the buy-and-hold benchmark. All available index data are used in Panel A. Panel B accounts for the availability of suitable investment instruments, and Panel C captures the publication date of Bouman and Jacobsen's (2002) study. "Δ" is the difference in a performance measure between the two simulated investment strategies. As described in Section 5.1, the results are based on 100,000 simulation runs in the first-step bootstrap for the simulation of the two strategies. The hypothesis tests in the second-step are based on Efron's (1979) standard bootstrap method (with 1,000 drawings, each consisting of 1,000 elements). An illustration of the bootstrap simulation environment is shown in Exhibit 6. The shift from the stock market into the cash market in May, and the reverse shift in October under the Halloween strategy are executed with transaction costs of 50 bps.
*** Denotes statistical significance at the 1% level.
** Denotes statistical significance at the 5% level.
* Denotes statistical significance at the 10% level.

The results for high transaction costs of 1.0% are shown in panel B of Exhibit 9. As expected, the dominance of buy-and-hold in terms of excess returns increases dramatically. Except for the MSCI Emerging Markets index, buy-and-hold now significantly outperforms the Halloween strategy in terms of Sharpe ratios.

In a final robustness check, we follow Andrade et al. (2013) and implement a leveraged version of the Halloween strategy, whereby no stocks are held from May through October, and a leveraged position of 200% stocks is accumulated from November through April. The simulations are implemented again over the most recent

Exhibit 8
Modified bootstrap simulation results.

	Strategy	Mean excess return p.a.	Volatility p.a.	Sharpe ratio
Panel A: period I (availability of stock market index data — 12/2012)				
S&P 500	Halloween	5.16	10.34	0.499
	Buy&Hold	7.12	15.97	0.446
	Δ/significance	−1.96/***	−5.63/***	0.053/***
EuroStoxx 50	Halloween	7.00	12.96	0.540
	Buy&Hold	6.11	19.84	0.308
	Δ/significance	0.89/*	−6.88/***	0.232/***
DAX 30	Halloween	8.43	14.95	0.564
	Buy&Hold	6.65	22.83	0.291
	Δ/significance	1.78/***	−7.88/***	0.273/***
CAC 40	Halloween	6.56	14.69	0.447
	Buy&Hold	6.03	21.61	0.279
	Δ/significance	0.53/—	−6.92/***	0.168/***
FTSE 100	Halloween	5.03	10.43	0.482
	Buy&Hold	4.56	17.11	0.267
	Δ/significance	0.47/—	−6.68/***	0.215/***
MSCI EM	Halloween	12.28	17.12	0.717
	Buy&Hold	12.42	27.01	0.460
	Δ/significance	−0.14/—	−9.89/***	0.257/***
Panel B: period II (availability of stock market funds — 12/2012)				
S&P 500	Halloween	5.16	10.34	0.499
	Buy&Hold	7.12	15.97	0.446
	Δ/significance	−1.96/***	−5.63/***	0.053/***
EuroStoxx 50	Halloween	0.36	12.63	0.029
	Buy&Hold	−2.78	19.19	-
	Δ/significance	3.14/***	−6.56/***	-
DAX 30	Halloween	8.28	15.26	0.543
	Buy&Hold	7.46	23.50	0.317
	Δ/significance	0.82/—	−8.24/***	0.226/***
CAC 40	Halloween	1.12	12.05	0.093
	Buy&Hold	−1.41	18.73	-
	Δ/significance	2.53/***	−6.68/***	-
FTSE 100	Halloween	2.10	8.54	0.246
	Buy&Hold	0.76	14.48	0.052
	Δ/significance	1.34/***	−5.94/***	0.194/***
MSCI EM	Halloween	11.10	16.24	0.683
	Buy&Hold	14.75	27.85	0.530
	Δ/significance	−3.65/***	−11.61/***	0.153/***
Panel C: period III (01/2003–12/2012)				
S&P 500	Halloween	4.36	9.26	0.471
	Buy&Hold	6.62	15.38	0.430
	Δ/significance	−2.26/***	−6.12/***	0.041/—
EuroStoxx 50	Halloween	1.52	12.25	0.124
	Buy&Hold	3.52	18.29	0.192
	Δ/significance	−2.00/***	−6.04/***	−0.68/***
DAX 30	Halloween	6.49	14.08	0.461
	Buy&Hold	10.10	21.21	0.476
	Δ/significance	−3.61/***	−7.13/***	−0.015/—
CAC 40	Halloween	2.26	11.65	0.194
	Buy&Hold	4.77	17.89	0.267
	Δ/significance	−2.51/***	−6.24/***	−0.073/***
FTSE 100	Halloween	3.24	8.10	0.400
	Buy&Hold	5.71	14.07	0.406
	Δ/significance	−2.47/***	−5.97/***	−0.006/—
MSCI EM	Halloween	11.10	16.24	0.683
	Buy&Hold	14.75	27.85	0.530
	Δ/significance	−3.65/***	−11.61/***	0.153/***

