TURN-OF-THE-MONTH EFFECTS IN EUROPEAN STOCK MARKETS BEFORE AND AFTER THE FINANCIAL CRISIS – AN EVOLUTIONARY FINANCE PERSPECTIVE

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Abstract

The wealth of owners of stock corporations is exposed to various phenomena affecting stock market prices. Of these calendar anomalies, we examine the turn-of-the-month (TOM) effect. Previous literature reveals only mixed results with regard to (changes of) the TOM pattern. Therefore, this paper aims to provide further insights by a comparison of crisis and non-crisis periods, applying an evolutionary finance approach, which is based on computational agent-based modelling. We analyse stock price developments in six European stock markets for the period 2000-2014 with a special focus on the financial crisis. For this purpose, we apply parametric and nonparametric event study techniques and find explanations of this effect, like volatility, trade volume and the business cycle. After testing for external factors, the study takes an alternative perspective based on the evolutionary finance approach, which is based on the biological principles of selection, mutation and dependence and shows the effects of shifted investment capital induced by revised strategies of investors who enter and exit corporate ownership by buying and selling at the stock market.

Keywords: Turn-of-the-month Effect, Market Efficiency, Evolutionary Finance, Financial Crisis

1. INTRODUCTION

One driver of the wealth of owners of stock corporations is the stock market price. Empirical studies provide statistically significant evidence that stock returns are higher during turns of the month compared to the other trading days of the same month. This "turn-of-the-month effect" (hereafter TOM) is documented by various analyses of American and European stock markets (originally, see Ariel, 1987) and is of interest to the shareholder according to his investment strategies and to the value of his assets due to the price behaviour. The existence of this calendar anomaly is a contradiction to even the weak form of the Efficient Market Hypothesis (EMH) of Fama (1970). The weak form of the EMH states that the market is efficient in processing historical (price) information so that forecasting stock price movements and especially excess returns cannot be obtained using this kind of past information.

The purpose of this study is to investigate the existence of this monthly effect in stock returns for the six stock market indexes of France (CAC40), Germany (DAX), Great Britain (FTSE100), Netherlands (AEX), Spain (IBEX) and Italy (MIB30) and their being influenced by the financial crisis. These six countries were selected because they cover about 75 percent of economic strength due to gross domestic product in Europe (International Monetary Fund, 2015). Furthermore, the paper tries to analyse the TOM with particular respect to possible variations of the effect due to financial crisis processes. Previous studies suggest that there have been significant changes in market anomalies since the financial crises processes started in 2007 (on "momentum crashes", see Daniel and Moskowitz, 2016). Based hereupon, our paper aims to close a research gap within the field of corporate ownership in two ways:

- So far, analysis of the relevance of the TOM effect in crisis compared to non-crisis periods is scarce.
- Using an evolutionary finance approach, which "uses evolutionary dynamics, such as mutation and selection, to study how trading strategies […] evolve" (Grootheer, 2006) promises to add valuable insights to research based on more traditional approaches.

Data covering 1008 months for the six countries from January 2000 through December 2014 show that the TOM effect is relevant over the whole period in all six markets. Parametric and nonparametric tests indicate a significant TOM pattern. However, the data also indicate that the pre-crisis period 2000 to 2006 (as defined by the NBER, see e.g. Aizenman et al., 2014; it should be taken into account, however, that during this period the dotcom bubble burst) includes about two thirds of the cumulative average return (CAR) of the TOM days for the entire period, while it was considerably weaker in crisis and post-crisis years 2007 to 2014 (according to Aizenman et al., 2014), suggesting that the crisis and its consequences had a strongly dampening effect. Likewise, the data signal a change in predominant investment strategies (from momentum to value) of heterogeneous stock market participants. Therefore, also the flows of funds among actors entering or exiting stock corporation ownership by buying and selling shares changed at the onset of the crisis, with a positive effect on TOM returns due to a beginning value market.

After a review of previous research (chapter 2) with respect to different calendar anomalies, chapter 3 explains data and methodology of our paper. Chapter 4 presents the results – i.e. general findings as well as robustness checks – of parametric and nonparametric tests with regard to TOM effects in our selection of European stock markets. Based hereupon, different explanations for the TOM effect are discussed, applying a particular evolutionary finance focus (chapter 5). The sixth and final chapter concludes.

2. PRIOR RESEARCH

The existence of different seasonal price anomalies affecting corporate owners' wealth is documented by various studies on different international capital markets. In this regard, those studies (Haugen and Lakonishok, 1988; Haug and Hirschey, 2006) show that in January, compared to any other month, a significantly higher return on stock markets can be expected ("January effect"). Other studies (Lakonishok and Smidt, 1988; Kamara, 1997) show that during the course of a week, returns are above average on Fridays and below on Mondays ("weekend effect"). In addition, there is a phenomenon called pre-holiday effect (Ariel, 1990; Merl and Neuhaus, 2008), meaning that on the last trading day before a public holiday returns are significantly higher than on common trading days. However, the turn-of-the-month effect shows significantly higher returns during the end of a month and the beginning of the following one compared to other days. The existence of this phenomenon has already been shown for different stock markets as described below.

