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"Sell not only in May" Seasonal Effects on Stock Markets

A b s t r a c t. Described in literature stock market anomaly still remains unexplained. In long time series regressions and wide geographical spread research, "Halloween effect" is significant on 19 amongst 73 markets, but also on 11 amongst 23 with long time series data. The data shows that abnormal returns could be realized also in strategies starting in October, November and December. We conclude that even with control of weather (sun hours), behavioral (sentiment index, number of IPOs) and macroeconomic (industrial production) factors, the effect persists.

K e y w o r d s: seasonal anomaly; behavioral factor; Halloween indicator; January effect; sell in May.

J E L Classification: G15; Q47; G10; G14.

Introduction

Seasonal anomalies are widely discussed in financial literature because of their unknown nature and relative simplicity in application as market strategies. "Halloween effect" as one of them is subject of many articles. It was analyzed and tested on broad range of markets in Bauman and Jacobsen (2002). Briefly speaking we can describe it as anomaly that is derived from old market saying: "Sell in May and go away". Halloween indicator is another name to similar strategy that is to have long position on the market

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from October 31 till April 30 each year – described in O'Higgins and Downes (1990). Although it has its beginnings only in market saying, numerous of studies has proven that it is still profitable and valid investment strategy. In our paper we focus on finding possible explanations of the anomaly. We use set of the variables representing fundamental and behavioral factors that could influence market participant's behavior. We verify hypothesis about the existence of similar effects for all strategies starting in winter and finishing in summer months. Weather factors has been broadly discussed as the possible reason of the anomaly, we address also this issue. Our research brings an important contribution to existing literature because we test Halloween effect in the context of behavioral variables. It allows to directly check if changes in investor sentiment are responsible for seasonal fluctuations. We used sentiment measure proposed by Baker and Wurgler (2007) which is solely based on market factors. We also analyzed the role of consumer confidence and industrial production. Secondly we directly test influence of daylight in seasonal anomalies based strategies to confirm or reject the hypothesis of its influence on Halloween effect. Thirdly we confirm the existence of similar seasonal effects not only in end of October – end of April period but also from end of September (November) till end of March (May).

1. Literature Review

Numerous of studies: Andrade, Chhaochharia and Fuerst (2013), Jacobsen and others (2005), Jacobsen and Visaltanachoti (2009), Zarour (2007), Lean (2011) have confirmed the existence and significance of Sell in May or Halloween effects. Researchers tried to explain the anomaly in many different ways. Bouman and Jacobsen (2002) in their research control for risk, January effect, changes in interest rates and volume and stated that even though the anomaly persists, they suggested summer holidays as the explanation of the anomaly (liquidity needs or changed risk aversion during vacations). Summer holiday as a reason of the anomaly is supported by Hong and Yu (2009) which concluded that trading activity drops in summer months, also recent findings of Kaustia and Rantapuska (2016) seems to be in favor of holiday's hypothesis. Kamstra, Kramer and Levi (2003) postulated Seasonal Affective Disorder (SAD) as the main reason of Halloween anomaly, their research however was heavily criticized in Kelly, Meschke (2010), Jacobsen and Marquering (2008, 2009). Maberly and Pierce (2004) questioned the existence of Halloween effect as caused by outliers in October 1987 and August 1998 but Haggard and Witte (2010) acquire the results using robust estimation technique and confirms significant Halloween anomaly. Jacobsen and others (2005) checked if Halloween effect is dependent on size, book to market or divided yield and conclude that it is not the case. Gerlach (2007) found that returns from October to December are higher because of macroeconomic announcements but Gugten (2010) reports that even with control of this factor Halloween anomaly still exists. Lucey and Zhao (2007) postulated that January effect is the reason, but those results were questioned by Haggard and Witte (2010), because of short sub periods used in Lucey and Zhao (2007) tests. Doeswijk (2008) hypothesizes that investors behavior is driven by optimism cycles. He stated that size and value factor do not influence “sell in May” effect, but behavioral factor – initial returns from IPOs has explanatory power. In study of Jacobsen and Zhang (2012a) they use sample of 108 markets and very long time series (21 of those markets have more than 1000 monthly observations). They provide thorough and detailed analysis of persistence and significance of the Halloween anomaly. Their findings confirm significant and strengthening Halloween effect. We rely on their studies therefore we will not replicate them in detailed way as Jacobsen and Zhang (2012a) to reaffirm existence of Halloween effect, instead we will focus on verification of possible explanations of the effect. In recent paper Jacobsen and Zhang (2012) analyze 317 years of United Kingdom stock prices data. Such long time data series allowed testing Halloween effect in 100- and 50- years subsample intervals. They report significant 0,56% higher winter returns than summer returns. May effect is present in all of their 100- and 50- years periods.

