TURN-OF-THE MONTH EFFECT FOR

THE EUROPEAN STOCK MARKET

by

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ABSTRACT

A central challenge to the Efficient Market Hypothesis (EMH) is the existence of stock market anomalies. The current study tries to examine turn of month effect on two European markets. This allows us to examine whether the seasonal patterns usually found in US data are also present in European data. According to the results, the average return for European stocks is higher for the last day of calendar months and the very first days of the following calendar months. The monthly effect is independent of other known calendar anomalies such as January effect documented by others, and also the results are consistent with the US results.

Key words: Anomalies, Calendar anomalies, Seasonal patterns, Turn of the month effect, European stock market,

DEDICATION

For

My Beloved

Masud

به نام او که بود

وقتی هیچ نبود

تقدیم به

مادر فداکارم و پدر مهربانم

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Introduction

The efficient market hypothesis (EMH) says that at any given time, asset prices fully reflect all available information.

The simple statement does not limit information to be strictly financial in nature. It may incorporate investor perceptions whether correct or otherwise. This richer interpretation of the EMH provides for variations from its stronger forms, which suggest that further data study, unless perhaps insider-based, is unlikely to be fruitful. The second derivative of an investor perception overlay on financial information allows for intuition, judgment and the quest for new tools that markets may discover in the pursuit of profits above the average.

The chief corollary of the idea that markets are efficient, that prices fully reflect all information, is that price movements do not follow any patterns or trends. This means that past price movements cannot be used to predict future price movements. Rather, prices follow what is known as a 'random walk', an intrinsically unpredictable pattern.

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In the world of the strong form EMH, trying to beat the market becomes a game of chance not skill. There will be superior performers generating better investment returns but only because statistically there are always some people above the average and others below. Hence, debate about the EMH becomes a question of whether active portfolio management works: is it possible to beat the market or are you better off avoiding the transactions costs and simply buying an index fund?

The answer to these questions depends not only on whether you accept the EMH but, if so, in what form[1].

Since the EMH was formulated, countless empirical studies have tried to determine whether specific markets are really efficient and, if so, to what degree. A paper called simply 'Noise' by the late Fischer Black says:

Noise in the sense of a large number of small events makes trading in financial markets possible. Noise causes markets to be somewhat inefficient, but often prevents us from taking advantage of inefficiencies. Most generally, noise makes it very difficult to test either practical or academic theories about the way that financial or economic markets work. We are forced to act largely in the dark.

A central challenge to the EMH is the existence of stock market anomalies: reliable, widely known and inexplicable patterns in returns.

Commonly discussed anomalies include size effects, where small firms may offer higher stock returns than large ones; and calendar effects, such as the 'January

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[1] The three forms are weak form, the semi-strong form and the strong form of the EMH.

effect' - which seems to indicate that higher returns can be earned in the first month compared to the rest of the year – the monthly effect and the 'weekend effect' or 'blue Monday on Wall Street effect' - which suggests that you should not buy stocks on Friday afternoon or Monday morning since they tend to be selling at slightly higher prices. There are also the supposed indicators of undervalued stocks used by value investors, such as low price-to-earnings ratios and high dividend yields.

But while there is no doubt that anomalies occur in even the most liquid and densely populated markets, whether they can be exploited to earn superior returns in the future remains open to question. If anomalies do persist, transactions and hidden costs may prevent them being used to produce out performance, as well as the rush of other investors trying to exploit the same anomalies. It may be possible that opportunities arise in quanta bursts and then disappear rather like the track in a cloud chamber. If so, by the time we wish to measure the recurrence of an event, it has occurred and passed by, unlikely to be repeated in the same form.

Further challenges to the EMH come from the study of behavioral finance, which examines the psychology underlying investors' decisions and uses it to explain such phenomena as stock price over-reaction to past price changes and stock price under-reaction to new information. Many studies seem to confirm the implication of over- and under-reaction that there are 'pockets of predictability' in

the markets: contrarian strategies of buying 'losers' and selling 'winners' can generate superior returns; and prices do tend to regress to the mean.

However, in the current study, there are some reasons for looking at European evidence on turn-of-month effect. First, this effect has been observed in each of a number of European countries independently. It is possible that this effect is also being generated within the whole region (by the facts that markets often follow each other's movement and that the turn-of-month occurs at the same time in all countries).

