Erasmus School of Economics

– Influence of economic recessions on calendar anomalies in the stock market –

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Abstract

In the literature over the years, no clear consensus has been reached regarding the explanatory variables of calendar anomalies in the stock market. In this paper, the influence of the macroeconomic variable ‘business cycle’ is investigated. Therefore, we look at differences in the presence of calendar anomalies between recession periods and non-recession periods. The recession periods observed are the samples of March-November 2001 and December 2007-June 2009. To test this, a dummy regression is used that includes a dummy for the recession period, a dummy for the tested anomaly and an interaction dummy. The tested anomalies are the January effect, the weekend effect, the day-of-the-week effect and the turn-of-the-month effect. Of these four effects, only the latter is found significant. Regarding the recession periods, the turn-of-the-month effect was only found present in the sample March-November 2001. The results of this paper thus provide a role for the effect of recession periods exclusively for the turn-of-the-month effect.

Contents

1 Introduction

In the stock market, an interesting phenomenon is the presence of calendar anomalies. In the last few decades, various researches have already been conducted investigating the different effects that are known as the calendar anomalies. Some important ones among which are the January effect, the weekend effect, the day-of-the-week effect and the turn-of-the-month effect. Most of the research assume 'normal' economic conditions. In other words, these researches observe a period in which both 'good' market conditions and 'bad' market conditions appear. Over this period, the significance of the calendar anomalies is investigated, after which the author usually attempts to give an explanation in case a significant effect is found. In this paper, we assume that under normal economic circumstances there are indeed such calendar anomalies. Evidence of this is shown, among others, in the papers written by Lakonishok and Smidt (1988) [1], Jaffe and Westerfield (1985) [2] and Van der Sar (2003) [3].

Fundamentally, the same effects as described above will be investigated in this paper. However, to link the hypothesis of the anomalies with the current stock market situation, I aim to investigate calendar anomalies in times of an economic recession. In this case, the hypothesis for some effects has to be adjusted. For example, in the case of the January effect we usually look for abnormal positive returns in January. In times of a recession, however, the average return may be negative in each month. Thus, in this case, the research question of whether the average returns in January are higher compared to other months may mean less negative instead. In my opinion, this research is both societal and scientifically relevant. Firstly, the results can be useful as a practical tool for anyone who is interested in investing or already has invested in the stock market. Especially during or after a financial crisis. Furthermore, the presence of anomalies indicates a shortcoming of the economic market hypothesis (EMH). The presence or absence of anomalies can be used as a proxy to assess to what extent the EMH holds during an economic recession.

This paper will have a broad central question, which will be answered by the use of two sub-questions. As mentioned above, the research will revolve around the question of whether calendar anomalies are present in times of an economic recession. Therefore, the central question is:

To what extent are calendar anomalies present in the stock market in times of an economic recession?

2 Theoretical framework

As mentioned in the introduction, this paper will have two sub-questions to answer the central question. The tested recession period can generally be divided into the period before, during and after the recession. In this paper, however, we only focus on the period of the recession itself. The reason is that with this research question, there is no for both the societal and scientific relevance for the other periods. Moreover, a distinction exists between the different economic recessions in terms of the severity. To compare the different recessions, I will look both at a severe recession (the great recession from December 2007 until June 2009) and a mild recession (early 2000s recession from March 2001 until November 2001). This distinction exists because a possible outcome of this research is that the significance of the anomalies will fade away the more severe the recession is, as was found by Vasileou and Samitas (V&S) (2015) [4] for the January effect in the Greek stock market. Thus, the two sub-questions are as follows:

Q1: To what extent are calendar anomalies in the stock market present during a mild economic recession?
Q2: To what extent are calendar anomalies in the stock market present during a severe economic recession?

Before we dive into the anomalies of the stock market and whether or not these are present, we will first address the behaviour of stock returns and its volatility. In the paper by Nyberg (2012) [5] , the author investigates the relationship between the conditional mean and the conditional variance. In contrast to previous literature in which macroeconomic variables approximate the state of the economy, the author uses a regime-switching GARCH-model. This method means that the binary value of the business cycle (the state of the economy) is modelled at the same time with the excess return. Following this method, a positive relationship between the stock returns and its variance is found. Also, the conditional variance turned out to be higher in times of a recession. In the paper by Chordia and Shivakumar (2002) [6], the authors explain the short-term returns of stocks (momentum) by time-varying expected returns. This paper finds that these expected returns depend on macroeconomic variables, among which the business cycle. In both papers, the behaviour of stock returns is explained by the state of the economy. However, Nyberg approximates the business cycle by making use of the excess stock returns, while Chordia and Shivakumar make use of (lagged) macroeconomic variables. This theory connects to this paper, in which we investigate the link between the business cycle (recession) and stock returns.