Some of the initial studies regarding "month-effects" can be ascribed to Ariel (1987). He pointed out that significant positive average returns occurred at the beginning and during the first half of a month on US stock exchange markets. On the opposite, average returns tended to zero during the second half of the month. Penman (1987) assumed financial communication policies of companies to be the cause of these price anomalies, as there is a tendency to publish good news at the beginning of a month whereas bad news are commonly made public during month's end. Jaffe and Westerfield (1989) found similar evidence for the Australian stock market, but not for the Japanese, Canadian and UK stock markets. Martikainen et al. (1994) showed a turn-of-the-month effect for stock markets in a global perspective.

Lakonishok and Smidt (1988) observed that cumulative average returns over a specific four day period (last trading day of a month plus the first three trading days of the following month) are higher than returns during trading days of the remainder of the month on US stock markets. Derived from Lakonishok and Smidt's observations, these variations in return can be traced back to seasonalities concerning cash flows of individuals and institutions. Cadsby and Radner (1992) analysed turn-of-the-month effects in ten countries and found evidence of a TOM pattern in six countries. Agrawal and Tandon (1994) observed significant turn-of-the-month effects in 11 countries out of a sample size of 18 countries other than the United States. Kunkel et al. (2003) showed excess returns during the turn-of-the-month for nineteen international indices, whereby TOM returns for 16 out of the 19 indices were statistically significant. In addition, Gopal (2006) also confirmed in his study on the US stock market that the turn-of-the-month effect is existent.

More recent studies are still documenting the turn-of-the-month effect. McConnell and Xu (2008) detected a TOM effect in 31 out of 35 countries and demonstrate that the effect is not caused by month-end buying pressure as measured by trading volume (trading volume is lower around TOM days), net flows to equity funds or volatility (volatility of stock returns around the turn of the month is lower than for the rest of the month). Further studies focus particular national markets, such as Depenchuk et al. (2010), who detected TOM effects for the Ukrainian stock market, or Karadžić and Vulić (2011), who observed a significant monthly effect in the Montenegrin market, when comparing the last week of a month to the rest of the month. Garcia-Blandon (2011) analysed turn-of-the-month effects in Latin America markets such as Brazil and Mexico. Al-Jafari (2011) stated in his study a monthly effect of the stock market returns of the Bahrain Bourse, but no significant differences between the two periods before (2003-2007) and after the financial crises (2008-2011). While analysing the Greek stock market from 2002 to 2012, Vasileiou (2013) showed that the financial crises did not result in negative returns on TOM days, so that the TOM effect prevailed during the recession period in Greece. A possible influence of the financial trend of a stock market on the TOM effect is confirmed, whereby the financial trend is closely linked to the economic growth of a country (see also Levine, 2005). Thus, the highest TOM returns occur during economic growth periods, while the lowest ROM (rest of the month) returns can be found during recession periods.

Although there is extensive research on TOM effects in general, only a small part of it provides knowledge about the impact of financial crises and crisis-induced market distortions on the TOM effect and corporate owners' wealth, respectively. Furthermore, explanations for (changes in the relevance of) the TOM effect show mixed results. This paper, therefore, tries to add further insights by a comparison of TOMs in crisis and non-crisis periods for several European stock markets, using an evolutionary finance approach.

3. DATA AND METHODOLOGY

3.1. European Stock Market Data

Data consist of daily closing prices of the six selected European stock market indices from January 2000 to December 2014 and were obtained from Bloomberg. The period of the study encompasses seven pre-crisis (2000-2006) and eight crisis-/post-crisis (2007-2014) years to analyse short-term and long-term effects. Summary statistics for the daily returns on each index are reported in Table 1. The number of daily returns ranges from 3784 to 3837, differences being due to public holidays. The mean return for all countries was negative (except for Germany), ranging from -0.0204 for Italy to -0.0004 for Great Britain. The standard deviation of the daily returns ranged from 1.2367 for Great Britain to 1.5524 for Germany.