I. Literature Review

For many years, it was believed (especially by academics) that stock prices follow a random walk, i.e. the best prediction of the next period's stock price is today's price plus a drift term. This would imply that stock returns are not predictable. There is growing evidence that stock market returns are predictable to some degree. The literature documents predictability of stock index returns from lagged returns, lagged financial and macroeconomic variables, and calendar dummies.

The guiding principle that asset markets are efficient and stock prices can be described by a random walk is simply stated, but its implications are many and subtle. The Efficient Market Hypothesis (EMH) has its roots in the pioneering work of Gibson (1889) who writes that "when shares become publicly known in

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an open market, the value which they acquire may be regarded as the judgment of the best intelligence concerning them", Gibson (1889, p.11). It should be stressed that the views regarding the EMH are not the results from doctrinaire beliefs, but result from a large body of empirical work. The EMH may be expressed in a number of alternative ways and the differences between these alternative representations can become rather entangled. The general idea behind the EMH is that asset prices are determined by the supply and demand in a competitive market with rational investors.

There are numerous studies report anomalous calendar dependencies in stock returns. In recent years there have been a number of empirical studies documenting unexpected or anomalous regularities in security rates of return. In addition to the widely studied relation between firm size and rate of return, a considerable body of empirical evidence documents the impact of seasonal patterns on security returns. These patterns appear to conflict with the theoretical notions of efficiency and rational expectations in the market for securities. Some of these seasonal regularities are related to the time of the day, the day of the week [Cross (1973), French (1980), Gibbons and Hess (1981), Jaffe and Westerfield (1985), Keim and Stambaugh (1984), and Lakonishok and Levi (1982)]. The weekend effect which has been identified in stock returns, the most salient characteristic of which is low or negative returns on Mondays, and some evidence suggests that the negative Monday returns could be more a manifestation of a calendar effect rather than a pure 'closed market effect'.

French (1980) finds that returns on days following mid-week holidays are not unusually low. Smirlock and Starks (1986) find that aside from positive first-hour returns, hourly returns on Mondays are negative and lower than their counterparts on other trading days. Further, Rogalski (1984) does find that, over a different time period, most of the negative return from the closing price on Friday, to the closing price on Monday, occurs while the market is closed over the weekend. Since the market is always closed on weekends, it is impossible to tell whether the negative return is due to the weekend or the fact that the market is closed.

A January effect in stock returns has also been noted. Rozeff and Kinney (1976) demonstrate that unusually high returns accrue to stocks during January, and Keim (1983), Roll (1983), and Reinganum (1983) note that these high January returns accrue disproportionately to small firms and especially during the early days of January. Tax-loss selling pressure has been advanced as the cause of the January effect, but the persistence of this phenomenon in some overseas markets with non-January tax year starting dates [Brown, Keim, Kleidon and Marsh (1983), Gultekin and Gultekin (1983)] suggests that the January effect may be in part an effect induced by the turn of the year - a 'calendar effect'. As for the turn of the year, [Haugen and Lakonishok (1988), Jones, Pearce, and Wilson (1987), Lakonishok and Smidt (1984), and Schultz (1985)] findings present a potentially serious challenge to classical models of market equilibrium and have stimulated the development of new theories that can account for them

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[Rock (1989), Admati and Pfleiderer (1988a, 1988b), and Foster and Viswanathan (1993)].

A number of stock market advisors have claimed that a monthly pattern exists, including Merrill (Merrill Lynch investment managers, 1966), Hirsch (senior editor, Business and Economics, Newsweek, 1979), and Fosback (investment researcher, 1976), who urged their clients to make use of the monthly pattern as a part of their trading strategies, for example by making planned purchases before the start and postponing planned sales until after the middle of the calendar month in order to capture the unusually high returns that accrue in the early days of calendar months.

On monthly effect subject, there are lots of studies which among those the most related ones can be identified by works done by Robert A. Ariel(1986) who has opened the issue and Lakonishok and Smidt (1988) who had the contribution to the subject and also Cadsby and Ratner (1991) who provided some international evidences.