Because there is not much research done on calendar anomalies tested during times of an economic recession, I base my hypothesis on both theoretical arguments and empirical research. Therefore, let us also take a look at the statistics of stock returns during recessions in general. This is an important aspect that is built upon in the hypothesis. According to a research paper of Russell investments, in the 30 US recessions since 1869, only 14 of them produced overall negative returns.[7] This means that for the other 16 recessions, the average returns were positive. However, the 'negative recessions' constituted for a return of -14,2% annualized and the 'positive recessions' for an average return of 9,8% annualized. These numbers indicate that, on average, a recession still generates an annualized negative return of 2,9%. The paper also differentiates between normal and heavy recessions. The latter includes the Great Depression (August 1929 – March 1933), the recession from May 1937 until June 1938 and the financial crisis (December 2007 – June 2009). This last one is used in this paper as well and constitutes for a total negative return of 34,8% annualized. The other recession investigated in this paper (March 2001 – November 2001) generated an annualized negative return of 3,9%. With these numbers taken into consideration, it is justified to assume that the overall stock returns will be negative in the recession periods discussed hereafter.

To start with, we build on the well-known paper by Lakonishok and Smith (1988) [1]. This means we assume that under 'normal' economic circumstances, the calendar anomalies that I will investigate are present. Empirical evidence of whether this assumption holds will be provided in this research. Intuitively, one of the causes for calendar anomalies throughout the year is the demand for stocks that is not constant. For example, on Mondays and at the end of the year there is relatively more sell-related activity on the stock market, while in January there is more buy-related activity. However, the difference is that in times of a recession, there is a general decrease in demand. This may fade away the differences in stock prices and returns that exist in times of normal economic circumstances.

The paper by V&S shows that this is the case for the January effect. However, the question is whether otherwise, the authors would have found a significant effect at all. For there to be a difference, there has to be a significant January effect in non-recession times. Among others, Gu (2003) [8] and Van der Sar (2003) [3] argue that the January effect has been declining since the 1980s and possibly is not present at all in the stock market. In the same paper, V&S prove that positive returns around the turn of the month are present in times of a recession. Vasileiou (2017) [9] also researched the day-of-the-week effect during both recession periods. The results of the different recessions investigated in this research, however, were not consistent. In the first recession period merely Thursday generated positive returns, while in the second recession this was the case for Tuesday. As there is no direct explanation for this difference in positive daily returns, the model used in this paper will perhaps create clarity on the significance of this effect.

Considering the weekend effect, however, Bush and Stephens (2016) [10] found significance in the currency market in the period of the financial crisis. They conclude that: ''The Monday effect has been observed in many studies as outlined in this paper and seems to occur when there is economic turmoil present in the global economy. When the economy is in a normal growth pattern, the effect seems to diminish or disappear altogether, which suggests that market efficiency holds in normal periods." This explanation hints towards the fact that calendar anomalies might be observable because there is no market efficiency due to a recession. Furthermore, Roy (2013) [11] also investigates the volatility of returns during an economic recession. In this research, Roy looks at the National Stock Exchange of Indian and the Bombay Stock Exchange and concludes that during economic recessions, there is higher volatility. This is in line with the conclusion of V&S in their paper.

Based on the literature described above and my expectations, I will formulate my hypothesis. I expect that during an economic recession, an overall decrease in stock prices will diminish the differences between the average returns of the weekdays (weekend effect, day-of-the-week effect), as well as the differences between the average returns of the months of the year (January effect) and days of the month (turn-of-the-month effect). Despite the paper by Bush and Stephens, I expect the calendar anomalies to fade away during a recession, as shown by Vasileiou. Concerning the January effect, I base my hypothesis on the papers by Gu, Van der Sar and other past literature. This means that I expect that there might not be a January effect observed at all. Even so, due to the market not being efficient during a recession, I imagine that we might observe the day-of-the-week effect, though I expect it not to be significant. On a final note, the two recessions that will be investigated differ in terms of severity. Although I suspect that the effect of a calendar anomaly fades away more in case of a more severe recession, I expect that in both sub-samples there will be no significant effects found.

