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MSc Economics & Business

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# Psychological Barriers on the Dutch Stock Exchange:

## An investigation of the AEX and its constituent equities



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## Preface and Acknowledgements

This thesis presents the results of research on the existence of psychological barriers on the Dutch Stock Exchange; a topic that particularly got my attention while the AEX struggled around the 200 point level in March 2009. Newspapers tended to refer to this level as a psychological barrier, but as an economist to-be I started wondering if there is any scientific justification for assigning special importance to particular index levels. This research paper is the final project for graduation as a Master of Science in Financial Economics at the Erasmus University Rotterdam.

Several people greatly contributed to the realization of this thesis. I would like to thank Simon Lansdorp for supervising this project, his helpful advice and very clear comments and Willem Verschoor for his time and effort. I am very grateful to Geert Mulder for giving advice on programming in VBA. Finally, I would like to thank my parents for all their support during my studies and my friends for being patient and always being interested in my research.

Nienke Corré

Delft, February 2010

NON-PLAGIARISM STATEMENT

By submitting this thesis the author declares to have written this thesis completely by himself/herself, and not to have used sources or resources other than the ones mentioned. All sources used, quotes and citations that were literally taken from publications, or that were in close accordance with the meaning of those publications, are indicated as such.

**Abstract**

The Dutch AEX and six of its constituents are examined for indications of psychological barriers. Often these barriers are associated with support and resistance levels and with a bandwagon effect. These effects are extensively investigated by studying clustering effects, return and volatility dynamics and crossing effects in the vicinity of hundred levels for the AEX and ten levels for the individual stocks. All tests explicitly allow for asymmetries across upward and downward price movements. Hundred levels of the AEX appear to function more or less as support and resistance levels. These barriers are less frequently approached and crossed than arbitrary index levels and in their vicinity conditional mean returns and variances are altered. Clustering and crossing effects of individual stocks cannot be consistently related to the existence of psychological barriers. As they do show return effects and some variance effects in the vicinity of ten levels, the existence of psychological barriers is not convincingly rejected. For both the AEX and its constituents the reaction of investors to upward and downward price movements turns out to be asymmetric in nature, indicating that it does make sense to allow for these asymmetries in barrier testing. Sentiments appear to be more sensitive to downward barrier breakings.

*JEL classification*: G14

*Keywords*: Market psychology; Psychological barriers; Price clustering; M-values; GJR-GARCH

## Table of Contents

## List of Tables

## List of Figures

# 1 Introduction

If we were to believe the popular financial press, there is no doubt: the existence of psychological barriers in stock indices is a fact. Examples of this widespread believe can be found in numerous newspaper articles from all over the world.

"This morning, at the opening of the stock exchange, the AEX fell below the psychologically important barrier of 200 points, hitting the lowest level since summer 1995." (NRC, 2009)[1]

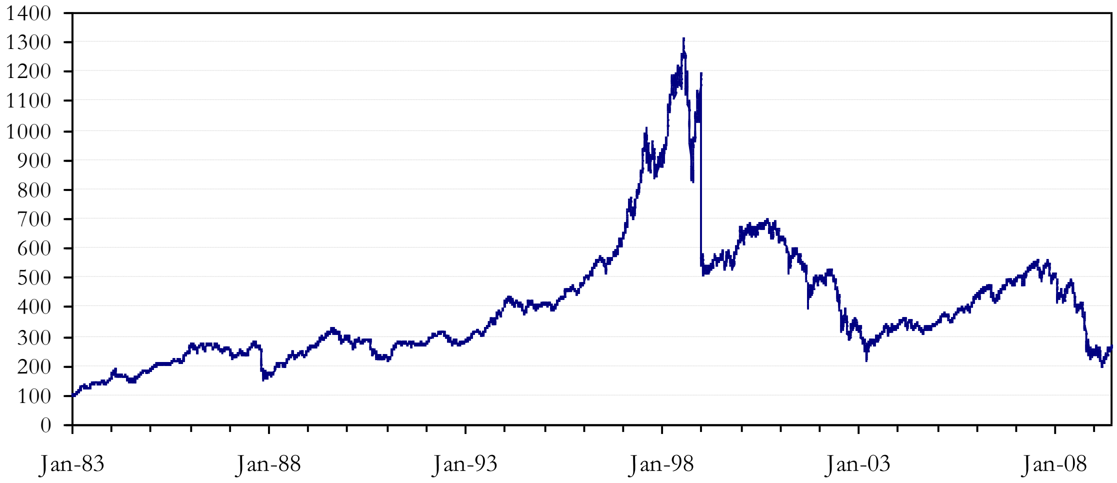
"Earlier this week, the Shanghai index fell below the important psychological barrier of 2,000, triggering widespread rumors that the government would intervene." (Financial Times, 2008)

"Technical analysts warned that the market could be set for more declines now that the S&P500 had breached the significant support level." (Financial Times, 2009)

But the academics are still not out.

This paper documents the concept of psychological barriers and examines the Dutch AEX and six Dutch stocks for indications of this phenomenon. Figure 1 displays the historical daily closing prices of the AEX, since its introduction in 1983. This graph can be interpreted as showing that the 300 and 400 point barrier during the late nineteen eighties and early nineteen nineties and the 700 point barrier in the early two thousands functioned as resistance levels, whereas the 200 point barrier appeared to be a support level several times. These apparent characteristics can, however, be due to chance alone. The evidence on the existence psychological barrier will be further investigated in this paper.

Figure 1 AEX daily closing prices




[1] Translated from Dutch to English.

In addition, price clustering will be investigated. Although literature on psychological barriers often comprises evidence of price clustering, Mitchell (2001) points out that the two concepts are not the same and not necessarily related. Price clustering is defined as some prices being observed more frequently than others. While psychological barriers are merely an interpretation of price behavior around key reference points, often multiples of hundred and thousand. A barrier thus can exist without any clustering being present, while clustering can occur where barriers are lacking. In some instances, nevertheless, the two concepts are interrelated since the potential reason for price clustering might be an explanation for a psychological barrier as well. This provides an incentive to include tests on price clustering when investigating psychological barriers.

Hence, psychological barriers can manifest themselves in price clustering, but it may be that they display themselves in other characteristics (too). Although there is no economic theory that states how stock prices and indices should behave in the presence of this type of mass psychology, psychological barriers are often associated with resistance and support levels. This implies that price movements are restrained close to the barrier and crossing of the barrier is more or less inhibited. As a result the return distribution might shift in the vicinity of a barrier i.e. the conditional mean and variance are altered. Furthermore, the existence of resistance and support levels might lead to a crossings effect, where barriers are less frequently crossed than other levels.

Even though no economic theory exists on the behavior of prices and indices in the presence of psychological barriers, it is unlikely that dynamics or, analogously, sentiments on the stock exchange are symmetric across upward and downward crossings of barriers. In general, downward movements appear to be steeper than upward movements and the corresponding clustering and crossing effects might therefore be weaker. On the other hand, return and variance effects might be stronger for downward crossings, as sentiments are perhaps more sensitive to downward breakings. Additionally, an explicit distinction between upward and downward crossings is in fact essential, since observations slightly above a barrier correspond to a post-crossing period for upward movements, whereas these observations relate to a pre-crossing period in case of a downward movement. Aggregation of these movements could obscure underlying effects.

It should however be noted that the existence of psychological barriers in stocks and stock indices contradicts some basic assumptions underlying economic theory and that it is an anomaly in this sense. A stock index tracks changes in the value of a group of stocks. The exact value of the index has no information value in itself. The fact that the Dow Jones fluctuates around the 9,000 points while the AEX varies around the 300 points does not tell us anything at all. Otherwise stated, rescaling of an index[2] would preserve all the relevant information on relative price movements. A similar reasoning applies to individual stocks, since the value of an individual stock depends on the number of outstanding stocks. Rescaling, by means of a (reverse) stock split, does not alter returns for an investor and preserves consequently all relevant information. Assigning more importance to particular values or digits of an index or stock would

[2] Multiplication by an arbitrary number.

contradict therefore the efficient market hypothesis since this hypothesis states that all information is already incorporated in the price. Besides, the assumption of rational investors would not be met.

Still, theories on the existence of barriers are found in different fields of research, including behavioral, economic and cultural literature. One of the more popular rationales for the existence of barriers is a type of herding behavior of investors. The inability of an index or stock to pass a certain level in an upward move is seen as a sign of weakness, causing a limiting of demand, while crossing the barrier is considered to be a sign of a strong market, leading to an increase in demand. This would contemporaneously clarify the bandwagon effect, the notion of a higher return after breaking through the barrier in an upward move and the observation of a lower than average return in a downward move.

Mitchell (2001) completes the overview of the factors contributing to the existence of barriers, mainly related to individual stocks. According to his paper an important source of barriers is the number preference embedded in our culture. The decimal system triggers a tendency to consider numbers in terms of tens or powers of ten, resulting in a grouping effect. Numbers are implicitly divided into different groups based on identical leading digits. The effect is that the difference between 960 and 990 is perceived to be smaller than the difference between 990 and 1,010 because the first two numbers belong to the same group in investors' minds[3]. Since the groups are separated by multiples of ten, special importance is assigned to these values, potentially creating barriers. The grouping effect is related to odd-ending pricing, derived from the marketing literature. This theory describes the focus of consumers, or investors in this context, on leading digits. In this perspective a 9.95 euro stock is perceived to be significantly cheaper than a ten euro stock, with associated effects on demand and supply. In addition, Mitchell (2001) considers psychological barriers from a behavioral perspective. Given that the true fundamental value of a company is unknown, investors are inclined to concentrate on the nearest round number as a proxy. This tendency forms the foundation of the aspiration level hypothesis, described by Sonnemans (2006). The aspiration level is the target price that investors have in mind for which they are willing to buy or sell an asset. Uncertainty regarding the right target will cause clustering of those targets at round numbers. Again, special importance is assigned to these round numbers. Finally, it must be noted that the existence of barriers may not only be due to behavioral factors. Sonnemans (2006) mentions option exercise prices at round numbers as a possible source of barriers since trading activity might intensify close to the exercise price. Whether this is a true source of barriers is questionable, Aitken et al. (1996) found less price clustering for Australian stocks with options traded on them.

These theories along with releases in the financial press imply that psychological barriers do exist. In academic research, however, the debate on the existence of the barriers is still going strong. This paper contributes both new empirical evidence and new, or adjusted, methodological aspects to the current literature. The Dutch AEX and six stocks listed on this index will be investigated, since research on the latter has received little attention in previous papers. Furthermore, the aim is to shed some new light on the discussion on psychological barriers by allowing for dynamic differences across upward and downward

[3] This effect is amplified by difference in units (e.g. hundreds vs. thousands)

movements through barriers in all tests. This study elaborates in this sense on the work done by Cyree et al. (1999), who allowed for asymmetries solely in return and variance effects. By incorporating potential asymmetries in clustering and crossing tests as well, new methodological aspects are added to the barrier literature.

The paper is organized as follows. Section 2 presents a review of the relevant empirical literature on both psychological barriers and price clustering. Thereafter, section 3 provides a description of the data. Section 4 contains the methodology and empirical analysis of clustering effects. Return and volatility dynamics in the vicinity of potential barriers are investigated in section 5. And section 6 will present the evidence on crossing effects. Finally, conclusions, implications and suggestions are outlined in section 7.

## 2 Literature overview

Price clustering and psychological barriers are two different concepts and represent therefore two strands of literature. Since they are interrelated in some instances, the potential reason for price clustering might be an explanation for a psychological barrier as well, literature on psychological barriers often incorporates evidence of price clustering. For this reason some of the literature on price clustering will be included in this section.

In the empirical research roughly four basic approaches to examine potential psychological barriers can be distinguished: tests on the distribution of the digits, analysis of the return dynamics around barriers, tests on the volatility around potential barriers and investigation of the number of barrier crossings.

Donaldson and Kim (1993) were amongst the first to report on the empirical evidence of psychological barriers. Their study followed upon a period in which the Dow Jones Industrial Average (DJIA) fought a battle around the 3000 point barrier according to financial market analysts. Donaldson and Kim (1993) analyzed the DJIA as well as the less well-known Wilshire Associates 5000 index for fifteen years, starting in 1974. A first indication of barrier existence is given by the finding that the frequency with which the DJIA closes around a 100-level is significantly lower than the rate of closings away from that level. And their study showed that, having broken through a barrier, the index falls or increases by more than average. Apparently the 100-levels in the DJIA worked as support and resistance levels, in the sense that these levels restrain the DJIA to move across in case of a downward and upward movement respectively. In the less-popular WA index as well as several simulated series similar effects were missing. Results suggest that in widely followed indices like the DJIA psychological barriers are present, consistent with the claims of the market analysts.

Subsequently, Ley and Varian (1994) expanded the evidence by investigating the DJIA over the period 1952 to 1993 and focusing particularly on the implications for market efficiency. In their initial investigation results were surprising. The 100-levels seemed to represent a 'launch pad' instead of a barrier as Donaldson and Kim (1993) concluded. This result, however, did not hold in subsamples. Apparently the launch effect was caused by a small fraction of the data. Furthermore, they found that the non-uniform distribution of the Dow-Jones' digits, also reported by Donaldson and Kim (1993), and the distribution of the digits of a simulated random walk were in fact very much alike. This led them to conclude that market efficiency is still present as there is little, if any, predictive power in the level of the DJIA.

Thereafter, Koedijk and Stork (1994) added to the, at that point in time, scarce evidence of psychological barriers by examining five different stock indices. In line with the evidence on the Dow Jones, the 100-levels in the Brussels' Stock Exchange, the FAZ General, the FTSE 100 and the S&P 500 index were approached relatively infrequently in the period 1980 to 1992. In addition, these values were crossed fewer times. Exception is the Nikkei, for which all results were insignificant. But, based on the results of a forecasting experiment, Koedijk and Stork (1994) concluded that the presence of psychological barriers does not induce predictability of stock returns, analogous to Ley and Varian (1994).