2. Data

In our study we divide used data into the following groups:

a) Stock markets monthly rates of return. All rates of return are calculated using last stock market session of the month closing price (in local currency). Closing prices are acquired from Routers database. The longest period covered is: Jan 1964 to Jun 2012[1].
b) US market sentiment is measured by Baker and Wurgler (2007) monthly sentiment index and acquired directly from Wurgler web-page[2]. It covers the period of July 1965 to Dec 2010.

[1] Different markets are covered with different periods as the effect of the fact that some analyzed market have shorter time series of required data.

[2] http://www.stern.nyu.edu/~jwurgler/

c) Number of Initial Public Offering (IPO) is calculated based on data obtained from Reuters One database. The longest period starts from Jan 1970 and finishes in Jun 2012.
d) Industrial production – gathered from World Bank Global Economic Monitor (GEM) database and OECD. Covers period between Jan 1991 to Jun 2012 depending on country.
e) Consumer Confidence Indicator (CCI) – acquired from OECD database. The longest period covered is: Jan 1964 to Jun 2012.
f) Sun hours – data comes from World Meteorological Organization, Hong Kong Observatory and national meteorological institutes of analyzed countries.

We analyze 73 indexes that cover 68[3] countries and 2 non-country indexes (MSCI World and CRB commodity index). The selection of countries was driven by maximum possible geographical coverage and data availability.

3. Methodology

First objective of this study is to find presence of "Sell in May and go away" (SiM) and Halloween (Hal) effects in a group of emerging and developed capital markets. For this purpose we used methodology similar to Bouman and Jacobsen (2002). Our second motive is to check hypothesis of significant role of daylight, U.S. market sentiment, number of IPOs, and CCI as possible causes of this effect. We also examine investing strategies starting in months other than May. Our tests imitate strategy that could be utilized by investors on stock markets. This approach is very similar to buy-and-hold except that it keeps long position for six months of each year and during the rest of the year it takes form of passive "out of the market" strategy. We are examining if the starting month of the strategy plays any role and creates similar to SiM anomalies and if yes, could it be explained by set of non-fundamental variables. This is the third motive of our study – to check if behavioral variables as postulated in Doeswijk (2008) are responsible for SiM/Hal and similar effects. To identify SiM and other month's seasonal effects we run following time series regressions (1) or (2) for each market:

$$\mathrm{R}_{\mathrm{t}}^{\mathrm{i}} = \mathrm{c}^{\mathrm{i}} + \alpha^{\mathrm{i}} * \mathrm{MON}_{\mathrm{t,adj}} + \tau^{\mathrm{i}} * \mathrm{JAN\_EFF}_{\mathrm{t}}^{\mathrm{i}} + \varepsilon_{\mathrm{t}}^{\mathrm{i}}\,, \tag{1}$$

if strategy include January,
or:

$$R_t^i = \mathrm{c}^{\mathrm{i}} + \alpha^{\mathrm{i}} * \mathrm{MON}_{\mathrm{t}} + \varepsilon_t^i\,, \tag{2}$$

[3] US and Chinese markets are represented by accordingly three and two indexes.