3 Data and methodology

3.1 Data

The data used in the sample is retrieved from the Thomson Reuters Eikon DataStream add-on in Excel. The index used to test for the desired effect is the S&P 500. This index includes 500 leading companies, has a market cap of 25,64 trillion as of June 2020 and covers for approximately 80 per cent of the available American market capitalization.[12] [13] Because we look at financial recessions that started in the United States, this index is suited to test for calendar anomalies during these economic recessions.

The specific data that will be investigated are the stock data of the last 20 years. This means that firstly the split samples from the two financial recessions of the past 20 years (COVID-19 crisis not included) will be observed. Additionally, the full period of 2000 until 2020 is examined. To exclude bias due to the COVID-19 crisis, the data used only goes up to January 1st, 2020. The reason only the last 20 years are investigated for this research, is because this paper aims to give a representation of the presence of calendar anomalies during a recession nowadays. When using data from earlier than this period, the danger of bias due to different political/economic circumstances and changes in information processing in the stock market is just too great. Specifically, the observed recessions are the ones that lasted from March 2001 until November 2001 and the one from December 2007 until June 2009. These are, thus excluding COVID-19, the last recessions of the past 20 years, according to the National Bureau of Economic Research (NBER).[14]

The variables that are used by the NBER as an indication to identify an economic recession are real GDP, real income, employment, industrial production and wholesale/retail sale. The closing prices and the returns for each day are used to measure the stock differences during the observed periods. To calculate the returns of the index, the natural logarithm is applied. This method means that the natural logarithm is taken of the closing price at point t divided by the closing price of the trading day prior. This comes down to the following equation:

$$Return = \ln \frac{Priceindex_t}{Priceindex_{t-1}} \tag{3.1}$$

We use the natural logarithm to control for continuously compounding. In the next tables, the data of the samples are summarized.

Table 1: Descriptive data recession period March – November 2001.

Variable	Observations	Mean	St.Deviation	Min	Max	Range
Return S&P 500	197	-0,0429%	1,3630	-5,0468%	4,2753%	9,3321%
Price index	197	1171,25	73,53	965,80	1312,83	347,03

Table 2: Descriptive data recession period December 2007 – June 2009.

Variable	Observations	Mean	St.Deviation	Min	Max	Range
Return S&P 500	412	-0,1158%	0,0237	-9,4695%	10,9572%	20,4267%
Price index	412	1118,27	245,86	676,53	1515,96	839,43

Table 3: Descriptive data full sample period January 2000 – January 2020.

Variable	Observations	Mean	St.Deviation	Min	Max	Range
Return S&P 500	5218	0,0151%	0,0117	-9,4695%	10,9572%	20,4267%
Price index	5218	1574,95	585,94	676,53	3240,02	2563,49

3.2 Methodology

3.2.1 General

The methods used in this paper exist out of statistical analyses. The data of the periods mentioned above will be collected and then tested for the desired effects. The fact that the dataset exists out of a large number of observations, though over a relatively small period, forecasts that the analyses should not be sensitive to biases. The coefficients will be measured using the ordinary least squares (OLS) method. As the observed periods are not very large, I am not afraid that the use of simple dummy regressions will limit the results of this paper, as the danger of autocorrelation is comparatively small. The statistical analyses will also be performed with the use of data transformed to logarithms to see if this method might give more significant results. One danger of my research that I do acknowledge is the fact that the observed periods are relatively small and thus can lead to insignificance.

In the analyses of the effects, for every regression, the one-period lag variable is added as well. After examining multiple models, this turned out to be the only significant autoregressive variable. When we consider macroeconomic factors, no control variable is necessary. The reason behind this is that the observed data is from the SP 500. Considering the properties of this index, we can assume that the macroeconomic movements and/or business cycles are already captured in the data. To avoid multicollinearity, macroeconomic control variables are thus omitted.

To both focus on the sub-questions and to test the hypothesis that a calendar anomaly diminishes more in times of a severe recession compared to a mild one, there will be two regressions in the full sample. In one case, the recession variable $State_{recession}$ will take value '1' if there is either a mild recession (March – November 2001) or a severe recession (December 2007 – June 2009). In the other case, the dummy will take value '1' only in case of a severe recession.

3.2.2 January effect

To test the January effect, only the data of the financial crisis of 2008 is relevant. For the other recession used in this paper, the month of January is absent. The plus side, however, is that we have two sets of data to test for the January effect (Jan 08 and Jan 09) in the financial crisis that lasted from December 2007 until 2009.

