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THE INDEX EFFECT – COMPARISON OF DIFFERENT MEASUREMENT APPROACHES

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Variables and Parameters in the Mean Equation

R_{Asset}	The continuously compounded return of the examined stock
R_{market}	The continuously compounded return of the S&P 500
$R_{abnormal}$	The part of the return that is not explicable by the used model in continuously compounded form
σ^2	The GARCH variance of the examined stock
α	An estimated constant
β_1	The level of impact of the market on the security
β_2	The level of impact of volume on the security
β_3	The level of impact of the price of oil on a security
β_4	The level of impact of the price of ore on a security
λ	The level of impact of the estimated GARCH variance on the assets mean
V	Volume in Dollars

Variables and Parameters in the Variance Equation

V_L	The long-run variance of the security
γ	The level of impact of the long-run variance on the actual variance
$\delta_{1\ldots q}$	The level of impact of the corresponding ARCH factor.
$\theta_{1\ldots p}$	The level of impact of the corresponding GARCH factor
ε^2_{t-q}	The ARCH(q) factor. The squared error of the q-lagged period
σ^2_{t-p}	The GARCH(p) factor. The variance of the p-lagged period
φ	The impact of volume on the GARCH variance
V	Volume

Index of tables

Index of Figures

Abstract

The purpose of this paper is to examine additions and deletions of the S&P500. Competing event studies will be performed to analyze the announcement effect with different benchmarks. The main components of the paper are a Market Model based event study and a GARCH(1,1)-M Model study. The GARCH-M Model assumes a relation between variance and mean of an asset, where the variance tends to follow a long-run variance, and is dependent upon the stock's preceding abnormal return and variance. The event study examines approximately 350 stocks over 240 trading days.

I have to confirm a positive index effect for additions and vice versa for deletions. Price, abnormal return, volume and variance of added stocks rise on the day after the announcement. My analysis reveal a semi-strong reversal and therefore are consistent with the Price Pressure Hypothesis and partly with the Imperfect Substitutes and the Visibility Hypothesis. The hypothesis of a significant lambda factor - the impact of the variance on the mean - has to be rejected for the additions and deletions of the S&P 500 for all event studies conducted. The analysis find significant ARCH and GARCH terms for the variance equation. The obtained lambda factors are not normally distributed. In the additions set the use of the GARCH(1,5)-M model seems to extenuate the index effect.

Introduction

The index effect is a wide spread phenomenon. Several studies, some of them are listed below, encountered abnormal returns for stocks being added to or deleted from an Index. Not only in the S&P 500 stocks seem to observe significant gains or losses depending whether the stocks are deleted or added to an index, although the informational content of an addition or deletion is quite questionable. An index is supposed to give an overview of a country's economy, but not to make a qualitative statement about the stocks contained in the index. The dimension of the index effect seemes to have changed several times since it was first reported in the 70'ies in different directions depending on the number of indexing portfolios and the investors' level of awareness of the index effect. This paper also intents to bring light to the question if additions and deletions exhibit a symmetric effect, which has not been reported so far. Apart from the direct examination of the effect, the 14 event studies included are going to be compared. The event studies are performed in the tradition of the methodology developed by Fama, Fisher, Jensen and Roll (1969). The different models recognize simultaneous information about the S&P500, trading volume and variance.

The paper tries to investigate whether it is useful to model clustered variances and if it is useful to impute a relevant influence of the variance on the mean return of a stock. The first assumption goes back to Mandelbrot (1963) and was described in many other studies (comp. Peters, 2001 and Campbell, Lo, McKinlay, 1997). The second assumption can be justified by the Capital Asset Pricing Model (CAP-M) that assumes risk aversion of investors. Elevated risk therefore has to be compensated by a higher mean return. Still the CAP-M is usually put in a long-run context, and not used as the basis for daily return data analysis.
The relatively high sample size of approximately 350 stocks analyzed, using daily data, over nearly one year and is supposed to give a broad picture of the index effect in the last decade.
In the next section I would like to present the common theories that are called on in order to explain the index effect.

The Efficient Market Hypothesis and the Index Effect – a contradiction?

All publicly available information should be contained in the price of an asset – as stated by the semi-strong form of the Efficient Market Hypothesis (EMH). This means as long as no new information is transmitted to the market, traders should be able to buy and sell as much as they want at the actual price.
In case the attachment to an index doesn't convey any information only few explanations for rising/declining prices remain:

- the Price Pressure Hypothesis (PPH)
- the Liquidity Hypothesis (LH)
- the Imperfect Substitutes Hypothesis (ISH)

The Price Pressure Hypothesis assumes a short-term increase in the stocks price due to large volume effects for the most part caused by index tracking funds. This Hypothesis sets boundaries to the EMH because a perfect incorporation of all public information in the prices meant also that prices react very fast to new information even if the information concerns investors' behavior. The hypothesis postulates a reversal for the added and deleted stocks. (Harris and Gurel, 1986)
The Liquidity effect is based on the fact that higher interest in the stock and an elevated transaction volume reduce the volatility and the transaction costs because of a lower spread and less asymmetric information and therefore lead to higher prices in the long run. The Liquidity Theory goes along with the EMH as publicly available Information doesn't need to be cost free. (Amihud and Mendelson, 1986 and Goetzmann and Garry, 1986)

The Imperfect Substitutes Hypothesis opposes the EMH, by declaring demand not perfectly elastic and therefore allowing a change in demand to lift the price e.g. index trackers need to buy an asset while not every possible supplier is indifferent between this stock and any other stock of the same value. Price changes are persistent in this framework and systematic abnormal returns are possible. (Shleifer, 1986)

Another explanation that is not directly designed to explain the effects of index composition changes is the Visibility Hypothesis (VH) that assumes stocks that draw the potential investors' attention are more likely to rise in price than others. The basic assumption is that there are more assets available than the average investor could investigate in and the demand for an asset is defined by the probability that the asset will be considered/analyzed and the conditional probability that the asset will be evaluated as underpriced after the examination. An addition to an index could significantly enlarge the probability that the added stock is taken into account by several investors that didn't consider to buy it before. Also a deletion could be an event attracting investors' attention. (Miller, 1977)

The EMH doesn't permit systematic abnormal returns based on public information. But is the recipe how to derive the right price using public information, a public information itself?

Empirical Studies

Nearly all of the empirical studies I examined reported positive abnormal returns for index additions around the announcement date as well as negative abnormal returns for deletions.

The difficulty to compare the results lies in the varying time frames, as well as in the different methods to compute the abnormal returns and the diverse markets/indexes in which the analysis have taken place.

I would like to sketch out what research in index changes has found and therefore I firstly present a table with results that are directly comparable to my findings and secondly give a broad overview of further research in this field.

Author	Time	Index	Sample	AD / AD+1	CAR +/- 20	CAR +/- 10	CAR 0/+10	CAR AD / ED
Shleifer 1986	1966-1983	S&P 500	246		2.90%		1.90%	
Harris / Gurel 1986	1973-1983	S&P 500	194	1.52%				
Dhillon / Johnson 1991	1978-1988	S&P 500	187 / 24	3.55%		3.17%	2.90%	
Beneish / Gardner 1995: Additions	1929-1988	Dow Jones Industrial Average	37	0.17%	5.01%	2.72%	-0.70%	
Beneish / Gardner 1995: Deletions	1929-1988	Dow Jones Industrial Average	31	-2.50%	-2.55%	-1.66%	-2.70%	
Gregoriou / Ioannidis 2003	1984-2001	FTSE 100	258 / 258	3.65%	18.28%	19.22%	4.43%	
Benish / Whaley 1996	1986-1992	S&P 500	103	3.07%			4.73	4.01
Lynch / Mendenhall 1997 Additions	1990-1995	S&P 500	34	3.98%				6.25%
Lynch / Mendenhall 1997 Deletions	1990-1995	S&P 500	15	-9.87%				13.30%
Georgi 2001 Additions	1990-2000	DAX	6	1.80%	16.00%	8.00%	1.00%	
Georgi 2001 Deletions	1990-2000	DAX	4	-0.50%	+/- 0.00%	+/- 0.00%	-1.50%	
Gerke / Fleischer 2003	1996-2002	MDAX	54 / 44	2.31%		5.05%	0.98%	
Bos 2000(1)	1988-2000	S&P 500	189					8.50%
Bos 2000(2)	1988-	S&P 400	269					6.30%

	2000							
Bos 2000(3)	1988-2000	S&P 600	403					5.40%
Deininger / Kaserer / Roos 2000	1990-1997	Dax 100						
Additions DAX 100	1990-1997	Dax 100	20	1.50%		2.00%	1.30%	
Additions DAX	1990-1997	Dax		2.79%		7.43%	6.77%	
Deletions DAX 100	1990-1997	Dax 100	22	-1.39%		-4.85%	-2.14%	
Deletions DAX	1990-1997	Dax		-0.53%		-1.57%	-2.24%	
Chen / Noronha / Singal Additions	1989-2000	S&P 500	218 / 62	5.45%				8.89%
Chen / Noronha / Singal Deletions		S&P 500		-8.46%				-14.40%
Brealey 2000	1994-1999						[CAR 0 /+8]	
Additions		FTSE ALL		1.30%			0.00%	
Additions		FTSE 100		-0.80%			-1.60%	
Deletions		FTSE ALL		-0.70%			-4.10%	
Deletions		FTSE 100		0.70%			-0.60%	

(Tab. 1)

Shleifer (1986) examined the S&P 500 using the Market Model and was the first to formulate the ISH, deriving from a divergence of analysts' opinion. In his earlier sample he found lower abnormal returns and a full reversal of the announcement effect. In the second part of his sample the reversal was weak and transitory, and the effect was larger.

Harris and Gurel (1986) claimed that price pressure was the reason for the announcement effect that experienced a complete reversal within 20 trading days. The paper also exhibits the increase of the effect over time.

Dhillon and Johnson (1991) made new information conveyed by the announcement responsible for an effect of the same dimension as Harris and Gurels findings, but only had a partial – one third - reversal over 60 days. Dhillon and Johnson used the Market Model to calculate abnormal returns.

Beneish and Gardner (1995) examined the Dow Jones Industrial Average from 1929 until 1988 and revealed an index effect rather before than after the event. They state that additions to the DJIA are unaffected while deletions experience a decrease in value on the announcement date, although their calculations show that additions are not unaffected, but increase in value in a different time frame. Beneish and Gardner explain the asymmetric behavior with lower trading volume and less available information for deleted stocks. The authors support the LH.

Gregoriou and Ioannidis (2003) use market adjusted returns and find enormous abnormal returns for the FTSE 100. They find evidence that volume, bid/ask-spread and the stocks' growth rate are significant factors for the development of a stock in the moment of an addition/deletion. They support the LH and explain the asymmetric outcomes (less effect for deletions) with information availability: Information about delisted Stocks expires over time, not on the announcement date.
Also a partial reversal over the 60 days following the announcement is reported.

Beneish and Whaley (1996) find a strong reversal of the announcement effect and again an increasing effect in the latter years of their study, but ascribe it to the changed policy of the S&P to announce changes prior to the effective date. They partly support the PPH and expect the effect to disappear as soon as index funds start to trade more flexibly.