Ley (1996) elaborated on his finding in Ley and Varian (1994) that even the two last digits of the integer value of a simulated random walk are not uniformly distributed. With this paper research on psychological barriers enters a new stage: authors started to improve upon existing methodology. According to this paper the non-uniformity can be explained by Benford's Law. Benford (1938) described the probability of occurrence of numbers as first and higher order digit in arbitrarily scaled data. It is illustrated that the first and second digit of some real-life data exhibit a non-uniform distribution, whereas the distribution of third and higher placed digits converges to a uniform distribution. Ley (1996) showed that the digits of the one-day return series of the DJIA and the S&P track the theoretical frequencies of Benford's Law.

De Ceuster et al. (1998) assumed that Benford's Law does not only apply to the returns on an index, but to the index itself as well. The rejection of the uniform distribution as the right benchmark is subsequently solved by using the empirical distribution of a Monte Carlo simulation based on the cyclical permutation[4] of actual returns. Based on this benchmark no support for the psychological barriers hypothesis is found for the DJIA, FTSE 100 and the Nikkei index. The authors concluded that former research on price clustering must be invalidated because of the use of the uniform distribution as benchmark. This claim is nevertheless still a source of discussion. Unlike De Ceuster et al. (1998), Mitchell (2001) states that clustering in financial data series is not a result of natural order and rejects Benford's Law for these series.

Around the same time Cyree et al. (1999) criticized the test design of previous research as well. Their focus was, however, on tests for return effects as conducted by Ley and Varian (1994) and Koedijk and Stork (1994) for instance. These previous studies aggregated upward and downward movements through barriers, which possibly offset each other, leading to an understatement of the significance of psychological barriers. Using a GJR specification, which is a variation of the GARCH model, they allowed for different effects of upward and downward movements through the barrier on as well the conditional mean as the conditional variance. This made them the first to report on variance effects in the context of psychological barriers. The authors showed that upward movements through barriers tend to increase expected returns, while the influence of a downward trend is undetermined. Concerning the variance, they

[4] A cyclical permutation of the returns is any $(R_t, R_{t+1},..., R_T, R_2, R_3,..., R_{t-1})$, implying that returns are shifted.

concluded that the conditional variance tends to increase during pre-crossing sub periods and decrease in the post-crossing sub periods.

Still, it lasted until 2004 before psychological barriers in individual stocks were investigated. This might be considered to be surprising as stocks are directly tradable, whereas indices are only indirectly traded by means of derivatives. Doucouliagos (2004) explored the existence of psychological barriers for Australian stocks. Unlike previous research, he stressed medium- to long term price movements rather than day-to-day price changes. These movements are captured by price swings, movements of the price by more a specified percentage lasting several days. The construction of price swings enables one to detect swing highs[5] and swing lows. Doucouliagos (2004) observed that there are specific price levels associated with those swing highs and swing lows, indicating that at some levels stock prices reverse direction as if these levels were psychological barriers. Surprisingly, he also found that some of these levels generate profitable opportunities. Exploitation of these opportunities is however restrained because of short selling restrictions on the Australian market.

Unaware of the work done by Doucouliagos (2004), Sonnemans (2006) presented evidence on psychological barriers for stocks listed at the AEX. He utilized the transition from guilder to euro to make qualitative inferences about investor behavior in individual stock trading. Results are in line with the odd-ending pricing hypothesis, the tendency of consumers to consider a price just below a round number as significantly lower than a round numbered price. Round number effects in guilders ceased to exist with the introduction of the euro on the Dutch stock market. Under the odd pricing hypothesis, round numbers are expected to function as resistance points. Consider for instance a barrier at ten approached from below. At a price of ten the odd pricing hypothesis predicts that the number of limit sell orders will increase, whereas buyers will become more reluctant to trade, making it hard to cross the barrier from below. Since the AEX stocks crossed multiples of ten less frequently than other whole numbers, the expectation of round number resistance points is approved.

The resistance property of round numbers is confirmed by Bagnoli et al. (2006) for stocks listed at the NYSE and Nasdaq in 2002. Net selling during the overnight period tends to follow upon a closing price just below a round dollar amount, causing a significant negative overnight return. When a stock price closes between .95 and .99 it is found to be more likely that this price was approached from below rather than from above. On the other hand, a closing price just above a round dollar amount triggers net buying during the overnight period, with a resulting significantly positive overnight return.

Most of the insights generated by previous research are employed by Dorfleitner and Klein (2009). They examined both the distribution of digits and the return and volatility dynamics for several European indices and individual stocks. Their main finding is that there are no systematic barrier effects, neither in the indices, nor in the stocks. The price movements inside the barrier band differ across indices and from stock to stock, causing an inconsistent return effect. Only for the variance effect they find some

[5] A swing high is created when the peak of a price path is higher than the surrounding peaks and vice versa for a swing low.

significance in several indices. Although the evidence for stock indices is less weak than for individual stocks, index barriers found in previous research seem to have disappeared.

The literature on psychological barriers is not solely focused on stock indices and individual stocks; it has also found its applications in other areas. Aggarwal and Lucey (2005) considered gold price series. Employing similar procedures as Donaldson and Kim (1993) and Cyree et al. (1999) amongst others, they find indications for psychological barriers at the 100-level. Significant evidence indicates that around these barriers the conditional mean is altered, even stronger evidence is found for changes in the variance. Lu and Giles (2006) studied the presence of psychological barriers in eBay auctions for professional football tickets. Following the methodology of De Ceuster et al. (1998) they do not obtain support for psychological barriers in the auctions.

## 3 Data

The data series examined in this research, all obtained from Thomson DataStream, include the Amsterdam Exchange Index (AEX) and six major stocks traded on the AEX: Akzo Nobel, Heineken, Reed Elsevier, Royal Dutch Shell A, TNT and Unilever Certs. Concerning the index, daily closing prices ranging from 08/01/1989 to 06/05/2009 were collected. For the first part of this sample the relevant currency is the Dutch guilder, from January 1999 onwards all stocks were listed in euros. Even though an index is invariant to a fixed rescaling of all its constituent equities, this conversion was, for convenience of option trading, applied to the index itself as well. DataStream adjusts the data series for this rescaling, in other words, all historical price and index levels are displayed in euro currency. The topic of psychological barriers requires the historical values of prices and index levels, and thus all observations preceding 1999 were multiplied by 2.20371[6].

For obvious reasons this conversion is applied to the individual stock price series as well. The examination window for these series slightly differs across the various stocks. A specific sample period for each stock is to ensure a more or less stable price dimension over the sample period under consideration. A stock split, for instance, alters the price dimension of a stock and consequently disturbs particular barrier effects. In stock selection process a few additional criteria were considered. Besides the occurrence of stock splits, the weight of the stock in the AEX was considered in the stock selection and the final criterion requires the stocks to have a notation at the AEX for their complete sample period. Appendix 1 includes information on the criteria for the six stocks. Furthermore, it should be noted that both daily unadjusted and adjusted closing prices were collected. The first series concerns closing prices as they were historically determined on the stock exchange and is utilized in all barrier tests. The latter series is adjusted for capital operations, such as stock splits, and serves to construct return series. In the context of psychological barriers the commonly used return definition is the one-day return, generated as follows:

[6] Sonnemans (2006) showed that investors started to "think in euros" immediately after the introduction of the euro on the stock market, even though it lasted until 2002 before the physical introduction of the euro.

$$R_t^d = \frac{lnP_t - lnP_{t-1}}{d_t} \times 100$$

where $P_t$ stands for the adjusted price or index level at time $t$ and $d_t$ for the number of days between trading days $t$ and $t$-$1$[7]. According to Ley and Varian (1994) this method provides a theoretically correct measure of returns because the periods over which the returns are calculated have equal length. Notwithstanding a small bias due to the averaging of returns over weekends and holidays, the use of one-day returns appears to be the preferred method in this framework. Concerning the occurrence of holidays during weekdays, these days were deleted from the dataset for the tests on price clustering and barrier crossings. Appendix 2 provides an overview of the days that were deleted. For examination of return and volatility effects, the use of one-day returns as defined in this section implies that the relevant one-day return for the non-trading day is the one-day return of the subsequent trading day.

Resulting summary statistics for the AEX and the six stocks are displayed in table 1. Minimum and maximum levels show a more or less single price dimension for each asset. Measures of skewness and kurtosis indicate deviations from normality for all series.

Table 1 Summary statistics

| Series | Minimum level (€) | Maximum level (Fl) | 1-day mean return (%) | Standard dev. (%) | Skewness | Kurtosis | N |
|---|---|---|---|---|---|---|---|
| AEX | 199.25 | 1315.64 | 0.0053 | 1.1912 | -0.1889 | 7.7100 | 5043 |
| Akzo Nobel | 16.53 | 126.70 | -0.0233 | 1.9617 | 0.2745 | 6.7019 | 2791 |
| Heineken | 19.68 | 113.80 | -0.0102 | 1.5801 | 0.0488 | 4.2960 | 2829 |
| Reed Elsevier | 7.61 | 39.10 | 0.0042 | 1.7459 | -0.1911 | 6.7266 | 3732 |
| Royal Dutch Shell | 15.38 | 124.60 | -0.0229 | 1.6319 | -0.1136 | 4.2768 | 3043 |
| TNT | 10.83 | 61.10 | -0.0148 | 1.9930 | -0.3477 | 6.1928 | 2792 |
| Unilever Certs. | 13.59 | 168.90 | 0.0020 | 1.5661 | -0.0030 | 5.5519 | 2968 |

Historical minimum levels are attained in the euro period, whereas all historical maxima were realized during the Dutch guilder era. Returns were obtained by taking the log differences of the unadjusted price levels. The final column reports the number of included observations.

Finally, the relevant barrier levels are to be defined for the AEX and its constituents. The potential barrier level depends on the price dimension of the specific asset. The essence of a psychological barrier is that a barrier crossing is a relatively rare event where investors assign special importance to. For the AEX psychological barriers are expected at 100-levels. As the price of individual stocks moves on a smaller scale, these series will be tested on barriers at 10-levels.

[7] Out of 5043 observations, 3937 (78.8%) have $d_t$=1, 26 (0.5%) have $d_t$=2, 983 (19.5%) have $d_t$=3, 30 (0.6%) observations have $d_t$=4 and 31 (0.6%) have $d_t$=5.

## 4 Price Clustering

This paper investigates the existence of psychological barriers in the AEX and six individual AEX-stocks. The literature distinguishes four basic approaches of investigation; tests on clustering in indices and stocks, examination of return and volatility effects and, lastly, assessment of the frequency of barrier crossings. Since it is not clear, either from economic theory or from previous literature, in what characteristic(s) a psychological barrier displays itself exactly, all four basic methods will be employed. This section elaborates on the first basic approach. The application of price clustering tests within the context of psychological barriers is described, associated results are presented and interpretation is given to the findings. The first part will deal with the standard tests as employed in previous papers on price clustering and subsequently new methodological aspects will be added to the existing literature by allowing for different effects across upward and downward crossings of potential barriers.

The closeness of an index or stock price to a potential psychological barrier is expressed by what became to be known as the M-value. For a potential barrier at, for instance, a 100-level this M-value consists of the last two digits before the decimal point, whereas the M-value for a barrier at a 10-level comprises the last digit before the decimal point and the first digit after the decimal point. Irrespective of the barrier level, the M-value takes on a value between zero and 99.

In the absence of barriers one would expect the distribution of the M-values to be uniform, i.e. the chance of observing a one equals the chance of observing a nine as the last digit of the integer value of the AEX. Psychological barriers might, however, result in deviations from the uniform distribution. The nature of these deviations is undetermined ex ante. On the one hand, investors' excitement might push the index or stock price away from the barrier once it is crossed, leading to fewer observations around barrier points. But on the other hand, since psychological barriers are often related to support and resistance levels, there might be clustering close to barrier levels. In general, a systematic deviation from uniformity provides a first indication that index or price behavior varies across different levels. Several tests can be performed to examine the uniformity property.

First, the M-values are constructed for the different series.

$$M_t = Integer(Modulo(\frac{P_t}{10^{l-2}} : 100)),$$

where *l* is the number of zeroes the potential barrier has and $P_t$ the level of the index or price of the stock at time *t*. The *modulo* function takes the remainder after dividing by 100 and the *integer* function cuts of the digits after the decimal point. A closing value of 313.63 points for the AEX, for instance, corresponds to an M-value of 13 as tests are for barriers at 100-levels. For tests at 10-levels, as for individual stocks, the correct M-value would be 36.

Subsequently, the vector *f(M)* is constructed, recording the empirical frequency of the 100 different M-values. Under the no barriers hypothesis the number of occurrences should be approximately equal for every M-value. Following the procedure employed by Ley and Varian (1994), a chi-square goodness-of-fit test is employed to explore the significance of differences.

$$X^2 = \sum_{M=0}^{M=99} \frac{\left(f(M) - E(f(M))\right)^2}{E(f(M))},$$

where *E(f(M))* is the expected frequency of every M-value, which is equal across the 100 M-values under the uniformity assumption. Significance levels are based on a test with 99 degrees of freedom.

For further examination of the distribution, the M-values are divided in ten disjunct categories of equal length, i.e. 05-14, 15-24… 95-04, as in Koedijk and Stork (1994). The chi-square goodness-of-fit test is repeated for this distribution with nine degrees of freedom. Since the category of interest in the context of psychological barriers is the symmetric band around the potential barrier, the data are split in two classes for the last chi-square goodness-of-fit tests. The first class includes the number of observations within the barrier band and the second class comprises the remaining observations. Both a ten point barrier band, including observations with an M-value between 95 and 04, and a twenty point barrier band, with M-values ranging from 90 to 09, will be considered. Advantage of this test is that it only accounts for differences between the expected and empirical number of observations inside the barrier band versus outside the barrier band; differences in frequencies within the 05-94 category for the first test and within the 10-89 category for the second test are excluded. Inferences are drawn from a test with one degree of freedom.