The methodology of past papers differs per research. For example, the papers by Lakonishok and Smidt (1988) [1] and Agrawal and Tandon (1994) [15] use a return-of-the-month concept to estimate the January effect. This means that for every month, a dummy is used and consequently the significance is observed. This concept is, in fact, the same concept as the day-of-the-week effect, in which the weekdays are used as dummies. In the paper by Haug and Hirschey (2006) [16], the paired difference test is used both over value-weighted and equal-weighted data. Consequently, the results of this method were observed over the many subsamples. This method is used as well by Seyhun (1988) [17]. Here, the author used a simple dummy regression to test for the January effect. This method was then tested for different samples categorized by market cap of the observed firms. The latter will not be done in this paper.

For the statistical part, a dummy regression is used to test for the January effect. This means that for January the dummy is set to $Month_{Jan}$=1, and for the other months of the year $Month_{Jan}$=0. In the split sample, which is the financial crisis of 2008, there will be a simple dummy regression. For the full period, however, there will also be controlled for recession periods over the whole sample. Thus, there will be three dummy variables. These variables are the January dummy, the recession dummy $State_{recession}$ and the interaction variable $Month_{Jan}$*$State_{recession}$. The latter will take value '1' if both the January dummy and the recession dummy have this value as well. Logically, if at least one of the other dummies takes the value of '0', the interaction dummy will take this value as well. As control variable, the one period lag variable (observed return of the day prior) is added as well. This means that the regression looks like the following:

$$R_t = \alpha_0 + \alpha_1 R_{t-1} + \alpha_2 D_{Jan} + \alpha_3 D_{recession} + \alpha_4 D_{Jan} * D_{recession} + \epsilon_t \tag{3.2}$$

After performing the statistical tests, the of the different samples can be observed. In the split sample, we observe whether the effect is present during the recession. In the full sample, the estimated interaction α measures the effect when a recession period and observations in January are combined. By comparing the α, the extent in which the presence of the January effect depends on the state of the market (recession versus non-recession) can be measured.

3.2.3 Weekend effect

For the weekend effect, there is no such problem that this effect can only be measured in one recessions period, meaning that this effect can be tested for both recessions. Statistically, for this effect, the same concept as in the January effect section is used. A dummy variable can be used once again to distinguish between Monday and the other days of the week. This can be projected as Day_{mon}=1 in case of the return observations on Monday and Day_{mon}=0 in case any other day of the week is observed.

In past papers, the same regression as we will use in the day-of-the-week effect (next section) is used. This means that for every weekday a dummy variable is created. Afterwards, the coefficient and significance of each weekday are observed. Among others, important papers that use this regression analysis include French (1980) [18], Keim and Stambaugh (1984) [19] and Lakonishok Maberly (1990) [20]. However, in this research, we look at both the weekend effect and the day-of-the-week effect. Because we look at both anomalies, in this section, we zoom in on the possible abnormal returns on Monday. Thus, the only distinction made in the dummy regression is between Monday and Tuesday-Friday. Like in the previous effect, the one-period lag variable is used to control for omitted variable bias.

For the weekend effect, the concept of an interaction effect will be used as well in the full sample. In the full-sample regression, there are three dummy variables, which are the Monday dummy, the recession dummy ($State_{recession}$) and the interaction dummy. As described in the 'January effect' section, the interaction α shows the effect of a recession period and, in this case, the Monday dummy combined. Comparing the different estimators will then show the link between the recession periods and the hypothesized presence of the weekend effect. The full regression will look like the following:

$$R_t = \alpha_0 + \alpha_1 R_{t-1} + \alpha_2 D_{mon} + \alpha_3 D_{recession} + \alpha_4 D_{mon} * D_{recession} + \epsilon_t \tag{3.3}$$

3.2.4 Day-of-the-week effect

In this section, all the days of the week will be tested for a significantly high return. Compared to the weekend effect, this means that for every weekday, there will be a dummy variable to be investigated. In the paper by Berument and Kiymaz (2001) [21], an Ordinary Least Square method with dummy variables for each weekday is used to identify the effect. Furthermore, in this paper, the authors argue that the assumption of a constant variance may result in inefficient estimates. The authors suggest allowing for a conditional variance to change for every day of the week. However, because of the limited number of observations, I think it is best to use a constant variance over all weekdays, though this might be a slight limitation of this research. In the test, the dummy variables D_{Mon}, D_{Tue}, D_{Wed}, D_{Tue} and D_{Fri} will be compared to observe whether there are significant differences in return. Also, the the one-period lag variable is added.