Table 1. General statistics related to daily returns on each index (2000-2014)

Country	*Number of observations*	*Mean (%)*	*Median (%)*	*S.D. (%)*	*Skewness*	*Kurtosis*
France	3835	-0.0085	0.0245	1.5077	0.0269	4.7859
Germany	3815	0.0101	0.0777	1.5524	-0.0111	4.3941
Great Britain	3784	-0.0004	0.0338	1.2367	-0.1465	6.2232
Netherlands	3837	-0.0121	0.0425	1.4870	-0.0754	6.3663
Spain	3790	-0.0032	0.0664	1.5276	0.1153	4.9065
Italy	3804	-0.0204	0.0446	1.5457	-0.1107	4.6602

Table 1 shows excess kurtosis (leptokurtic) and skewness of the returns of any of the six stock markets. Testing for normality nevertheless, the Kolmogorov-Smirnov test leads to a rejection of the normal distribution assumption at the 1% level for all six countries. Although the validity of standard parametric tests (which presuppose a normal distribution) used in early anomalies research has been questioned (and led some researchers to inappropriate adjustments, see Connolly, 1989), it is generally agreed that parametric tests – like t-test, OLS regression and analysis of variance (ANOVA) – are fairly robust to mild violations of assumptions, especially in large samples (Kunkel et al., 2003). They are also more sensitive to small differences in the magnitudes of return that are being measured. Nevertheless, nonparametric methods have been demonstrated to be almost as powerful as parametric methods in detecting differences in ANOVA procedures and, when OLS assumptions are not given, can be even more powerful (Hunter and May, 1993). To address these aforementioned concerns, both parametric and nonparametric tests are used (see also Kunkel et al., 2003).

3.2. Hypotheses

Thus, the methodological approach of this paper is as follows: Referring to a significant 4-day TOM period (last trading day of the month and the first three trading days of the following month, see also Lakonishok and Smidt, 1988 as well as Kunkel et al., 2003) around the turn of the month, we test for the first hypothesis:

H1: European stock markets show a significant 4-day TOM period pattern.

Hereafter, we test our second hypothesis on the relation of TOM and ROM returns, i.e.

H2: Compared to ROM returns, TOM returns are significantly higher.

For the latter purpose, the following OLS regression of daily returns onto a dummy variable is run for each country in terms of a parametric test (see also Pettengill and Jordan, 1988) to examine a possible TOM effect:

$$R_t = \alpha + \beta^* D_{TOM} + \varepsilon_t \qquad (1)$$

where: R_t is the return on Day t; α is the intercept representing the mean return for the ROM period; D_{TOM} is a binary dummy variable for the TOM period; the coefficient β represents the difference between the mean TOM return and the mean ROM return; and ε_t is the error term. Then a nonparametric Wilcoxon signed rank (WSR) test is performed, which is a paired difference test (difference in medians rather than means) that controls for any seasonal monthly effect and parallels the layout of the parametric two-way ANOVA but is free of the distributional assumptions required under regression or ANOVA procedures. The significance of the parametric and nonparametric tests is considered given if the p-value (probability of error) is less than 0.1.

In the next step, the robustness of the TOM effect is analysed by dividing the whole period into two sub-periods. Finally, possible explanations of the TOM effect will be discussed and analysed with a special focus on an evolutionary finance perspective.

4. RESULTS

4.1. Main Findings

General statistics for the 4-day TOM period and the trading days of the rest-of-the-month are reported in Table 2.

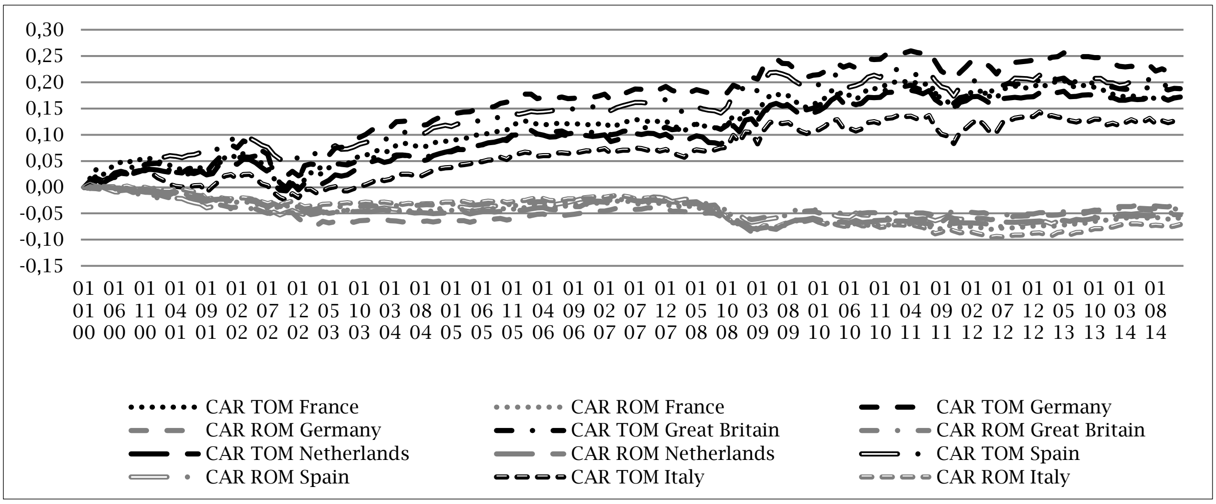
Table 2. General statistics on TOM and ROM returns (2000-2014)