The test statistics and corresponding significance levels for which uniformity will be rejected are shown in table 2. For all assets the hypothesis of uniformity across the hundred M-values is rejected at better than a one percent significance level. When those M-values are divided in ten disjunct categories of equal length uniformity is rejected as well. Results are only slightly less convincing when differences within the category of observations outside the barrier band are excluded. With a ten point barrier band uniformity cannot be rejected for one stock, whereas uniformity is rejected for all individual stocks with a twenty point barrier band, but not convincingly so for the AEX. So far, however, the evidence points to a non-uniform distribution of the M-values.

Non-uniformity does, however, not necessarily imply the presence of psychological barriers, clustering can occur where barriers are absent and vice versa. Notwithstanding, the underlying reason for the two phenomena might be the same. Furthermore, caution should be taken when drawing conclusions from the previous tests' results for two reasons. First, a chi square goodness-of-fit test assumes the sample values to be independently distributed. Index levels and stock prices are known though to exhibit strong autocorrelation patterns. For the relevant barrier levels, all M-value series are characterized by a strong pattern of first order autocorrelation as well, as displayed in table 3.

Table 2 Distribution of M-values

| | | | 10 point barrier band | 20 point barrier band |
|---|---|---|---|---|
| | $\chi^2(99)$ (p-value) | $\chi^2(9)$ (p-value) | $\chi^2(1)$ (p-value) | $\chi^2(1)$ (p-value) |
| AEX | 190.10** | 71.42** | 16.83** | 3.45 |
| | (0.00) | (0.00) | (0.00) | (0.06) |
| Akzo Nobel | 195.21** | 71.05** | 2.09 | 9.99** |
| | (0.00) | (0.00) | (0.15) | (0.00) |
| Heineken | 329.86** | 176.36** | 12.31** | 23.43** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Reed Elsevier | 1309.99** | 862.66** | 65.81** | 42.54** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Royal Dutch Shell | 264.67** | 168.07** | 3.83* | 10.29** |
| | (0.00) | (0.00) | (0.05) | (0.00) |
| TNT | 246.49** | 130.78** | 16.44** | 36.43** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Unilever Certs. | 206.92** | 94.26** | 5.43* | 7.88** |
| | (0.00) | (0.00) | (0.02) | (0.00) |

Results of chi-square goodness-of-fit tests with the null hypothesis of uniformly distributed M-values. The $\chi^2(99)$ and $\chi^2(9)$ statistics show results of uniformity tests across every single M-value and ten disjunct categories of M-values respectively. The last two columns display the results of uniformity tests across a category of observations inside a barrier band and a category of observations outside the barrier band. In the first column the ten point barrier band is considered, the last column concerns the twenty point barrier band.

Table 3 Autocorrelation coefficients

| | Correlation coefficient | |
|---|---|---|
| | Index/Price | M-value |
| AEX | 0.998** | 0.804** |
| Akzo | 0.996** | 0.690** |
| Heineken | 0.996** | 0.685** |
| Reed Elsevier | 0.999** | 0.840** |
| Royal Dutch Shell | 0.998** | 0.673** |
| TNT | 0.994** | 0.806** |
| Unilever | 0.998** | 0.677** |

First-order autocorrelation coefficients for the AEX index, stock price levels and M-values. ** Indicates significance at 1% significance level. Higher order coefficients are not significant and therefore omitted.

Due to these autocorrelation patterns, chi-square values reported in table 2 may not be correct. Non-uniformity might be a consequence of psychological barriers as well as a consequence of autocorrelation patterns. Second, some research considers Benford's Law to be the right benchmark for a chi square test rather than the uniform distribution. Benford (1938) presented the probability of occurrence of numbers as first and higher order digit in arbitrarily scaled data, like a stock index for instance. Table 4 shows the unconditional distribution of the first three digits. For higher order digits the distribution converges to the uniform distribution.

Table 4 Benford's Law

| Digit | First place | Second place | Third place |
|---|---|---|---|
| 0 | 0.000 | 0.120 | 0.102 |
| 1 | 0.301 | 0.114 | 0.101 |
| 2 | 0.176 | 0.108 | 0.101 |
| 3 | 0.125 | 0.104 | 0.101 |
| 4 | 0.097 | 0.100 | 0.100 |
| 5 | 0.079 | 0.097 | 0.100 |
| 6 | 0.067 | 0.093 | 0.099 |
| 7 | 0.058 | 0.090 | 0.099 |
| 8 | 0.051 | 0.088 | 0.099 |
| 9 | 0.046 | 0.085 | 0.099 |

The unconditional distribution of the first, second and third digit of arbitrarily scaled data according to Benford's Law. The distribution of higher order digits is approximately uniform as stated by this law.

Formal tests on the characteristics of Benford's Law in this dataset will be omitted. Benford's Law would only apply to series with a fixed number of digits before the decimal point for the complete sample period, since one can only determine for these series which frequency distribution to apply. E.g. for an index that varies between 100 and 999 points, the first digit of the M-value for a 100-level test will be the second digit of the index level at any point. Given that solely the Reed Elsevier and TNT stocks, with a range between five and 70 euros, exhibit this property, frequency distributions of the M-values will merely be inspected to see if they exhibit a decaying pattern.

Goodness-of-fit tests identify deviations from proposed distributions; information regarding the direction of these deviations is however lacking. By dividing the empirical frequency of all classes by the expected frequency under the uniformity assumption, information is obtained regarding the nature and cause of deviations from uniformity. Ratios higher than one signal clustering, whereas values below one indicate a relatively low density of observations in the vicinity of barriers.

The resulting series for the individual M-values and for the ten M-value classes will be omitted, since drawing conclusions from large series is not straightforward when no clear pattern emerges. Both the hundred individual M-values and the ten M-value classes show no consistent clustering close to barriers or away from barriers neither do they show a decaying pattern as would be the case under Benford's Law.

Table 5 The empirical frequency versus expected frequency of M-values

| | 10 point barrier band | | 20 point barrier band | |
|---|---|---|---|---|
| | 95-04 | 05-94 | 90-09 | 10-89 |
| AEX | 0.83 | 1.02 | 0.95 | 1.01 |
| Akzo | 1.08 | 0.99 | 1.12 | 0.97 |
| Heineken | 0.80 | 1.02 | 0.82 | 1.05 |
| Reed Elsevier | 1.40 | 0.96 | 1.21 | 0.95 |
| Royal Dutch Shell | 0.45 | 1.01 | 0.88 | 1.03 |
| TNT | 0.77 | 1.03 | 0.77 | 1.06 |
| Unilever Certs. | 1.13 | 0.99 | 1.10 | 0.97 |

This table shows the empirical frequencies of the M-values in the different classes, as defined in the top panel, divided by their expected frequencies under the assumption of a uniform distribution. Values higher than one indicate clustering in the corresponding class.

Table 5 displays the results for the barrier band versus non-barrier band class. Results are mixed across the assets: four assets show clustering inside the barrier band, whereas three assets show a concentration of observations outside the barrier band. These results indicate that non-uniformity might be merely caused by autocorrelation patterns than by psychological barriers, as no systematic deviations are found. A more formal test of this postulation is given by a barrier proximity test. By means of a dummy regression the nature of deviations from proposed distributions and the link with potential psychological barriers is explored:

$$p(M) = \alpha + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + \varepsilon \,,$$

where *p(M)* is the relative frequency of the 100 M-values. Following Koedijk and Stork (1994) the included dummy variables are $D_1$, $D_2$ and $D_3$, satisfying the following conditions:

$D_1 = 1$ if $M = 97,98,99,00,01,02$ $\qquad D_1 = 0$ otherwise

$D_2 = 1$ if $M = 94,95,96,03,04,05$ $\qquad D_2 = 0$ otherwise

$D_3 = 1$ if $M = 90,91,92,93,06,07,08,09$ $\qquad D_3 = 0$ otherwise

Under the no-barriers null hypothesis *a* should be close to 0.01 and the *β*-values are expected to be insignificant. Significance of the *β*-values indicates the presence of systematic deviations from uniformity. A negative *β* implies less density around the barrier, whereas positive *β*'s correspond to a concentration of observations in the vicinity of the proposed barriers.

The advantage of this approach is that autocorrelation is no longer an issue, since the independent variable is not a time series. Table 6 gives the estimated coefficients of the barrier proximity test and their respective significance level.

Table 6 Barrier proximity regression for clustering effects

| | $\alpha_0$ (p-value) | $\beta_1$ (p-value) | $\beta_2$ (p-value) | $\beta_3$ (p-value) |
|---|---|---|---|---|
| AEX | 1.1031** | -0.2102* | -0.0648 | 0.0426 |
| | (0.00) | (0.01) | (0.42) | (0.55) |
| Akzo Nobel | 0.9701** | 0.1765 | 0.0929 | 0.172 |
| | (0.00) | (0.12) | (0.41) | (0.08) |
| Heineken | 1.0455** | -0.1444 | -0.3623* | -0.1886 |
| | (0.00) | (0.31) | (0.01) | (0.13) |
| Reed Elsevier | 0.9466** | 0.6741* | 0.1562 | 0.0445 |
| | (0.00) | (0.01) | (0.53) | (0.84) |
| Royal Dutch Shell | 1.0291** | -0.0107 | -0.3173* | -0.1174 |
| | (0.00) | (0.93) | (0.01) | (0.28) |
| TNT | 1.0571** | -0.2575* | -0.3530** | -0.2560* |
| | (0.00) | (0.03) | (0.00) | (0.02) |
| Unilever Certs. | 0.9742** | 0.1597 | 0.1653 | 0.0783 |
| | (0.00) | (0.16) | (0.14) | (0.42) |

The table reports parameter estimates of the barrier proximity test, regressing the relative frequency of the M-values on three dummy variables, taking on the value one if the M-value is more or less close to a potential barrier. Significance on the 5% and 1% levels are denoted by * and **, respectively.

In a similar study by Koedijk and Stork (1994) five major world indices were considered and for $\beta_i$ negative values were found that approached zero as $i$ increased. Results for the AEX are generally in line with this study; apparently stock indices tend to close relatively infrequently in the vicinity of hundred levels. Where an average of one percent is expected, the AEX closes on average 0.8929% at M-values 97, 98, 99, 00, 01 or 02. For individual stocks the results are mixed. No consistent pattern emerges across the individual $\beta$ values, which is not surprising given the previous results. Therefore the barrier proximity test is replicated with successively different combinations of dummy variables included. As table 7 shows, these replications give a heterogeneous picture of individual stock price behavior as well.

Table 7 Consecutive barrier proximity regressions for clustering effects

| | $p(M) = \alpha_0 + \beta_1(D_1 + D_2 + D_3)$ | | $p(M) = \alpha_0 + \beta_1(D_1 + D_2)$ | | $p(M) = \alpha_0 + \beta_1 D_1$ | |
|---|---|---|---|---|---|---|
| | $\alpha_0$ (p-value) | $\beta_1$ (p-value) | $\alpha_0$ (p-value) | $\beta_1$ (p-value) | $\alpha_0$ (p-value) | $\beta_1$ (p-value) |
| AEX | 1.0131** | -0.0654 | 1.0170** | -0.1413* | 1.0126** | -0.2096* |
| | (0.00) | (0.18) | (0.00) | (0.02) | (0.00) | (0.01) |
| Akzo Nobel | 0.9701** | 0.1496* | 0.9857** | 0,119 | 0.9906** | 0.1559 |
| | (0.00) | (0.02) | (0.00) | (0.15) | (0.00) | (0.16) |
| Heineken | 1.0455** | -0.2275** | 1.0283** | -0.2362* | 1.0063** | -0.1053 |
| | (0.00) | (0.01) | (0.00) | (0.02) | (0.00) | (0.47) |
| Reed Elsevier | 0.9466** | 0,2669 | 0.9507** | 0.4111* | 0.9604** | 0.6503** |
| | (0.00) | (0.07) | (0.00) | (0.02) | (0.00) | (0.01) |
| Royal Dutch Shell | 1.0291** | -0.1454** | 1.0184** | -0,1533 | 0.9988** | 0.0196 |
| | (0.00) | (0.05) | (0.00) | (0.09) | (0.00) | (0.88) |
| TNT | 1.0571** | -0.2855** | 1.0338** | -0.2820** | 1.0128** | -0.2132 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.09) |
| Unilever Certs. | 0.9742** | 0,1288 | 0.9814** | 0,1554 | 0.9915** | 0.1425 |
| | (0.00) | (0.05) | (0.00) | (0.06) | (0.00) | (0.20) |

Reported are parameter estimates of three different barrier proximity tests. *P(M)* is the relative frequency of the M-values. $D_1$, $D_2$ and $D_3$ take on the value one if the M-value falls in an interval close to the barrier as specified in section 4. * and ** indicate significance at the 5% and 1% level, respectively.

Strong evidence is found for systematic behavior of the Reed Elsevier stock price; coefficients show that clustering appears inside the barrier band and weakens when moving farther away from the potential barrier. In addition, systematic behavior is found for TNT stocks, be it in the opposite direction: within the barrier band significantly lower frequencies are observed than outside the barrier band. Heineken and Royal Dutch Shell are characterized by less density close to potential barriers as well; it is remarkable though that significance in this case is mainly due to the second dummy, while one would expect this dummy to have a weaker link with the potential barrier than the first dummy has. Finally, Akzo Nobel and Unilever Certificates show almost no sign of systematic behavior inside and outside the proposed barrier bands. This latter finding is not surprising, given that their chi-square statistics were hardly significant.

