Do currency value variations explain April stock return effects?

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ABSTRACT

This research evaluates properties of April effects in stock returns. Recent research identifies an April effect in stock returns. This effect involves positive abnormal stock returns in April. Another line of research examines the extent that currency value fluctuations explain stock index returns. This paper combines these two lines of research. Specifically, this paper examines if abnormal April returns exist after controlling for the effects of currency value changes. This analysis evaluates daily stock index data from 1971 through 2019. Results show the April effect persists after controlling for currency value variations.

Keywords: Stock Indexes, Currency Value, Market Anomalies, Seasonal Stock Returns, April Effect

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INTRODUCTION

Extensive studies related to stock market anomalies exist. Research suggests that some anomalies persist over time while others dissipate or reverse over time. The research here examines one of these anomalies. The presence of unusually large stock returns in April is a stylized fact. However, academic literature has only recently addressed this issue by documenting the statistical significance of these returns and providing theories for why these returns occur. Recent research posits the underlying cause for abnormal returns in April lie in U.S. tax code incentives (Jalbert, 2022). Specifically, Jalbert (2022) argues these abnormal returns occur because investors fund tax deferred retirement accounts near the April 15th tax filing deadline. The resulting inflow of funds into markets produces abnormal returns.

Other research argues that index returns provide an unreliable measure of wealth changes because of fluctuations in underlying currency values (CV) (Jalbert, 2012). Jalbert (2012) creates new stock indexes by adjusting existing indexes to reflect CV levels. Evidence shows CV-adjusted indexes differ markedly from the original indexes in return levels, risk and distribution of returns.

The current paper combines these two lines of research. This research examines the April effect in stock returns while holding constant CV change effects. Results show the April effect displays robustness to changes in CVs. Specifically, results show positive abnormal returns in April for currency-adjusted indexes. These results further the existing knowledge of stock market anomalies and the April effect.

LITERATURE REVIEW

No direct research examines the impact of changes in currency value (CV) on April effects in stock returns. Indeed, no known research examines the impact of CV changes on any calendar-based stock market anomaly. To provide background we provide a discussion of two related literature streams. The first on currency adjusting stock indexes. The second on stock market anomalies and the presence of an April effect.

Both stock prices and CV changes impact investor wealth. Jalbert (2012) provided a seminal article on CV adjusted stock indices. His approach used the United States Federal Reserve's Broad and Major indexes as CV measures. Empirical examination revealed significant deviations between unadjusted and adjusted returns. For example, results for 1985 show S&P 500 Index raw and CV adjusted returns differed by nearly 14 percent. Results also reveal return distribution differences. Moreover, CV changes explain more than eight percent of combined changes in wealth.

Jalbert (2014) extended his earlier research by using a longer dataset and the Dollar Index (DXY) to measure CV, finding that CV variation explains more than fourteen percent of total wealth changes. Jalbert (2016) examined time-sequence characteristics of CV adjusted stock indexes. He finds Granger causality exits in a bidirectional format between currency adjusted (CA) indexes.

This line of research continued with an examination of tick-by-tick data. Jalbert (2015a) used intraday data to identify relationships between high and low values. Data revealed that CV changes account for more than fifteen percent of wealth changes. Jalbert (2015b) examined c Granger causality effects using tick-by-tick data. He found bidirectional cointegration between various CA indexes.

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Some researchers argue gold more accurately reflects wealth than currencies (Hammes and Willis, 2005). Jalbert (2017) uses gold as an underlying wealth measure. He adjusts stock indexes to represent their value in gold. Annual return differences between unadjusted and CA indexes show deviations of up to 32 percent. Further, differences exceed fifteen percent in over sixty percent of annual observations.

Thus far CA index research examined only U.S. stock indexes. In 2021, Jalbert expanded the research to evaluate international indexes (Jalbert, 2021). Results reveal strong currency effects. Specifically, CV changes account for up to 31 percent of overall changes in wealth. Like earlier findings for U.S. indexes, results show raw, and adjusted indexes possess different return distributions.

A plethora of research examines calendar-based stock market anomalies. Rozeff and Kinney (1976) initially identified the January effect. This effect involves January stock returns that exceed those during other months of the year. Many authors extended this research including Lakonishok, Shleifer, Thaler and Vishny (1991) who identified a look-good effect. This effect occurs when institutional investors modify their portfolios to produce positive appearing year-end statements. They argue these portfolio modifications drive the January effect. Some authors find a more prevalent January effect among small firms (Roll, 1983). Reinganum (1983) found tax loss selling drives the January effect. Patel (2016) finds a smaller January effect in recent years suggesting the phenomenon may be disappearing.