Lynch and Mendenhall (1997) use market adjusted returns to examine the effect of a change in composition of the S&P 500 on the added / deleted stock. After a strong reversal the paper reveals a little, persistent effect and supports the ISH as well as the PPH. Stronger effects for deletions are reported.

The Study of Georgi (2001) examines the DAX and reports a strong response, in the announcement period for stocks added/deleted to the index. The effect takes place rather before the announcement and so insider trading and/or information anticipation is assumed to be the reason. The numbers I put in the table are not exact as I took them from the graph in the paper. The sample size is also too low to make statistically significant statements, but the paper shows that there is no big difference between the Market Model and using market adjusted returns.

Gerke and Fleischer (2003) examine the MDAX using market adjusted returns and report significant abnormal returns to the biggest extent arising before the announcement. A complete reversal after the effective rearrangement of the index drove the authors towards promoting the PPH, although only a weak reversal took place in the earlier part of the sample.

The Study of Bos (2000) is published by the S&P Quantitative Services and reports a significant positive effect for stocks being added to the S&P indexes. The study uses the Market Model to calculate abnormal returns between the announcement date and the date of the effective change of the S&P's composition. The study also takes into account long term effects and reveals positive abnormal returns one year after the reconstruction of the indexes around 20%.

Deininger, Kaserer and Roos (2000) examine the DAX and DAX 100 and find abnormal returns, rather after the announcement date, using market adjusted returns. They also assure the trend of growing abnormal returns – especially for additions. The amount of funds following the indexes is mentioned as a possible reason for that trend.

Chen, Noronha and Singal (2002) find asymmetric abnormal returns for the S&P 500 with a stronger effect for deletions. They report that the complete negative abnormal returns of the deletions are being recovered after 60 trading days and therefore don't find strong evidence against perfectly elastic demand curves. The asymmetry leads them to the conclusion that investor awareness could be the reason for the abnormal returns, as this is the only hypothesis not predicting symmetric behavior. Newly added stocks gain more attention than lately deleted stocks loose.

Brealey (2000) observes the FTSE 100 and in contrast to Gregoriou and Ioannidis he finds weak abnormal returns and relates them to the increasing number of index followers. A complete reversal is encountered for FTSE All Share additions. And astonishingly he finds negative abnormal returns for FTSE 100 additions on the announcement day.

Several other papers conducted research in related fields, but can't be compared to the previous papers directly because the resulting data doesn't fit into the table or because the defined event is different to changes in the index composition.

Denis, McConnel, Ovtchinkov and Yu (2002) analyzed the S&P 500 between 1987 and 1999 and compared stocks being included to an index to benchmark companies. As analysts on average give better prospects of earnings per share for newly added stocks, they assume the event not to be information free. They find significant increases in the earnings per share (eps) as well as in the forecasted eps. On average the forecasts predict to high eps, which results in more accurate forecasts for newly added stocks (that rather exhibit elevated eps).

Gervais, Kaniel and Mingelgrin (1998) examine the relation between change in volume and change in return for stocks traded at NYSE. They discover a positive relation that supports the theory that increased attention, generating higher trading volume leads to higher returns (consistent with Steiner and Heinke, 1977). The authors preclude autocorrelation, liquidity and elevated risk from accounting for the effect. The strong dependence between volatility and volume makes the paper comparable to my findings, that suggest that volatility is an especially bad factor for estimating deletions' returns. The paper reveals also that the high-volume return premium is in particular valid for stocks performing badly over the last 50 trading days. Other studies have taken the leverage effect into account in order to incorporate this phenomenon.

Pruitt and Wei (1989) used an average sample size compared to the table shown above to demonstrate that with an increasing number of indexers the effect of an inclusion grows within the S&P 500 . Still they postulate that the effect is temporary and show that demand is very elastic. According to their findings the liquidity demanded by indexers derives from non institutional investors.

Steiner and Heinke (1997) study the introduction of the MDAX in Germany and register negative abnormal returns for the stocks that should be included in the new index on the announcement date and even earlier. This reaction experienced a partial reversal and on the effective date of the establishment of the MDAX positive abnormal returns could be found for the next 27 days.
The authors state that price pressure is not likely to be the reason for the encountered effect.
The results shouldn't be overvalued because all events took place on the same day, which involves several statistical problems. Other disturbing factors might have been of importance.

Neumann and Voetmann (2002) investigate in the effect of the change of the index weights for the Dow Jones STOXX. The old weight was determined by the market capitalization and the new weight is defined by free floating stocks. This should imply that index funds should also adjust their portfolios and could result in a price reaction like the one observed for index inclusions (exclusions). Neumann and Voetmann find an effect of 0.5% for stocks experiencing a higher weight in the index after the change (-1.33% for downgraded stocks). They support the PPH and report a complete reversal although the reported table doesn't show any change from –1/ +1 to –1/+10 for low float companies. Their long run graph shows significant and persisting abnormal returns of about 4.7% and 0% for high and low-float companies. The event happened on one day for all the examined stocks, which brings several bias possibilities with it and makes statistical evaluation of the results difficult.

Quinn and Wang (2003) present a very comprehensive paper that aims at adjusting the index policy to the increasing demand of index funds. The authors examine the S&P 500, the S&P 1500, the Russell 3000, the NASDAQ 100 and the Dow Jones TMI additions from 1999 to 2002. The results couldn't be presented in the table shown above, because it was the rearrangement date of the index defined as the event, not the announcement day. The authors discovered outsized abnormal returns for a long run window (-50/+50) from 2% to 10% including a reversal of about two thirds. Only for the Dow Jones TMI barely significant data was found. The Russell 3000 exhibits its abnormal returns earlier than the S&P, but that could be explicable because the announcement takes place 15 days earlier for the Russell 3000. An astonishing fact mentioned in this paper is that percentage of the market capitalization held by institutional index funds is higher for the S&P whereas the additions to the Russell 2000 are subject to a higher impact of the effect. The increasing number of index funds over the last decades was usually held responsible for the increasing effect.

Hyland and Swidler (2002) analyzed the NZSE 40 (New Zeeland), where the announcement of an index change takes place at least 3 months before the actual event. The additions experience the highest abnormal returns about 5 months before the inclusion to NZSE 40 and don't show significant abnormal returns once the reconstruction has been accomplished. The authors put the Visibility Hypothesis against the PPH and do not find any support of the PPH, because the stocks don't fall in price after the effective inclusion. Monthly returns and the relatively low sample size (31 additions, 22 in the clean sample) let the outcome of the study rather be a trace than a statistical proof.

Biktimorov, Cowan and Jordan (2003) have undertaken research on the Russell 2000 in the period from 1991 until 2000. They find significant abnormal returns before the date of reconstruction as well as a complete reversal within 20 trading days. Their sample size is 4321 and 3092 for additions and deletions, respectively. The specialty of the study is that they make a difference between stocks being added or deleted purely, and stocks that are shifted from Russell 2000 to Russell 1000 or the other way. The sample size for the shifts is still large enough to find significant abnormal returns that differ strongly from the pure additions and deletions. The shifts experience an effect by far larger and seemingly delayed in comparison to the pure additions. No reversal is reported for the shifts. The figures have not been reported in the table shown above because no actual date of announcement is analyzed but the date of reconstruction. The Russell adds and deletes companies on the market value criterion and this "gradual announcement" makes it difficult to compare the study to the ones in the table.

Wagner (2003) compares the Market Model to an alternative approach where the conditional variance is dependent upon trading volume and the return is a function of the conditional variance. The subjects of the study are initial public offerings in the "Neuer Markt" index of emerging German industries. The result of the study is that the alternative model generates significantly lower abnormal returns (in 9 of 10 cases) and therefore further investigation with a higher sample size could be interesting. The method of incorporating volume in the GARCH variance term as a regressor was applied on single stocks by Lamoureux and Lastrapes (1990). They find that the significancy of ARCH and GARCH terms tends to disappear if volume is added to the variance equation.

Kim and Kon (1994) compare different models for modeling stock price return. They compare the EGARCH(1,3)-M model with the GARCH(1,3)-M (see below) and find that EGARCH fits better on stock indexes returns while the GARCH(1,3)-M specification has its advantages in modeling single stock returns. They consistently find a positive influence of the variance on the mean return. Conclusively Kim and Kon support the GJR (Glosten, Jagannathan and Runkle, 1993) model - differentiating between positive and negative shocks - for analyzing individual shocks.

Data and Methodology

In the following sections I would like to outline the prevailing circumstances of the event studies in this paper.

Event definition

The event is defined as the announcement that a stock has been added to or deleted from the S&P 500 between the 1st of July 1990 and the 30th of November 2002. The event study examines an 8 week window around the day of the announcement of a change in the S&P 500 composition, using daily close prices, obtained from datastream.

The size of the event window has been chosen to make the study comparable to other studies in that field and to capture any pre-announcement effects as well as possible reversals. Some studies report a reversal in the long run e.g. within 60 days. The event study won't be able to bring further evidence or reject these long-run findings, although a reverting trend should also be visible within 20 trading days after addition or deletion.

The event date is defined as the day of the actual announcement, because in the case that a restructuring of an index conveys relevant information, this is the of the transition of the information. The event window consists of 41 trading days 20 days before the event and 20 days after the announcement has taken place.

Selection Criteria

Not all of the additions and deletions could be incorporated in the event studies for several reasons.

Some of the stocks have been deleted and added again under a different name, some of the changes are due to mergers. Changes of the S&P 500 for these reasons were excluded. Also for most of the stocks that were deleted because of bankruptcy data was not available in the complete event window and therefore not included into my analysis. An upward bias is introduced in the sample of the deletions, because bankruptcy is a major reason for the removing a stock from the S&P 500 and few of these cases exhibit complete data for the 20 days following the deletion. Luckily the bias results rather in underestimating the examined effect than in overestimating, so that it could be regarded as an additional factor of robustness proving the existence of an announcement effect in the deletions' set.

The lack of available data was also a major reason to exclude stocks from my analysis. The data for the examined stocks had to be available at least 220 days before the event and 20 days following the announcement, otherwise the stocks could not be incorporated in my primary studies. The examined period was set to maximize the number of examined days regarding the availability of data according to the formula: max. [(number of examined days) x (number of stocks with available data for the number of examined days)]. As a check for robustness and to include the highest amount of data I formed another sample for all stocks with data available between 120 days before and after the announcement date. Most of the stock returns were available in both periods of relative event-time and therefore the two samples are strongly overlapping.

The whole sample consists of firms with a remarkable market capitalization, but the benchmark is the S&P 500 that requires market capitalization for membership. So there is no bias regarding companies' market capitalization.

One more potential bias, induced by the selection of data could be that some additions were deleted in the S&P mid- or small-cap just before being added to the S&P 500, whereas deletions are rarely added to another index after their deletion. For that reason, comparing the additions and deletions will be difficult, because the mentioned bias could make me underestimate the effect also for additions. Biktimorov, Cowan and Jordan (2003) show that the effect differs for stocks that are shifted from one index to another.

The raw sample consisted of 692 additions and deletions. 245 of the deletions are due to mergers and acquisition as well as name changes and spin-offs. From the remaining 101 deletions 8 were removed because data was not available in the whole event period, giving an idea of the dimension of the bias that only survivors are included in the analysis. 6 of the deleted stocks were removed because the data in the estimation period was incomplete or error-prone. Finally the analysis of the deletions' set contains 87 deletions.