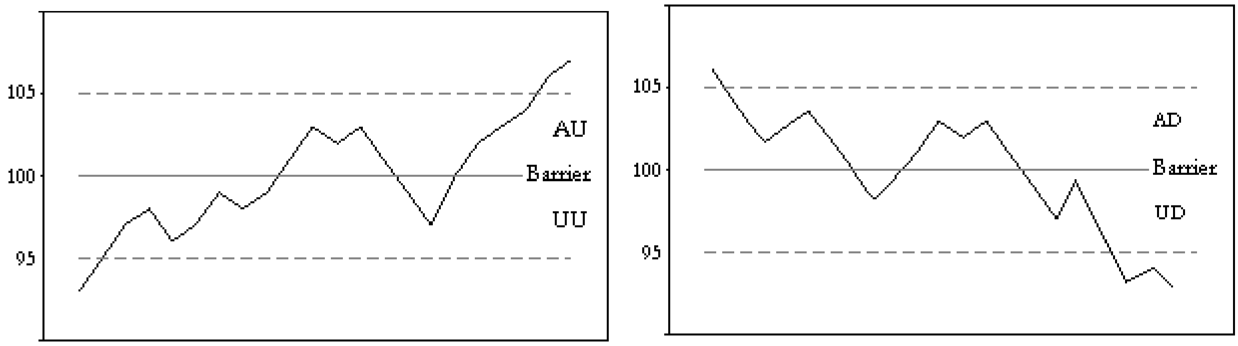
Even though tests on clustering are widely used in previous studies on psychological barriers, Cyree et al. (1999) point to the inability of this method to allow for different effects from upward and downward movements through a barrier. Tests are to be revised to account for potential different clustering effects across upward and downward movements of the AEX and the six stocks. Given that none of the earlier studies has focused on this aspect, some new methodological procedures are required. Before turning to the more technical approach to this problem, the difference between upward and downward movements through the barrier needs to be defined. This is not as straightforward as it might seem, as generally a specific barrier is crossed multiple times in either direction after being crossed for the first time. Since the nature of investor behaviour in the vicinity of barriers is undetermined, upward and downward crossings are defined under two different sets of conditions.

The first definition focuses more on short term fluctuations around barriers, whereas long term price developments are considered in the second definition. Both approaches concentrate mainly on the observations inside the barrier band. In the short term approach the distinction between upward and downward crossings is relatively simple and is solely determined by the direction in which the barrier band is initially entered. All observations inside the barrier band belong to an upward movement when the barrier band is initially entered from below. When the barrier band is primarily entered from above, all observations in the barrier band pertain to a downward movement. This implies that a barrier crossing in reverse direction is possible, provided that the index or stock closed at least one day outside the barrier band. In the following, use of this definition will be denoted by the superscript *s*.

In the long term approach the distinction between upward and downward crossings is determined by a small set of rules, but in most cases a graph of the price path shows a clear distinction as well. In general, if a specific barrier is higher than the barrier crossed previously, observations in the barrier band pertain to an upward movement. Is a particular barrier lower than the barrier crossed before, all observations in the barrier band belong to a downward movement. The distinction is however less clear when the index crosses a barrier, moves away from the barrier and subsequently crosses the barrier in reverse direction. This requires a decision rule. A new barrier crossing in reverse direction is recorded if the index or stock moved away at least fifty points or five euro, respectively, and if the barrier band was left for thirty days or more. On March 21, 2007, for instance, the AEX crossed the five hundred point barrier in upward direction. Moving in an upward trend, the barrier band was left seven trading days later to arrive at a local maximum of 561.90 points on July 16, 2007. From this point onwards the index moved down to a closing value of 487.06 points on August 16, 2007. As the AEX left the barrier band for 96 trading days and exceeded the 550 points during this period, this latter barrier crossing is considered to be a downward barrier crossing. The two requirements serve to ensure that short term overshootings are not taken into consideration. Application of this long term definition is indicated by the superscript *l*.

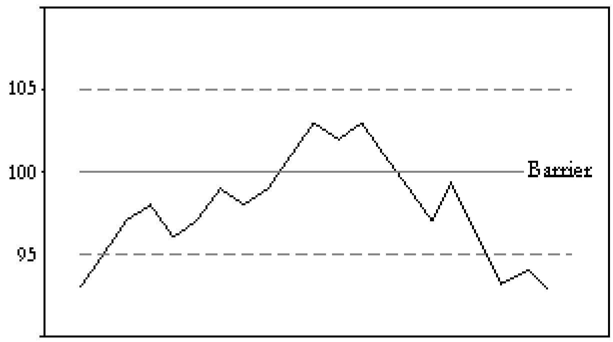
Having made a distinction between upward and downward movements, the observations inside the barrier band are allocated to four different regimes. Regime *UU* (under upward) is defined for all observations just below the potential barrier, provided that the index or stock is in an upward movement. All observations just above the barrier under the latter condition belong to regime *AU* (above upward). When the index or stock is in a downward movement, observations just below and above the barrier pertain to regime *UD* (under downward) and *AD* (above downward), respectively. This procedure thus records the number of trading days the index spends inside the barrier band, either below or above the barrier, and allows for different behaviour around upward and downward crossings of the barrier. Figure 2 gives a graphical representation of the regimes for a ten point barrier band, which includes observations with an M-value between 95 and 99 and between 00 and 04. Additionally, a twenty point barrier band will be considered.

Figure 2 Graphical representation regimes AU/UU and AD/UD




Investigation of clustering effects around barriers during upward and downward crossings requires a minor adjustment when the short term definition is applied. Observations within the barrier band are solely included when they belong to a series where the entire barrier band is intersected. This adjustment serves to omit a bias caused by autocorrelation patterns. Figure 3 gives a graphical example of a data series that will be excluded from the clustering tests. The unadjusted series can be applied in return and volatility tests.

Figure 3 Graphical representation excluded observations




In the absence of barriers regime *AU* and *UU* are expected to contain approximately an equal number of observations, implying that in an upward movement the AEX closes just above the barrier as often as it closes just below the barrier. Under this null hypothesis the number of observations belonging to regime *UD* and *AD* will be roughly equal as well. A concentration of observations in regimes *AD* and *UU*, however, indicates the presence of respectively support and resistance levels. Chi-square goodness-of-fit tests with one degree of freedom are employed to draw inferences.

The resulting test values for the short term definition of barrier crossings appear in table 8. Again, test results should be interpreted with caution, since autocorrelation might cause deviations from uniformity in this situation as well.

Table 8 Asymmetric clustering tests under the short term definition

| | 10 point barrier band | | | | | | 20 point barrier band | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | UU | AU | $\chi^2(1)$ (p-value) | UD | AD | $\chi^2(1)$ (p-value) | UU | AU | $\chi^2(1)$ (p-value) | UD | AD | $\chi^2(1)$ (p-value) |
| AEX | 45 | 65 | 3.64 (0.06) | 34 | 36 | 0.06 (0.81) | 140 | 184 | 5.98* (0.01) | 53 | 90 | 9.57** (0.00) |
| Akzo | 33 | 28 | 0.41 (0.52) | 30 | 33 | 0.14 (0.71) | 80 | 75 | 0.16 (0.69) | 78 | 91 | 10.46** (0.00) |
| Heineken | 36 | 29 | 0.75 (0.39) | 24 | 25 | 0.02 (0.89) | 46 | 44 | 0.04 (0.83) | 35 | 59 | 6.13* (0.01) |
| Reed Elsevier | 52 | 60 | 0.57 (0.45) | 54 | 39 | 2.42 (0.12) | 81 | 73 | 0.42 (0.52) | 37 | 68 | 9.15** (0.00) |
| R.D. Shell | 37 | 32 | 0.36 (0.55) | 34 | 35 | 0.01 (0.90) | 67 | 54 | 1.40 (0.24) | 71 | 77 | 0.24 (0.62) |
| TNT | 41 | 20 | 14.22** (0.00) | 21 | 21 | 0.00 (1.00) | 63 | 35 | 8.00** (0.00) | 28 | 30 | 0.07 (0.79) |
| Unilever | 35 | 34 | 0.01 (0.90) | 45 | 45 | 0.00 (1.00) | 96 | 87 | 0.44 (0.51) | 51 | 45 | 0.38 (0.54) |

The ten point barrier band considers all observations with an M-value ranging from 95 to 04. The twenty point barrier band includes all observations with an M-value between 90 and 09. Observations are excluded when the barrier band is not entirely intersected. $UU^s$ and $AU^s$ include all observations under the barrier and above the barrier, respectively, provided that the barrier band is initially entered from below. When the barrier band is primarily entered from above observations under the barrier pertain to $UD^s$ and observations above the barrier belong to $AD^s$. The $\chi^2(1)$ statistic explores differences between regime $UU^s$ versus $AU^s$ and regime $UD^s$ versus $AD^s$. * and ** indicate significance at 5% and 1% levels, respectively.

In the presence of support and resistance levels and a bandwagon effect, movements across the barrier are more or less restrained, but having crossed the barrier, the price moves relatively fast away from the barrier. Therefore a high density of observations before the barrier is "definitively" broken is expected. Considering a ten point barrier band, no significant differences are found in the number of days the assets spend under and above the barrier. Furthermore, deviations are not observed in one single direction. The significant difference for the TNT stock is, therefore, expected to be caused by autocorrelation patterns. With a ten point barrier band no convincing support is found for the existence of support and resistance levels. With a twenty point barrier band, however, some weak evidence is found. In general, stocks close more frequently under the barrier in an upward movement than above the barrier, albeit is not significantly for five out of six stocks. For downward movements they show a similar, but slightly stronger effect; the stocks tend to close above the barrier more frequently than under the barrier. Results for the AEX itself are significant, but partly contradict the hypothesis, since the AEX tends to close more often above the barrier for both upward and downward movements. The results for the long term definition of upward and downward movements are inconclusive as well and are therefore not included in the main text but in appendix III.

Overall, it can be concluded that no systematic clustering effects exist in the individual stock prices; dummy coefficients in barrier proximity tests do not exhibit a consistently positive or negative sign, neither do they converge towards zero while moving away from the proposed barriers. Allowing for different clustering effects across upward and downward crossings, individual stock prices seem to linger somewhat in a broad barrier band before breaking the barrier. For the AEX itself results are in line with existing barrier studies as the index closes relatively infrequently in a symmetric band around the barrier. When different effects from upward and downward crossings are allowed for, no effects are found that can be related to the existence of psychological barriers.

## 5 Return and volatility effects

Psychological barriers are often associated with support and resistance levels; price movements close to the barrier are restrained and intersection of the barrier is more or less inhibited. The notion of support and resistance levels implies furthermore that, having crossed the barrier, the index or stock price decreases or increases by more than average; an effect that came to be known as the bandwagon effect. Hitherto no structural evidence is found for the presence of support and resistance levels or for the existence of a bandwagon effect. In general, the dynamics of the return series is expected to change in the vicinity of a barrier and thus is investigation of return and volatility dynamics essential. In this section both the return and the volatility effects will be examined as tests for these dynamics are closely related. Throughout the entire section tests will allow for different effects across upward and downward crossings, aggregation might obscure underlying dynamics. Moreover, return and variance effects might be stronger for downward crossings, as sentiments are perhaps more sensitive to downward breakings. The first part of this section will discuss the upward and downward regimes; subsequently these regimes will be incorporated in return and volatility models and in the last part the results will be reviewed.

In presence of support and resistance levels and a bandwagon effect, dynamics differ across the period before and the period after the crossing of a barrier. Additionally, asymmetries across upward and downward movements through the barrier are not unlikely. This section will build on the specifications of the previous section; in order to account for differences, dummy variables for the four different regimes will be included when modeling the return and variance dynamics. Since the nature of investor behavior in the vicinity of barriers is undetermined, this study will employ a total of four different specifications of dummy variables. Following Cyree et al. (1999), the first and second set assume the dynamics to change during a fixed period before and after the barrier crossing and will be referred to as a period specification. In the first period specification $UB^s$ (upward before) is defined for the five day period prior to every single upward movement through a barrier, $UA^s$ (upward after) for the period after having reached the barrier from below and $DB^s$ (downward before) and $DA^s$ (downward after) for respectively the five days before and after every downward movement through a barrier. To test for robustness, ten day periods are considered as well. The second period specification is a small modification of the first. Tests are repeated under the assumption of changing dynamics solely during the five and ten day period before and after the first crossing of specific barrier levels. In contrast to the first specification of the dummy variables, barrier crossings are considered from a merely long term perspective. This method still differentiates between upward and downward movements and employs dummy variables $UB^l$, $UA^l$, $DB^l$ and $DA^l$.

Since the exact day the index or stock will cross the barrier is uncertain in advance, it seems unlikely that this definition of the dummy variables provides the best description of the underlying process. Therefore, return and volatility dynamics are also examined using a so called barrier band specification with the dummy variables *UU*, *AU*, *UD* and *AD*, as defined in the previous section on clustering. It is assumed that investors start to behave differently as soon as the index or stock enters a symmetric barrier band of either ten or twenty points around the proposed barriers. Again, movements will be considered from both the long term and short term perception. Table 9 gives an overview of the definitions of the resulting four different dummy regimes.

Table 9 Dummy variable sets

| | Short term developments($^s$) | Long term developments ($^l$) |
|---|---|---|
| Period specification (*UB, UA, DB, DA*) | Observations 5/10 days before and after crossings, every single barrier crossing is considered in its corresponding direction | Observations 5/10 days before and after crossings, solely the first crossing of a specific barrier on a long term included |
| Barrier Band specification (*UU, AU, UD, AD*) | All observations inside the barrier band, the direction of barrier band entrance determines the direction of crossings | All observations inside the barrier band, long term price developments determine the direction of crossings |

Specifications of the four different dummy specifications as employed in the return and volatility tests.