Country	*TOM*			*ROM*			*CAR TOM*	*GARR TOM*	*CAR ROM*	*GARR ROM*
	Mean (%)	*S.D (%)*	*Median (%)*	*Mean (%)*	*S.D (%)*	*Median (%)*	*(%)*	*(%)*	*(%)*	*(%)*
France	0.096*	1.213	0.110	-0.033	1.324	0.030	17.15	0.092	-5.94	-0.036
Germany	0.125**	1.180	0.140	-0.017	1.333	0.035	22.56	0.124	-3.32	-0.020
Great Britain	0.104***	0.981	0.100	-0.023	1.040	0.020	18.81	0.103	-4.25	-0.025
Netherlands	0.096*	1.123	0.100	-0.028	1.227	0.030	17.20	0.093	-5.29	-0.030
Spain	0.109**	1.147	0.085	-0.028	1.332	0.030	19.67	0.107	-5.10	-0.032
Italy	0.070	1.143	0.120	-0.042*	1.310	0.005	12.46	0.069	-7.10	-0.043

*Note: * Denotes statistical significance for a two-tailed t test at the 10% level.*
*** Denotes statistical significance for a two-tailed t test at the 5% level.*
**** Denotes statistical significance for a two-tailed t test at the 1% level.*

In all six countries, the average TOM return is higher than the corresponding ROM return on the respective stock market. With the exception of Italy, the average TOM returns are significantly different from zero. Thus, our finding support hypothesis H1. The TOM pattern is most significant for Great Britain due to the low standard deviation of returns (standard error of means in percent is the lowest of all countries with 0.0410). However, in all six countries, the average ROM returns are negative, even weakly significant for Italy. The geometric average rate of return (GARR) per year for the TOM returns ranges from 0.069 for Italy to 0.124 for Germany. Overall, the GARRs are slightly below the arithmetical returns for all countries. The cumulative average return (CAR) of the average TOM returns varies from 12.46 percent for Italy to 22.56 percent for Germany. Figure 1 shows the CAR of the average TOM and ROM returns for all countries. In addition, between 2003 and 2006, the CAR increased considerably during the post-dotcom-bubble period.

Figure 1. Cumulative average returns of TOM and ROM returns for all countries (2000-2014)



Having supported our first hypothesis – that an apparent TOM pattern exists in general –, a TOM effect is tested directly by comparing TOM returns to ROM returns. The results of the regression in equation (1) are reported in Table 3. The coefficients of the TOM dummy variables show that in every country the differences between average TOM and ROM returns are significant (most significant for Great Britain due to the lowest standard error of means). The F-statistics confirm the second hypothesis – of significant higher TOM than ROM returns for all countries. Thus, the first test finds a TOM effect in all six countries included in the study. The next test, the WSR test, is based only on the ranks of the paired differences between TOM and ROM returns. The results of this test also show a significant TOM effect in all six countries over the entire period. Thus, the findings support hypothesis H2, too.

Table 3. Tests for the TOM effect 2000-2014

Country	*α*[a]	*β*[a]	*F test p value*[a]	*WSR test p value*[b]
France	-0.033	0.132**	0.016**	0.015**
Germany	-0.017	0.151**	0.014**	0.004***
Great Britain	-0.023	0.130***	0.004***	0.000***
Netherlands	-0.028	0.128**	0.028**	0.009***
Spain	-0.028	0.142**	0.015**	0.016**
Italy	-0.042*	0.112**	0.069*	0.013**

Note: [a] *The α, β and F test are for the following regression:* $R_t = \alpha + \beta^* D_{TOM} + \varepsilon_t$
[b] *The WSR test is a nonparametric paired difference test between the monthly TOM and ROM returns.*
****, ** and * denote statistical significance for a two-tailed t test at the one, five and ten percent levels.*

4.2. Robustness Checks

Hereafter, we test the robustness of the TOM effect by dividing the observation period into two sub-periods from 2000-2006 (pre-crisis) and 2007-2014 (crisis/post-crisis), especially for analysing the influence of the financial crisis during the second period. Table 4 demonstrates that in the first period, five of six countries, except Italy, show a significant TOM pattern. However, in the second period, none of the indices shows a significant TOM pattern, although the average returns are still positive. Accordingly, the financial crisis and its consequences seem to have mitigated the TOM. Furthermore, the average TOM return of all six countries has more than halved from the first (0.143) to the second sub-period (0.063). The ROM returns have hardly changed within the two periods, except for Germany and Italy. The average volatility of all six countries of the TOM and ROM returns has risen slightly from the first (TOM: 1.059; ROM: 1.162) to the second subperiod (TOM: 1.201; ROM: 1.353).