The number of additions is reduced by 36 because of name-changes and spin-offs. 50 additions were removed because the data was not available or error-prone, 261 stocks remained.

In some cases data of single days were changed for matters of reason to provide a continuous progression of the share price:

Enrons return for t=3 (relative event time) was set to 1.175 from 117.5.

Pan Am return for t=2 was set to 1, formerly a return of 100 was reported, which must have meant 100% as the price doubled.

Volume data was not available for single trading days of AT&T, Chase Manhattan and Sealed Air Company and were set to zero.

The Estimation Window and the Event Window

The data for each stock consists of 241 days. Day 221 is the announcement date, which forms the event window together with the 20 days before and after the announcement. The 200 trading days preceding the first day of the event window are used to estimate the parameters that are going to be applied in the event window. This is the estimation period for the primary analysis.

The secondary analysis are based on the same amount of examined days per stock but half of the data is available after the event. Therefore the event period lasts from day 101 to 141 in this framework and the data available for estimation are the 100 trading days before and after the event window. Though it is impossible to run a regression in an interrupted period I accepted inducing sever statistical problems by artificially combining the two parts of the estimation window. The results of the sample with the split estimation window are statistically not relevant, but from my point of view it can be valued as an index of robustness that this sample's results don't differ much from the results of the proper sample.

The Standard and Poors 500

The index consists of 500 stocks, that are supposed to give an overview of the U.S. economy, especially regarding big companies. Profitability is only one of the five major criteria that has to be accomplished by a company to be added to the S&P 500. The company has to be profitable in four consecutive quarters. The company requires 3 billion dollar market capitalization and at least half of it available to the market and in packets, smaller than 5%. The stock also needs to generate a turnover of about one third of its capitalization. The last important criterion is that the stock improves the representativeness of the S&P 500 regarding the U.S. economy. Funds cannot be part of the S&P 500.

The selection criteria for companies being added to the S&P 500 are not very clear which leaves as much space to the S&P Committee to follow their own judgment as to outsiders' speculation about the committees advantage in selecting profitable stocks.

On average the S&P 500 exhibits a very low return on the day following the announcement of the addition of a stock and a negative return on the day after a deletion. This is possible because the deleted stocks decrease in value and with them the S&P500, while the stocks that are going to be added cannot drive the index upwards yet. It could be a sign that some bias is incorporated in the analysis, because the S&P 500 and a stock within the index are not perfectly independent. And the S&P500 is possibly not the only imaginable benchmark for the added stocks. An overestimation of the announcement effect for the additions could result from that asymmetry, but the bias is very weak.

Benchmark Models

The calculation of abnormal returns requires a definition of what are normal returns. Different models were proposed in the literature over the last decades. The following section describes the models that are incorporated in this paper as benchmarks for the returns that the added and deleted stocks experienced.

The Market Model

Two different models to calculate (ab)normal returns are commonly found in the event study literature: the (OLS) Market Model and the Market Adjusted Model. The Market Adjusted Model bases on the fact that assets' average return is the market return and the difference between both is declared the abnormal return.

$$E(R_{asset}) = R_{market} + \varepsilon$$
$$R_{abnormal} = R_{asset} - R_{market}$$

The Market Adjusted Model is not consistent with the Capital Asset Pricing Model, because systemic risk is not equal for any asset. The Market Adjusted Model doesn't take into account, that market fluctuations do not affect all assets the same way.
The Market Model, on the contrary distinguishes between stocks that correlate strongly with the market and ones that correlate rather weakly according to Brown and Warner (1980).

$$E(R_{asset}) = \alpha + \beta_1 R_{market} + \varepsilon$$
$$R_{abnormal} = R_{asset} - (\alpha + \beta_1 R_{market})$$

α is an estimated constant. Its practical implication could be regarded as the influence of the constant risk-free rate of return.
β is the extent to which the asset is dependent on the market.
Brown and Warner (1985) leave the question open if Market Adjusted returns or returns adjusted via Market Model are more exact to fit the normality assumption and which has the higher power in prediction. This paper concentrates on the market model as the benchmark for the GARCH-M

Model and leaves the Market Adjusted returns aside, following the CAP-Model in the sense of taking the company-specific dependence on the market into account.[1]

The Multifactor Models

From the Market Model the Multifactor Model is easily derived by adding more factors than the dependence on the market (β_1). For example many multifactor models depend on the price of oil. Also exchange rates, raw materials like ore, indexes of sectors, etc. could be part of a multifactor model.

$$E(R_{asset}) = \alpha + \beta_1 R_{market} + \beta_3 P_{oil} + \beta_4 P_{ore} + \ldots + \varepsilon$$

I include two multifactor models as benchmarks in this paper. One is dependent upon the market and upon trading volume of the specific stock. It has the form:

$$E(R_{asset}) = \alpha + \beta_1 R_{market} + \beta_2 V + \varepsilon$$

$$R_{abnormal} = R_{asset} - (\alpha + \beta_1 R_{market} + \beta_2 V)$$

The other model is dependent on the market as well as the estimated GARCH(1,1) Variance (see below). Only for this model the event period is a subset of the estimation period. Therefore the parameters are already fitted to the condition that additions and deletions are examined. This model has no predicting character at all and forfeits a major part of its significance already by extending the estimation period to the event window, but also because it allows for another degree of freedom when the regression of the variance and the regression of the mean equation were run separately. The GARCH(1,1) – 2 step model has the form:

$$E(R_{asset}) = \alpha + \beta_1 R_{market} + \lambda \sigma^2 + \varepsilon$$

$$R_{abnormal} = R_{asset} - (\alpha + \beta_1 R_{market} + \lambda \sigma^2)$$

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[1] The Capital Asset Pricing Model splits up the total return in the return on time and the return on risk (Sharpe, William F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk, *Journal of Finance*, 19 (3), 425-442). Therefore the model usually has the form: $E(R_{asset}) = R_{interest} + \beta\ (R_{market} - R_{interest}) + \varepsilon$ Where beta is a measure for the exposure to systemic risk. In the case of the Market Model beta represents the correlation with the market and alpha the combination of the risk-free interest rate and it's weight. Within the CAP-Model framework beta is usually estimated by setting all other factors constant. The market Model leaves alpha a variable and estimates alpha as well as beta.

The components of the model (β_1, λ and α) are estimated by ordinary least squares(OLS).

The Generalized Autoregressive Conditional Heteroscedasticity Model

Autoregressive conditional heteroscedasticity stands for the fact that a time series variance is not constant, but influencing its own future value.
The ARCH (q) model proposes to derive the expected variance by addressing weights to the squared errors of q former periods and to the long run variance.

$$\sigma^2_t = \gamma V_L + \delta_1 \varepsilon^2_{t-1} + \delta_2 \varepsilon^2_{t-2} + \ldots + \delta_q \varepsilon^2_{t-q}$$

The ARCH(q) model assumes clustered variances that are reverting to a long term mean for long run forecasts. Short run forecasts are highly dependent upon the previous periods.
The GARCH model was developed by Bollerslev (1986) from the ARCH model by Engle (1982). It adds the previously forecasted variance to the variables, that lead to the actual variance. This makes it easy to update the variance forecast for every period without calculating a polynomial of e.g. the 6^{th} order, without losing the information of earlier shocks.
The GARCH model is specified by brackets, that show how many lagged squared errors (ARCH factors) and how many lagged variances (GARCH factors) are recognized by the model.
(G)ARCH-M model by Engle, Lilien and Robins (1987) takes into account that there might be a dependence between risk and return as proposed by the Capital Asset Pricing Model. It conditions the mean of the process on the conditional variance. The disadvantage of the GARCH model is, that information about the past is incorporated in squared form and so no difference can be made between positive and negative fluctuations, although the leverage effect might cause bigger volatilities for negative returns than for positive ones (comp. Kim and Kon, 1994). The GARCH process is stationary if a long run effect persists. In the case that no long run effect has a significant influence on the variance, the process can also be thought of as an Exponentially Weighted Moving Average (EWMA), as stated by Hull (2002).
The variance term for the GARCH(1,1)-in Variance process is defined as:

$$\sigma^2_t = \gamma V_L + \delta_1 \varepsilon^2_{t-1} + \theta_1 \sigma^2_{t-1}$$

γ is the weight of the long run variance V_L. γ has to be nonnegative to ensure a positive variance.
δ_1 is the weight of the squared prediction error ε in the previous period.

θ_1 is the weight of the variance of the previous period (σ^2_{t-1}).

δ and θ and γ V_L are going to be estimated by Ordinary Least Squares.

First I calculated the abnormal returns for the Market model with underlying GARCH(1,1) variance and found very few differences to the standard Market Model approach as I will show in a later section. This model only assumes clustered variances but no influence of the variance on the mean return.

Then I tested the influence of the variance on returns. The idea was that even if abnormal returns don't decrease significantly it might lead to symmetry of abnormal returns of additions and deletions to incorporate the variance, in case that the increased variance has a negative effect on expected returns. (It would be hard though to justify that finding theoretically)

For this purpose I applied the GARCH-M model where the conditional variance enters the mean equation:

$$R_{asset} = \alpha + \beta_1 R_{S\&P500} + \lambda \sigma^2_t + \sigma \varepsilon$$

$$R_{abnormal} = R_{asset} - (\alpha + \beta_1 R_{S\&P500} + \lambda \sigma^2_t)$$

$$\sigma^2_t = \gamma V_L + \delta_1 \varepsilon^2_{t-1} + \theta_1 \sigma^2_{t-1}$$

where ε is assumed to be approximately normally distributed $\varepsilon \sim N(0;1)$ and independent from $R_{S\&P500}$ to ensure orthogonality between the regressed variable and the regressor according to Wagner (2003). $R_{S\&P500}$ is drawn from a distribution that might be fat tailed but for reasons of simplicity will be assumed to be distributed normally with $\mu > 0$. Again the 3 factors α, β_1, λ are estimated via OLS and form an abnormal return in the event window, that will be compared to the abnormal return of the Market Model.

The next step was to perform an analysis that uses trading volume as a variance regressor in the GARCH term.

$$\sigma^2_t = \gamma V_L + \delta_1 \varepsilon^2_{t-1} + \theta_1 \sigma^2_{t-1} + \varphi V$$

This incorporation of volume partly follows Fleming, Kirby and Ostdiek (2001) who state that variance is partly explicable by volume. They argue that volume shocks don't have the persisting effect on variance that is assumed for return shocks in a GARCH(1,1) model. Still the authors propose an exponential GARCH model that deals with unexpected volume aiming at explaining a bigger part of the volatility. This paper's approach is to separate the part of the variance that is explicable by volume from the unexplained variance. Now it is tested if incorporating only the inexplicable part of the variance in the mean equation brings any improvement in explaining the returns in the moment of an addition or deletion.