Still the results of the period specification and barrier band specification are not expected to strongly deviate, as the period preceding a barrier crossing usually coincides with observations inside the barrier band. In general, estimation of the return and volatility dynamics will be based on one-day returns, to ensure that all periods have equal length.

Having generated the dummy series and the one-day return series, we next turn to the question of how to model return and volatility dynamics. Research on daily stock return dynamics proposes the use of generalized autoregressive conditionally heteroskedastic (GARCH) models, as developed by Bollerslev (1986), or some variation on this model. These models capture one of the key characteristics of financial return series: volatility clustering. This phenomenon is described by Mandelbrot (1963) as follows: 'large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes'. Engle (1993) asserts that the standard GARCH is in general an excellent model for most of the financial data series. Many extensions of the GARCH model have, however, been developed. Kim and Kon (1994) suggested the Glosten, Jagannathan and Runkle (GJR) approach for daily returns of individual stocks and the exponential GARCH model for indices. Whereas Franses and Van Dijk (1996) concluded that the GJR model cannot be recommended and that QGARCH model provides the best description of the underlying generating process of weekly returns. While Peters (2001) arrives at yet another conclusion, as he found that the GJR outperformed the EGARCH and GARCH model for daily returns of the FTSE and DAX 30 indices. This finding is again in contrast to Forte and Manera (2002), who did not find a single dominant model amongst the non-linear variants of the GARCH model for daily returns of European stock indices including the AEX. Overall, the GJR-GARCH model seems to provide the best representation of the daily return generating process for both stock indices and individual stocks.

In a standard GARCH model, the conditional variance of the error term in a conditional mean equation depends both on its own lag(s) and on the previous value(s) of the squared error. Some argue though that financial market volatility increases more after a negative shock than after a positive shock of the same magnitude. The GJR specification[8] elaborates on this by adding a lagged indicator variable that allows for asymmetries. Since financial theory suggests that increases in risk should be rewarded with a higher return, the conditional variance is added to the return equation. This results in a GJR-in-mean model with four dummy variables, specified as follows for the period specification dummy variables:

$$R_t^d = a_0 + b_1 R_{t-1}^d + b_2 h_t + b_3 UB_t + b_4 UA_t + b_5 DB_t + b_6 DA_t + \varepsilon_t$$

where $\varepsilon_t \middle| F_{t-1} \sim N(0, h_t)$,

$$h_t = \alpha + \beta_1 h_{t-1} + \beta_2 \varepsilon_{t-1}^2 + \beta_3 \varepsilon_{t-1}^2 I_{t-1} + \beta_4 \varepsilon_{t-1}^2 UB_t + \beta_5 \varepsilon_{t-1}^2 UA_t + \beta_6 \varepsilon_{t-1}^2 DB_t + \beta_7 \varepsilon_{t-1}^2 DA_t$$

where $I_{t-1} = 1$ if $\varepsilon_{t-1} < 0$

$I_{t-1} = 0$ otherwise

In this model $R_t^d$ is the one-day return, $h_t$ is the conditional variance and $\varepsilon_t$ the unexpected return conditional on the information set $F_{t-1}$. A total of four different model specifications will be tested for. Corresponding dummy variables are defined in the previous, both for the short and long term perspective. For the barrier band specification *UB*, *AU*, *DB* and *DA* are replaced by *UU*, *AU*, *AD* and *UD*. Following Akgiray (1989), the mean equation includes an AR(1) term in the base case. Likewise, Franses and van Dijk (1996) mention that the included number of lags should be zero or small, as the opportunity to forecast $R_t$ from its own past is generally limited. In this context general-to-specific modeling will be applied, implying that this term will be eliminated in case of non significance. Furthermore Franses and van Dijk (1996) recommend the inclusion of one ARCH term ($\varepsilon_{t-1}^2$) and one GARCH term ($h_{t-1}$) in the variance equation. The multiplication of the dummy variables by the lagged squared residuals serves to guarantee asymptotic normality of the standard errors as Cyree et al. (1999) states.

In order to estimate the AR(1)-GJR(1,1) model maximum likelihood is employed. Unfortunately, analytical solutions are not available for the more involved models. A numerical procedure is utilized to maximize the log-likelihood function. This optimization technique requires plausible initial parameter guesses to avoid ending up with local optima rather than global optima. For this reason models might need to be re-estimated with different starting values. In addition, the residuals may not be conditionally normally distributed. Therefore quasi-maximum likelihood covariances and standard errors are computed as described by Bollerslev and Wooldridge (1992).

Cyree et al. (1999) mention that coefficients being significantly different from zero in either the mean or the variance equation can be considered to be evidence of the existence of barriers. As the dummy

[8] The GJR-GARCH model is in fact similar to the Threshold GARCH model introduced by Rabemananjara and Zakoian (1993), which employs the conditional standard deviation rather than the conditional variance.

variables are conditioned on the index or stock price being in an upward or downward move, significant coefficients are expected[9] and are thus not necessarily an indication of barrier existence. The point of interest in this context is the disparity between the coefficients under and above the barrier or, depending on the model specification, the difference between the pre- and post-crossing period. The notion of a psychological barrier implies dynamics are somehow restrained as the index or stock price approaches the barrier. After the barrier is being crossed these restraints will expire and consequently dynamics are altered. To assess this effect a Wald test is employed, with the null hypothesis of no difference in coefficients under and above the barrier or before and after the barrier crossing. Inferences are drawn from a chi-square distribution, as the error terms are expected to exhibit a non-normal distribution. Still, some of the regression results are enclosed in this section to provide an overview of the sequential steps in the employed methodology.

At first sight, regression results appear to be broadly similar in terms of significance and sign of the coefficients across all four model specifications. All estimations show some significant effects in return dynamics close to the proposed barriers, except for the long term barrier band specification model. Apparently, return dynamics are not structurally altered inside the barrier band, when long term price developments are considered. Therefore, results for this specification will be omitted. Furthermore, regression outputs of solely one model specification will be discussed in further detail, since our main interest does not lay in the values of the coefficients itself but merely in the differences between the coefficients under and above the barrier. Tables 10 and 11 show the regression results for the twenty point barrier band model with a short term distinction between upward and downward movements.

Starting with the mean equation, we see that the lagged return variable turns out to be significant for only one stock and is consequently eliminated from six out of seven equations. None of the assets shows a significant relation between one-day return and conditional variance. Nevertheless, most interesting in the context of psychological barriers are the coefficients of the dummy variables for observations under and above the barrier for both upward and downward movements through the barriers. The coefficients of UU and AU are positive and significant for all assets. Coefficients for AD are negative and significant for all assets, except for Reed Elsevier, and coefficients of UD are negative as well, but significant for all seven assets. Thus far, the results for the upward regime and downward regime are not surprising. The difference in dynamics across the observations under the barrier and above the barrier is, however, of more relevance than the value of the coefficients itself. In the presence of support and resistance levels for instance, the absolute value of the conditional mean return might increase during periods following a barrier crossing. The second and third column of table 12 display the test results for conditional mean return differences. During an upward movement into the barrier band only the AEX, Akzo Nobel and TNT show significantly higher average returns above the barrier than under the barrier. For all assets, however, the difference between coefficients $b_3$ and $b_4$ has a negative sign. Test results for the coefficients $b_5$ and $b_6$ are more pronounced as all assets exhibit on average significantly lower returns

[9] For conditional returns this conjecture is evident. Black (1976) and Campbell and Hentschel (1992) demonstrate that decreases in stock prices are associated with increases in volatility and vice versa.

under the barrier than above the barrier when the barrier band is entered in a downward movement. Wald test results are reported for the long term period specification model as well, since this test is key to mean and variance effect testing. For completeness, regression results of this specific model are added in appendix V. Compared to the barrier band specification some remarkable results emerge; the absolute value of the conditional mean return is higher during the five day period preceding the first crossing of a specific barrier than during the respective post-crossing period. This difference is significant for five out of seven assets both for upward and downward crossings. These findings are surprising, since one would expect the pre- and post crossing period to partly coincide with observations inside the barrier band and hence to give similar results.

Turning to the variance equation, the equation shows that in general both the ARCH-term ($\varepsilon_{t-1}^2$) and the GARCH-term ($h_{t-1}$) are positive and significantly different from zero, as expected. Besides, adding up the coefficients of both terms gives for all assets a value close to one, signifying that volatility strongly persists through time. The GJR-term ($\varepsilon_{t-1}^2 I_{t-1}$) is significant at least at a 5% level for six out of seven assets, confirming the asymmetric effects of positive and negative shocks on volatility. Still, the focus of this study is on the dummy variables. In general the dummy coefficients display no consistent link between presence in the vicinity of a barrier and volatility effects as the majority of coefficients is insignificant. Solely the results for the dummy variable UD show some consistency; four out of seven coefficients are significant and all coefficients have a positive value. Notwithstanding the insignificant results, Wald tests are performed to explore the volatility differences under and above the barrier. The fourth column of table 10 shows that in general variance remains unchanged under and above the barrier, when the barrier band is entered in an upward movement. For barrier entrances in downward movements, results are again well-defined. All assets exhibit on average a higher volatility under the barrier than above than barrier, provided that the barrier band is entered in a downward movement. For three assets this effect is significant. Yet again, the period specification gives some unexpected results, particularly for the downward barrier crossings. While according to the barrier band specification variance tends to increase under the barrier, the three significant coefficients of the period model indicate an increase in variance during pre-crossing sub periods.

Overall, the results indicate that mean and variance effects do exist, but the exact dynamics are not consistent. Resulting values from the barrier band specification provide evidence supporting the existence of a bandwagon effect in the short term dynamics of the AEX and its constituents; returns tend to increase above the barrier when the barrier band is entered in an upward movement and further decrease under the barrier when the barrier band is entered in reverse direction. In addition, variance increases under the barrier for latter movements. Isolating the first barrier crossing measured on a longer term, reverse effects are found during the five day period before and after these crossings; the absolute value of conditional mean returns is consistently higher during pre-crossing periods. An extension of the pre- and post-crossing sub periods to ten days gives for both the mean and variance equation smaller disparities

Table 10 Mean equation of the GJR-in-mean twenty point barrier band model

| | $\alpha_0$ (p-value) | $R_{t-1}^{d}$ (p-value) | $h_t$ (p-value) | $UU_t$ (p-value) | $AU_t$ (p-value) | $AD_t$ (p-value) | $UD_t$ (p-value) |
|---|---|---|---|---|---|---|---|
| AEX | 0.0238 | | -0.0021 | 0.0703* | 0.2141** | -0.2771** | -0.5737** |
| | (0.16) | | (0.89) | (0.05) | (0.00) | (0.00) | (0.00) |
| Akzo Nobel | -0.0539 | | 0.0176 | 0.3515** | 0.7891** | -0.4510** | -0.9260** |
| | (0.22) | | (0.24) | (0.00) | (0.00) | (0.00) | (0.00) |
| Heineken | -0.0069 | | 0.0037 | 0.5180** | 0.7611** | -0.3214** | -0.9781** |
| | (0.84) | | (0.84) | (0.00) | (0.00) | (0.00) | (0.00) |
| Reed Elsevier | 0.0502 | | -0.0082 | 0.2855* | 0.5431** | -0.1225 | -0.5381** |
| | (0.18) | | (0.60) | (0.04) | (0.00) | (0.06) | (0.00) |
| Royal Dutch Shell | 0.0158 | | -0.0123 | 0.5155** | 0.6730** | -0.3728** | -1.1215** |
| | (0.66) | | (0.50) | (0.00) | (0.00) | (0.00) | (0.00) |
| TNT | -0.0517 | -0.0517* | 0.0133 | 0.2117** | 0.7037** | -0.2496* | -1.5651** |
| | (0.14) | (0.01) | (0.29) | (0.00) | (0.00) | (0.01) | (0.00) |
| Unilever Certs. | 0.0196 | | 0.0002 | 0.2120* | 0.3083** | -0.2378** | -0.7231** |
| | (0.61) | | (0.99) | (0.02) | (0.00) | (0.00) | (0.00) |

The table reports regression results for the mean equation of the GJR barrier band specification as described in section 4.2. Besides a constant term, the conditional mean equation includes the one-day lagged return, provided that the coefficient is significant, the contemporaneous variance and four indicator variables. Indicator variables are solely assigned to observations inside the twenty point barrier band. UU is the indicator variable for observations under the barrier provided that the barrier band is entered from below, AU includes all observations above the barrier band under the latter condition. AD and UD are indicators for the observations above and under the barrier, respectively, when the barrier band is initially entered in a downward move. The GARCH-models are optimized using the Marquardt algorithm and estimated with heteroskedasticity consistent covariance. * indicates significance at the 5% level and ** at the 1% level.