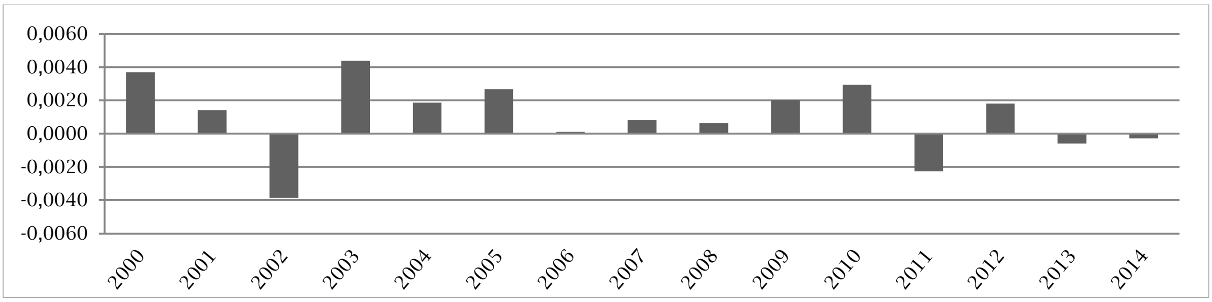
Table 4. Statistics on TOM and ROM returns (2000-2006 and 2007-2014)

Country	TOM (2000-2006)		ROM (2000-2006)		TOM (2007-2014)		ROM (2007-2014)	
	Mean (%)	S.D (%)	Mean (%)	S.D (%)	Mean (%)	S.D (%)	Mean (%)	S.D (%)
France	0.143*	1.140	-0.037	1.209	0.055	1.252	-0.030	1.391
Germany	0.207**	1.189	-0,055	1.361	0.056	1.172	0.013	1.289
Great Britain	0.126**	0.912	-0.032	0.952	0.087	1.071	-0.017	1.125
Netherlands	0.117*	1.133	-0.034	1.218	0.078	1.102	-0.026	1.250
Spain	0.184***	1.028	-0.026	1.159	0.046	1.282	-0.031	1.510
Italy	0.083	0.949	-0.022	1.073	0.058	1.332	-0.055*	1.549

*Note: * Denotes statistical significance for a two-tailed t test at the 10% level.*
*** Denotes statistical significance for a two-tailed t test at the 5% level.*
**** Denotes statistical significance for a two-tailed t test at the 1% level.*

Subsequent Figure 2 shows that the crisis years 2007 and 2008 have no negative, but a dampening effect on the TOM pattern. It is also obvious that in the post-crisis period (2009-2014), the TOM pattern is weaker than in the pre-crisis years (2000-2006). Therefore, the financial crisis could have had not only an immediate short-term but also a long-term impact on the TOM effect. Yet, the decline of the TOM pattern in the crises years is not as strong as in 2002 (after the dotcom crisis) and 2011 (after the first peak of the European sovereign debt crisis). However, this mitigation of TOMs could have been caused by more general market processes as well: Some researchers argue that market anomalies have an inbuilt tendency to slowly disappear due to being arbitraged away by the (adjustment) of investors' actions (see, e.g., Chordia, Subrahmanyam & Tong, 2014; Akbas et al., 2015).

Figure 2. Average annual TOM returns of the sample countries (2000-2014)



The mitigating effect during the crisis can be seen especially in the cumulative data (Table 5) and due to further calculations of the data related to the share of months with higher TOM than ROM returns. The CAR TOM in the first period for all countries researched averaged 66.17 percent (11.89 of 17.97) of the entire CAR TOM (Table 5). Particularly, France, Germany and Spain achieve a significant drop of the TOM pattern between the two periods (on average for all three countries -65.15 percent). For Great Britain, Netherlands and Italy, the decline is more attenuated. The overall CAR ROM on average hardly changes between the two periods, as only Germany and Italy show a stronger variation.

In the first period, the share of months with higher TOM than ROM returns is on average for all countries 61.25 percent, with 54.22 percent for France to 63.86 percent for the Netherlands and Italy. In the second period, the average drops to 52.08 percent, meaning that it declines by 9.17 percentage points. This means that during the financial crisis not only a dampening TOM pattern existed, but also a weakened stability of the pattern related to the share of the month with higher TOM than ROM returns.