The table reports the results from the modified bootstrap simulations and shows the mean annual excess return, the volatility of excess returns, and the Sharpe ratio of the simulated Halloween strategy and the buy-and-hold benchmark. In comparison with our original bootstrap design in Exhibit 7, this alternative approach guarantees that the monthly structure of any given year is maintained. All available index data are used in Panel A. Panel B accounts for the availability of suitable investment instruments, and Panel C captures the publication date of Bouman and Jacobsen's (2002) study. "Δ" denotes the difference in a performance measure between the two simulated investment strategies. As described in Section 5.1, the results are based on 100,000 simulation runs in the first-step bootstrap for the simulation of the two strategies. The hypothesis tests in the second-step are based on Efron's (1979) standard bootstrap method (with 1,000 drawings, each consisting of 1,000 elements). An illustration of the bootstrap simulation environment is shown in Exhibit 6. The shift from the stock market into the cash market in May, and the reverse shift in October under the Halloween strategy are executed with transaction costs of 50 bps.

*** Denotes statistical significance at the 1% level.
** Denotes statistical significance at the 5% level.
* Denotes statistical significance at the 10% level.

January 2003–December 2012 sample period (period III). Panel A in Exhibit 10 gives the results, assuming transaction costs of 0.50% (the base case). As expected, leveraging the Halloween strategy results in higher excess returns but also higher volatilities compared to buy-and-hold. Except for the EuroStoxx 50 and the CAC 40, we observe significantly higher excess returns for the Halloween strategy than for buy-and-hold. However, note that the leveraged Halloween strategy exhibits significantly higher volatilities in all cases. This

Exhibit 9
Bootstrap simulation results with different transaction costs.