Another line of research examines the sell in May and go away phenomenon. This research finds higher returns occur between November and April. One study found higher returns occurring in more than 90 percent of markets (Bauman and Jacobson, 2002). Other research identifies abnormal end of month returns (Arial 1987; and Lakonishok and Smidt, 1988). More recent evidence confirms continued existence of month-end effects (Sharma and Narayan, 2014)

Weekend effects research examines stock return variations by proximity to weekends. Cross (1973) found lower returns on Monday than Friday. More recent evidence shows this effect continues to occur, though at a reduced level Zilca (2017). Authors commonly attribute weekend effects to firms waiting until after markets close on Friday to announce bad news. Merrill (1966) first documented a holiday effect in stock returns whereby large positive abnormal returns occur on the trading day before a holiday. Evidence indicates this effect continues to appear in markets (Kudravatsey, 2019).

Articles, including Reinganum (1983), examine how tax policies impact stock returns. Jalbert (2022) argues that money flowing into tax deferred accounts around the April 15th tax filing deadline produce abnormal returns. He compares index returns on sixteen trading days around April 15th to returns for the remainder of the year. Results show a large April effect. Event window daily returns exceed return during the remainder of the year by as much as eight times. Lower risk levels accompany the higher returns. Results hold both for both domestic and International indexes. He argues international results imply investors place considerable IRA funds into foreign investments.

DATA AND METHODOLOGY

The analysis here relies on two data sources. Historical stock index level and volume data were obtained from Stooq.com. Data collection included daily closing levels for five U.S. indexes. Dollar value data were obtained from yahoo.com. The DXY index measures U.S. dollar values. Data covers the period 1971-2019. The analysis involved merging Stook and Yahoo data by date to form a single dataset. Stock index observations without corresponding DXY data were removed from the analysis. Table 1 (Appendix) shows the indexes examined.

Next, the process involved grouping data by time-period related to retirement account evolution. While the first introduction of tax advantaged accounts occurred in 1964, data here begins in 1971. The first sample period covers the entire available data extending from 1971 through 2019. The second sample period relates to the creation of Individual Retirement Accounts in 1975**.** The April 1976 tax-filing season represents the first expected market response. To evaluate effects of this change the paper examines the 1976-2019 period. The third examination period focuses on the Economic Recovery Tax Act (ERTA) of 1981. This law substantially increased IRA popularity. Annual IRA contributions increased by nearly sixfold from 1981 to 1982, with an expected response in 1983 and later years. The third data sample covers the 1983-2019 period.

The analysis here supplements acquired data by creating additional variables. Tax filing day indicates the date by which U.S. Federal income tax returns must be filed. Most commonly tax filing day occurs on April 15th. Exceptions occur, when April 15th occurs on a Saturday, Sunday or holiday. In these instances, tax filing day occurs on the following trading day. Tax filing day Relative (TDR) reflects the difference between any given trading day and Tax filing day with tax filing day assigned a TDR of zero. When April 15th equals tax filing day, the TDR for April 16th equals one and the TDR for April 17th equals 2. Similarly, the TDR for April 14th and April 13th equal -1 and -2 respectively. Tax filing day remained April 15th from 1955-2019 which encompasses the sample period examined here. Tax filing day changed in 2020 and 2021 to accommodate COVID induced limitations. Specifically, in 2020 and 2021, tax filing day occurred on July 15th and May 17th respectively. These changes imply an unpredictable market response. For this reason, data for this study ends in 2019.

The methodology here uses an event window variable to indicate the expected response time frame. No evidence provides guidance on when the market responds to tax filing effects. The analysis here conveniently uses a response window including sixteen trading days surrounding tax filing day. An indicator variable called Window, is set to one for data points within the period including tax filing day, ten days before tax filing day, and five days following tax filing day. When observations fall outside the event window, the Window variable is zero. The sample includes 12,264 observations, of which 784 occur during the event window and 11,480 occur outside the event window.