if strategy does not include January.
Where: R_t^i is the monthly rate of return calculated for *i*-th market index (from 1 to 73), $\mathrm{MON_{t,adj}}$ is the dummy variable equal 1 when month *t* falling into the period of 6-months strategy initiated in the last day of month MON (except Jan) and finishing in last day of month MON + 6 (except Jan) and 0 otherwise. $JAN\_EFF_t^i$ is the dummy variable equal 1 when (t=Jan), 0 otherwise. $\mathrm{MON_t}$ is the dummy variable equal 1 when month *t* falling into the period of 6-months strategy initiated in the last day of month MON and finishing in last day of month MON + 6 and 0 otherwise; t symbolize time and MON symbolize months (Jan, Feb, …, Dec).

For instance if we analyze strategy starting in last day of April (MON = Apr) regression (1) takes the following form: $R_t^i = \mathrm{c^i} + \mathrm{\alpha^i} * APR_{t,adj} + \varepsilon_t^i$ and means that dummy variable $APR_{t,adj}$ is equal 1 for months May till Oct and 0 otherwise[4]. In the case of strategy starting in last day of October (MON = Oct) regression (2) takes form of: $R_t^i = \mathrm{c^i} + \mathrm{\alpha^i} * OCT_{t,adj} + \tau * JAN\_EFF_t^i + \varepsilon_t^i$ and means that dummy variable $OCT_{t,adj}$ is equal 1 for months Nov, Dec, Feb, Mar, Apr and 0 otherwise. Dummy variable $JAN\_EFF_t^i$ is equal 1 for Jan and 0 otherwise.

In this part of the research we estimated 876 regressions (73 markets times 12 different starting months for our strategies). In these regressions we used estimation method introduced by Huber (1973) (function rlm() in R program)[5]. We run regressions (1) and (2) with controlling (when possible – i.e. on 30 markets due to unavailability of data for other markets) for growth rate of industrial production as macroeconomic measure of business cycle and Consumer Confidence Index – expressing consumer confidence that can be proxy of investor sentiment (as in e.g. Qiu, Welch, 2006). After identification of seasonal effects we moved to examining possible explanations of them. For ten markets with longest available IPO history (US, UK, Japan, Canada, Australia, China, Hong Kong, India, South Korea and Taiwan) we can run time series regressions where number of IPOs, U.S. market sentiment, macroeconomic variable controlling for cyclical changes (industrial production) and dummy variable representing each month, describe rates of return of selected market indices. In this approach we assume ad hoc that

[4] We analyze monthly rates of return, but strategy is named after the level of index in given month so when strategy starts in the *last day* of month MON, the first rate of return is for month MON+1.

[5] Relying on Jacobsen and Zhang (2012a) where coefficients obtained from GARCH and OLS models are similar we did not run GARCH regressions.

sentiment of U.S. investors affects other markets because of large capital flows and primary role of American stock exchange. There is no stock market related[6] sentiment index data for other than US countries publically available. We also used the proxy of stock market sentiment for other markets – Consumer Confidence Indicator, delivered by OECD. We could not conduct this analysis for all the markets in our sample due to not enough IPO observation and lack of sentiment data, therefore we chose only ten mentioned above markets. Ten regressions for each market used in this part of analysis take form of equation (3):

$$R_t^j = d^j + \sum_{k=1}^{k=11} \beta_k^j * MON_{t,k}^j + \gamma^j * IPO_t^j + \\ +\zeta^j * SENT_t^{US} + \omega * INDPR_t^j + \varepsilon_t^j, \quad (3)$$

where: R_t^j is the monthly rate of return calculated for *j*-th biggest market index (from 1 to 10) in month *t*, $MON_{t,k}$ is the dummy variable that takes value 1 when month of measured rate of return is equal respectively k = Jan, Feb, Mar, … Nov, otherwise 0. IPO_t^j symbolizes number of IPOs in month *t* for market *j*, $SENT_t^{US}$ is the Baker-Wurgler sentiment index in month *t*, $INDPR_t^j$ is percentage change in industrial production in month *t*, for country *j*.