The next model is a modified version of the GARCH(1,1)-M model that includes more lag operators in the variance equation. The GARCH(1,5)-M model is supposed to test to test whether including more lagged variances leads to better results, compared to the GARCH(1,1) model and whether a cyclical trend can be identified in the variance equation. The variance equation has the form:

$$\sigma^2_t = \gamma V_L + \delta_1 \; \varepsilon^2_{t-1} + \theta_1 \; \sigma^2_{t-1} + \ldots .. + \theta_5 \, \sigma^2_{t-5}$$

The incorporation of more lagged variances doesn't increase the information examined by the analysis, but allows, so to speak, a fine tuning of the weights addressed to earlier forecasts. The outcome of this analysis could probably identify a cyclical tendency within 1 week, because the lagged variances can affect the actual variance with a different level of impact.

Continuously compounded returns are used because they seem to have properties that rather fit the assumption of normally distributed errors than simple returns.
Cumulative abnormal returns will be calculated for the event window, also a cross-section of the analyzed companies around the event date.
All calculations and estimations were made using the e-views software.
I developed a tool within the e-views environment to facilitate the execution of the multiple regressions, because more than 7000 regressions had to be executed. The program collects all the relevant facts from the results of the regression models and saves them.

The Hypothesis

The general hypothesis H_0 for all event studies is that there is no announcement effect.
Starting from this hypothesis the paper tries to compare the different models and their outcomes. Special emphasis will be laid on the lambda factor for the GARCH-M models and its significance in order to examine if these methods lead to a more powerful tool for benchmarking the announcement effect. I will report the estimated factors and their statistics as well as the variance of the abnormal returns in the event period to compare the models. The hypothesis that there is no effect at all is not stressed, because the effect is evident for every analysis conducted.

The Deletions From the S&P 500

The deletions set in general offers a variety of results, depending on the selected benchmark model. In many cases a modest reversal could be identified. Only the claim that negative abnormal returns occur and occur before the announcement can be based on all different models, that I used to examine the announcement effect. The reason which suggests itself that insider trading is not deniable for this sample. The examined sample consists of 87 stocks.
The results are presented in tables that on the left side show the CAR for different periods and on the right side you will find the properties of the AR in the event window. On the bottom of each table the estimated parameters of the regression and the information criteria of the estimation period are listed.

The Market Model

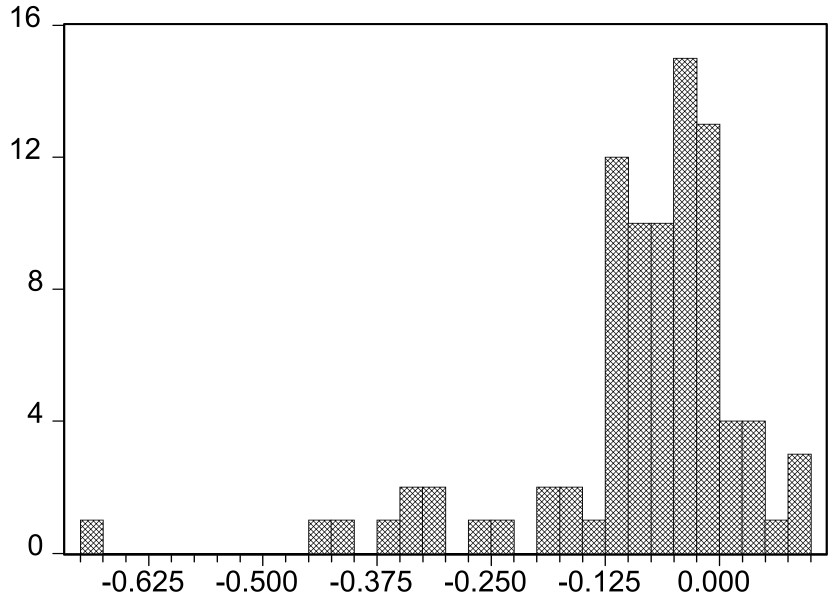
My findings regarding the deletions from the S&P500 were very close to Chen, Noronha and Singal (2002), when I applied the standard Market Model. I found that the deletions experience a negative abnormal return of 8.69% on the day following the announcement. Chen, Noronha and Singal found a decrease in price of 8.46% on that day. Also Lynch and Mendenhall (1997) report a decrease of the same dimension: 9.87%. The difference could be explicable by the fact that knowledge about the Index Effect is increasing and more arbitrageurs are profiting from it. The examination of Lynch, Mendenhall took place a few years earlier. Also the applied model of market adjusted returns could lead to a slightly different outcome.

CAR	Market Model	Mean	-0.0056
0/+1	-0.0869	Median	-0.0019
-20/+20	-0.2292	Std. Dev.	0.0191
-10/+10	-0.2444	Skewness	-2.6945
0/+10	-0.0614	Kurtosis	10.8943
α	-0.0014	R^2 adjusted	0.0952
β	0.8131	AIC	-4.1221

(TAB 2.1)

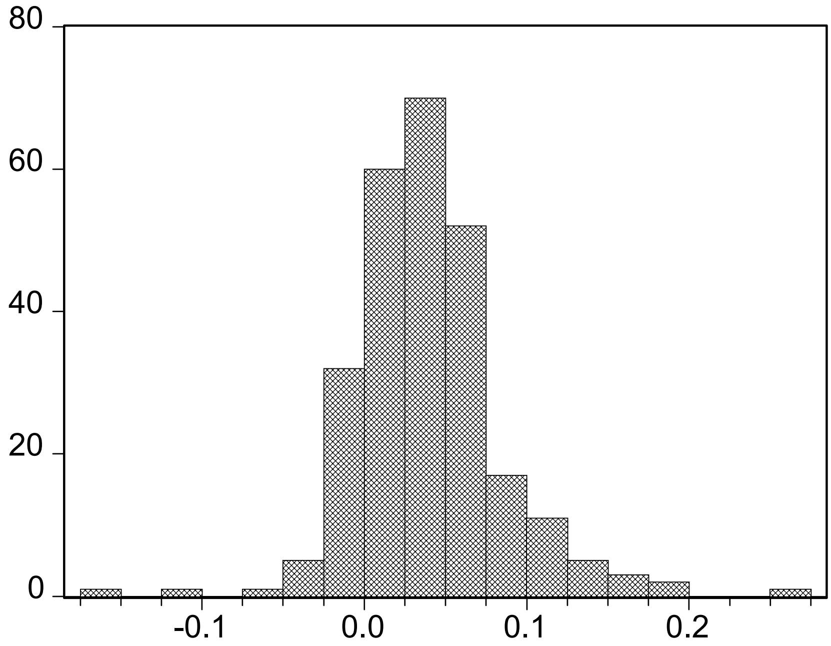
On day AD+2 the CAR reaches -0.2924 and recovers about 20 % in the 4 weeks after that. This leads me to the assumption that a part of the Index effect is only temporary. The coefficient alpha is calculated by OLS and represents the impact of the interest rate in the CAP-M framework. Surely in reality it is barely common to have a negative interest rate, but the value is obtained from a regression and adjusts the mean of the deletions set, because the deletions don't keep pace with the market. This is not a contradiction to the CAP model.

The relevance of the market factor "beta" is not questionable; it has a t-statistic of more than 4. Whereas the t-statistic of alpha is only 0.7. The figures show the cross-sectional abnormal returns on the day folowing the announcement for the deletions (upper) und the additions (lower).



Series: CROSSECTION	
Sample 1 87	
Observations 87	
Mean	-0.086921
Median	-0.058602
Maximum	0.094625
Minimum	-0.680061
Std. Dev.	0.122067
Skewness	-2.125053
Kurtosis	9.178887
Jarque-Bera	203.8774
Probability	0.000000

(Figure 1)



Series: CROSSSECTION	
Sample 1 261	
Observations 261	
Mean	0.039681
Median	0.036660
Maximum	0.257611
Minimum	-0.154695
Std. Dev.	0.044431
Skewness	0.597046
Kurtosis	6.863862
Jarque-Bera	177.8637
Probability	0.000000

(Figure 2)

The GARCH in Variance Model

When I assumed clustered Variances I had a very similar outcome. Minimum, maximum and the standard deviation of the abnormal returns didn't differ significantly from the abnormal returns derived by the simple Market Model. The correlation with the market turned out to be higher when clustered variances are assumed. Therefore abnormal returns exhibit a lower mean, because the prediction of the normal return is related more closely to the market which has a positive mean return in the event window. The t-statistics for the coefficients alpha and beta did not alter from the previous analysis.

CAR	GARCH in VAR	Mean	-0.0067
0/+1	-0.0867	Median	-0.0025
-20/+20	-0.2734	Std. Dev.	0.0192
-10/+10	-0.2607	Skewness	-2.6463
0/+10	-0.0688	Kurtosis	10.5240
α	-0.0006	R^2 adjusted	0.0781
β	0.9341	AIC	-4.1867

(TAB 2.2)

The GARCH (1,1) in Mean Model

Following Wagner (2003) I wanted to examine whether including the conditional variance of the previous model in the mean equation leads to lower abnormal returns. Also a decreased variance of the abnormal returns would be an indicator for the ability of the Garch in Mean Model to relate the variance and the return in the case of a deletion.

CAR	GARCH-M (1,1)	Mean	-0.0250
0/+1	-0.2814	Median	-0.0061
-20/+20	-1.0248	Std. Dev.	0.0574
-10/+10	-0.9674	Skewness	-3.4817
0/+10	-0.5026	Kurtosis	14.7875

A	-0.0102	R^2 adjusted	0.0734
B	0.8187	AIC	-4.1662
Λ	-0.9677	z (λ)	0.1522
Abs (λ)	8.4285	z (abs. λ)	0.6294

(Tab 2.3)

The negative abnormal returns encountered by the GARCH in variance model increase tenfold for the GARCH-M (1,1) model, also the standard deviation over the event window seems to rise in the same dimension, explicable by the elevated negative abnormal return, because nearly half of the event period has no abnormal returns at all in either cases .In comparison to the previous models, the more negative alpha, the comparable beta and additionally the negative lambda should lower the expected return by far, and therefore lead to lower negative – or even positive – abnormal returns. This is not the case and one way to explain it, is that the lambdas that are negative correspond to lower average variances than the positive lambdas. There must be quite some imbalance in the distribution of the lambda factors, or maybe a correlation between the encountered variance in the event window and lambda, because the average GARCH variance in the event window for the regarding stocks is higher than 0.01, combining this with the negative average lambda of about –1, the impact of the GARCH effect is in mean bigger than the impact of the alpha factor. The sample of all 87 lambda factors shows a standard deviation of about 19. Only 4 of the lambda factors are significant on the 5% level. When I calculated the average lambda after excluding the two biggest outliers from the sample I obtained an average lambda of 1.2808. The reason is that the two outliers are both negative (-121.5528 and –74.6022). This lambda factor seems to be more suitable to explain the strongly negative abnormal returns. Comparing the crossectional abnormal return on the day after the announcement with the one generated by the Market Model, no big differences can be reported, but one company has a big impact on the result: An extraordinarily high expectation leads to a negative abnormal return of about 1200% for Harnischfeger Industries, inc. This stock is one of the few that exhibits a significantly positive lambda in the estimation period and it drives the mean of the whole analysis. The stock experienced significant problems in the estimation period and a bankruptcy close to the event date and therefore I suppose that the high leverage substantiated the connection between mean and variance. The obtained z-value of the lambda factor doesn't let me conclude that additional, relevant information is conveyed by including the conditional variance in the mean equation on average. This puts doubt on the GARCH in mean model, but it is still possible that the relevant information was not incorporated in the mean equation in the correct way.