Table 11 Variance equation of the GJR-in-mean twenty point barrier band model

| | $\alpha_0$ (p-value) | $h_{t-1}$ (p-value) | $\varepsilon_{t-1}^2$ (p-value) | $\varepsilon_{t-1}^2 I_{t-1}$ | $\varepsilon_{t-1}^2 UU_t$ (p-value) | $\varepsilon_{t-1}^2 AU_t$ (p-value) | $\varepsilon_{t-1}^2 AD_t$ (p-value) | $\varepsilon_{t-1}^2 UD_t$ (p-value) |
|---|---|---|---|---|---|---|---|---|
| AEX | 0.0131** | 0.9087** | 0.0410** | 0.0744** | -0.0122 | -0.0133 | 0.0044 | 0.1788* |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.47) | (0.61) | (0.83) | (0.01) |
| Akzo Nobel | 0.0639** | 0.9029** | 0.0299** | 0.1120** | -0.0779** | 0.0146 | -0.0211 | 0.1238* |
| | (0.00) | (0.00) | (0.01) | (0.00) | (0.00) | (0.77) | (0.44) | (0.02) |
| Heineken | 0.0137* | 0.9551** | 0.0136 | 0.0401** | 0.0441 | 0.0409 | 0.0058 | 0.0983** |
| | (0.02) | (0.00) | (0.06) | (0.01) | (0.49) | (0.24) | (0.79) | (0.01) |
| Reed Elsevier | 0.0292** | 0.9369** | 0.0395** | 0.0257 | 0.0014 | 0.0218 | -0.0082 | 0.0365 |
| | (0.00) | (0.00) | (0.00) | (0.10) | (0.94) | (0.43) | (0.42) | (0.20) |
| Royal Dutch Shell | 0.0383* | 0.9129** | 0.0403** | 0.0475* | 0.0214 | -0.0043 | -0.0128 | 0.3177** |
| | (0.02) | (0.00) | (0.00) | (0.03) | (0.53) | (0.92) | (0.68) | (0.00) |
| TNT | 0.0431** | 0.9231** | 0.0293* | 0.0728** | -0.0863** | 0.0447 | -0.0297 | 0.2826 |
| | (0.00) | (0.00) | (0.03) | (0.00) | (0.00) | (0.12) | (0.23) | (0.10) |
| Unilever Certs. | 0.0180** | 0.9467** | 0.0214* | 0.0476** | 0.0007 | 0.0147 | -0.0165 | 0.0770 |
| | (0.00) | (0.00) | (0.01) | (0.00) | (0.99) | (0.73) | (0.35) | (0.22) |

Reported are the regression results for the variance equation of the GJR barrier band specification as described in section 4.2. The variance equation contains a constant term and a standard GARCH-term, ARCH-term and GJR-term, which adds to the volatility if the lagged residual is negative. The indicator variables are added to the variance equation as well, multiplication by the squared residual serves to ensure asymptotic normality of the standard errors. The Marquardt algorithm and heteroskedasticity consistent covariances are applied in the optimization process. * denotes significance at the 5% level, ** denotes significance at the 1% level.

Table 12 Wald test for differences in dynamics

| | Barrier band specification (short term) | | | | Period specification (long term) | | | |
|---|---|---|---|---|---|---|---|---|
| | $b_3 - b_4$ (p-value) | $b_5 - b_6$ (p-value) | $\beta_4 - \beta_5$ (p-value) | $\beta_6 - \beta_7$ (p-value) | $b_3 - b_4$ (p-value) | $b_5 - b_6$ (p-value) | $\beta_4 - \beta_5$ (p-value) | $\beta_6 - \beta_7$ (p-value) |
| AEX | -0.1458** | 0.3092** | 0.0045 | -0.1580* | 0.2756* | -0.7377* | -0.0478 | 0.3054 |
| | (0.00) | (0.01) | (0.88) | (0.02) | (0.01) | (0.01) | (0.25) | (0.19) |
| Akzo Nobel | -0.4376** | 0.4750** | -0.0925 | -0.1449* | 0.3005 | -1.0873** | 0.1291 | 0.1839 |
| | (0.00) | (0.01) | (0.10) | (0.02) | (0.49) | (0.01) | (0.06) | (0.08) |
| Heineken | -0.2067 | 0.6534** | -0.0011 | -0.0925 | 0.9171** | -0.9671** | 0.3062* | 0.1948** |
| | (0.37) | (0.00) | (0.99) | (0.08) | (0.01) | (0.01) | (0.02) | (0.00) |
| Reed Elsevier | -0.2525 | 0.4138** | -0.0169 | -0.0372 | 0.4328 | -1.6283** | 0.0551 | 0.2989* |
| | (0.24) | (0.01) | (0.64) | (0.20) | (0.38) | (0.01) | (0.73) | (0.03) |
| Royal Dutch Shell | -0.1575 | 0.7486** | 0.0257 | -0.3304** | 0.6473** | -0.4936 | 0.0046 | 0.3380** |
| | (0.29) | (0.00) | (0.67) | (0.00) | (0.00) | (0.25) | (0.94) | (0.00) |
| TNT | -0.4360** | 1.2982** | -0.1307* | -0.2955 | 1.0887* | 0.2384 | -0.1370 | -0.1065 |
| | (0.01) | (0.00) | (0.01) | (0.11) | (0.02) | (0.70) | (0.10) | (0.54) |
| Unilever Certs. | -0.0963 | 0.4852** | -0.0137 | -0.0934 | 0.5733** | -0.9514* | 0.0083 | 0.1057 |
| | (0.44) | (0.00) | (0.87) | (0.16) | (0.00) | (0.01) | (0.92) | (0.11) |

The table displays the results of Wald tests. For the barrier band specification, $b_3 - b_4$ and $b_5 - b_6$ test for differences in conditional mean return under and above the barrier for, respectively, an upward and downward movement into the twenty point barrier band, $\beta_4 - \beta_5$ and $\beta_6 - \beta_7$ test for differences in the conditional variance under similar conditions. Concerning the period specification, $b_3 - b_4$ and $b_5 - b_6$ explore differences in conditional mean return during a five day period before and after, respectively, the first long-range upward or downward crossing of a specific barrier, $\beta_4 - \beta_5$ and $\beta_6 - \beta_7$ investigate differences in conditional variances under analogous stipulations. Reported is the difference between the relevant coefficients and the p-value, based on a chi-square distribution. * indicates significance at the 5% level, ** at the 1% level.

between the coefficients, but increases the number of significant differences in the variance equation[10]. This suggests that the effects surrounding the first crossing on a long term are relatively robust. At this point, it should be noted that significant return and volatility effects specifically apply to the *period* before and after the first crossing on long term, they are nonexistent when the barrier band around these crossings is considered. It is not straightforward to justify these apparent disparities. Prices typically temporarily fluctuate around the barrier after the first crossing. Under the period specification these fluctuations, whether under or above the barrier, are all incorporated in the post-crossing period. However, under the barrier band specification the post-crossing period is not relevant, the location of the observation, either under or above the barrier, determines the regime. This will result in disparities. Dynamics differ across the first crossing and crossings following on a shorter time horizon and it is of importance whether one considers the barrier band or the period surrounding the potential barrier.

## 6 Barrier crossings

The existence of support and resistance levels in financial asset prices might display itself in crossing effects. As for the clustering tests, the nature of deviations in presence of psychological barriers is undetermined in advance. On the one hand, indices or stock prices might fluctuate around barriers for some time before they are being crossed definitively, resulting in a large number of barrier crossings. On the other hand, barriers might be less frequently crossed than other arbitrary levels as intersection of the barrier is more or less inhibited. Once the barrier is being crossed investors' excitement might push the index or stock price away from the barrier. This effect is, however, relatively unexploited, even though it can be considered to be an obvious potential effect of a psychological barrier. Koedijk and Stork (1994) and Sonnemans (2006) are the only ones to report on transgressional effects in the context of psychological barriers. Tests for crossing effects are in fact similar to tests on price clustering and therefore this section will administer an identical structure as section four. Hence, starting with the standard tests as employed in the paper by Koedijk and Stork (1994) on transgressional effects and subsequently adding new methodological aspects to the existing literature by allowing for different effects across upward and downward crossings of potential barriers.

Once more the M-values are utilized. The vector *t(M)* is constructed, containing the frequency with which each of the 100 different M-values is transgressed. To create *t(M)* the M-value at time *t* ($M_t$) was compared to the M-value at time *t-1* and all intermediate M-values were counted as being crossed. In addition, a crossing is recorded for $M_t$ itself in case of an upward movement and for $M_{t-1}$ in case of downward movements and logically no crossing is recorded during zero return days. Hence, an increase in the AEX from 313.63 to 315.12 points, for instance, gives crossings at the M-values 14 and 15, whereas crossings would be recorded at 13 and 12 in case of a decrease from 313.63 to 311.34 points. Iteration of this procedure for the sample period under consideration generates the vector *t(M)*. Appendix V contains the

[10] This apparent contradiction is due to the fact that an increase in the number of observations, which occurs if the number of days to which the dummy variable applies increases, reduces estimation uncertainty.

programming code written for the construction of *t(M)*. Under the no-barriers null hypothesis the number of crossings is expected to be approximately uniform across the 100 M-values. To test whether all the crossings have an equal chance of occurring, the chi square goodness-of-fit test is applied.

$$X^2 = \sum_{M=0}^{M=99} \frac{\left(t(M) - E(t(M))\right)^2}{E(t(M))},$$

where *E(t(M))* is the expected frequency of crossing each M-value, which equals the total number of crossings divided by hundred. Again, tests are based on the 99 degrees of freedom distribution. For further investigation the two additional chi square goodness-of-fit tests as described by section 4 are replicated for the vector *t(M)*; the distribution of crossed M-values divided in ten disjunct categories of equal size is examined and the allocation of M-values crossings between the barrier band and the non-barrier band is investigated. Addition of latter tests serves to reveal if the crossing patterns of the first goodness-of-fit test are in fact related to potential barriers as differences outside the barrier band are gradually left out. Results of all goodness-of-fit tests are displayed in table 13.

Table 13 Distribution of crossing effects

| | | | 10 point barrier band | 20 point barrier band |
|---|---|---|---|---|
| | $\chi^2(99)$ (p-value) | $\chi^2(9)$ (p-value) | $\chi^2(1)$ (p-value) | $\chi^2(1)$ (p-value) |
| AEX | 425.93** | 319.98** | 765.70** | 107.88** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Akzo Nobel | 290.52** | 219.49** | 9.07** | 22.84** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Heineken | 394.60** | 324.53** | 0.04 | 0.01 |
| | (0.00) | (0.00) | (0.84) | (0.91) |
| Reed Elsevier | 1161.21** | 975.28** | 53.10** | 47.08** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Royal Dutch Shell | 181.15** | 147.92** | 1.73 | 4.68* |
| | (0.00) | (0.00) | (0.19) | (0.03) |
| TNT | 705.65** | 545.41** | 80.03** | 183.98** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Unilever Certs. | 173.47** | 122.38** | 0.00 | 0.45 |
| | (0.00) | (0.00) | (0.96) | (0.50) |

Results of chi-square goodness-of-fit tests with the null hypothesis of a uniform distribution for the number of crossed M-values. The $\chi^2(99)$ and $\chi^2(9)$ statistics show results of uniformity tests across every single M-value and ten disjunct categories of M-values respectively. The last two columns display the results of uniformity tests across a category of observations inside a barrier band and a category of observations outside the barrier band. In the first column the ten point barrier band is considered, the last column concerns the twenty point barrier band.

The null hypothesis of an equal number of crossings is convincingly rejected for all assets for both the 100 M-values and the ten disjunct categories. When solely differences between the observations inside the barrier band and the observations outside the barrier band are considered, results are less homogeneous. Uniformity of the distribution of crossed M-values cannot be rejected for two out of seven assets with a twenty point barrier band and for three out of seven assets with a ten point barrier band. Since test results thus far might be influenced by autocorrelation patterns, crossing patterns in the vicinity of proposed barriers are to be further investigated.

First, the nature of deviations is investigated by dividing the empirical frequency of the vector *t(M)* by the expected frequency under the uniformity assumption. This procedure is replicated for the ten disjunct classes of crossed M-values and for the barrier band and non-barrier band class. Results for the latter class of observations are recorded in table 14. As no clear pattern emerges in the resulting series for the individual M-values and for the ten M-value classes their results are not included. Values below one are an indication of barriers being less frequently crossed than would be expected under the no barriers null hypothesis.

Table 14 Empirical frequency versus expected frequency of crossings

| | 10 point barrier band | | 20 point barrier band | |
|---|---|---|---|---|
| | 95-04 | 05-94 | 90-09 | 10-89 |
| AEX | 0.81 | 1.02 | 0.86 | 1.03 |
| Akzo | 1.07 | 0.99 | 1.07 | 0.98 |
| Heineken | 1.00 | 1.00 | 1.00 | 1.00 |
| Reed Elsevier | 1.25 | 0.97 | 1.16 | 0.96 |
| Royal Dutch Shell | 0.97 | 1.00 | 0.97 | 1.01 |
| TNT | 0.74 | 1.03 | 0.74 | 1.07 |
| Unilever Certs. | 1.00 | 1.00 | 0.99 | 1.00 |

This table shows the empirical frequencies of crossing the M-values in the different classes, as defined in the top panel, divided by their expected frequencies under the assumption of a uniform distribution. Values higher than one indicate a relatively higher frequency of crossings in the relevant class.

As for the price clustering tests, resulting fractions are inconsistent. Three stocks show an increased density of crossings inside the barrier band, whereas four assets experienced fewer crossings inside the barrier band. Fractions remain alternating when leaving out the stocks with non-significant crossing effects. Once again the impression arises that deviations from uniformity are merely caused by autocorrelation patterns than by the presence of psychological barriers.

Former mentioned link between systematic crossing patterns and the potential presence of psychological barriers is more formally examined by means of the barrier proximity regression test.

$$s(M) = \alpha + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + \varepsilon ,$$

where $s(M)$ comprises the relative number of crossings of each M-value. $D_i$ encompasses the M-values close to zero, with a higher index $i$ indicating M-values less close to zero, or equivalently, further away from the potential barrier. The dummy variables are defined in a similar fashion as in section 4.

In the absence of barriers $a$ is approximately equal 0.01 and the dummy-coefficients are insignificantly different from zero. Negative $\beta$'s correspond to relatively few barrier crossings and would provide a strong case for the presence of support and resistance levels. Positive values for $\beta$ relate to a concentration of crossings close to barriers and are compatible with the presence of psychological barriers as well. In general, in the presence of barriers $\beta_i$ should approach zero as $i$ increases. As table 15 shows, the regression broadly confirms the impression that deviations from uniformity are merely caused by autocorrelation patterns.