As mentioned above we run similar to (3) regressions but with Consumer Confidence Indicator (CCI) for each country. Symbolic representation of this regression is following:

$$R_t^j = g^j + \sum_{k=1}^{k=11} \gamma_k^j * MON_{t,k}^j + \eta^j * IPO_t^j + \\ +\mu^j * SENT_t^{CCI,j} + \psi * INDPR_t^j + \varepsilon_t^j, \quad (4)$$

where: all symbols as previously except $SENT_t^{CCI,j}$ which is CCI for *j*-th country.

Both (3) and (4) equations were tested for autocorrelation and possible ARCH effects – when found we applied accordingly MA and/or ARCH models, after that statistical properties of models was test again and this procedure was repeated till elimination of autocorrelation or ARCH effects. Results of those estimations are presented in tables 1 and 2.

Next step in exploring possible reasons of seasonal effects is to include in regressions weather variable (sunlight). In this part we tested returns directly

[6] Like in Baker and Wurgler sentiment index, that is based exclusively on market data.

from described previously 6-month strategies. In cross sectional regressions we regressed average returns from those strategies in the following manner[7]:

$$R^{i}_{strav,m,n} = h^{i} + \chi^{i} * SUN^{i}_{strav,m,n} + \delta^{i} * M^{n}_{t} + \\ +\pi * RISK^{i}_{strav,m,n} + \varepsilon^{i}_{t}\ , \qquad (5)^{8}$$

where: $R^{i}_{strav,m,n}$ is average rate of return for six month strategies starting at the end of month *m* and at the end of month *n* – six month later in sequence for each of *i*-indexes; $SUN^{i}_{strav,m,n}$ ($RISK^{i}_{strav,m,n}$) is average number of sunlight hours (standard deviation) for six month strategies starting at the end of month *m* and at the end of month *n* – six month later; M^{n}_{t} is the dummy variable with value 1 for the second month of pair (*m*, *n*); symbol *m* and *n* marks pairs of months [(Jan, Jul), (Feb, Aug), … (Jun, Dec)] with six months “distant” from each other.

We used pairs of data vectors to avoid multicollinearity due to the fact that we are using averages that in other regression settings would cause overlapping problem. We also wanted to compare averages between cold and hot halves of the year across the countries. We repeated calculations described in equation (5) but only for markets on which we found presence of SiM effect.[9]

4. Results

The outcomes of our analysis generally support existence of Sell in May and Halloween effect but also seasonal effects in other months. We can observe that[10] estimated α^{i} coefficients from (1) or (2) are mostly negative for strategies starting at the end of northern hemisphere spring months (Mar, Apr, May) and mostly positive for strategies beginning in last days of autumn months (Sep, Oct, Nov). Numbers of markets that can be characterized by SiM effect vary from 19 to 31 (11 to 21) when we use 0.10 (0.05) p-values for judging the significance of α^{i}. Comparing to the total number of ana-

[7] We cannot use longitudinal (time series cross sectional) regressions due to lack of publically available time series data for numbers of sun hours in each month of the particular year.

[8] We also run this regression with additional $\varphi^{i} * IPO^{i}_{strav,m,n}$ part, where $IPO^{i}_{strav,m,n}$ is average number of IPOs but because of only few countries having those date appropriately frequent i.e. without too many “zeros”, we do not report those low power regressions, even if they have similar results.

[9] We also run regressions with control of latitude of cities where analyzed stock exchanges are located; those results are similar and not presented here, but available upon request.