The Dollar Index (DXY) controls for changes in currency values (CV) and effects of these changes on the April effect. Consider a stock index having a value of L_t on day t. The same day DXY level equals DI_t. Then the DXY adjusted index, AL_t, equals the unadjusted index divided by DXY in decimal form as shown in Equation 1.

$$AL_t = \frac{L_t}{DI_t \, X \, \frac{1}{100}} \qquad (1)$$

Daily returns were calculated for each adjusted index. Reflect on an index that has a day t level of AL_t. On the previous day the index level equaled AL_{t-1}. The natural log of these price relatives equals the compounded daily return, DR_t. To improve the visual presentation, results are converted to percentage form. Equation 2 shows the calculations:

$$DR_t = LN\left(\frac{AL_t}{AL_{t-1}}\right) X\, 100 \qquad (2)$$

The analysis here focuses on examining mean returns, standard deviation of returns and return distributions. To facilitate easy comparison of means the methodology uses a Mean Ratio. Similarly, to compare standard deviation levels, the approach uses Standard Deviation Ratios**.** The Means Ratio compares mean returns within the event window to non-event window mean returns. Similarly, the Standard Deviation Ratio compares event-window standard deviation of returns to those outside the event window. Equations 3 and 4 show calculations for the Mean Ratio, MR, and Standard Deviation Ratio, SDR, respectively. EWM and EWSD equal the event-window mean return and Standard Deviation of returns respectively. OWM and OWSD represent the outside of event window return and standard deviation respectively,

$$MR = \frac{EWM}{OWM} \qquad (3)$$

$$SDR = \frac{EWSD}{OWSD} \qquad (4)$$

A MR equaling one indicates event-window returns equal those outside the event window, implying no April effect exists. MRs higher than one reveals higher event-window returns, supporting the April effect phenomenon. MR lower than one suggest the presence of a reverse April effect. The SDR carries an analogous interpretation.

RESULTS

The analysis begins with mean and variance tests. The tests compare currency-adjusted event-window daily returns to the currency-adjusted daily returns outside the event window. The theory presented here suggests event-window average mean returns exceed outside event-window average returns, leading to the formal hypothesis:

Ho1: Event-window returns equal outside event window returns.

Ha1: Event-window returns exceed outside event window returns.

Tables 2, 3 and 4 (Appendix) report results for three time periods examined. Table 2 (Appendix) shows results for the 1971-2019 period. The sample includes 12,264 observations, with 784 occurring in the event window and 11,480 occurring outside the event window. Results indicate significantly higher currency-adjusted event-window returns. The largest difference appears for the Dow Jones Transportation index (DT). Means Ratio reveals event-window currency-adjusted returns 5.184 times larger than out of event-window currency-adjusted returns. The NASDAQ has the smallest difference at 2.280 times. The t-test for differences in means and Wilcoxon test both reveal one percent significant differences for the Dow Transportation (DT) and Industrial (DJI) indexes. Differences at the five percent level occur for the broader S&P 500 (SP) index.

Table 2 (Appendix) also presents standard deviation and variance analysis. Rational market behavior suggests that higher returns correspond to higher risk leading to the formal hypotheses:

Ho2: No differences exist between event- and non-event-window variance.

Ha2: Non-event window variance is lower than event-window variance.

Columns six through eight of Table 2 (Appendix) show the results. Standard Deviation Ratio results show that four of five indexes have lower standard deviation in the event period. Standard Deviation Ratio for the Dow Jones Utility index (DU) shows event-window standard deviation equals 82.16 percent of the out of event-window standard deviation. For the NASDAQ index, event-window variance exceeds non-event-window variance by 1.24. With a Dow Jones Transportation index exception, F-values reveal statistical significance for the differences.

Rational market behavior suggests that stock return distributions do not change throughout the year. Given statistically significant differences in standard deviation and returns noted above, we examine this contention with the Kolmogrov-Smirnov test for equal distributions. Formally, we examine the hypothesis:

Ho3: Event-window return distributions equal outside event-window return distributions.

Ha3: Event-window return distributions differ from outside event-window return distribution.

Column 9 of Table 2 (Appendix) results show that DJI, SP and DT produce significantly different return distributions in the event and outside event periods with 5 and 10 percent significance levels. The DU and NASDAQ show no differences in overall return distributions.