Table 15 Barrier proximity test for crossing effects

| | $\alpha_0$ (p-value) | $\beta_1$ (p-value) | $\beta_2$ (p-value) | $\beta_3$ (p-value) |
|---|---|---|---|---|
| AEX | 1.0347** | -0.2579** | -0.1552** | -0.1239** |
| | (0.00) | (0.00) | (0.00) | (0.01) |
| Akzo Nobel | 0.9821** | 0.0709 | 0.1045 | 0.0919* |
| | (0.00) | (0.18) | (0.05) | (0.05) |
| Heineken | 1.0004** | 0.0229 | -0.0290 | -0.0009 |
| | (0.00) | (0.74) | (0.67) | (0.99) |
| Reed Elsevier | 0.9612** | 0.3677* | 0.1249 | 0.1153 |
| | (0.00) | (0.02) | (0.44) | (0.42) |
| Royal Dutch Shell | 1.0076** | -0.0409 | -0.0287 | -0.0422 |
| | (0.00) | (0.31) | (0.48) | (0.23) |
| TNT | 1.0657** | -0.2825** | -0.3919** | -0.3153** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Unilever Certs. | 1.0023** | 0.0151 | -0.0198 | -0.0255 |
| | (0.00) | (0.70) | (0.61) | (0.46) |

The table reports parameter estimates of the barrier proximity test, regressing the relative frequency of the number of crossings per M-value on three dummy variables, taking on the value one if the M-value is more or less close to a potential barrier. Significance on the 5% and 1% levels are denoted by * and **, respectively.

Regarding the stocks, none of the assets, except for Reed Elsevier and TNT, shows significant coefficients in vicinity of the potential barriers. Moreover, the $\beta_i$ parameters of the six stocks are not consistently positive or negative, nor do they show a consistent increase or decrease as $i$ increases. Hence, concerning individual stocks, no connection is found between the existence of psychological barriers and specific crossing effects. By exception, the AEX does display a clear link between potential barriers and crossing effects as the index crosses values close to hundred levels and the hundred levels itself relatively infrequently. While moving away from the potential barrier the effect diminishes; the relative frequency of crossing M-values 97, 98, 99, 00, 01 and 02 is 0.7768% and this value increases to 0.8795% for M-values 94, 95, 96, 03, 04 and 05 and to 0.9108% for the digits 90, 91, 92, 93, 06,07, 08 and 09. These findings correspond to the conclusions of Koedijk and Stork (1994) that stock indices tend to cross potential barriers relatively infrequently.

The crossing regressions are repeated with successively different combinations of the three dummy variables included in the equation. Results from these tests do not add to the previous results and are therefore omitted.

As this study concentrates on the different effects of upward and downward crossings through potential barriers, the question remains whether upward and downward movements exhibit different crossing effects. Downward movements appear to be steeper than upward movements and it seems not unlikely to assume that the corresponding crossing effects are therefore weaker. Perhaps the insignificancies for individual stocks are influenced by upward and downward movements' effects canceling out. To investigate this effect more formally, the existing methodology does not satisfy. Furthermore, it is unavoidable to deviate from the clustering methodology, as the point of interest is no longer a band around the potential barrier, but merely the barrier itself. Yet the framework employed in previous sections can still be useful in this respect. The distinction between upward and downward crossings, developed in the section on price clustering, from a both a short and long term point of view is preserved.

Additionally, the concept of a period specification and a barrier band specification, stemming from return and volatility tests, will be administered. Eventually clustering tests are performed under three different specifications.

Under the first specification the average number of barrier crossings is calculated during the period the index or stock spends inside the twenty point barrier band. In this, the direction in which the barrier band is initially entered determines the distinction between upward and downward crossings. This procedure thus considers short term movements.

Table 16 Average number of barrier crossings during the period inside the barrier band

| | Number up | Crossings (average) | Number down | Crossings (average) |
|---|---|---|---|---|
| AEX | 31 | 1,90 | 27 | 1,30 |
| Akzo Nobel | 35 | 1,40 | 40 | 1,40 |
| Heineken | 29 | 1,34 | 18 | 1,33 |
| Reed Elsevier | 4 | 7,50 | 5 | 2,60 |
| Royal Dutch Shell A. | 34 | 1,24 | 36 | 1,61 |
| TNT | 11 | 1,91 | 10 | 1,60 |
| Unilever Certs. | 34 | 1,65 | 31 | 1,65 |

This table considers crossing effects under the first specification. The total number of upward and downward movements into the barrier band over the complete sample period is reported in, respectively, the second and fourth column. Columns three and five contain the average number of barrier crossings during the period the index or price spends inside the barrier band. Each first time the barrier is being crossed in included in the average.

For the AEX slightly more barrier crossings are observed during upward movements compared to downward movements. Results for the individual stocks are mixed. For most stocks the difference across upward and downward movements is fairly small, particularly for Akzo Nobel, Heineken and Unilever, and it does not point in one single direction, compare Shell and TNT for instance. A substantial difference is only observed for Reed Elsevier. This is, however, caused by one outlier in the upward movements and can therefore not be considered as evidence of a consistent crossing effect. No formal statistical tests are performed on these results; the number of crossings is not normally distributed, so a student t-test would not be feasible. Besides, statistical tests would not add to the interpretation of the results in relation to psychological barriers.

The second and third specification focus on crossing effects associated with long term price developments of the AEX and its constituents as defined in section four. The second specification is in fact equivalent to the period specification in return and volatility effect tests. The number of barrier crossings in counted during a fixed period after the first barrier crossing measured on a long term. Two fixed periods are considered, to ensure the robustness of the results. These fixed periods are set to 30 and 60 trading days. For both periods results are presented in table 17. Even though the differences are small, resulting averages point predominantly in similar direction; the number of barrier crossings tends to be slightly higher during the post crossing periods of upward movements than during the periods following a downward crossing. These results indicate that our presumption of weaker crossing effects for downward crossings might be right. For the two exceptions on this pattern, the 30-day post crossing period for

Heineken and the 60-day post crossing period for Royal Dutch Shell, the difference between upward and downward movements is rather small. Hence, the impression arises that allowing for asymmetries is relevant in crossing tests as well.

Table 17 Average number of barrier crossings during a fixed post-crossing period

| | Number up | Crossings (average) | | Number down | Crossings (average) | |
|---|---|---|---|---|---|---|
| | | 30 days | 60 days | | 30 days | 60 days |
| AEX | 20 | 2,20 | 2,90 | 17 | 2,00 | 2,76 |
| Akzo Nobel | 11 | 3,91 | 5,10 | 16 | 2,25 | 3,75 |
| Heineken | 10 | 2,80 | 5,30 | 12 | 2,83 | 4,58 |
| Reed Elsevier | 4 | 5,25 | 7,50 | 6 | 3,50 | 4,80 |
| Royal Dutch Shell A. | 16 | 2,75 | 4,47 | 11 | 2,45 | 5,18 |
| TNT | 5 | 4,60 | 6,80 | 5 | 3,60 | 5,80 |
| Unilever Certs. | 22 | 3,05 | 3,52 | 16 | 2,69 | 3,06 |

The average number of barrier crossings during the 30- and 60-day period following the first barrier crossing on a long term in either upward or downward direction. This first barrier crossing is not included in the average. Columns "number up" and "number down" contain the number of, respectively, long term upward and downward crossings of potential barriers in the sample. For the AEX the number of crossings following the barrier crossing of 11/20/1998 is not incorporated, as the introduction of the euro and the associated rescaling does not allow for a 30-day post crossing period.

To assess this notion further, a final test specification is employed. Once more, crossing effects associated with long term price developments are examined. The assumption of a fixed post-crossing period is replaced by a flexible post-crossing period. This flexible post-crossing period incorporates barrier crossings for as long as the barrier is not "definitively" transgressed. This is either the case if a new barrier is crossed or if the index has left the twenty point barrier band for at least thirty days and moved away at least fifty points or five euro during that period. Subsequently, the average number of crossings before the barrier is definitively broken is calculated for both directions, upward and downwards. Results of this procedure are reported in table 18.

Results are in line with findings under former specification. Nevertheless, differences between upward and downward crossings are somewhat more pronounced. Both the AEX and the individual stocks, except for Unilever, have a tendency to cross the barrier more frequently after the first barrier breaking in upward direction than they do in case of a barrier breaking in downward direction. Still, it should be noted that the number of barrier crossings strongly varies from barrier breaking to barrier breaking. As the number of barrier crossings does not exhibit a normal distribution and since the total number of first long term barrier crossings is small, a student-t test cannot be performed. Therefore a more formal conclusion cannot be derived. The large variance in the number of crossings, however, does tell us that the practical value of the difference between upward and downward crossing is limited.

Table 18 Average number of barrier crossings during a flexible post-crossing period

| | Number up | Crossings (average) | Number down | Crossings (average) |
|---|---|---|---|---|
| AEX | 20 | 5,10 | 17 | 4,18 |
| Akzo Nobel | 11 | 8,82 | 16 | 5,63 |
| Heineken | 10 | 8,50 | 12 | 6,58 |
| Reed Elsevier | 4 | 15,50 | 6 | 6,83 |
| Royal Dutch Shell A. | 16 | 6,88 | 11 | 6,64 |
| TNT | 5 | 10,60 | 5 | 6,80 |
| Unilever Certs. | 22 | 5,09 | 16 | 5,94 |

The average number of barrier crossings before the index or stock crosses a new barrier or leaves the twenty point barrier band for at least thirty days and moves away fifty points or five euro from the specific barrier. Columns "number up" and "number down" record the number of, respectively, long term upward and downward crossings of potential barriers in the sample. For the AEX the number of crossings following the barrier crossing of 11/20/1998 is not incorporated, as the introduction of the euro and the associated rescaling does not allow for a 30-day post crossing period.

In general, individual stocks prices do not exhibit consistent crossing effects; the sign of the dummy variables in barrier proximity tests is not identical among the test assets, neither does the value approximate zero for higher order dummy variables. To explore the nature of observed deviations further, asymmetries in crossing effects were still investigated. The three specifications signify the existence of asymmetric crossing effects when long term price developments are considered. The individual stocks tend to cross barriers less frequently during downward movements compared to the upward movements. Former result is found in the AEX itself as well. Furthermore, the AEX shows the tendency to cross the proposed barriers relatively infrequently in general. Relating the results of table 14 in symmetric tests part to the results of table 18 in the asymmetric tests part, it can be concluded that the crossing effect in the AEX exists and is particularly pronounced during downward movements. A similar conclusion applies to Shell and TNT. The fact that the density of barrier crossings is higher for Heineken, Unilever, Akzo Nobel and Reed Elsevier cannot be related to an overrepresentation of upward barrier crossings, for instance. For each asset the higher density of barrier crossings during upward movements therefore only holds relative to downward movements and not necessarily relative to other arbitrary levels. It appears that downward movements are in fact steeper. During upward movements the assets seem to linger more around the barrier before continuing.

## Conclusion

The aim of this paper was to further investigate the existence of psychological barriers in stock indices and individual stocks. Of particular interest was the asymmetric behavior across upward and downward movements through barriers. This study covers three areas of importance in the context of psychological barriers. First, it was shown that the AEX tends to close relatively infrequently in the vicinity of hundred levels. For individual stocks no consistent pattern emerges. However, when differences across upward and downward movements are allowed for, individual stock prices show a tendency to linger in a broad barrier band in the period preceding the barrier crossing. On the other hand, these effects no longer apply to the AEX itself.

For the second area of investigation a GJR-GARCH model with indicator variables in both the conditional mean and variance equation, to allow for asymmetries, was employed. Additionally tests were performed from both a long term perception of barrier crossings and a short term view on crossings. Regarding the latter, results of both the AEX and its constituents provide evidence supporting the bandwagon effect, i.e. movements across the barrier are more or less restrained, but having crossed the barrier, the price moves relatively fast away from the barrier. These effects are predominantly present when the barrier band is entered in downward direction. Furthermore, these movements are characterized by an increase in variance under barrier levels, albeit not significantly so for the majority of equities. However, dissimilar return and variance effects are found when barrier crossings are considered from a longer term view and when the focus is shifted from the barrier band around the barrier to the period surrounding the barrier crossing. Pre-crossing periods are characterized by significantly higher absolute returns and variances, particularly for downward movements. Effects do not differ in terms of significance neither in terms of sign across the AEX and the individuals stocks.

For the final area of investigation, crossing effects, the distinction between the index and its components is found to be relevant again. Individual stocks do not show a connection between the existence of psychological barriers and crossing effects, whereas the AEX crosses the proposed barrier levels relatively infrequently. This effect for the AEX is particularly pronounced when long term downward barrier breakings are considered in isolation. Separating the long term upward and downward barrier crossings for the individual stocks as well, it is found that the number of barrier crossings tends to be lower for downward barrier breakings than for upward barrier breakings; indicating the existence of asymmetric behavior among investors across upward and downward barrier crossings.

In sum the AEX and its constituent equities behave differently around possible barriers. Indications are found that the hundred levels of the AEX function more or less as support and resistance levels, with the barriers being less frequently approached and transgressed than arbitrary index levels and with an alteration of conditional returns and variances. The reaction of investors to upward and downward movements turned out to be asymmetric in nature, indicating that it does make sense to allow for these asymmetries in barrier testing. Sentiments appear to be more sensitive to downward barrier breakings. For individual stocks the clustering and crossing effects are not consistently related to the existence of psychological barriers. The existence of psychological barriers in individual stocks is, however, not rejected as significant return effects in the vicinity of ten levels are found together with some significances in variance effects. Individual stocks show up to be sensitive to asymmetries as well; downward movements exhibit stronger indications of barrier presence.

Even though the findings contradict the efficient market hypothesis and the assumption of rational investors in a sense, they do not necessarily imply predictability of stocks returns or the existence of consistent abnormal returns through specific trading strategies as Koedijk and Stork (1994) and Ley and Varian (1994) state.