The purpose of the paper "A Monthly Effect in Stock Returns" by Ariel (1986), is to point out the existence of what has been called a 'semi-monthly effect' in stock returns. The data span the years 1963 through 1981 (19 years). Ariel's definition of the first part of the month includes the last trading day of the previous month. His justification for this is that the average rate of return on the last trading day of

a month is high.[2] This paper documents a curious anomaly in the monthly pattern of stock index returns: "stocks appear to earn positive average returns only around the beginning and during the first half of calendar months, and zero average returns during the second half". This 'monthly effect' is independent of other known calendar anomalies such as the January effect documented by others and appears to be caused by a shift in the mean of the distribution of returns from days in the first half of the month relative to days in the last half.

As it is at least possible that these new facts are really chimeras, the product of sampling error and data mining so, for this reason, Ariel (1986) considers that important to test for the existence of these regularities in data samples that are different from those in which they were originally discovered.

The reported tests employ the Center for Research in Security Prices (CRSP) value-weighted and equally-weighted stock index returns to represent the returns accruing to stocks. He shows histograms of the arithmetic mean returns for the nine trading days before and after the start of each month for both the CRSP equally weighted and value-weighted indices; each daily mean is estimated from 228 daily observations [i.e. nineteen years times twelve months]. He provides

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[2] It must be mentioned that such a justification is questionable because it relies on an examination of the data

histograms of the daily arithmetic mean returns for the nine trading days before and after the start of each calendar month (1963-1981) for both the CRSP equally-weighted and value-weighted indexes. Nine rather than ten or more days were selected for presentation to prevent overlap between day + 10 and day - 10 of the following month in the minority of months having fewer than twenty trading days. The global mean is estimated from the returns to all trading days in this nineteen-year period.

The histograms resulted from the study show positive returns at the beginning of the month, starting on the last trading day of the previous month and continuing through the first half of the new month, followed by predominantly negative returns after the mid-point of the month.

He believes it is convenient henceforth to define a 'trading month' as extending from the last trading day (inclusive) of each calendar month to the last trading day (exclusive) of the following calendar month [i.e., the last trading day of each calendar month is included with the following month].

If each trading month is divided evenly in half [with the odd middle trading day, if any, discarded] the mean daily return from the first half of trading months significantly exceeds the mean daily return from the last half of trading months.

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However, no individual seeking to capitalize on the monthly pattern in stock returns would hold stocks for only a single day. Since the high-return and low-return days cluster in the first and last halves of trading months, respectively, cumulative returns over these half months constitute an economically more relevant measure of the monthly effect. Statistically, he also shows standard difference-of-the-means test comparing the mean cumulative return over the first nine days of trading months with the mean cumulative return over the last nine days of trading months, both for the entire 1963 to 1981 period and for four sub-periods.

The difference of the means test employs the first nine trading days to proxy for the 'first half and the last nine trading days to proxy for the 'last half' (since the test requires a fixed and equal number of days in the first and last halves). By convention in all the tests, he extends the 1963-1981 time periods from the last trading day of 1962 (inclusive) through the last trading day of 1981 (exclusive), and likewise for all the sub-periods examined.

For the entire 1963-1981 period, for both indexes, the t-statistic[3] is statistically significant, thereby showing that the mean cumulative return from the first half of trading months significantly exceeds the mean cumulative return from the second

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[3] Hypothesis testing for a single sample mean.

half of trading months. In each of the four sub-periods for both indexes the point estimate of the mean return from the first half of trading months exceeds the point estimate of the mean return from the last half of trading months, and the t-statistic for the difference of the mean is significant (at the 0.05 level) in six of the eight comparisons. Doing the F-test, he also proves that interestingly the F-test applied to the ratio of the estimated variances of first nine-day and last nine-day cumulative returns cannot reject the hypothesis of equal variances at the 0.05 level. By using the □-test, he compares the return from the first half of a trading month with the return from the last half of that same month.

He applies a difference-of-means test presupposes a normal distribution of the cumulative half month stock returns. According to the □2-test[4] statistics, for both indexes, for the full 228 months of data, the null hypothesis is rejected for all confidence levels.

The results show that the magnitude of the semi-monthly effect is by no means small. According to Ariel (1986), during the nineteen years studied, the market's

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[4] Hypothesis testing for the mean of one sample with known variance to determine whether a sample x from a normal distribution with standard deviation sigma could have mean m. The result, h = 0, means that we cannot reject the null hypothesis.

entire cumulative advance occurred during the first half of trading months, with the last half of trading months contributing nothing.