Combined results from Table 2 (Appendix) suggest higher event-window returns, rejecting hypothesis one. These higher returns come with lower risk which rejects Hypothesis 2, but in the opposite direction from anticipated. Moreover, the return distribution changes during the event window. Formally, the data rejects hypothesis one. Null hypothesis two is solidly rejected, but in the opposite direction from the anticipated result. Mixed results occur for hypothesis three, but generally suggest rejection of the null hypothesis.

Table 3 (Appendix) shows results for the 1976-2019 period. The sample includes 11,028 observations, of which 704 occur during the event window and 10,324 occur outside the event window. Means tests reveal smaller differences than reported for the 1971-2019 trading period for four indexes. The largest Means Ratio equals 4.957 for the DT index, compared to 5.184 in the earlier period. The Dow Jones Utilities (DU) index produced a larger differential at 4.579 compared to 3.656 for the earlier period. Three indexes produce five percent significance level t-test results. The DU index produced ten percent significance level t-test results. NASDAQ differences did not reach the ten percent significance level.

Standard deviation and variance analysis reveals four indexes with significantly lower event-window variance and standard deviation. The smallest Standard Deviation Ratio (SDR) equaled 0.8756. Dow Jones Transportation results reveal no significant difference in standard deviation between the event window and out of event window periods. The NASDAQ reveals a SDR of 1.515 indicating higher event-window risk levels. Kolmogrov-Smirnov test results indicate the S&P 500 index produced significantly different even-window and out of event window return distributions.

Table 4 (Appendix) shows 1983-2019 results. The sample includes 9,284 observations, of which 592 occur during the event window and 8,693 occur outside the event window. Means

Ratio (MR) results indicate similar means differences to those reported earlier. The Dow Jones Transportation (DT) index shows 5.241 times higher event-window returns. Four indexes produce significant differences, though the S&P 500 index significance level declined from five to ten percent. Standard Deviation Ratio (SDR) results mirror those from the earlier time periods. However, the Kolmogrov-Smirnov test indicates different return distributions for three indexes in this sample period compared only one significant difference in the 1972-2019 period.

A final data examination utilized ordinary least squares regression analysis to gain additional insights. The response variable, DR_t is the currency-adjusted continuously-compounded daily return. Window variable is set to one for event-window observations and 0 for observations not in the event window. A variable ε_t represents random, unexplained, remainders. Equation 5 depicts the equation estimated:

$$\mathrm{DR_t} = \alpha + \beta_1 \left(\mathrm{Window}_t\right) + \varepsilon_t \qquad (5)$$

Table 5 (Appendix) presents regression analysis results. Panels A shows results for the 1971-2019 examination period. Panel B shows outcomes of the 1976-2016 examination period. Panel C shows outcomes of the 1983-2019 sample examination. In each case, results indicate significant Window coefficients for the DJI and DT indexes, suggesting the presence of an April effect. The significance level declines from 5 percent to ten percent in the 1983-2019 sample period. Column 5 reveals low R2 statistics for each regression. Given the many things that impact stock returns, low R2 values do not surprise.

CONCLUDING COMMENTS

Previous research documents the existence of an April effect in stock returns as measured using index levels. Jalbert (2012 and 2014) attribute these abnormal returns to U.S. tax advantaged accounts that motivate individuals to invest money around the April 15th tax filing deadline. These inflows of money produce abnormal returns. Other research shows that currency-adjusted indexes differ markedly in level and distribution characteristics from raw indexes reported in the financial press. This paper combines these two lines of research to determine the extent to which currency fluctuations explain April effects in stock returns.

Provided empirical analysis examines daily levels of five U.S. indexes. Data covers the period of 1971-2019 divided into three subperiods related to the evolution of tax deferred accounts. The analysis excludes data after 2019 because COVID pandemic related changes to the U.S. tax code imply an unpredictable stock return response. Results show the April effect persists in currency value (CV) adjusted stock indexes with both higher returns and lower standard deviations occurring in the event window. Overall, the results imply that CV fluctuations do not explain April stock return effects.

Like most research, this research has limitations. The analysis here begins the sample period one year after relevant legislation took effect. Some might argue for using adoption year as a beginning date rather than the following year as was done here. Future research might examine sensitivity of results presented here to the examination date selected. The research here examined a sixteen-day event window surrounding the tax filing deadline. Future research might consider other event windows.