This is the same model that is used by Gibbons and Hess (1981) [22]. With this model, the full sample will test if there is a day-of-the-week effect and, if so, which particular day generates significantly higher returns. The split sample will be considered as well to observe if there is such an effect to be detected. Building on this evidence, the effect will be tested using a slightly more complicated model. In this model, there will be an extra variable $D_{recession}$, and an interaction dummy that links the particular day that offers a higher return (DOTW) with the recession dummy:

$$R_t = \alpha_1 R_{t-1} + \alpha_{mon} D_{mon} + \alpha_{tue} D_{tue} + \alpha_{wed} D_{wed} + \alpha_{thu} D_{thu} + \alpha_{fri} D_{fri} + \alpha_2 D_{recession} + \alpha_3 D_{DOTW} * D_{recession} + \epsilon_t \tag{3.4}$$

Comparing the different estimators will assess the influence of a recession period on the day-of-the-week effect.

3.2.5 Turn-of-the-month effect

To capture the turn-of-the-month (TOM) effect, we have to define the days that are part of the period of the TOM. These are the days that are shown to have offered comparatively a higher return in research conducted over the last couple of decades. There is no strict definition of the TOM period. In the paper by Lakonishok and Smidt (1988), the period is defined as the last day of the previous month and the first three days of the month thereafter (day -1 to day 3). However, in the paper by Liu (2013) [23] the period of day -4 until day 2 proved to generate the highest return while the paper by Kayacetin and Lekpek (2016) [24] suggested that the period of day -3 until day 1 generate the highest return. In conclusion, only after a statistical analysis, I will be sure on which days the TOM effect is the strongest in my samples if it is present at all. To measure this effect, a distinction should be made between the TOM days and the rest-of-the-month days (ROM). The different mean returns of every day of the month will be used to test multiple TOM periods (e.g. day -1 to day 3 or day -2 until day -2) against the mean returns of the ROM period. For all the tests, the null hypothesis $_{TOM}{=}_{ROM}$will be tested and be concluded based on the t-statistics.

In this case, once more the split samples and the full sample are used. First, the TOM days are observed in the full sample and split sample. After this observation, the days in the TOM period can be labelled with a dummy variable as $Period_{TOM}$=1. To assess the effect in times of a recession, the recession periods are labelled with the dummy $State_{recession}$. In this final model, the estimated interaction dummy will then complete the model to assess the link between the recession period and the turn-of-the-month effect. Furthermore, the one-period lag variable is included. In the literature mentioned above, this regression is used as well to test for the TOM effect, except for the lag variable.

$$R_t = \alpha_0 + \alpha_1 R_{t-1} + \alpha_2 D_{TOM} + \alpha_3 D_{recession} + \alpha_4 D_{TOM} * D_{recession} + \epsilon_t \tag{3.5}$$

4 Results

4.0.1 January effect

In the full sample without the recession and the interaction variables, we observe no (significant) January effect. Logically, we also do not observe the effect in either of the split samples of the two recessions. This confirms my hypothesis based on past literature, which argues that the January effect has faded since the 1980s. In the analysis with the recession dummy and the interaction dummy $Month_{Jan}{*}State_{recession}$, it can be observed that there is no significance in these dummies. This is very intuitive as there is no significant January effect in the split samples either. Below the summarized test statistics of each sample and the corresponding regression coefficients can be found.

Table 4: Results of the January effect.

	Mar - Nov 01	Dec 07 - Jun 09	2000-2020 (no recession dummy)	2000-2020 (with recession dummy)	2000-2020 (with recession dummy = Dec 07 - Jun 09)
Constant	-.0001 (0.917)	-.0010 (0.418)	.0002 (0.250)	.0003** (0.032)	.0003* (0.055)
January effect	-.0029 (0.486)	-.0029 (0.351)	-.0004 (0.486)	-.0001 (0.804)	-.0001 (0.859)
Return S&P 500 (1 period lag)	.0503 (0.500)	-.1526** (0.012)	-.0736*** (0.003)	-.0751*** (0.002)	-.0750*** (0.002)
Recession				-.0011 (0.213)	-.0012 (0.322)
Recession* January effect				-.0027 (0.362)	-.0026 (0.406)
Observations	196	411	5217	5217	5217
Prob >F	0.6004	0.0349	0.0090	0.0063	0.0087
R^2	0.0075	0.0244	0.0055	0.0072	0.0071

* significance at 10% level
** significance at 5% level
*** significance at 1% level

4.0.2 Weekend effect

As in the previous section, there is no effect found in the full sample without the recession and interaction variables. In the split samples of the recession, we do not find a significant weekend effect either. This means that there is no weekend effect present in our sample. Intuitively, the interaction dummy $D_{mon}{*}D_{recession}$is not significant either. Below the summarized test statistics of each sample and the corresponding regression coefficients can be found.