Table 5. Statistics on CAR TOM and CAR ROM (2000-2006 and 2007-2014)

Country	CAR TOM 2000-2006 (%)	CAR TOM 2007-2014 (%)	CAR ROM 2000-2006 (%)	CAR ROM 2007-2014 (%)
France	11.86	5.29	-3.07	-2.87
Germany	17.17	5.39	-4.61	1.29
Great Britain	10.46	8.35	-2.62	-1.63
Netherlands	9.67	7.53	-2.80	-2.49
Spain	15.30	4.37	-2.14	-2.96
Italy	6.89	5.57	-1.84	-5.26
All countries	11.89	6.08	-2.85	-2.32

Finally, it can be stated that the robustness of the TOM pattern and the TOM effect has suffered since the financial crisis and this could have an impact up to the post-crisis years (Figure 2 already showed negative average TOM returns since 2013).

5. EXPLANATIONS

In this chapter, we try to elaborate reasons for the change in the TOM effect with the onset of the crisis based on the entire sample period. Hereafter, trading volume and volatility of TOM days are examined more closely, to see if the results of

McConnell and Xu (2008), which demonstrate that the TOM effect is not caused by higher trading volume or higher volatility of returns, can be confirmed. Secondly, the influence of the economic trend on the TOM effect is analysed to test the findings of Vasileiou (2013), whereafter the economic growth rate has a positive influence on the TOM effect. Thirdly, we introduce a new perspective based on evolutionary finance to improve the economic analysis of changes in the TOM pattern.

5.1. Trading Volume, Volatility, and GDP

Table 6 presents the results of the correlations between the TOM returns on the one hand and the corresponding volatility of the TOM days and the trading volume of the TOM days on the other hand. If higher TOM returns are caused by higher volatility or higher trading volume, it is to be expected that the correlation between these data is significantly positive and a change in the TOM effect would induce lower volatility and trading volume. The correlations due to volatility for all six countries are negative (also for the two sub-periods), for France and Great Britain even significantly. As Table 4 has already illustrated, the volatility of the ROM days for both sub-periods is higher than for the TOM days. Thus, the volatility (which represents the risk) seems not to be a decisive factor for the TOM effect and changes in the effect. In addition, the trading volume around TOM days is negatively correlated with corresponding TOM returns, at least for Germany and Great Britain (also for the two sub-periods; complete and reliable data from Bloomberg for the entire period were available only for the two countries). The share of months with a higher trading volume around TOM days than ROM days is for Germany over the entire period 49.6 percent and for Great Britain 51.2 percent. Even between the two periods, there are no significant differences. The share increases for Germany from 49.4 percent in the first period to 49.8 percent in the second period. In Great Britain, the share rises from 50.6 percent to 51.8 percent. Thus, the trading volume also seems not to be a decisive factor for the TOM effect or changes in the effect.

Table 6. Correlations between TOM returns and corresponding volatility/trading volumes (2000-2014)

Country	*TOM Volatility*	*TOM Trading Volume*
France	-0.1715**	n.a.
Germany	-0.0604	-0.0635
Great Britain	-0.1271*	-0.0791
Netherlands	-0.0735	n.a.
Spain	-0.0632	n.a.
Italy	-0.1048	n.a.

*Note: * Denotes statistical significance for a two-tailed t test at the 10% level.*
*** Denotes statistical significance for a two-tailed t test at the 5% level.*

Referring to another potential explanatory variable, Table 7 shows the respective gross domestic product (GDP) growth for the observation period on an annual basis.

Table 7. Gross domestic product growth in percent 2000-2014

Country	*2000*	*2001*	*2002*	*2003*	*2004*	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*	*2013*	*2014*
France	3.88	1.95	1.12	0.82	2.79	1.61	2.38	2.36	0.20	-2.94	1.97	2.08	0.18	0.66	0.18
Germany	3.19	1.84	0.02	-0.73	0.70	0.88	3.88	3.38	0.81	-5.56	3.95	3.72	0.61	0.41	1.58
Great Britain	3.77	2.67	2.45	4.30	2.45	2.81	3.04	2.56	-0.33	-4.31	1.91	1.65	0.66	1.67	2.99
Netherlands	4.25	2.13	0.10	0.29	2.03	2.16	3.52	3.70	1.71	-3.77	1.40	1.66	-1.06	-0.49	1.01
Spain	5.05	4.00	2.88	3.19	3.17	3.72	4.18	3.77	1.12	-3.58	0.02	-0.62	-2.09	-1.29	1.39
Italy	3.71	1.77	0.25	0.15	1.58	0.95	2.01	1.47	-1.05	-5.48	1.71	0.59	-2.77	-1.70	-0,43

Source: International Monetary Fund, 2015

Table 8 shows that the correlations between annual average TOM returns and GDP growth are not significant. The average TOM return of a growth year is lower than to the returns of recession periods in four out of six countries (except for the Netherlands and Spain), implying that the respective economic trend is not responsible for (changes of) the TOM effect.