I didn’t encounter any significant reversal over the four weeks following the exclusion. The lowest CAR is obtained on day 15 after the deletion.

The Extended GARCH (1,5) in Mean Model

CAR	GARCH-M (1,5)	Mean	-0.0049
0/+1	-0.1064	Median	-0.0019
-20/+20	-0.2001	Std. Dev.	0.0232
-10/+10	-0.2130	Skewness	-2.4363
0/+10	-0.0311	Kurtosis	11.3929
α	-0.0066	R^2 adjusted	0.0528
β	0.8130	AIC	-4.1683
λ	-0.1181	z (λ)	-0.0027
Abs (λ)	1.6879	z (abs. λ)	0.4000

(Tab 2.4)

This method delivers by far better results. The outcome is not comparable to the GARCH (1,1) outcome, but rather to the standard Market Model. The abnormal return is lower, and the standard deviation of the abnormal returns is slightly higher than in the Market Model. The lowest cumulative abnormal return is reached on day 4 after the deletion (-31.87 %). Impact and significance of the lambda factor decrease significantly in comparison to the previous model. I find a high level of significance for the GARCH(3) factor, this implies that the used method incorporates the increased volatility for stocks on Mondays.
An astonishing difference to the previous model is that a negative lambda in deed leads to a lowered expectation of returns in the second half of the event period. I assume that lambdas and variances of certain stocks are not correlated in this model, may it be because the positive and negative lambdas are distributed differently among the stocks or because the variances have changed significantly. The encountered absolute abnormal returns are somewhat lower than in the other cases. This difference though is not necessarily big enough to cope with the increased number of degrees of freedom that are generated by introducing four more variables in the variance equation.
Again the lambda factor is distributed with a high standard deviation (4.6) around 0 among the deleted stocks.

In the crossection the model generates abnormal returns comparable to the market model on the day after the announcement. The out-liers in the GARCH(1,1)-M and the GARCH(1,1) – Regressed Variance models are not encountered when more lagged variances are included in the analysis.

This method doesn't seem any more exact to me than the standard market model approach, although the mean of the abnormal returns is lower than in the market model. The reason for this is, that the standard deviation is higher than in the Market Model, also I couldn't find a statistically relevant lambda factor. The GARCH in mean (1,5) model is not able to extenuate the effect around the announcement date.

The GARCH-M (1,1) Regressed Variance Model

CAR	GARCH-M(1,1) Reg.Var	Mean	-0.0001
0/+1	-0.0649	Median	0.0013
-20/+20	-0.0024	Std. Dev.	0.0176
-10/+10	-0.0430	Skewness	-1.4473
0/+10	0.0761	Kurtosis	6.6705
α	-0.0087	R^2 adjusted	0.0436
β	0.6421	AIC	-4.2662
λ	1.1040	z (λ)	0.1822
Abs (λ)	1.8849	z (abs. λ)	0.3884

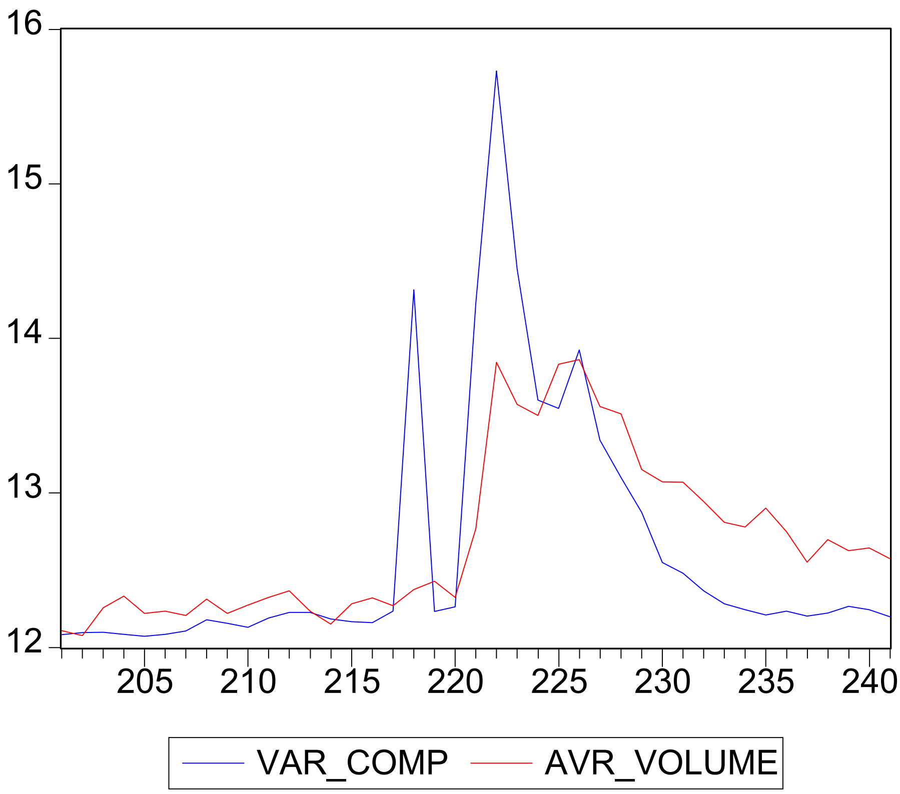
(Tab 2.5)

In this model I used the log-volume to regress the variance. This approach is designed to separate the variance in two parts: the part explicable by volume and the rest. The analysis shows that the results using only the part of the variance that is not explicable by volume might lead to better results. Using this method I encountered the lowest abnormal return on the day after the announcement so far and also the standard deviation of the abnormal returns is lower than for any other model. The value of lambda indicates the highest encountered impact of the variance on the price. But the level of impact is not easily comparable to the other models, because the variance is reduced by the regression, which means that a higher lambda factor is required to ensure an impact of the same dimension. This analysis is the only one that reveals a clear reversal for the stocks within the 20 trading days following the announcement, this reversal is even a complete reversal. The reverting trend seems to continue after the event window, at least no reduction in slope can be identified for the cumulative abnormal return when the former value is about to be recovered.

In the crossection one stock is conspicuous. Enron has an average insignificant lambda of about -0.9 and it shows a positive abnormal return of about 175% on the day after the announcement. The reason is that its variance increases enormously even before the event date.

In general the positive lambda leads to low abnormal returns on the day following the announcement, because the GARCH(1,1) variance around the announcement date is about seven times higher than it is before the event whereas the regressing factor – log. volume - increases by about 10%.

Kim and Kon (1994) describe that the significance of the ARCH and GARCH terms decrease as soon as volume is added in the variance equation. My findings do not support this result. The figure shows log. volume and the GARCH(1,1) variance. In order to compare the two series the variance was stretched on the same starting level as log volume: var_comp=$\sigma^2 * 70 + 11.3$. The day following the announcement is t=222.



(Figure 3)

I conducted another analysis that used the regressed variance, but also included 5 GARCH terms in the variance equation. The result was very similar to the GARCH-M (1,5), only the standard

deviation was insignificantly higher and the mean of the abnormal returns a little bit lower. Therefore I'm not presenting an extra table for the obtained values.
In this analysis the regression of the variance did neither lead to a diminution of the effect nor to a reversal. I observe an insignificant average lambda of 0.2059.

GARCH(1,1) – Two Step Model

Another try was to calculate a Garch (1,1) variance first and then make a least squares regression afterwards in a separate step including a constant, the market and the derived variance in the sense of o multifactor model. This approach has the disadvantages that it includes another degree of freedom and it includes the event period in the estimation period. Also the result is not very interesting as it doesn't differ much from the standard approach.

CAR	GARCH (1,1) – 2 Step Method	Mean	-0.0074
0/+1	-0.1014	Median	-0.0013
-20/+20	-0.3022	Std. Dev.	0.0250
-10/+10	-0.2949	Skewness	-2.3981
0/+10	-0.1197	Kurtosis	9.4974
α	-0.0111	t (α)	-0.6802
β	0.7870	t (β)	4.3793
λ	-0.3972	t (λ)	0.2040
R^2 adjusted	0.1374	AIC	9.8458

(Tab. 2.6)

Volume Supported Market Model

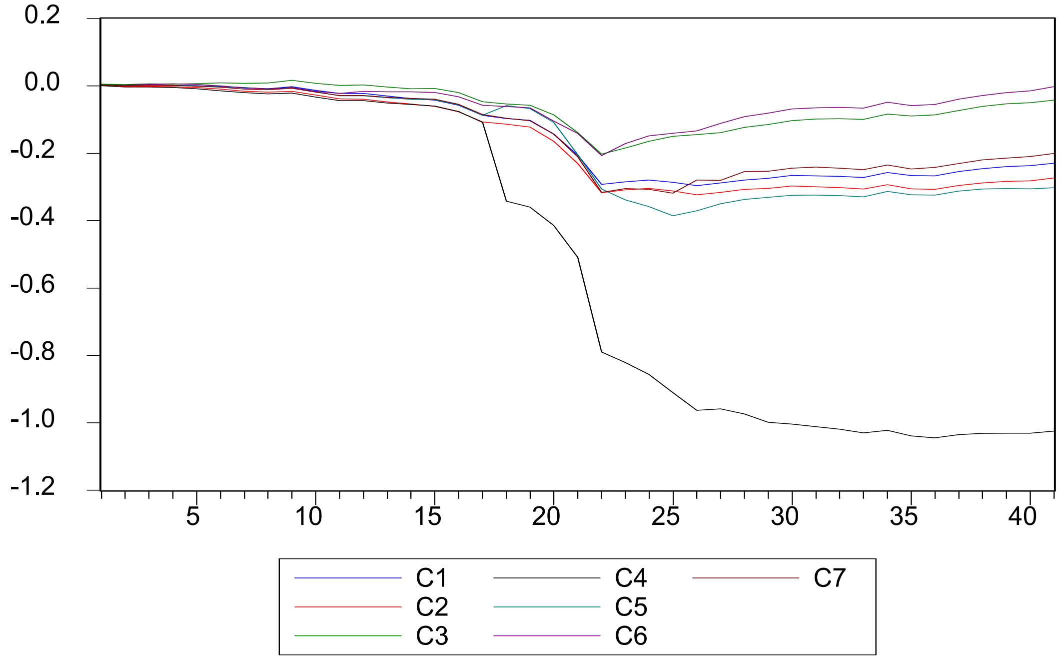
I also conducted an analysis, based on the market model, including volume as a further regressor of the stock price. This was preformed to make clear whether the additional information in the GARCH (1,1) Regressed Variance Model was the only reason for the enhanced result, whether an alternative method of incorporating the information leads to similar results.