Table 5: Results of the weekend effect.

	March - Nov 01	Dec 07 - Jun 09	2000-2020 (no recession dummy)	2000-2020 (with recession dummy)	2000-2020 (with recession dummy = Dec 07 - Jun 09)
Constant	-.0001 (0.917)	-.0010 (0.418)	.0002 (0.250)	.0003** (0.032)	.0003* (0.055)
January effect	-.0029 (0.486)	-.0029 (0.351)	-.0004 (0.486)	-.0001 (0.804)	-.0001 (0.859)
Return S&P 500 (1 period lag)	.0503 (0.500)	-.1526** (0.012)	-.0736*** (0.003)	-.0751*** (0.002)	-.0750*** (0.002)
Recession				-.0011 (0.213)	-.0012 (0.322)
Recession* January effect				-.0027 (0.362)	-.0026 (0.406)
Observations	196	411	5217	5217	5217
Prob >F	0.6004	0.0349	0.0090	0.0063	0.0087
$\mathbf{R^2}$	0.0075	0.0244	0.0055	0.0072	0.0071

* significance at 10% level
** significance at 5% level
*** significance at 1% level

4.0.3 Day-of-the-week effect

In the full sample and split samples, there is no DOTW effect found. As the statistical concept of the interaction term in the DOTW effect was to interact with the particular day that generated particularly high returns, this analysis is not possible. This is not much of a problem, however, as there would no significant effect have been found because of the insignificance in all the samples. Below the summarized test statistics of each sample and the corresponding regression coefficients can be found.

Table 6: Results of the day-of-the-week effect.

	Mar - Nov 01	Dec 07 - Jun 09	2000 - 2020 (no recession dummy)
Monday	-.0012 (0.644)	-.0039 (0.214)	-.0002 (0.685)
Tuesday	.0001 (0.963)	.0015 (0.586)	.0005 (0.199)
Wednesday	-.0020 (0.385)	-.0029 (0.242)	.0002 (0.626)
Thursday	.0029 (0.167)	-.0008 (0.742)	.0004 (0.234)
Friday	-.0019 (0.325)	.0004 (0.843)	-.0001 (0.750)
Return S&P 500 (1 period lag)	.0667 (0.362)	-.1460** (0.015)	-.0734*** (0.003)
Observations	196	411	5217
Prob >F	0.6006	0.1275	0.0883
$\mathbf{R^2}$	0.0218	0.0317	0.0061

* significance at 10% level
** significance at 5% level
*** significance at 1% level

4.0.4 Turn-of-the-month effect

As the first step, the average returns of the days around the turn of the month are observed to determine which specific days form the TOM period. The results can be found in graph 1 (full sample), graph 2 (recession December 2007 – June 2009) and graph 3 (recession March – November 2001). In every sample, day -1 and day 1 generate on average positive returns. In the full sample, the average return difference on these days is quite large compared to the other days around the TOM.

Secondly, multiple periods around the TOM are tested. The period of these two days (-1, +1) turned out to be the only significant TOM dummy in the regression model within the full sample. This period is thus used as the TOM dummy in the split samples as well. In the recession samples, the TOM dummy is only found significant in the recession of March until November 2001. This observation is in line with the hypothesis that a recession diminishes the effect of an existing anomaly more, the more severe the recession is.

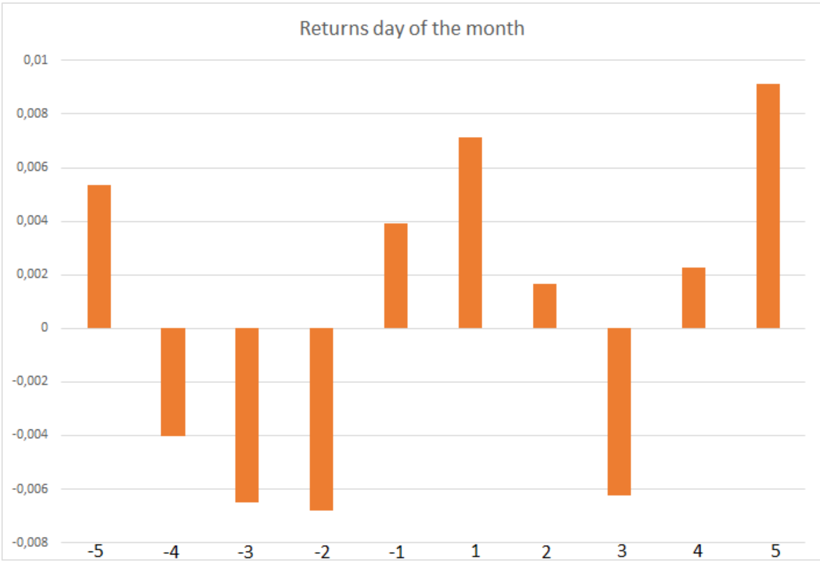

Figure 4.1: Average returns of the TOM effect (sample March - Nov 01)