	Strategy	Mean excess return p.a.	Volatility p.a.	Sharpe ratio
Panel A: transaction costs of 0.1%				
S&P 500	Halloween	5.15	9.32	0.553
	Buy&Hold	6.51	15.35	0.424
	Δ/significance	−1.36/***	−6.03/***	0.129/***
EuroStoxx 50	Halloween	2.42	12.33	0.196
	Buy&Hold	3.61	18.32	0.197
	Δ/significance	−1.19/***	−5.99/***	−0.001/−
DAX 30	Halloween	7.37	14.16	0.520
	Buy&Hold	10.07	21.14	0.476
	Δ/significance	−2.70/***	−6.98/***	0.044/−
CAC 40	Halloween	3.10	11.76	0.264
	Buy&Hold	4.86	17.90	0.272
	Δ/significance	−1.76/***	−6.14/***	−0.008/−
FTSE 100	Halloween	4.10	8.16	0.502
	Buy&Hold	5.77	14.04	0.411
	Δ/significance	−1.67/***	−5.88/***	0.091/***
MSCI EM	Halloween	11.95	16.35	0.731
	Buy&Hold	14.68	27.81	0.528
	Δ/significance	−2.73/***	−11.46/***	0.203/***
Panel B: transaction costs of 1.0%				
S&P 500	Halloween	3.24	9.16	0.354
	Buy&Hold	6.60	15.38	0.429
	Δ/significance	−3.36/***	−6.22/***	−0.075/**
EuroStoxx 50	Halloween	0.49	12.14	0.040
	Buy&Hold	3.52	18.27	0.193
	Δ/significance	−3.03/***	−6.13/***	−0.153/***
DAX 30	Halloween	5.37	13.93	0.385
	Buy&Hold	10.11	21.17	0.478
	Δ/significance	−4.74/***	−7.24/***	−0.093/***
CAC 40	Halloween	1.29	11.55	0.112
	Buy&Hold	4.92	17.91	0.275
	Δ/significance	−3.63/***	−6.36/***	−0.163/***
FTSE 100	Halloween	2.14	7.98	0.268
	Buy&Hold	5.75	14.05	0.409
	Δ/significance	−3.61/***	−6.07/***	−0.141/***
MSCI EM	Halloween	10.07	16.07	0.627
	Buy&Hold	14.88	27.94	0.533
	Δ/significance	−4.81/***	−11.87/***	0.094/***

The table reports the results from bootstrap simulations and shows the mean annual excess return, the volatility of excess returns, and the Sharpe ratio of the simulated Halloween strategy and the buy-and-hold benchmark. In comparison with our modified bootstrap design in Exhibit 8, this alternative uses different transaction costs. In particular, the shift from the stock market into the cash market in May, and the reverse shift in October under the Halloween strategy are executed with transaction costs of 0.1% (Panel A) or 1.0% (Panel B). The sample period is 01/2003–12/2012 (latest subsample after publication of Bouman and Jacobsen's (2002) study). "Δ" denotes the difference in a performance measure between the two simulated investment strategies. As described in Section 5.1, the results are based on 100,000 simulation runs in the first-step bootstrap for the simulation of the two strategies. The hypothesis tests in the second-step are based on Efron's (1979) standard bootstrap method (with 1,000 drawings, each consisting of 1,000 elements). An illustration of the bootstrap simulation environment is shown in Exhibit 6.

*** Denotes statistical significance at the 1% level.
** Denotes statistical significance at the 5% level.
* Denotes statistical significance at the 10% level.

volatility effect implies that the higher excess returns of the Halloween strategy are overcompensated in simulations with the DAX 30 and the FTSE 100, because in both cases the leveraged Halloween strategy is dominated by the buy-and-hold strategy in terms of Sharpe ratios (for the FTSE 100, this difference is not statistically significant).

When we reduce the transaction costs to the lower 0.1% rate in panel B in Exhibit 10, the leveraged Halloween strategy becomes more attractive than the passive benchmark. The Halloween strategy exhibits a significantly higher Sharpe ratio than the buy-and-hold strategy for the S&P 500, the FTSE 100, and the MSCI Emerging Markets index. However, buy-and-hold still dominates in terms of Sharpe ratios for the EuroStoxx 50 and the CAC 40 even with low transaction costs (although the differences are again not significant).

Overall, we find that leveraging may allow us to enhance the return potential of the Halloween strategy, but at the cost of substantially higher volatility. However, it is important to consider that not all institutional or private investors are allowed to implement leveraged investment strategies (e.g., due to regulatory restrictions and solvency restraints).

6. Concluding remarks

This study examines the long-standing "Sell in May and Go Away" investment strategy based on the Halloween effect. Using the full sample with the maximum length of historical index data, we find that our regression analyses confirm the existence of the Halloween effect. These findings are in line with prior studies. However, when we explicitly consider the time period during which adequate investment instruments were available for an effective implementation of the Halloween strategy, and further take into account the publication date of Bouman and Jacobsen's (2002) study, both our regression results and the results from our simulated investment strategies show that the Halloween effect has weakened or even disappeared recently. In fact, we conclude that this simple and well-known investment rule, which nowadays can be implemented by most private and institutional investors without any impediments, does not provide an ongoing "free lunch." Our findings are in line with the theory of efficient capital markets, and investors should only consider applying the Halloween strategy in the future with caution.