CAR	Market Model & Volume	Mean	-0.0010
0/+1	-0.0642	Median	0.0015
-20/+20	-0.0423	Std. Dev.	0.0167
-10/+10	-0.0996	Skewness	-2.1196
0/+10	0.0403	Kurtosis	8.1888
α	-0.0007	t (α)	-0.4364
β	0.7968	t (β)	4.1803
β_2	2.50E-08	T of Volume	-0.0772

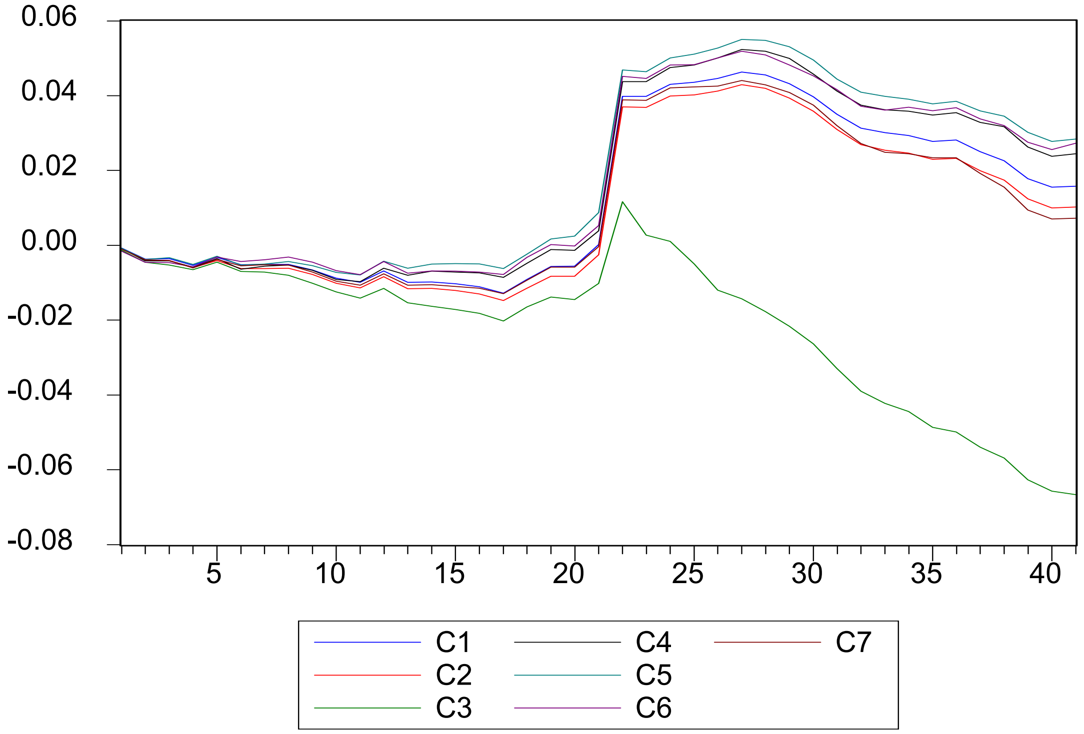
(Tab 2.7)

This method shows a strong reversal comparable to the GARCH (1,1) Regressed Variance Model. And the positive factor of the volume leads to a reverting trend that was not recognized in the Standard Market Model approach. The weight factor of volume seems responsible for a lower expected return although it is positive. The most reasonable explanation seems that a negative correlation between volume and the weight of volume, obtained by OLS regression, is causing the abnormal return to behave against the intuitive expectation. This correlation should have a similar extent as the correlation between the regressed variance and its weight in the GARCH (1,1) Regressed Variance Model. I can't tell if that is just a coincidence, because in fact the regression should have purged the influence that the volume has on the variance, but it seems that the correlation in this model persists even after the process of the regression – even using log. volume for the regression.

In my opinion most of the effect that shrinks the standard deviation of the GARCH (1,1) Regressed Variance Model is due to the additional information, that was included when the variance was regressed by the log. volume.



(Figure 4)



(Figure 5)

The upper graph describes the CAR of the deletions set.

The lower graph plots the additions' CAR. t=22 is the day following the announcement.[2]

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[2] C1 = standard market model
C2 = GARCH(1,1) in Variance
C3 = Market Model & Volume
C4 = GARCH(1,1) in Mean
C5 = GARCH(1,1) two-step model
C6 = GARCH(1,1) Regressed Variance Model
C7 = GARCH(1,5) in Mean

Additions to the S&P 500

The results of the additions to the S&P 500 differ in four major points from the deletions. Firstly the abnormal return around the announcement date is positive, secondly the effect seems to be weaker for the additions than for the deletions. The different methods of examination do not lead to such different results in comparison to the deletions set and the date of the announcement rather coincides with the reported effect. The examined sample contains 261 stocks.

The Market Model

CAR	ARETSTD	Mean	0.0004
0/+1	0.0397	Median	-0.0008
-20/+20	0.0158	Std. Dev.	0.0067
-10/+10	0.0450	Skewness	5.0704
0/+10	0.0349	Kurtosis	30.3451
α	0.0009	t (α)	0.4635
β	1.0017	t (β)	8.6798
R^2 adjusted.	0.1523	AIC	-4.6779

(Tab 3.1)

The stocks tended to decrease in value before the announcement. On day 3 before the event the first significant, positive abnormal return is obtained. The abnormal returns remain positive until day 8 after the announcement. From this point on the CAR drops from ca. 4.5% to ca. 1.6% on day 20 after the event. This means that roughly half of the value gained in –3/+8 is lost in the course of the reversal. There is no indication, that the reversal stops on day 20 after the announcement.

My findings regarding the cumulative abnormal returns are on the lower bound of the abnormal returns that were found by the authors mentioned above. Dhillon, Johnson (1991) found an abnormal return on the day following the announcement of 3.55%, when I found 3.97%. This astonished me, because after the increase of the effect in the years after 1970 the abnormal returns coming along with an addition to an index seemed to diminish in the preceding decade. Beneish and Gardner (1995) examined the Dow Jones Industrial Average and found a cumulative abnormal return of 2.72% in the period between 10 days before and 10 days after the announcement, which is not so far from my results. But in their paper the effect took place before the announcement while my findings show that a positive effect starts only three days before the announcement and is not very strong, the slope of the cumulative abnormal returns increases significantly on the announcement date. This suggests that insider trading in the Dow Jones Industrial Average is a bigger problem than it is in the S&P 500. Gerke and Fleischer (2003) found an effect of a similar extent for the German MDAX, but the reversion seemed to start earlier in their case. They discover a lower CAR for 0/+10 than the abnormal return on the announcement date. When I examined the S&P 500 the reversal started approximately 8 days after the announcement, so that the CAR of 0/+10 was still higher than the abnormal return on the day after the announcement. I can agree with Lynch and Mendenhall (1997), stating deletions from the S&P are affected more strongly than additions, I also found the same extent of the effect on the day following the announcement, that they found.

In comparison to the deletions in this sample the regression put out a positive value for alpha, because the stocks that are added to an index perform a little better than the index within the year before the event.

The same argument is valid for the increased beta coefficient. Alpha is statistically questionable, whereas the beta coefficient has a t-statistic of 8.7 and is therefore significant on the 1% level.

The GARCH in Variance Model

CAR	STDGARCH	Mean	0.0002
0/+1	0.0395	Median	-0.0009
-20/+20	0.0102	Std. Dev.	0.0067
-10/+10	0.0424	Skewness	5.0582
0/+10	0.0335	Kurtosis	30.2633
α	0.0010	z (α)	0.5772
β	0.9785	z (β)	7.4353
λ	0.0000	z (λ)	0.0000
R^2 adjusted	0.1368	AIC	-4.7144

(Tab 3.2)

When I assumed an underlying GARCH (1,1) variance the outcome is not very different. Within the whole event period the abnormal returns of the market model excel the abnormal returns of the

GARCH in variance model without any identifiable pattern. The reason for that is the slightly higher alpha coefficient. Though beta is lower than in the prior analysis, in order to compensate for a 0.0001 rise in the alpha coefficient the beta coefficient had to decrease approximately by 0.73 on average. The additions show a higher value for beta, when examined using the GARCH in variance model than for beta calculated using the standard market model approach. The standard deviation doesn't alter for the GARCH in variance method; this is another fact that leads me to the conclusion that only the increased alpha coefficient is responsible for a lower level of abnormal returns, that behave the same way as for the market model. The t-statistics of alpha and beta do not differ significantly from the ones obtained by the market model approach.

On the day after the announcement I could reject the hypothesis of negative mean returns with a p-value of 81%, using the crossectional abnormal returns. The preceding day I could reject the same hypothesis with a p-value of only 66%. In both cases I assumed a normal distribution for the abnormal returns.

GARCH (1,1) in Mean

CAR	GARCH (1,1) -M	Mean	0.0006
0/+1	0.0399	Median	0.0039
-20/+20	0.0245	Std. Dev.	0.0067
-10/+10	0.0510	Skewness	4.9755
0/+10	0.0374	Kurtosis	29.7275
α	0.0011	z (α)	0.8063
β	0.9479	z (β)	5.9062
λ	0.4299	z (λ)	-0.0164
R^2 adjusted	0.1315	AIC	-4.6293

(Tab 3.3).

When I related the results of the GARCH (1,1) in mean analysis with the outcomes of the standard and the GARCH in variance approach I was very astonished, because the results are very close to each other. In the deletions set the different analysis came to more varying results.

This method generates the highest abnormal returns so far, over the event period. The difference in the abnormal return on the day after the event is exactly the difference in the mean abnormal

return. Therefore I conclude that the GARCH(1,1) in Mean model doesn't let me anticipate the announcement effect in any way.
From day 20 before the announcement date the CAR decreases constantly until -0.0086 is reached 4 days before the announcement. Then little abnormal returns until the day after the announcement can be identified, the CAR rises strongly this day. On day 6 after the announcement (CAR: 0.05238) the reversal begins to reduce the CAR until about one third of the total announcement effect is left after 4 weeks.
The standard deviation is insignificantly higher for the GARCH in Mean analysis than for the Market Model approach. The mean standard deviation of the log. returns of the added stocks is nearly equal to the standard deviations of the abnormal returns obtained by the different approaches. I can barely find statistical advantage of modeling abnormal returns regarding the standard deviation.
The increased alpha factor leads to lower abnormal returns in comparison to the previous analysis. The reduction in beta is in mean negligible. Like in the deletions set I might again assume either a correlation between the estimated lambda and the observed variance in the event period or between the beta factor and the S&P 500 return in the event period in order to explain the increased abnormal returns. I concentrate on the lambda factor and preclude the possibility that beta is strongly correlated with the market returns. In this analysis the correlation had to be negative, so that a positive average lambda leads to lowered expected returns, especially because also the median of the lambdas is positive. Like in the deletions set a significant lambda factor could not be identified for the whole sample, only 8 of 261 lambda factors were significant on the 5% level. Compared to the results of Kim and Kon (1994) the obtained values of lambda show an extremely high standard deviation in the cross-section and a relatively low significance. In their sample 7 of 33 stocks turned out to be significantly dependent on the conditional variance on the 5% level.
The results for the cross-section of the companies in the day following the announcement don't vary significantly from the result of the preceding analysis.
The GARCH(1,1) in Mean model generates higher abnormal returns than the standard market model and the abnormal returns show a higher standard deviation. I can find no point in preferring the GARCH(1,1) Model to the standard approach for explaining the behavior of stocks in the moment of a inclusion to the S&P 500.