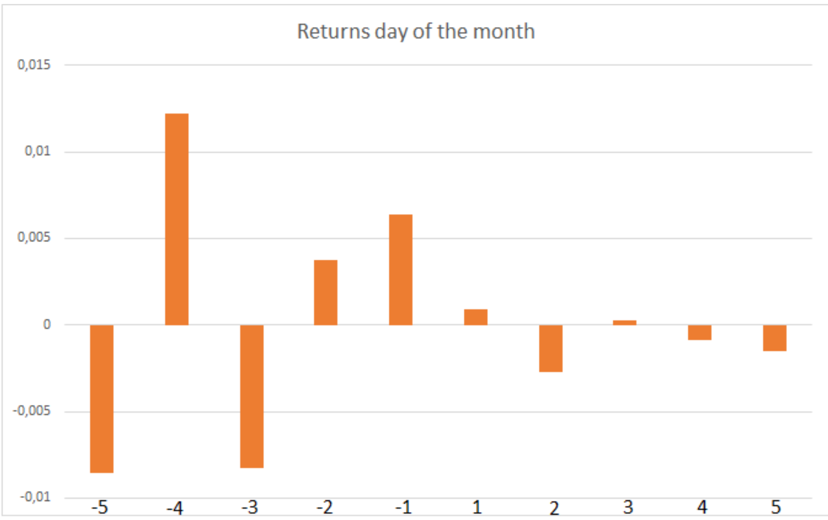

Figure 4.2: Average returns of the TOM effect (sample Dec 07-June 09)

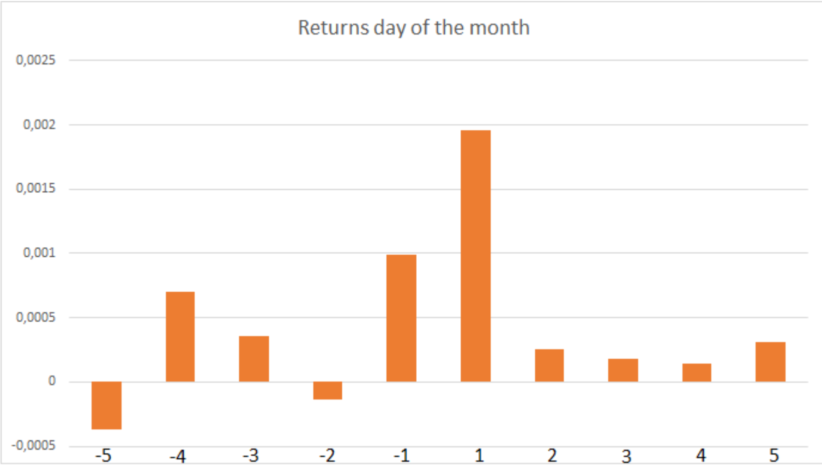

Figure 4.3: Average returns of the TOM effect (sample 2000-2020)

In the final regression of the full sample including the interaction dummies, there is no significant effect found in case of the recession dummy accounts for both recessions. In case the recession dummy only accounts for the heavier recession, the TOM becomes more significant. This confirms our hypothesis: the effect that an anomaly fades away in times of recession is comparatively stronger in case of a more severe recession. The results found suggest that the TOM effect is still present in combination with a mild recession. Below the summarized test statistics of each sample and the corresponding regression coefficients can be found.

Table 7: Results of the turn-of-the-month effect.