[10] Exact can be provided upon request.

lyzed indices (73) those numbers seem to be small, but what is worth noticing out of 10 stock exchanges which total capitalization corresponds to over 70% of World Federation of Exchanges (WFE) global capitalization, seven have significant SiM effect[11]. Seasonal effects are valid for most important and with the longest data series stock market indices. We did not test presence of SiM effect in particular sub periods (due to relative short data samples) but according to the newest research of Jacobsen and Zhang (2012, 2012a) we can conclude that SiM effect is persistent over time. Our results with respect to the emerging markets with relatively short data series are similar to mentioned in Jacobsen and Zhang (2012a) paper and we conclude that even if SiM effect is not present for all selected markets it can be due to lack of long time series data for them. One scratch on surface of hypothesis proving persistence of SiM effect is significantly lower number[12] of SiM and Hal effects when we run our tests and start our samples just after Bouman and Jacobsen publication in 2002. Similar conclusion could be found in Jacobsen and Zhang paper: only three markets[13] are characterized by significant “Halloween effect” in period 2001–2011. Again those results could mean the disappearing SiM and Hal anomalies after making them publicly known in scientific papers or it just could be caused by relatively short time series. Other additional and not less interesting question is about the presence and persistence of January effect and its share in Halloween effect. Our results suggest that January effect plays less important role in observed seasonal anomalies. For six-months strategies that include January, only in eight to eleven (depending on the months used in estimates) regressions given by equation (1) τ^i parameter is significant with p-value of 0.05.

Another test conducted in this research checks if – in regressions based on time series data – seasonal effects still exist after controlling for number of IPOs, level of US sentiment index and changes of industrial production. In time series regression analysis we need to acquire reasonable amount of data. While both descriptive variables: US sentiment index (or Consumer Confidence Index) and industrial production have continued time series, the number of IPO for most of the markets is characterized by incomparably higher number of “zero” data due to not as often as in the largest markets occurrence of IPOs. We choose the following approach to solve this prob-

[11] Members of World Federation of Exchanges (WFE) are the biggest and most important stock exchanges in the world; data from WFE, December 2012.

[12] Results can be provided upon request.

[13] Table 5 in Jacobsen and Zhang (2012a).

lem: in regressions (3) and (4) we include only those markets that meet two following conditions:

1. Has at least 50 observations
2. Has 95% or more of non-zero IPO data (i.e. number of non-zero IPO months – counted from given month to end of analyzed period – divided by the number of months in analyzed period is equal or greater then 0.95)

This simple algorithm provides us ten indices that can be characterized by frequent IPOs for longer period of time. Outcomes of equation (3) and (4) presented in tables 1 and 2 are similar. We can find there that statistically significant seasonal effects – represented by coefficients related to particular months, exist. Tables 1 and 2 shows January effect existing in Korea, UK, Hong Kong and India[14]. Most of the statistically significant seasonal anomalies, with negative coefficients, fall in the periods between April-September (or similarly: May–October) and it causes the cumulative rate of returns of 6-months investing strategies performing better, when started in Autumn months. Even with behavioral and macroeconomic control variables we still observe seasonal effects in all (excluding Taiwan) markets. Significantly lower rates in winter months means falling prices of stock indexes that leads to lower cumulative returns in six months strategies. Results[15] of estimation of equation (1) and (2) show us that higher rates of returns occur not only for strategies lasting from end of October till end of April (Hallowen effect) but the same is true for September – March and November – May. Such coincidence with much different from each other seasons of the year could convince us that it is the weather factor that cause seasonal effects. Indeed many authors like Kamstra, Kramer and Levi (2003), Cao and Wei (2005), Saunders (1993), Hirshleifer and Shumway (2003) support such thesis. From the other hand there is broad literature that criticize weather factor as cause of SiM and Hal effects, for instance: Jacobsen and Marquering (2008), and more recently Kaustia and Rantapuska (2016). The final step in our analysis is to examine postulated in literature role of sunlight in seasonal anomalies. To check this, we run cross-sectional regressions described in equation (5). We tested 6-months-strategies rates of returns, with risk (average standard deviation for time of the strategy) as control variable[16].

[14] January effect disappear after controlling for Consumer Confidence indicator in the case of Korea and Hong Kong – see table 2.

[15] Results available upon request.