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APPENDIX

Table 1: Indexes Evaluated

Index	Abbreviation
Dow Jones Industrial	DJI
S&P 500	SP
Dow Jones Transportation	DT
Dow Jones Utilities	DU
NASDAQ Composite	NASDAQ

This table shows indexes examined along with the abbreviation used throughout the paper.

Table 2: Means and Standard Deviation Examination: 1971-2019 Sample

Index	Mean	MR	t-test	Wilcoxon	SD	SDR	F-Value	KS
DJI		4.992	-2.47***	2.37***		0.9025	1.23***	1.442**
Event Window	0.1218				1.0592			
Outside Event	0.0244				1.1736			
Full Sample	0.0307				1.1668			
SP								
Event Window	0.0963	3.634	-1.73**	1.73**	1.0864	0.9169	1.19***	1.31*
Outside Window	0.0265				1.1848			
Full Sample	0.0303				1.1789			
DT								
Event Window	0.1462	5.184	-2.35***	2.37***	1.3551	0.9578	1.09	1.43**
Outside Window	0.0282				1.4148			
Full Sample	0.0358				1.4113			
DU								
Event Window	0.0563	3.656	-1.14	0.6253	0.9651	0.8612	1.35***	0.9458
Outside Window	0.0154				1.1206			
Full Sample	0.0180				1.1113			
NASDAQ								
Event Window	0.0823	2.280	-0.77	1.06	1.6368	1.24	1.54***	0.9194
Outside Window	0.0361				1.3200			
Full Sample	0.0390				1.3425			

This table examines currency-adjusted returns, standard deviations and return distributions. Data extends from 1971-2019. Daily returns equal: $DR_t = \ln\left(\frac{AL_t}{AL_{t-1}}\right)X100$, where AL_{t-1} and AL_t indicate currency-adjusted index levels on day t-1 and t respectively. Event window contains sixteen trading days including ten market open days prior to, tax filing day, and subsequent five market open days. Event window and outside Event window refer to the proximity to the tax filing deadline. Full Sample refers to the full sample period. SD denotes the standard deviation. MR and SDR signify the mean and standard deviation ratios respectively. The sample includes 12,264 observations, of which 784 occur during the event window and 11,480 occur outside the event window. Means Ratio measures the division of event-window values by outside event-window values. T-test reflects the standard one-tailed test for mean differences. Wilcoxon shows one-tailed Z statistic values. The F-value column shows variance difference test F-Statistics. KS shows results of an equal distribution test based on the Kolmogrov-Smirnov methodology. The notation ***, ** and * reflect significance in the standard fashion.

Table 3: Means and Standard Deviation Examination: 1976-2019 Sample

Index	Mean	MR	t-test	Wilcoxon	SD	SDR	F-Value	KS
DJI								

Event Window	0.1228	4.670	-2.28**	2.13**	1.0815	0.9157	1.19***	1.369
Outside Window	0.0263				1.1811			
Full Sample	0.0324				1.1752			
SP								
Event Window	0.1020	3.604	-1.68**	1.63*	1.1181	0.9842	1.15**	1.291*
Outside Window	0.0283				1.2001			
Full Sample	0.0330				1.1951			
DT								
Event Window	0.1507	4.957	-2.21**	2.20**	1.3907	0.9660	1.07	1.334
Outside Window	0.0304				1.4397			
Full Sample	0.0381				1.4369			
DU								
Event Window	0.0815	4.579	-1.61*	1.291*	1.0035	0.8756	1.30***	1.058
Outside Window	0.0178				1.1460			
Full Sample	0.0218				1.1375			
NASDAQ								
Event Window	0.0909	2.25	-0.86	1.014	1.5150	1.1203	1.25***	0.7552
Outside Window	0.0404				1.3523			
Full Sample	0.0437				1.3641			

This table examines currency-adjusted returns, standard deviations and return distributions. This analysis examines data from 1976-2019. Daily returns equal: $DR_t = \ln\left(\frac{AL_t}{AL_{t-1}}\right) X100$, where AL_{t-1} and AL_t indicate currency-adjusted index levels on day t-1 and t respectively. Event window contains sixteen market open days including ten market-open days prior to, the filing deadline, and the subsequent five market open days. Event and Outside Event reference proximity to the tax filing deadline. Full Sample refers to the full sample period. SD denotes the standard deviation. MR and SDR signify the mean and standard deviation ratios respectively. The sample includes 11,028 observations, of which 704 occur during the event window and 10,324 occur outside the event window. Means Ratio measures the division of event-window values by outside event-window values. T-test reflects the standard one-tailed test for mean differences. Wilcoxon shows one-tailed Z statistic values. The F-value column shows variance difference test F-Statistics. KS shows results of an equal distribution test based on the Kolmogrov-Smirnov methodology. The notation ***, ** and * reflect significance in the standard fashion.