	Mar - Nov 01	Dec 07 - Jun 09	2000-2020 (no recession dummy)	2000-2020 (with recession dummy)	2000-2020 (with recession dummy = Dec 07 - Jun 09)
Constant	-.0007 (0.462)	-.0016 (0.177)	.0001 (0.611)	.0003* (0.079)	.0002 (0.143)
TOM effect	.0073*** (0.007)	.0052 (0.359)	.0015** (0.037)	.0010 (0.113)	.0013* (0.051)
Return S&P 500 (1 period lag)	.0592 (0.429)	-.1544** (0.011)	-.0735*** (0.003)	-.0752*** (0.002)	-.0752*** (0.002)
Recession				-.0015* (0.082)	-.0017 (0.153)
Recession* TOM effect				.0042 (0.284)	.0034 (0.547)
Observations	196	411	5217	5217	5217
Prob >F	0.0229	0.0247	0.0008	0.0008	0.0011
R^2	0.0155	0.0252	0.0062	0.0082	0.0078

* significance at 10% level
** significance at 5% level
*** significance at 1% level

5 Conclusion

With the use of dummy regression analyses, we have looked at the presence of calendar anomalies in the stock market, in particular the January effect, the weekend effect, the DOTW and the TOM effect. Furthermore, we have observed whether the presence of a recession makes a difference when observing these calendar anomalies. In past literature, the findings concerning calendar anomalies have been ambiguous. Papers by French (1980) [18], Jaffe and Westerfield (1985) [2], Lakonishok and Smidt (1988) [1], Lakonishok and Maberly (1990) [20] and others provide evidence in of the mentioned calendar anomalies. Later on, papers by Gu (2003) [8], Van der Sar (2003) [3], Vasileiou and Samitas (2015) [4], Vasileiou (2017) [9] and others show that calendar effects are fading away or have completely disappeared in the stock market. This paper is mostly in line with the latter (more recent) group of finance literature. There is no January, weekend or DOTW found in the stock market, suggesting that these effects are indeed fading away. This paper does, however, provide evidence for a TOM effect, in which the TOM period exists out of month days (-1, +1). Concerning the subsamples, the TOM effect only appears to be significant in a mild recession and not in a more severe recession. From this, we conclude that the TOM is still present in the stock market, and only fades away in times of a severe recession.

6 Discussion

In this paper, the role of recession periods concerning anomalies in the stock market is investigated. It turned out that only the TOM effect is still significantly relevant in the stock market, and in severe recessions, this effect fades away. The finding that other effects (January effect, weekend effect, DOTW effect) are not observed, is a bit unexpected but in line with relatively recent literature. The absence of the January effect is already mentioned in the papers by Gu (2003) [8], Van der Sar (2003) [3] and Vasileiou and Samitas (2015) [4]. The absence of the weekend and DOTW effect is a bit surprising, but it is very intuitive. This paper does not dive deeper into the reasons why calendar anomalies might be disappearing, though the weekend/DOTW effect may be disappearing due to the same reasons that the January effect is disappearing. One can, for example, think about more efficient information processing so that the market equilibrium is easier restored.

Of all the investigated anomalies, we thus have only observed a significant TOM effect. The TOM effect can be ascribed to increased liquidity at the end of the month (Booth, Kallunki, Martikainen, 2001) [25]. With this in mind, we can interpret our results as that the increased liquidity at the end of the month has a relatively stronger effect on the stock market than the mechanisms behind the January effect, weekend effect or DOTW effect. Out of these effects, the weekend and DOTW effect generally have a more behavioural origin (French, 1980), which might thus be outdated. The January effect, however, is in the literature also explained as an effect of increased liquidity. Haugen and Lakonishok (1987) [26] argue that the January effect is a consequence of window dressing (institutional traders) and tax-loss selling (individual traders). Curiously, both the TOM and January effect are consequences of increased liquidity at the end of the month/year although only the TOM is found significant. This implies that there are other factors at stake as well, and it might be interesting to investigate this in the future.

Before concluding the discussion, a few remarks have to be made concerning the limitations and weaknesses of this study. Starting with the data, although the SP 500 is a good indicator of the global economy, the index does not account for small-cap companies and has a market beta of 1.0. This means that the results are not representative of indices with mostly small-cap companies or with a very high/low market beta. Furthermore, the dummy regression performed in this paper is a rather simple method. In this paper, past regression models are followed, but perhaps more control variables should be included (apart from the one period autoregressive variable). Also, an unconditional variance is assumed, meaning that for every month/weekday the same variance is estimated. This method is used to simplify the analyses but may be incorrect.

The important findings of this research are that the calendar anomalies of the January effect, weekend effect and DOTW effect are fading away in the stock market. The TOM effect, however, persists but fades away in times of a severe economic recession (financial crisis 2008). As mentioned, it would be interesting to investigate the reason why the aforementioned calendar anomalies are not observable in the stock market anymore, but the TOM effect still is. This stand would be an interesting starting point for future research.

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