Lakonishok and Smidt (1988), during the study "Are Seasonal Anomalies Real? A Ninety-Year Perspective" use 90 years of daily data on the Dow Jones Industrial Average to test for the existence of persistent seasonal patterns in the rates of return. In this article, they provide evidence on several seasonal return anomalies (the turn of the week, the turn of the month, the turn of the year, and holidays) over a long period of time using a uniform data base and methodology.

The study is based on the daily closing prices of the Dow Jones Industrial Average (1897 -1986), practically the whole time that a U.S. security market index has existed. They examine monthly, semi-monthly, weekend, holiday, end-of-December, and turn-of-the-month seasonalities. Their sample period is considerably longer than that used in earlier studies and as compared to Ariel (1985, 1987), they added 65 years of new data (the end-of-December effect and the turn-of-the-month effect had not been thoroughly explored previously). They added little new data for the monthly seasonals and present results mainly for completeness.

Their study includes data from the first trading day in 1897 (January 4) through 1986 (June 11), approximately 90 years.

They showed that during the ninety years span study, all of the market's cumulative advance occurred around the first half of the month, the second half contributed virtually nothing to the cumulative gain. The impact of this effect on stock returns is not subtle; its impact is of the same order of magnitude as the well-known weekend effect documented by French (1980) and Gibbons and Hess (1981).

Cadsby and Ratner *(1991)*, through their paper "Turn Of Month and Pre-Holiday Effects on Stock Returns: Some International Evidence" examine turn-of-month and pre-holiday effects on international markets. Turn-of month effects are significant in Canada, the UK, Australia, Switzerland, and West Germany.

Pre-holiday effects are significant in Canada, Japan, Hong Kong, and Australia. The absence of these effects in certain markets suggests that they originate from country-specific institutional practices. According to them, all countries exhibiting pre-holiday effects do so before local holidays; only Hong Kong does so before US holidays. This reinforces them to the conclusion that such anomalies are not generated solely by American institutions. They believe there are two reasons for looking at the international evidence on turn-of-month and pre-holiday effects. First, weekend effects and turn-of-year effects have been observed in a number of countries. It is possible that these effects are being generated independently within each of these countries. Alternatively, the study believes that it is possible

that the effects are generated by US institutions alone and spread throughout the world by US investors trading on foreign markets. The study shows that as weekends and turn-of-years occur at the same time in all countries, therefore, it is difficult to distinguish between these two possibilities.

According to their study, turn-of-months are of no help in this respect. However, holidays occur at different times in different countries. They show if anomalies are being generated by US institutions and then spread to other countries, they should expect to observe abnormally high returns internationally on days before US holidays. If, on the other hand, countries are generating anomalies independently, they should expect to see abnormally high returns on days before local holidays. Thus, the examination of security returns prior to holidays in a variety of countries provides a unique opportunity to distinguish between anomalous patterns originating in the US and those originating in other countries. Proposed explanations of calendar anomalies are often institution-specific. Therefore, it is in their interest to determine whether such anomalies originate solely in the context of US institutions or arise independently in other countries as well.

Their second reason is that standard statistical tests performed on US financial data are difficult to interpret and may be seriously misleading because of the large number of studies employing American data. The surprising and seemingly systematic patterns that emerge from these studies could reflect nothing more

significant than the intensive scrutiny to which this single data set had been subjected. Their best solution to this unintentional 'data mining' problem is to test hypotheses suggested by observable patterns in US data on different data sets as argued by Lakonishok and Smidt (1988). They show the results of the tests for anomalous patterns in international security returns prior to both local and US holidays.

II. Data

The current study includes daily data from January 2001 through December 2005. The source is Morgan Stanley Capital International[5]. The construction methodology of the MSCI Euro indices aims to produce investable indices that accurately capture the country and industry weights of the underlying European equity market.

MSCI European Indices and Benchmarks include:
- MSCI EURO INDEX includes 10 Euro land countries, 130 securities* and captures approximately 90% market cap of and tracks broader MSCI EMU benchmark.

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[5] MSCI is a leading provider of equity, fixed income and hedge fund indices, and related products and services. MSCI estimates that over USD 3 trillion is benchmarked to its indices on a worldwide basis.