[16] We also run these regressions with additional average IPO factor but, due to lack of frequent IPOs in most countries we do not present these results. In case of behavioral variables, where we want to preserve the same source of data and methodology of calculations -

Table 1. Coefficients of estimation of equation (3) – d, $\beta_k, \gamma, \zeta, \omega$ for particular market

Variable	Australia	Canada	China	Japan	Korea
JAN	–0.01	–0.01	–0.04	–0.01	–0.06*
FEB	–0.01	–0.02	0.01	–0.02	–0.02
MAR	–0.02	–0.03*	–0.02	0.01	–0.01
APR	–0.02	–0.02	–0.01	0.01	0.02
MAY	0	0	0.02	–0.02	–0.03
JUN	–0.03*	–0.03**	–0.06	–0.01	–0.04
JUL	–0.01	–0.01	–0.06	–0.02	–0.02
AUG	–0.02	–0.02	–0.04	–0.01	–0.03
SEP	–0.03**	–0.04**	–0.03	–0.03	–0.03
OCT	–0.01	–0.01	–0.07	–0.03*	–0.06*
NOV	–0.02	–0.02	–0.02	0	–0.01
$SENT^{US}$	–0.01*	–0.01**	0.04**	–0.02***	–0.01
INDPR	0.72	–0.18	2.17***	0.29	0.51*
IPO	0	0	0	0	0.01**
d	0.02	0.02	0.01	0.01	0.02
Variable	UK	US	Hong Kong	India	Taiwan
JAN	–0.03**	–0.01	–0.04*	–0.09**	–0.04
FEB	–0.02	–0.02	0.01	–0.07*	–0.01
MAR	–0.02	–0.02	–0.04**	–0.05	–0.02
APR	–0.01	–0.01	0	–0.01	–0.01
MAY	–0.03**	–0.01	0	–0.05	–0.01
JUN	–0.02	–0.03**	–0.02	–0.06	–0.04
JUL	–0.01	–0.02	0	0	–0.01
AUG	–0.02	–0.02	–0.03	–0.03	–0.03
SEP	–0.03*	–0.02	–0.02	0	–0.03
OCT	–0.01	–0.01	0	–0.07*	–0.03
NOV	–0.01	–0.01	–0.01	–0.04	–0.02
$SENT^{US}$	–0.01*	–0.01***	–0.02*	–0.11***	–0.05**
INDPR	0.36	–0.72***	1.79***	0.69	0.69***
IPO	0	0	0	0	0
d	0.03**	0.02**	0.02	0.05	0.02

Note: table contains estimations of coefficients from equation (3). Significance levels: *** – 0.01, ** – 0.05, * – 0.10. Data cover maximum possible period for each market. IPO^j symbolizes number of IPOs in month for market j, $INDPR$ marks growth rate of industrial production for each market, $SENT^{US}$ symbolizes Baker-Wurgler sentiment index.

we could not include CCI factors in cross sectional regressions of 6 months strategies because CCI is calculated by OECD in the way that six months moving averages have the same values.

Table 2. Coefficients of estimation of equation (4) – $g, \gamma_k, \eta, \mu, \psi$, for particular market