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Table 4: Means and Standard Deviation Examination: 1983-2019 Sample

Index	Mean	MR	t-test	Wilcoxon	SD	SDR	F-Value	KS
DJI								

Event Window	0.1294	4.082	-2.09**	2.169**	1.0952	0.9086	1.21***	1.4800**
Outside Window	0.0317				1.2053			
Full Sample	0.0378				1.1988			
SP								
Event Window	0.1093	3.526	-1.61*	1.831***	1.1424	0.9278	1.16**	1.3410*
Outside Window	0.0310				1.2313			
Full Sample	0.0360				1.2258			
DT								
Event Window	0.1520	5.241	-2.01**	2.087	1.4372	0.9679	1.07	1.4576**
Outside Window	0.0290				1.4848			
Full Sample	0.0368				1.4820			
DU								
Event Window	0.0821	4.189	-1.41*	1.321*	1.0343	0.8664	1.33***	1.1541
Outside Window	0.0196				1.1938			
Full Sample	0.0236				1.1844			
NASDAQ								
Event Window	0.0773	1.977	-0.56	0.7864	1.6160	1.1377	1.29***	0.6588
Outside Window	0.0391				1.4205			
Full Sample	0.0415				1.4337			

This table examines currency-adjusted returns, standard deviations and return distributions. This analysis examines data from 1983-2019. Daily returns equal: $DR_t = \ln\left(\frac{AL_t}{AL_{t-1}}\right) X100$, where AL_{t-1} and AL_t indicate currency adjusted index levels on day t-1 and t respectively. Event window contains sixteen market open days including ten market open days preceding, the filing deadline and subsequent five market open days. Event and Outside Event reference proximity to the tax filing deadline. Full Sample refers to the full sample period. SD denotes the standard deviation. MR and SDR signify the mean and standard deviation ratios respectively. The sample includes 9,284 observations, of which 592 occur during the event window and 8,693 occur outside the event window. Means Ratio measures the division of event-window values by outside event-window values. T-test reflects the standard one-tailed test for mean differences. Wilcoxon shows one-tailed Z statistic values. The F-value column shows variance difference test F-Statistics. KS shows results of an equal distribution test based on the Kolmogrov-Smirnov methodology. The notation ***, ** and * reflect significance in the standard fashion.

Table 5: Daily Return Regression Analysis

Index	Intercept	Coefficient	T-Statistic	R2
Panel A: 1971-2019 Sample				
DJI	0.02432	0.09749	2.26**	0.0004
SP	0.02645	0.06980	1.60	0.0002
DT	0.02791	0.11827	2.27**	0.0004
DU	0.01532	0.4101	1.00	0.0001
NASDAQ	0.04338	0.03553	0.56	0.0000
Panel B: 1976-2019 Sample				
DJI	0.02612	0.09665	2.11**	0.0004
SP	0.02832	0.07365	1.58	0.0002
DT	0.03040	0.12027	2.15**	0.0004
DU	0.01778	0.06368	1.44	0.0002
NASDAQ	0.04044	0.5049	0.95	0.0001
Panel C: 1983-2019 Sample				
DJI	0.03166	0.09779	1.92*	0.0004
SP	0.03103	0.07831	1.50	0.0002
DT	0.02896	0.12303	1.95*	0.0004
DU	0.01960	0.06246	1.24	0.0002
NASDAQ	0.03909	0.03817	0.63	0.0000

This table shows results of the regression $DR_t = \alpha + \beta_1(\text{Window})$. Window constitutes an indicator variable set to zero for observations outside the event window and 1 for observations within the event window. The event window contains sixteen market open days including ten market open days preceding, the filing deadline and subsequent five market open days. Daily returns equal $DR_t = \ln\left(\frac{AL_t}{AL_{t-1}}\right) X\,100$, where AL_{t-1} and AL_t represent currency-adjusted index levels on day t-1 and day t respectively. Notation ***, ** and * indicate significance in the standard fashion.