Exhibit 10
Bootstrap simulation results with leverage.

	Strategy	Mean excess return p.a.	Volatility p.a.	Sharpe ratio
Panel A: transaction costs of 0.5%				
S&P 500	Halloween	8.64	19.31	0.447
	Buy&Hold	6.54	15.40	0.425
	Δ/significance	2.10/***	3.91/***	0.022/−
EuroStoxx 50	Halloween	2.93	24.94	0.117
	Buy&Hold	3.56	18.31	0.194
	Δ/significance	−0.63/−	6.63/***	−0.077/***
DAX 30	Halloween	12.75	29.63	0.430
	Buy&Hold	9.98	21.11	0.472
	Δ/significance	2.77/***	8.52/***	−0.042/*
CAC 40	Halloween	4.52	23.78	0.190
	Buy&Hold	4.83	17.89	0.270
	Δ/significance	−0.31/−	5.89/***	−0.08/***
FTSE 100	Halloween	6.25	16.71	0.374
	Buy&Hold	5.74	14.08	0.408
	Δ/significance	0.51/***	2.63/***	−0.034/−
MSCI EM	Halloween	23.01	35.72	0.644
	Buy&Hold	14.89	27.93	0.533
	Δ/significance	8.12/***	7.79/***	0.111/***
Panel B: transaction costs of 0.1%				
S&P 500	Halloween	10.30	19.54	0.527
	Buy&Hold	6.45	15.30	0.422
	Δ/significance	3.85/***	4.24/***	0.105/***
EuroStoxx 50	Halloween	4.72	25.32	0.186
	Buy&Hold	3.58	18.33	0.195
	Δ/significance	1.14/*	6.99/***	−0.009/−
DAX 30	Halloween	14.71	30.23	0.485
	Buy&Hold	10.09	21.15	0.477
	Δ/significance	4.62/***	9.08/***	0.008/−
CAC 40	Halloween	6.23	24.27	0.257
	Buy&Hold	4.88	17.96	0.272
	Δ/significance	1.35/**	6.31/***	−0.015/−
FTSE 100	Halloween	7.98	16.96	0.471
	Buy&Hold	5.65	14.07	0.402
	Δ/significance	2.33/***	2.89/***	0.069/**
MSCI EM	Halloween	25.14	36.51	0.689
	Buy&Hold	15.01	27.98	0.536
	Δ/significance	10.13/***	8.53/***	0.153/***

The table reports the results from bootstrap simulations with leverage and shows the mean annual excess return, the volatility of excess returns, and the Sharpe ratio of the simulated Halloween strategy and the buy-and-hold benchmark. In comparison with our modified bootstrap design in Exhibit 8, this alternative holds no stocks from May through October and a leveraged position of 200% stocks is accumulated from November through April. The sample period is 01/2003–12/2012 (latest subsample after publication of Bouman and Jacobsen's (2002) study). The shift from the stock market into the cash market in May, and the reverse shift in October under the Halloween strategy are executed with transaction costs of 0.5% (Panel A) and 0.1% (Panel B). "Δ" denotes the difference in a performance measure between the two simulated investment strategies. As described in Section 5.1, the results are based on 100,000 simulation runs in the first-step bootstrap for the simulation of the two strategies. The hypothesis tests in the second-step are based on Efron's (1979) standard bootstrap method (with 1,000 drawings, each consisting of 1,000 elements). An illustration of the bootstrap simulation environment is shown in Exhibit 6.

*** Denotes statistical significance at the 1% level.
** Denotes statistical significance at the 5% level.
* Denotes statistical significance at the 10% level.

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