Variable	Australia	Canada	China	Japan	Korea
JAN	–0.01	–0.01	–0.03	–0.01	–0.04
FEB	–0.01	–0.01	0.01	–0.01	–0.01
MAR	–0.03*	–0.03**	–0.02	0	0.01
APR	–0.02	–0.02*	–0.01	0	0.01
MAY	–0.01	–0.01	0.01	–0.03*	–0.03
JUN	–0.03**	–0.04***	–0.07*	–0.02	–0.03
JUL	–0.01	–0.01	–0.06	–0.02	0
AUG	–0.02	–0.02	–0.04	–0.02	–0.02
SEP	–0.04**	–0.04***	–0.03	–0.03*	–0.01
OCT	0	–0.01	–0.06	–0.03*	–0.05*
NOV	–0.02	–0.02	–0.03	0	–0.01
$SENT^{CCI}$	0	0	0	0.01***	0
INDPR	0.44	–0.24	1.85***	0.33*	0.56**
IPO	0	0	0	–0.001*	0.01**
g	–0.36	–0.25	0.03	–0.88***	0.27
Variable	UK	US	Hong Kong	India	Taiwan
JAN	–0.03**	–0.01	–0.03	–0.07**	–0.04
FEB	–0.02	–0.02	0	–0.06*	–0.02
MAR	–0.02	–0.02	–0.04*	–0.03	–0.04
APR	–0.01	–0.01	0	–0.01	–0.02
MAY	–0.03**	–0.01	–0.01	–0.06*	–0.03
JUN	–0.02*	–0.03*	–0.03	–0.05	–0.04
JUL	–0.01	–0.01	0	–0.02	–0.03
AUG	–0.02*	–0.02*	–0.03	–0.04	–0.05
SEP	–0.03**	–0.02	–0.02	0.01	–0.03
OCT	–0.01	0	0	–0.05	–0.06
NOV	–0.01	–0.01	–0.02	–0.04	–0.02
$SENT^{CCI}$	0.01**	0	–	–	–
INDPR	0.19	–0.74***	1.96***	0.33	0.59***
IPO	–0.0006**	0	0	0	0
g	–0.35*	–0.12	0.03	0.06**	0.04

Note: table contains estimations of coefficients from equation (4). Significance levels: *** – 0.01, ** – 0.05, * – 0.10. Data cover maximum possible period for each market. IPO symbolizes number of IPOs in month t for market j, $INDPR$ marks growth rate of industrial production for each market, $SENT^{CCI}$ symbolizes Consumer Confidence indicator for market j. For Hong Kong, India and Taiwan CCI data are not available.

The results of these regressions prove that sunlight hours have no significant explanation power in the tested models[17]. Even if we limit our sample to

[17] Results available upon request.

these markets on which SiM effect is present, sunlight is significant only in one of our regressions.

Conclusions

Financial market puzzle described by Bouman and Jacobsen (2002) is still unsolved. Controlling for macroeconomic conditions (industrial production), behavioral variables (Consumer Confidence Index, number of IPOs and Baker–Wurgler sentiment Index) and weather factor (sun hours) did not cause disappearing of "Sell in May" or "Halloween" effects. We can conclude that answer for those anomalies should not be searched in Sun cycles, industrial production changes or investors sentiment, as some studies suggest. Existence of persisting for longer time anomalies is calling for new research, although after Bauman and Jacobsen publication the effect is fading – maybe because of exploitation of "Sell in May" and "Halloween" strategies or it is just short term disappearance of the anomaly. From the other hand more rigorous analysis shows that not only May but all spring/autumn months anomalies are present on many stock markets. We can conclude that old market saying is still able to deliver some positive rates of return to the investors who want to listen to it.

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"Sell not only in May". Efekty sezonowe na rynkach akcji

Z a r y s t r e ś c i. Opisywana w literaturze anomalia sezonowa (upraszczając: „sprzedaj w maju, kupuj w październiku") nadal pozostaje niewyjaśniona. W przeprowadzonych regresjach, bazujących na długich szeregach czasowych oraz na licznej grupie indeksów giełdowych, efekt Halloween jest istotny statystycznie w 19 spośród 73 badanych indeksów, ale także w 11 spośród 23 indeksów z najdłuższymi dostępnym szeregami czasowymi. Wyniki badań wskazują, że ponadprzeciętne zyski mogą zostać zrealizowane również w strategiach zaczynających się w innych miesiącach jesiennych. Stwierdzono, że także po włączeniu do testowanych modeli zmienny kontrolnych dotyczących pogody, sentymentu inwestorów, zmiennych makroekonomicznych – badana anomalia nadal istnieje.

S ł o w a k l u c z o w e: anomalie sezonowe; czynniki behawioralne; efekt Halloween; efekt stycznia.