The Extended GARCH (1,5) in Mean Model

CAR	ARET1 (1,5)	Mean	0.0002
0/+1	0.0392	Median	-0.0005
-20/+20	0.0073	Std. Dev.	0.0067
-10/+10	0.0427	Skewness	4.8925
0/+10	0.0323	Kurtosis	29.1001
α	0.0007	z (α)	0.6977
β	0.9207	z (β)	5.9568
λ	0.5661	z (λ)	0.0838
R^2 adjusted	0.1075	AIC	-4.6174

(Tab. 3.4)

The GARCH(1,5) in Mean Model yields the lowest (cumulative) abnormal return for the event period of all analysis of the added stocks. Like in the deletions set the result is relatively close to the Market Model result. If one could speak of a extenuation of the announcement effect when the average return of the stocks on day 1 after the addition is 0.04045, the market model is able to explain 0.00077320 of this return and the GARCH(1,5) model explains another 0.00046996, so this is the case. The statistical relevance though tends to zero because of the low extenuation and the increased number of degrees of freedom. Five of six ARCH and GARCH parameters are significant on the 5% level and all six are significant on the 10% level. Like in the deletions set the analysis reveals an especially high significance for the GARCH(3) factor.

The GARCH-M (1,1) Regressed Variance Model

In this analysis the variance is calculated by GARCH(1,1) estimation and regressed by log. volume. The result is partly comparable with the corresponding analysis in the deletions set:
Beta shrinks to two thirds of its level, the average lambda increases significantly and the standard deviation lies slightly below all the other analysis' standard deviation so far.

CAR	GARCH-M(1,1) Reg.Var	Mean	0.0007
0/+1	0.0398	Median	0.0053
-20/+20	0.0273	Std. Dev.	0.0067
-10/+10	0.0495	Skewness	5.0258
0/+10	0.0363	Kurtosis	30.0294
α	-0.0005	z (α)	-0.1023
β	0.6800	z (β)	4.0239
λ	1.5888	z (λ)	0.2764
R^2 adjusted	0.0887	AIC	-4.7041

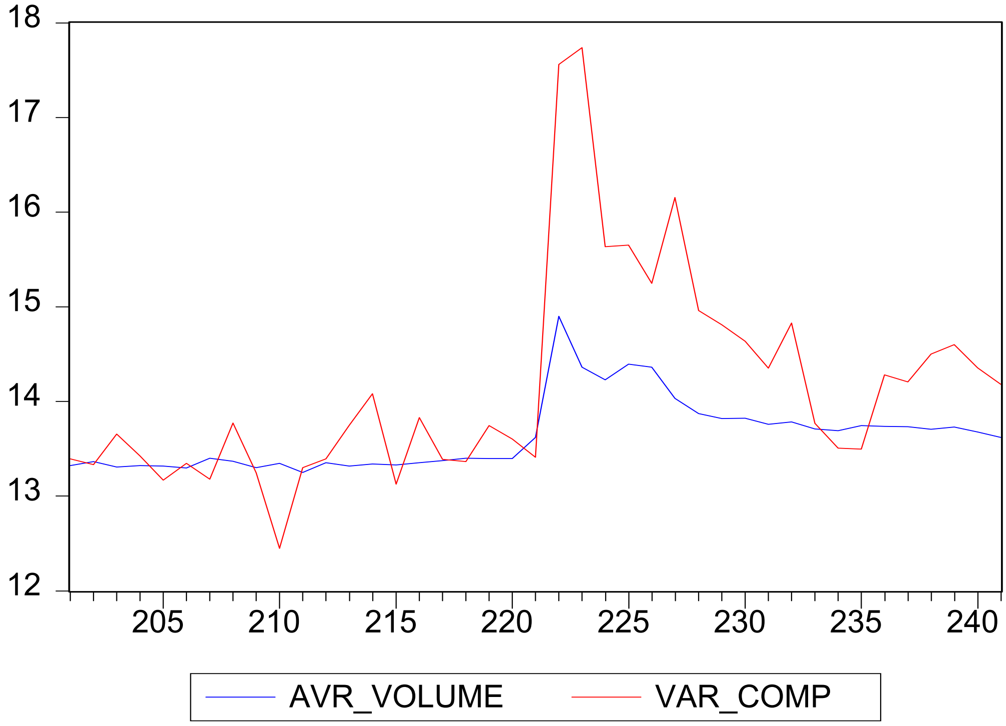
(Tab 3.5)

This method exhibits abnormal returns higher than the ones obtained by the Market Model for nearly all 41 days of the event period, but for the day following the announcement and the preceding day lower abnormal returns are found. The GARCH variance is quite stable at about 0.00095 until the day following the event when the variance rises to 0.00125. The average log volume rises for the day of the event from 13.62 to 14.90. I assume that the factor that incorporates the log.volume in the variance equation is nonnegative, because it's not conditioned on the number of transactions (Jones, Kaul, Lipson, 1994) and this implies that the conditional variance rises significantly for the day following the announcement. Alpha is constant. I can state that not the relatively weak dependence upon the market accounts for the lower abnormal return on the day following the event and the preceding day, because the market's return is very low on this day in mean. So it must be the influence of the regressed variance that extenuates the announcement effect.

When I added further lag operators to the regressed variance analysis to combine the GARCH(1,5) method with the regressed variance method, corresponding to the analysis of the deletions set. I found strongly decreasing values for alpha, beta and lambda and their significance. The incorporation of the log. volume had nearly no effect on the standard deviation, but the CAR rose sparsely. Only in the cross section of the abnormal returns between the examined stocks the performed operation shows a slightly lower standard deviation for the day after the addition.

All in all this analysis couldn't combine the advantages of the GARCH(1,5) and the GARCH(1,1) – regressed variance models. Standard deviation as well as mean value lie above the lowest value obtained in the two other analysis, to say nothing of statistical relevance and the increased number of degrees of freedom.

The picture shows the average trading volume and the obtained GARCH(1,1) variance. The conditional variance was multiplied by 14000 in order to fit the variance and log. trading volume in an expressive picture.



(Figure 6)

GARCH (1,1) – 2 Step Method

This model has statistic difficulties, but from my point of view the output is the most interesting, because the extenuation of the announcement effect is more distinct in this case than in any other, especially if I take the higher general level of abnormal returns into account. This effect is also visible in the lowered standard deviation and should partly be attributed to the relatively high factor of impact of the GARCH variance, that is also called lambda in the upper table. I suppose that it is not only the higher impact of the variance but also how the factors are distributed among the sample, because integrating the event period in the estimation period allows the regression to allocate higher factors to the stocks reacting stronger in the moment of an addition.

CAR	GARCH (1,1) – 2 Step Method	Mean	0.0007
0/+1	0.0382	Median	0.0087
-20/+20	0.0284	Std. Dev.	0.0065
-10/+10	0.0524	Skewness	4.8924
0/+10	0.0357	Kurtosis	29.0093
α	0.0002	t (α)	-0.1631
β	0.9868	t (β)	13.3744
λ	1.8408	t (λ)	0.2003
R^2 adjusted	0.1832	AIC	10.3754

(Tab. 3.6)

Volume Supported Market Model

CAR	Market Model & Volume	Mean	-0.0016
0/+1	0.0219	Median	-0.0145
-20/+20	-0.0667	Std. Dev.	0.0047
-10/+10	-0.0188	Skewness	3.0518
0/+10	-0.0227	Kurtosis	16.4380
α	-0.0008	t (α)	-0.2853
β	0.9983	t (β)	8.7161
β_2	1.05E-008	t (Volume)	0.0000

(Tab. 3.7)

This multifactor model generates lower abnormal returns than any other model, but the mean return is even negative in the announcement period. When I tested log. volume in stead of volume in this model as the third factor, I came to a negative mean of about 0.0010 and a standard deviation of 0.0061, which neither solved the problem of negative abnormal returns in the event period nor yielded a moderated abnormal return for the day following the announcement. The problem is that this method relies on trading volume and the event period exhibits a very high level of trading volume that is not limited to the announcement date but clearly visible within the whole period of 41 days.

Results For the Split estimation window analysis

I described before, that I analyzed two different samples. The results for this sample are not very sound, because the estimation period consists of two separate periods, that were artificially combined in order to assemble a continuous estimation period. The results of this analysis should mainly grant for robustness of the previous results, therefore I won't add all the analysis' statistics here, I will rather lay stress on the differences.

The two sets of deletions differ more from each other than the additions. The lambda I obtained in the split event-window analysis for the various equations seemed rather positive than negative but still insignificant. The extent of the effect is weaker in mean as well as in standard deviation when I investigated the split-window sample. This is valid for all analysis of the deletions but the regressed variance method. The GARCH(1,1)-M approach yields a CAR of ca. –80% over the event period.

In the additions' set quite the contrary is true. Only the multifactor model relying on trading volume shows a lower mean and standard deviation. All other analysis find lower expected returns and a higher standard deviation. The decreased absolute abnormal returns for the market model including volume must result from the higher average level of volume in this estimation period.

All in all it can be said that the event period exhibits a high level of trading volume. In the case of the deletions the volume is quite constant and seems to regress slowly to the former value after the event period. The additions clearly show a monotonously increasing trading volume over the whole 220 days before the announcement, starting from a higher level than the mean deletion set volume and a constant trading volume on a high level after the event period.

Correlation

The deletions set drew my attention because the lambda factor and the estimated GARCH (1,1) variance seemed to correlate. I assumed that a stock that shows a higher lambda in the estimation period - it reacts relatively positive to an increase in variance – , experiences a higher variance when it is deleted from the S&P 500. This didn't seem intuitive to me and therefore I tried to examine the outcome more deeply. I calculated the correlation between the mean variance in the

event window and the lambda factor obtained in the estimation period. I used the data from the GARCH-M (1,1) analysis and found a positive correlation of less than 3%. When I corrected the correlation for the two outliers in the mean variance vector I already found a correlation of 8.7%.This correlation is very weak, but considering the wide spread distribution of the lambda values and the relatively narrow distribution of the variances I still assume that this must be the reason why lower lambdas lead to higher expected returns in the event window average. The implication of this correlation might be that some risky stocks react positively on an increasing variance but investors value the deletion from the S&P 500 as a failure of the company strategy. Companies being close to bankruptcy could fit the described pattern. A model that accounts for the leverage effect could possibly evade the correlation.
The alternative explanation would be that betas and market returns in the event window were strongly correlated, at least for the GARCH(1,1) in Mean analysis. I doubt this dependence from the statistical point of view because of the low impact of the beta factor and the rather narrow distributions of the betas and the market returns among the sample. Even if this correlation was statistically proovable by the sample data I couldn't imagine a reasonable explanation. It had to be a random outcome, because how can one stocks beta affect the market or vice versa, when the stock is deleted from the S&P 500? This relation between beta and the market can't be distinct.

Information Criteria

The adjusted R^2 indicates the percentage of the actual variation in the returns explained by the regression. Comparing the obtained values for the adjusted R^2 with the paper of Wagner (2003) I find, that the in sample fit is quite low, ranging from about 7% to 15%, depending on the model and the set of data. Even more striking is that the R^2 adjusted for the GARCH analysis is lower than for the standard Market Model approach, analyzing the S&P 500. As I could detect substantial differences between the additions and deletions, I assume that the set of data used by Wagner (German stocks after an initial public offering) was different enough to cause the discrepancy. The in sample fit for the additions was significantly higher than for the deletions. This becomes even more clear looking at the Akaike information criterion (AIC); the values of the deletions exceed the additions' values. The lowest AIC was found for the GARCH in Variance model applied on the additions. Still all AIC are distributed closely around –4 with a standard deviation of about one for all sets of data and models of examination. The information criteria of the GARCH(1,1) –2 Step Model are not included in this comparison because of its statistical questionability. The AIC as well as the R^2 are much higher.