- MSCI EMU BENCHMARK includes 10 Euro land countries, 343 securities*

aims to capture 60% of underlying Euro land countries' total market cap.

- MSCI EUROPE BENCHMARK includes 15 European countries, 599 securities*

aims to capture 60% of underlying pan-European countries' total market cap.

*As at December 31, 1998

The MSCI Europe Index and the MSCI EMU Index are the leading European benchmarks used by institutional investors. The countries that qualified for the initial phase of the EMU, starting January 1, 1999, are: Austria, France, Netherlands, Belgium, Germany, Portugal, Finland, Ireland, Spain, and Italy.

The MSCI Europe index consisted of the following 16 developed market country indices: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom.

The current study emphasis is on employing the data of MSCI Europe Index because it includes more countries (16) compared to the other indices (10 countries).

To replicate the same tests for the US, the S&P 500 index with dividend is also employed. The results could be considered as a benchmark for European results.

III. Methodology

According to Lakonishok and Smidt (1988), turn-of-month is defined as the last and first three trading days of the month. We follow that convention here. Almost, in all cases, TOM (turn-of-month days) returns exceed NTOM (other days) returns. The null hypothesis that the difference between TOM and NTOM returns equals zero is tested by estimating the following dummy variable regression for each index:

$$R_t = \phi_1 + \phi_2 DTOM_t + e_t \tag{1}$$

Where

$t = 1.....T,$

R_t = holding period return on index for day t,

ϕ_1 = average return at NTOM days,

ϕ_2 = the difference of the average return at TOM and NTOM days,

$DTOM_t$ = dummy variable which equals one for TOM days and zero otherwise,

e_t = a zero mean, random disturbance term.

There are three possibilities for the alternative hypothesis. Here, we are only interested in the result if TOM returns were actually higher. In this case, the alternative hypothesis is H1: TOM > NTOM.

The significance level is related to the degree of certainty we require in order to reject the null hypothesis in favor of the alternative. We reject the null hypothesis

if the probability of observing our sampled result is less than the significance level. For a typical significance level of 5%, $\alpha = 0.05$, the probability of incorrectly rejecting the null hypothesis when it is actually true is 5%. The p-value is the probability of observing the given sample result under the assumption that the null hypothesis is true. If the p-value is less than α, then we reject the null hypothesis[6].

The outputs for hypothesis test functions also include confidence interval[7] that is equivalent to being unable to reject the null hypothesis at a significance level of 0.05. Conversely if the confidence interval does not contain the true hypothesized quantity, then we reject the null hypothesis at the level of significance.

MATLAB 6.5 was used to conduct the analysis.

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[6] For example, if $\alpha = 0.05$ and the p-value is 0.03, then we reject the null hypothesis but the converse is not true. If the p-value is greater than α, we have insufficient evidence to reject the null hypothesis.

[7] A confidence interval is a range of values that have a chosen probability of containing the true hypothesized quantity.

IV. Results

Average returns are calculated for the MSCI European index (daily data) over period of interest. Turn of month (TOM) is defined as the last and first three trading days of the month. The null hypotheses that the difference between TOM and NTOM (other days of month) returns equals zero is tested by means of a t-test constructed using appropriate dummy variable regression as described in the section III. The TOM results, as are shown through following table, are significantly greater than zero at the 5% level using a one-tailed test, and the null hypothesis is rejected. The difference (TOM-NTOM) is also significantly positive.

Table.1

The results from the daily returns calculated for the Europe Index, Jan2001-Dec2005. Turn of month is defined as the last and first 3 trading days of the month. The null hypotheses of the zero difference in returns is tested by a t-test using the dummy variable regression (as given in section III)

Europe Index (Jan01-Dec05)	TOM	NTOM	TOM-NTOM
	.0019	.0004	.0015
t-value	(4.1357)	(1.9177)	(2.8051)
R^2	0.011		
Adj. R^2	0.008		