Table 8. Correlations between average TOM return of the year and GDP growth, as well as average TOM return in economic growth and recession periods (2000-2014)

Country	*Correlation*	*Growth Mean (%)*	*Recession Mean (%)*
France	0.0832	0.0009	0.0024
Germany	-0.1000	0.0007	0.0050
Great Britain	0.0190	0.0010	0.0015
Netherlands	-0.0230	0.0014	-0.0003
Spain	0.3653	0.0016	0.0012
Italy	-0.0260	0.0004	0.0009

5.2. An Evolutionary Finance Approach

Since the variables volatility, trading volume and economic trend do not provide satisfactory results for explaining the TOM effect or its variations, we suggest a new perspective, which is based on evolutionary finance. According to Hens and Schenk-Hoppé (2005), evolutionary finance refers to the principles of selection and mutation, as formulated by Charles Darwin (1859), and transfers them to strategies of financial market actors. The gist of evolutionary finance is to explain the dynamics of financial markets with the help of biological models of evolution, in particular mutation, selection, and survival of the fittest (Grotheer, 2006, also the early contribution of LeBaron, 1995). Correspondingly, evolutionary finance tries to answer which set of strategies (e.g. Growth-, Small-Cap-, Value-, Momentum-, Global-, Dividend Yield- or Sector-Strategies) an investor would expect to be present in the market and how to find the best response to any such market (Amir et al., 2005). Thus, it is relevant which performance a strategy has generated (hence the importance of the strategy in the population mix increases) to see where the capital will flow next time. More rational investors will change their (so far rather unsuccessful) strategies into ones deemed more successful ones, while a declining number of investors retain their inferior strategies (Hens et al., 2011), so that less capital is allocated according to the latter. This market interaction finally generates wealth dynamics and has an impact on asset prices (Evstigneev et al., 2008). However, shifts in preferences for investment strategies at best lead to temporary equilibria, as successful arbitraging destroys its own foundation (if e.g. investors decide to turn to growth strategies/securities, the prices of the latter will rise, reducing their attractiveness, indirectly making non-growth strategies more attractive again). Table 9 confirms the wealth dynamics during the financial crisis as large amounts of (especially European) shares were sold and traded for liquidity by former corporate owners, subsequently causing a value market.

Table 9. Flow of funds 2007-2008

Asset classes	*2007 net inflows (billion USD)*	*2008 net inflows (billion USD)*
Equity US	-34.62	-27.15
Equity Japan	-24.15	-11.55
Equity Western Europe	-42.34	-57.95
All Equity Funds	-232.10	66.49
Money Market Funds	216.42	455.39

Source: EPFR Global, 2016

The methodology that is used so far by evolutionary finance is computational agent-based modelling (Hens and Schenk-Hoppé, 2005; Rekik and Boujelbene, 2014). Mainly the interaction between two artificial market groups (momentum trader and value investors) is focused by this new approach of financial research (Chiarelli et al., 2002; Anufriev and Bottazzi, 2012), as empirical results show permanent abnormal returns (momentum in the mid-term and value in the long-term) of these strategies (De Bondt and Thaler, 1985; Jegadeesh and Titman, 1993; Rouwenhorst, 1998; Gaunt, 2000; Daske, 2002; Hurn and Pavlov, 2003; Asness et al., 2013). The results of recent evolutionary finance research emphasize that, due to performance, a value investment is the only evolutionarily stable strategy (Evstigneev et al., 2008; Hens et al., 2011), whilst without the behaviour of the momentum trader, who buys because of rising asset prices and can cause therefore price bubbles, the opportunities of undervalued stocks and therefore a value strategy would not exist (Hens, 2006, 2012). Both strategies are therefore interdependent in an evolutionary sense (like “foxes and rabbits”, as coined by Grotheer, 2006). The presumption is obvious that the TOM effect is affected by this relatedness of the two strategies, so that it is established above all in developing value periods, while it is reduced after a stock bubble burst due to momentum periods. Likewise, it can be explained based on the recurring value periods why the TOM effect is permanent.

In the following, the hypothesis is to be tested that TOM returns are higher especially in value phases than for the rest of the period (including momentum phases). Following Campbell and Shiller, the cyclically adjusted price-to-earnings ratio (hereafter CAPE) is a good measure for a fair valuation (see Campbell and Shiller 1988, 1998 on the US-; analogously Taboga, 2011, on the Euro-market; here, data for the six European countries were obtained from Bloomberg and Star Capital, 2016). It is defined as the stock price divided by the average of ten years of earnings adjusted for inflation. The major disadvantage of the classical price-earnings-ratio is that corporate earnings are extremely volatile, which can be corrected by a ten year average of earnings (Star Capital, 2016). According to Shiller, a CAPE level of 22 draws the line between over- and undervaluation of a market (and therefore separate momentum and value phases, see Shiller, 2016; Star Capital, 2016).