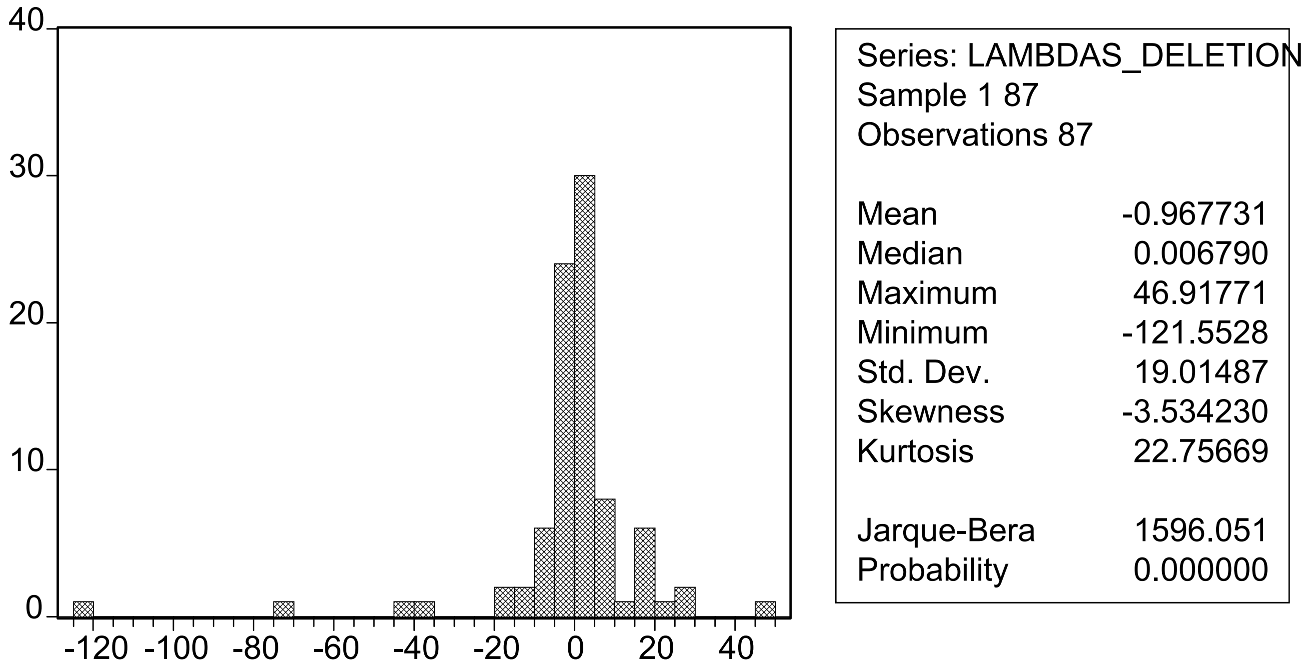
The big amount of data relative to the few parameters to estimate grants that the regressions are not overfittet. This is also visible in the relatively low R^2, that indicates that the in sample performance of the various models is not high enough to cause fear of overfitting. Only the 2 step model could be overfitted. Another problem for non-linear analysis is Data-Snooping. It is not a danger for the performed analysis, because the underlying set of data was defined before the first regressions were run. The presented results are the only ones that were calculated. In general an analysis that explains a big part of the variation of the base value has to be controlled well for Overfitting[3] and Data-Snooping[4], but the results of the performed analysis in this paper were rather the opposite.

Normality

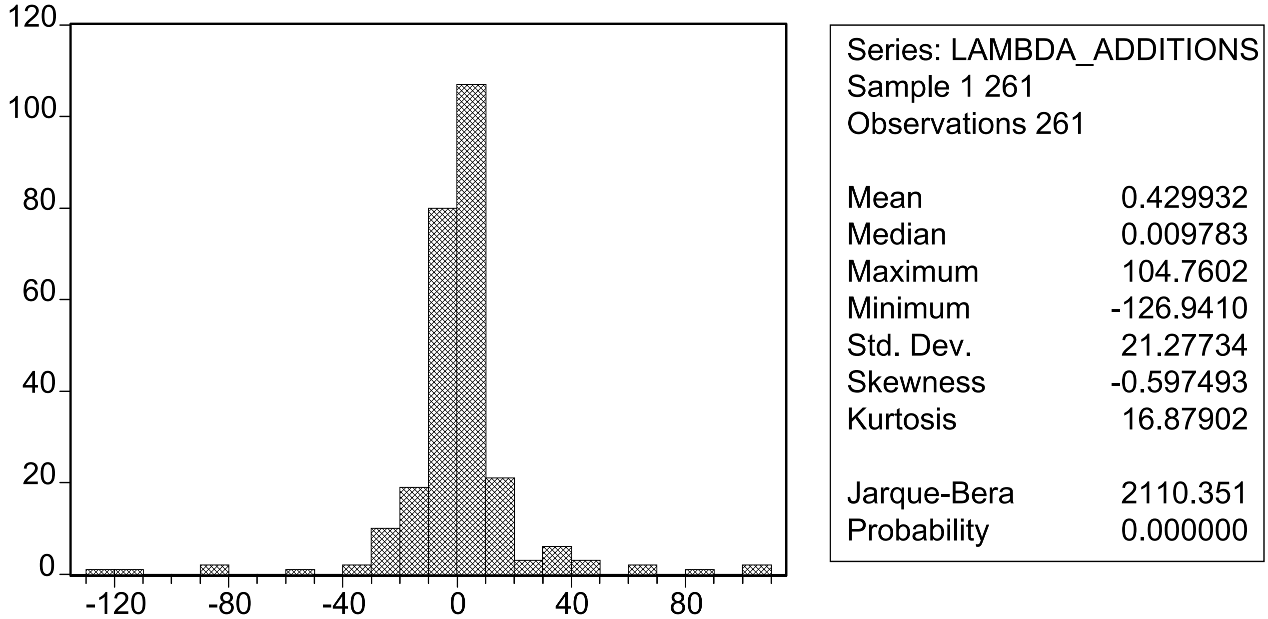
According to the Jarque-Bera statistic the assumption of normally distributed abnormal returns can be rejected on an extremely low level of significance for all analysis within the event period, but the Jarque-Bera statistic might be insignificant because the residuals weren't standardized for the performed estimation procedure. The same is true for the obtained lambdas. Also the mean log. returns of the deletions over the event period don't seem to be normally distributed with a Jarque-Bera statistic exceeding 130. For the mean log. returns of the additions during the event period the hypothesis of normally distributed returns can not be rejected on a reasonable level of significance. For additions as well as deletions normally distributed mean log. returns can't be rejected in the estimation period. The following figures will show the distribution of the estimated lambdas for the deletions and the additions (GARCH (1,1)-M).

[3] „Overfitting occurs when a model fits „too well", in the sense that the model has captured both random noise as well as genuine non-linearities." (Campbell, Lo, McKinlay, The Econometrics of financial markets, p. 523)

[4] Data-Snooping biases arise when we ignore the fact that many specification searches have been conducted to obtain the final specification of a model we are fitting to the data. Even if a model is in fact incorrect, by searching long enough over various datasets and/or parameter values, we are likely to find some combination that will fit the data. (Campbell, Lo, McKinlay, The Econometrics of financial markets, p. 523)



(Figure 7)



(Figure 8)

Volume and Variance

The collected data lets me conclude that trading volume is a very important factor for the S&P Committee when it comes to an addition to the S&P 500. Decreasing volume doesn't seem to be a major reason for deletions, although the level of trading volume is significantly lower for the stocks in the deletions set. The conditional variance of the deletions set is about tenfold the variance of the additions. Therefore also the level of variance could be an important factor for the committee. On the other hand this could be regarded as a validation of the leverage effect that postulates higher variances for losses than for gains. (Black, 1976)

Conclusion

I have to confirm abnormal returns for stocks being affected from index recomposition. The effect seems to be stronger for deleted stocks than for added stocks. I also have to confirm a partial reversal within the 20 trading days following the restructuring of the S&P 500. The deletions recover about one fifth of the losses accumulated around the announcement while the additions lose between one third and half of the gains. There is no indication that the reversal ends with the event period.

From my point of view it is hard to tell which hypothesis (PPH, LH, ISH, VH) is supported by the results of the analysis. The hypothesis that fits the observed reversal is the Price Pressure Hypothesis. The reason of the short-term price effect must be imperfectly elastic demand or supply and the explanation for the imperfect elasticity might be the Imperfect Substitutes Hypothesis if the Visibility Hypothesis is considered. The ISH postulates that different market participants value the same stock differently. This could have many reasons: Asymmetric information, different modeling of the price out of the available information, transaction costs, market access and more. But another essential point is whether the process of modeling any price has even taken place in recent days or not. This is why the Visibility Hypothesis could be used to explain the short-term part of the relevance of the Imperfect Substitutes Hypothesis. And the validity of a short-term ISH could lead to a reversal and a congruency with the PPH. I can't make a reasonable statement about the Liquidity Hypothesis on the basis of my studies, because a main assumption of the theory remains untouched by my analysis – the lowered transaction costs. On the one hand I may support the statement of augmented volume for stocks added to the S&P500 but on the other hand I can't comment on the proposal that therefore the variance decreases in the long run.

I cannot prove that the GARCH models achieve enhanced results for stocks being added or deleted to the S&P 500, although some partial results were interesting. Assuming a GARCH variance seemed to explain a little part of the announcement effect within the additions set, and also the GARCH(1,5)-M approach extenuated the announcement effect, especially if the abnormal return was conditioned on its mean. Whereas improvement of explaining abnormal returns in the moment of a deletion was hard to find; only the GARCH(1,5)-M model generated low abnormal returns for the event period, but could not extenuate the effect in the moment of the addition at all.

I identify one major problem applying a GARCH model to additions and deletions of the S&P 500. The variance of the stocks – mainly so called "blue chips" – is relatively low in the estimation period and much higher in the event period. It seems that the event causes a rise in variance of a dimension that beforehand in the estimation period could not be accounted for, because of a lack of similar events. This problem might be proven by the distribution of the lambda factors among the stocks and it is especially true for the deletions set. The distribution of the lambdas is very fat-tailed.

Improvements to the models proposed by this paper could probably be made if the variance was negatively conditioned on the liquidity of a company to account for the leverage effect and its implications on risk. An asymmetric model, as proposed by Pagan and Schwert (1990) or the model by Glosten, Jaganathan and Runkle (1993) that also discerns between positive and negative innovations with a dummy variable, could be the appropriate measures for further analysis. Also Cheung and Ng (1992) perform an EGARCH model that is conditioned on firm size and find significant dependence of returns on variances. Another idea would be to find exogenous values for reasonable lambdas to apply on additions and deletions instead of estimating a specific lambda for every stock. It seems that stocks that are added and deleted behave rather like other stocks that were added or deleted and not so much like they used to behave in a preceding period.

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