Figure1. Histogram of the Arithmetic Mean Returns for the TOM and NTOM Days
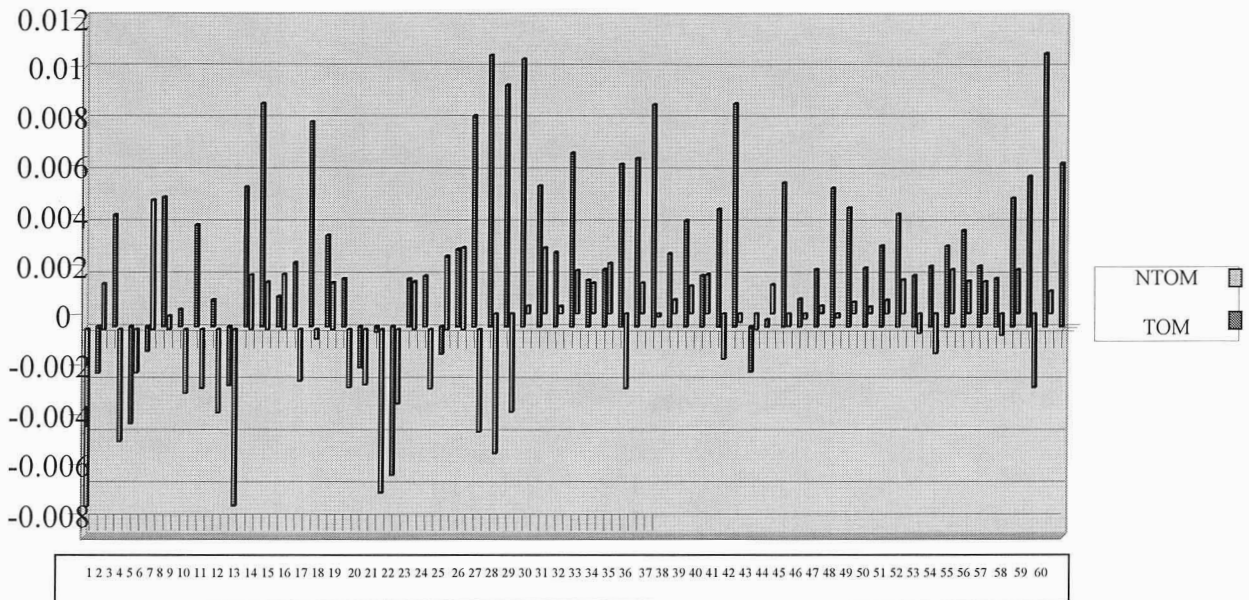
- X axis shows the average return at TOM and NTOM days.

- Y axis shows the related 60 months during the time period (Jan 2001-Dec.2005 respectively)

Figure 2. The Difference of the Means

TOM-NTOM
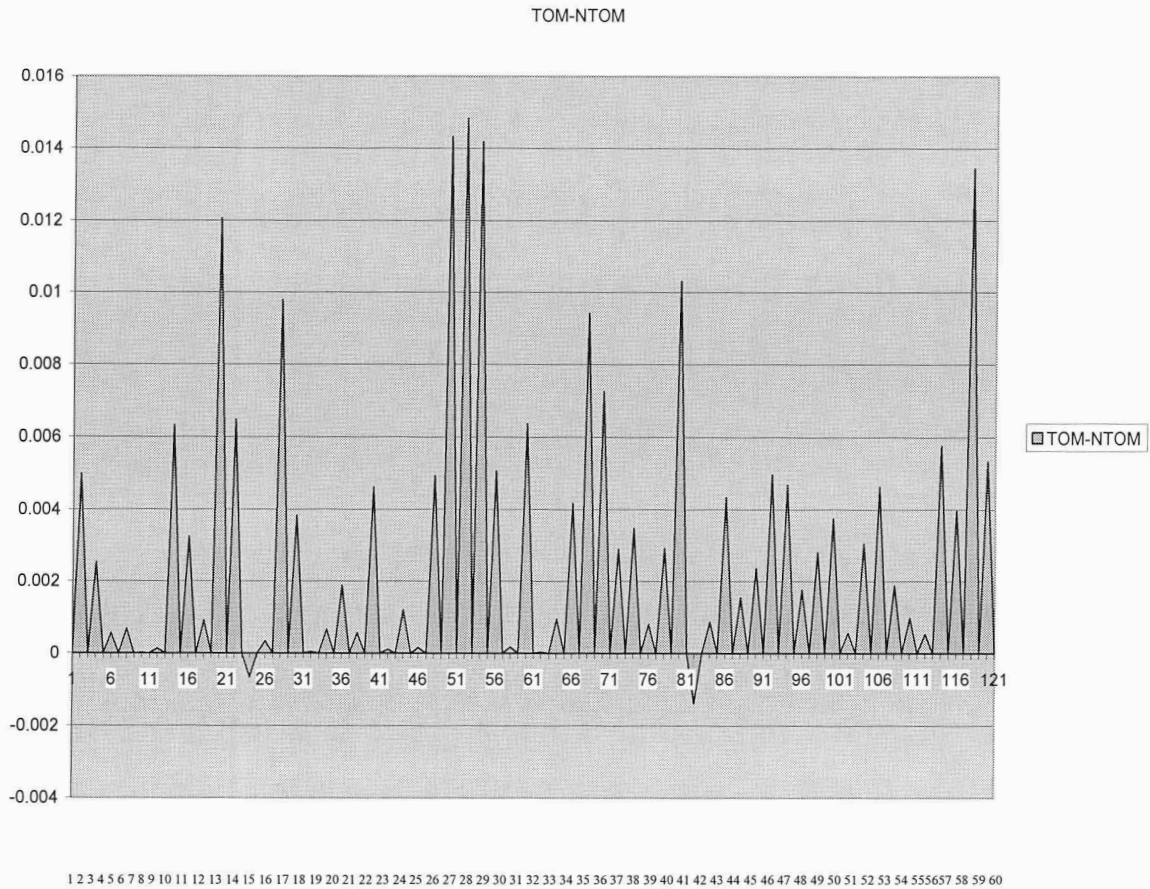
- X axis shows the difference of average returns of TOM and NTOM days.