This study encompasses four value phases (CAPE lower than 22) for the six European countries which cover almost 30 percent of the entire period (October 2002, February 2003 to March 2003, July 2008 to November 2010, and, finally, August 2011 to January 2013) and correspond to the respective crises (dotcom bubble, financial crisis and the European debt crisis). The strongest value market and even TOM effect was due to the financial crisis between July 2008 and November 2010 as the average CAPE for the six European countries reached a minimum value of 18.71, and thus was 14.9 percent lower than the fair valuation of 22.

Table 10 confirms the hypothesis of higher (at least weakly significant for France and Great Britain) TOM returns during value phases for four out of six countries (on average for all countries 24.47 percent higher than for the rest of the period including momentum phases). Only Germany and Spain show higher TOM returns during the rest of the period. Especially the German market has a strong inverse pattern. The effect of higher TOM returns during value phases increases to 46.68 percent when taking out the data of the German market. The robustness of this effect is also affirmed by the results of the median (median for TOM returns is 21.90 percent higher on average for all countries during value phases than for the rest of the period). Looking closer at the value phase between 2008 and 2010 (thus one year after the onset of the financial crisis) it can be stated that the mean TOM return for all countries is almost twice as high as for all value phases.

Table 10. TOM returns during value phases (2000-2014)

Country	*TOM value phases*	*TOM rest of the period*	*TOM value phase (2008-2010)*	*TOM value phases*	*TOM rest of the period*
	Mean (%)	*Mean (%)*	*Mean (%)*	*Median (%)*	*Median (%)*
France	0.142*	0.078	0.244	0.160	0.100
Germany	0.081	0.144	0.212	0.100	0.150
Great Britain	0.158*	0.084	0.212	0.180	0.090
Netherlands	0.127	0.085	0.261	0.140	0.110
Spain	0.099	0.114	0.207	0,070	0.100
Italy	0.093	0.061	0.179	0.120	0.080
All countries	0.117	0.094	0.219	0.128	0.105

*Note: * Denotes statistical significance for a two-tailed t test at the 10% level.*

The results of Table 10 combined with the outcomes of the computational evolutionary finance research suggest that the TOM returns reach a higher level, especially after momentum phases when stock prices drop again. Likewise, the data of Table 10 suggest that due to recurring value phases between 2000 and 2014, the TOM effect is permanent. Finally, it can be stated that the TOM effect was on the one hand subject to significant changes by the financial crisis (overall a dampening effect until 2014), but on the other hand especially during value phases (as for example after the financial crisis) the TOM effect becomes stronger.

6. SUMMARY AND CONCLUSIONS

This study analyses daily returns of stock market indexes of six European markets for the period 2000-2014. We detect significant TOM effects at European stock markets that affect corporate owners' wealth. Based hereupon, it is possible to determine whether the financial crises had an impact on the TOM effect. To test for the TOM effect, parametric and nonparametric statistical tests are used. The first test employed is an OLS dummy variable regression model that compares the TOM returns to ROM returns. The second test is a nonparametric WSR test that examines the matched-paired TOM-ROM returns. Both kinds of test results show that a significant TOM effect exists in all of the six European countries of the sample. As well, there is statistical evidence that the financial crises have dampened the TOM effect in any of the six countries, so that average TOM returns have more than halved in the "crisis and post-crisis period" compared to previous years, suggesting that financial markets have become more efficient. This study as well confirms that changes in the TOM pattern are not related to volatility, trading volume or the general macroeconomic trend, but possibly to changes in the mix of strategies in the market, above all between momentum and value investors.

While it provides valuable insights with regard to the calendar anomaly of the TOM effect, our study is not without limitations. Instead, possible refinements could be attempted with regard to content as well as method. The methodology could be refined by additionally including standardized cumulative abnormal returns (originally, see Patell, 1976). Also, the integration of a least trimmed square regression (according to Rousseeuw, 1984) could enhance the statistical power of the calculated returns (see Sorokina et al., 2013). Contentwise, it would be interesting to research if explanations of further calendar anomalies (such as the January, the Holiday or the Halloween effect, see Kumar, 2017, for a recent survey) can be improved by revised strategies of the corporate owners, too. Future research might also be focused on extended time series or stock markets outside the European Union, in particular North America and Asia. This conceptual extension would allow for a comparison of results in order to detect country-specific TOM-factors.

Altogether, the evolutionary finance perspective could offer interesting ways of future research with regard to market anomalies and price behaviour, which can help corporate owners to better understand market processes, reduce their information asymmetries, and improve their (risk adjusted) returns.

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