Since this study focused specifically on incorporation of asymmetries in all barrier tests, the scope of assets was limited. Future research might concentrate on asymmetries in the in barrier studies popular Dow Jones index, other well known indices or the, in this field of research unexploited, upcoming markets' indices. Furthermore, as this is the first study employing methodology that allows for asymmetries, future studies might build on this.

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## Appendix I

Table 19 Stock selection criteria

| Stock | Category | From | To | Weight | Since | Stock splits |
|---|---|---|---|---|---|---|
| Akzo Nobel | 1000 Basic Materials | 07/01/1998 | 06/05/2009 | 4.1% | 1983 | - |
| Heineken | 3000 Consumer Goods | 05/05/1998 | 06/05/2009 | 3.0% | 1983 | 05/04/2004 (0.8)<br>05/01/2001 (0.8) |
| Reed Elsevier | 5000 Consumer | 10/05/1994 | 06/05/2009 | 3.3% | 1986 | - |
| Royal Dutch Shell A. | 0001 Oil and Gas | 06/30/1997 | 06/05/2009 | 15.0% | 1983 | 07/20/2005 (0.5) |
| TNT | 2000 Industrials | 06/29/1998 | 06/05/2009 | 2.4% | 1998 | - |
| Unilever Certs. | 3000 Consumer | 10/13/1997 | 06/05/2009 | 15.0% | 1983 | 05/22/2006 (1/3) |

The six investigated AEX stocks with their respective category and examination window. The column “weights” comprises the weight of the stocks in the composition of the AEX as they are established by NYSE Euronext on March 2 2009. The fifth column reports the year the specific stock was included in the AEX. Stocks splits occurring in the examination window are presented in the final column, with the split factor between brackets.

## Appendix II

Table 20 Closing days of the Dutch Stock Exchange

| Day | Date | Sample period |
|---|---|---|
| New year's day | January 1 | 1989-2009 |
| Good Friday | Various | 1989-2009 |
| Easter Monday | Various | 1989-2009 |
| Queen's Day | April 30 | 1989-2001 |
| Labor Day | May 1 | 2002-2009 |
| Liberation Day | May 5 | 1995 |
| Ascension Day | Various | 1989-2001 |
| Whitsunday | Various | 1989-2009 |
| Christmas Day and Boxing day | December 25 and 26 | 1989-2009 |
| New Year's Eve | December 31 | 1989-1999 |

Data generated by Euronext.com (Kalender van de handelsdagen)

## Appendix III

Table 21 Asymmetric clustering tests under the long term definition

| | 10 point barrier band | | | | | | 20 point barrier band | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | UU | AU | $\chi^2(1)$ (p-value) | UD | AD | $\chi^2(1)$ (p-value) | UU | AU | $\chi^2(1)$ (p-value) | UD | AD | $\chi^2(1)$ (p-value) |
| AEX | 151 | 175 | 1.77 (0.18) | 48 | 53 | 0.25 (0.62) | 379 | 371 | 0.09 (0.77) | 130 | 98 | 4.49* (0.03) |
| Akzo | 81 | 80 | 0.01 (0.94) | 70 | 84 | 1.27 (0.26) | 182 | 160 | 1.04 (0.23) | 142 | 168 | 2.18 (0.14) |
| Heineken | 56 | 44 | 1.44 (0.23) | 50 | 81 | 7.34** (0.01) | 127 | 90 | 6.31* (0.01) | 81 | 172 | 32.37** (0.00) |
| Reed Elsevier | 139 | 242 | 27.85** (0.00) | 56 | 94 | 9.63** (0.00) | 208 | 416 | 69.33** (0.00) | 99 | 200 | 34.12** (0.00) |
| R.D. Shell | 96 | 93 | 0.05 (0.83) | 55 | 35 | 4.44* (0.04) | 194 | 179 | 0.60 (0.44) | 110 | 64 | 12.16** (0.00) |
| TNT | 99 | 63 | 8.00** (0.00) | 29 | 26 | 0.16 (0.69) | 169 | 157 | 0.44 (0.51) | 54 | 53 | 0.01 (0.92) |
| Unilever | 91 | 86 | 0.14 (0.71) | 77 | 87 | 0.61 (0.43) | 181 | 171 | 0.28 (0.59) | 139 | 174 | 3.91* (0.05) |

The ten point barrier band considers all observations with an M-value ranging from 95 to 04. The twenty point barrier band includes all observations with an M-value between 90 and 09. UU and AU include all observations under the barrier and above the barrier, respectively, provided that the index or stock is in a long term upward movement. When the index or stock is in a longer term downward movement, observations under the barrier pertain to UD and observations above the barrier belong to AD. The $\chi^2(1)$ statistic explores differences between regime UU versus AU and regime UD versus AD. * and ** indicate significance at 5% and 1% levels, respectively.

## Appendix IV

Table 22 Mean equation of the GJR-in-mean long term period specification

| | $\alpha_0$ (p-value) | $R^d_{t-1}$ (p-value) | $h_t$ (p-value) | $UB^l_t$ (p-value) | $UA^l_t$ (p-value) | $DB^l_t$ (p-value) | $DA^l_t$ (p-value) |
|---|---|---|---|---|---|---|---|
| AEX | 0.0148 | | 0.0123 | 0.3550** | 0.0794 | -1.0266** | -0.2888 |
| | (0.34) | | (0.48) | (0.00) | (0.28) | (0.00) | (0.19) |
| Akzo | -0.0241 | | 0.0110 | 0.8337** | 0.5324 | -1.2333** | -0.1500 |
| | (0.58) | | (0.51) | (0.00) | (0.14) | (0.00) | (0.66) |
| Heineken | 0.0107 | | -0.0124 | 0.9725** | 0.0895 | -0.6246* | 0.3281 |
| | (0.75) | | (0.48) | (0.00) | (0.65) | (0.02) | (0.15) |
| Reed Elsevier | 0.0212 | | -0.0027 | 0.7027 | 0.2700 | -1.1412* | 0.4859 |
| | (0.57) | | (0.87) | (0.06) | (0.48) | (0.01) | (0.18) |
| Royal Dutch | 0.0023 | | -0.0075 | 0.7439** | 0.0961 | -0.7536** | -0.2606 |
| | (0.95) | | (0.68) | (0.00) | (0.52) | (0.00) | (0.43) |
| TNT | 0.0073 | | -0.0027 | 0.7782** | -0.3105 | -0.7903* | -1.0287 |
| | (0.85) | | (0.84) | (0.01) | (0.32) | (0.04) | (0.07) |
| Unilever | 0.0027 | | 0.0036 | 0.6826** | 0.1093 | -1.1890** | -0.2377 |
| | (0.94) | | (0.85) | (0.00) | (0.41) | (0.00) | (0.26) |

Regression results for the mean equation of the GJR specification for the long term period specification model are reported. Besides a constant term, the conditional mean equation includes the one-day lagged return, provided that the coefficient is significant, the contemporaneous variance and four indicator variables. UB is the indicator variables for the five day period preceding the first long-range crossing of a specific barrier in an upward move, UA represents the five day period after a barrier crossing under latter conditions. DB and DA are indicators for the five day period before and after, respectively, the first crossing measured over longer term of a barrier in a downward move. The GARCH-models are optimized using the Marquardt algorithm and estimated with heteroskedasticity consistent covariance. * indicates significance at the 5% level and ** at the 1% level.

Table 23 Variance equation of the GJR-in-mean long term period specification

| | $\alpha_0$ (p-value) | $h_{t-1}$ (p-value) | $\varepsilon^2_{t-1}$ (p-value) | $\varepsilon^2_{t-1}I_{t-1}$ (p-value) | $\varepsilon^2_{t-1}UB^l_t$ (p-value) | $\varepsilon^2_{t-1}UA^l_t$ (p-value) | $\varepsilon^2_{t-1}DB^l_t$ (p-value) | $\varepsilon^2_{t-1}DA^l_t$ (p-value) |
|---|---|---|---|---|---|---|---|---|
| AEX | 0.0112** | 0.9236** | 0.0248** | 0.0696** | -0.0052 | 0.0425 | 0.3485** | 0.0431 |
| | (0.00) | (0.00) | (0.03) | (0.00) | (0.79) | (0.09) | (0.01) | (0.73) |
| Akzo | 0.0581** | 0.9083** | 0.0222* | 0.1054** | 0.0083 | -0.0404* | 0.1620* | -0.0207 |
| | (0.01) | (0.00) | (0.02) | (0.00) | (0.11) | (0.04) | (0.05) | (0.54) |
| Heineken | 0.0157** | 0.9339** | 0.0275** | 0.0666** | 0.2514* | -0.0613** | 0.1134* | -0.0846** |
| | (0.01) | (0.00) | (0.00) | (0.00) | (0.03) | (0.00) | (0.03) | (0.00) |
| Reed | 0.0282** | 0.9385** | 0.0403** | 0.0220 | 0.0565 | 0.0014 | 0.1734 | -0.1259* |
| | (0.01) | (0.00) | (0.00) | (0.15) | (0.47) | (0.99) | (0.06) | (0.03) |
| R.D. Shell | 0.0353** | 0.9262** | 0.0328** | 0.0351* | 0.0257 | 0.0192 | 0.3311** | -0.0231 |
| | (0.00) | (0.00) | (0.00) | (0.04) | (0.43) | (0.57) | (0.00) | (0.30) |
| TNT | 0.0213** | 0.9531** | 0.0089 | 0.0585** | -0.0545 | 0.0824 | 0.0509 | 0.1573 |
| | (0.00) | (0.00) | (0.51) | (0.01) | (0.26) | (0.15) | (0.50) | (0.18) |
| Unilever | 0.0166** | 0.9457** | 0.0230* | 0.0475** | 0.0045 | -0.0039 | 0.0779 | -0.0279 |
| | (0.01) | (0.00) | (0.01) | (0.00) | (0.91) | (0.93) | (0.09) | (0.35) |

The table reports regression results for the variance equation of the GJR specification as given in section 4.2. The variance equation contains a constant term and successively standard GARCH-term, ARCH-term and GJR-term, which adds to the volatility if the lagged residual is negative. The indicator variables are added to the variance equation as well, multiplication by the squared residual serves to ensure asymptotic normality of the standard errors. The Marquardt algorithm and heteroskedasticity consistent covariances are applied in the optimization process. * denotes significance at the 5% level, ** denotes significance at the 1% level.

## Appendix IV

The programming code below, employed in Visual Basics in Excel, constructs the vector *t(M)*. In green a description of the subsequent commands.

```
Sub Doorrekenen()

    Sheets("Calculations").Select

    Dim w As Integer
     For w = 3 To 102 Step 1 'Run down the 100 M-values
     ActiveSheet.Cells(w, 14).Value = "0" 'Setting all M-values to zero
     Next w
     ActiveSheet.Cells(3, 15).Value = "0" 'Setting the numerator for the number of zero return days to zero

Dim a As Integer
Dim ColumnSize As Integer
ColumnSize = ActiveSheet.Cells(7, 4).Value 'This cell contains the number of observations

For a = 1 To ColumnSize - 1 Step 1 'Loop over the entire column of observed M-values

     Dim p As Integer
     p = ActiveSheet.Cells(a, 1).Value 'M-value today
     Dim q As Integer
     q = ActiveSheet.Cells(a + 1, 1).Value 'M-value tomorrow
     Dim r As Integer
     r = ActiveSheet.Cells(a, 2).Value 'Price level today
     Dim s As Integer
     s = ActiveSheet.Cells(a + 1, 2).Value 'Price level tomorrow

'SITUATION 1:
If p > q And r < s Then 'The price went upwards through a barrier (M-value 100)

     Dim countup100 As Integer 'The M-values up to 99
     For countup100 = p + 1 To 99 Step 1 'p itself not included
     ActiveSheet.Cells(countup100 + 3, 14).Value = ActiveSheet.Cells(countup100 + 3, 14) + 1
     Next countup100

     Dim countup0 As Integer 'The M-values from zero onwards
     For countup0 = 0 To q Step 1
     ActiveSheet.Cells(countup0 + 3, 14).Value = ActiveSheet.Cells(countup0 + 3, 14) + 1
     Next countup0

'SITUATION 2:
ElseIf p < q And r > s Then 'The price went downwards through a barrier (M-value 100)

     Dim countdown0 As Integer 'The M-values down to 0
     For countdown0 = p To 0 Step -1
```

```
        ActiveSheet.Cells(countdown0 + 3, 14).Value = ActiveSheet.Cells(countdown0 + 3, 14) + 1
        Next countdown0

        Dim countdown100 As Integer 'The M-values from 99 onwards
        For countdown100 = 99 To q + 1 Step -1
        ActiveSheet.Cells(countdown100 + 3, 14).Value = ActiveSheet.Cells(countdown100 + 3, 14) + 1
        Next countdown100

    'SITUATION 3:
    ElseIf q > p Then 'Price increase (no barrier crossing)

        Dim countup As Integer
        For countup = p + 1 To q Step 1 'p itself not included
        ActiveSheet.Cells(countup + 3, 14).Value = ActiveSheet.Cells(countup + 3, 14).Value + 1
        Next countup

    'SITUATION 4:
    ElseIf p > q Then 'Price decrease (no barrier crossing)

        Dim countdown As Integer
        For countdown = p To q + 1 Step -1 'q itself not included
        ActiveSheet.Cells(countdown + 3, 14).Value = ActiveSheet.Cells(countdown + 3, 14).Value + 1
        Next countdown

    'SITUATION 5:
    ElseIf p = q Then 'No price move

        ActiveSheet.Cells(3, 15).Value = ActiveSheet.Cells(3, 15) + 1

        End If

    Next a

    End Sub
```