- Y axis shows the related 60 months during the time period (Jan 2001-Dec.2005 respectively)

The same regression has been also done for MSCI EMU Index and the results were almost identical because both indices include the major European countries (Europe index also includes 6 more small European countries). The following figure shows the identical trend of the two mentioned indices.

Figure 3. EMU INDEX vs. EUROPE INDEX
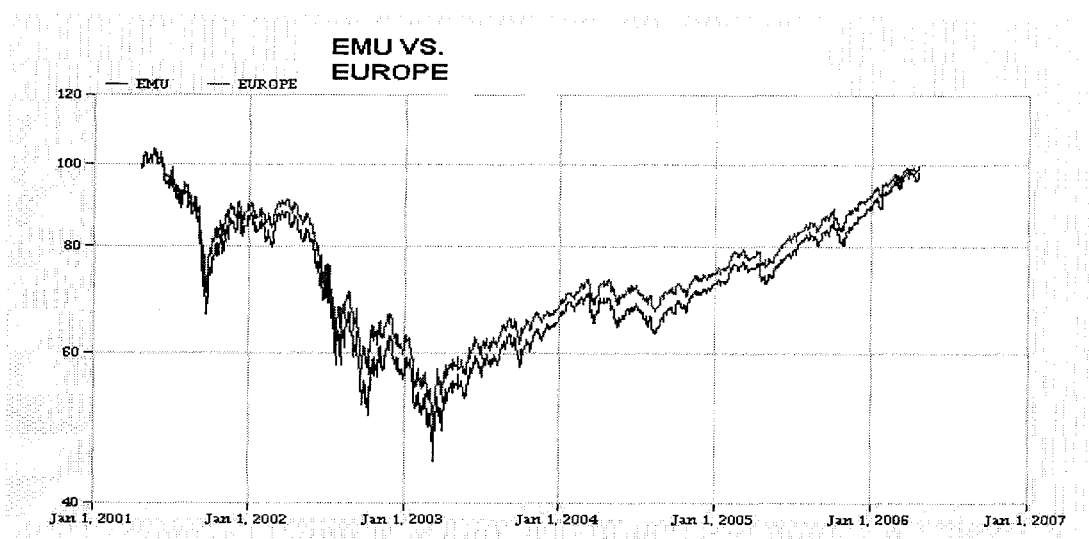
- Source: MSCI

The results from the dummy variable regression using S&P data and the equation from the Section III are also similar indicating that the TOM returns show a significant difference compared to NTOM daily returns of the index with a significant t-value for both shorter and longer periods (see Table 2).

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Table.2

The results from the daily returns calculated for S&P Index over calendar periods of Jan2001-Dec2005 and Dec1989-Apr2006. Turn of month is defined as the last and first 3 trading days of the month. The null hypotheses of the zero difference in returns is tested by a t-test using the dummy variable regression (as given in section III-Methodology)

S&P Index	TOM	NTOM	TOM-NTOM
Jan01-Dec05	.0013	.0007	.0006
t-value	(2.8913)	(1.9161)	(3.0741)
R2	.0032		
Dec89-Apr06	.0017	.0003	.0014
t-value	(4.7025)	(2.7759)	(4.1836)
R2	.0029		

V. Discussion of the Results

This study examines the presence of turn-of-month effect in European stock market while turn of month is defined as the last and first three days of the month. The study provides some evidence that days around the turn of the month exhibit high rates of return and the magnitude of this effect is not small. The current study uses US results as a benchmark for European results.

However, considering the other studies, the non-universality of such effect suggests that the anomalies are linked to local practices and institutions. Ogden (1990) hypothesizes that turn of month effect in the US may result from the interest and principal payments on debt and dividend payments on equity occur at the turn of month. Perhaps the similar pattern of payments in Europe exhibiting turns of month effect. Usually, various explanations for the monthly effect are considered, including the possibility that it is confounded with the January effect. Roll (1983) has showed that there is a tendency for significant excess return in January with much of the effect concentrated in the first few days of the month for the stocks of small firms.

In order to test the situation, a 95% confidence interval of the mean returns for all trading months excluding January were examined and the results (for TOM and NTOM respectively) are 0.0022 and 0.0003 indicating that when we consider all

months except January, there is still the monthly effect in the rest of the months and the difference (TOM-NTOM) is still significant (t-test is 2.9425).

Table.3

The results from the daily returns calculated for the Europe Index, Jan2001-Dec2005 excluding January. Turn of month is defined as the last and first 3 trading days of the month. The null hypotheses of the zero difference in returns is tested by a t-test using the dummy variable regression (as given in section III)

Europe Index (Jan01-Dec05. January excluded)	TOM	NTOM	TOM-NTOM
	0.0022	0 .0003	0.0015
t-value	(4.8159)	(2.1834)	(2.9425)

As Marquering and Verbeek (2002) believe, unlike the US (January), the strongest month in the UK stock market is December. The fact that we do not observe a January effect in Europe could be due to the fact that the major countries of the region (like UK) usually don't use December 31 as the tax year-end.

To examine the predictable seasonal patterns in monthly returns, although you (statistically) reject the random walk model and find predictability in returns, one

should be careful in interpreting these results. Rejecting the random walk model does not necessarily imply that we can profit from this predictability in practice. Rather than looking only at the statistical significance we should also examine the economic significance of the predictability to see if we can still exploit this predictability out-of-sample and after correction for risk considerations and transaction costs.[8]

The literature on time-series return predictability[9] can be divided into three "branches": return predictability using lagged prices or returns, lagged financial and macroeconomic variables, and calendar dummies. For all of the three branches above, we should be aware of the danger of data snooping. If you try a great number of different variables to predict stock returns, you will eventually find some variables that have statistically significant predictive power, so apparently there is a genuine relationship. Thus, because so many variables have been tried, it is not surprising that one eventually finds variables with forecasting power. The danger is that it works well within the sample, but will have no predictive power out-of-sample.

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[8]Marquering and Verbeek (2001)

[9]Individual stock returns, on the other hand, tend to be negatively auto-correlated on a daily and weekly frequency, possibly due to overreaction effects and market microstructure effects (Jacobsen, 1999).

VI. Conclusion

In summary, the average returns are persistently anomalous over a shorter and longer period of time (2001-2005 and 1989-2006) around the turn-of-the month days. In order to examine if the January effect could be the possible cause for the turn-of-month effect, the test was redone while the month of January was excluded and the pattern around the turn of the month was still consistent. The variety of the other possible causes for this turn of month effect could be considered as differing mean returns, small firm effect, dividend effect and economic announcements[10] effect. A view also held by market technicians is that markets and stock prices are not moved by fundamentals, but by market sentiment. The existence of these patterns in the data may need to be considered in other empirical studies.

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[10] Which occur in the last or first days of the month on stock returns.

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