A Market Model with Time-Varying Moments and Results on Neuer Markt Stock Returns

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Abstract

The well-known market model of returns is considered as an empirical specification for modeling returns in the aftermarket for German Neuer Markt initial public offerings (IPO's). In order to account for time-varying return variance after the IPO, model innovations are autoregressive conditional heteroskedastic, volume enters the conditional variance equation and expected return is a function of conditional variance. It is shown that the proposed model has non-critical stationarity and extremal return features. Empirical results follow from a sample of Neuer Markt stocks traded during the first two years after initial listing. There is evidence of different distributional characteristics, including abnormal performance within a period of roughly six months of aftermarket trading. Conditioning abnormal returns on estimated aftermarket return variance yields lower levels of statistical significance than the standard approach.

Key Words: market model, event study methodology, ARCH, aftermarket IPO returns, trading volume

JEL Classification: C20, G14

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1. Introduction

The market model has a long tradition in the empirical finance, economics and accounting literature where it found wide application in studies of stock return behavior. The model is based on a statistical setting which typically includes a market factor orthogonal to idiosyncratic noise. Following the seminal work by Fama, Fisher, Jensen, and Roll, it serves as a model of equilibrium returns in event study investigations (e.g. MacKinlay (1997) and Campbell et al. (1997)). Refining the standard approach, various modifications were proposed in the literature. Early work considering the effect of autoregressive conditional heteroskedasticity (ARCH) around an event is the simulation study by Böhmer et al. (1991). Franks et al. (1991) propose a multi-factor approach to measuring abnormal performance. A detailed discussion of the traditional versus the so-called conditional event study methodology is given by Prabhala (1997). In contrast to the traditional methodology, the latter accounts for the possibility that company announcements are deliberate management decisions and happen conditional on the arrival of prior information. Hence, rational market participants may form expectations prior to the occurrence of an event. Still, Prabhala concludes that traditional inference is capable of testing for the existence of information effects. Needless to say, despite to its wide use, the market model and the event study methodology are subject to a number of econometric shortcomings: Coutts et al. (1994) critically review the methodology and point out potential sources of misspecification.

The aim of the present paper is twofold. First, it is to present a generalized version of the traditional market model. Second, it is to provide an application not in the context of a classical event study, but as an examination of German Neuer Markt IPO aftermarket returns. Apart from fitting the model and estimating abnormal returns, distributional return properties and particularly tail behavior are analyzed.

Considering the first point, the paper adds to the precision of potential market model specifications by proposing a modification which takes fluctuations in trading volume into account, thereby referring back to a suggestion by Lamoureux and Lastrapes (1990). The refinement of the model allows for time-varying conditional return variance where particularly volume data are used to account for changes in the level of stochastic variance. Furthermore, a time-varying risk premium is modeled as a function of conditional variance (Engle et al. (1987)) and, in our setting, relates to trading volume. In summary, the proposed model has two observable and one unobservable variable determining conditional returns, namely the market factor, trading volume and conditional return variance.

The proposed model allows us to derive estimates of market beta and other model parameters while taking potential time-variation in first and second moments into account. Apart from the issue of heteroskedasticity which relates to estimation efficiency, modeling time-varying moments e.g. in event studies is economically relevant for an unbiased measurement of abnormal returns: It is well-known that information events have effects on volatility and trading. Hence, so-called “abnormal” returns around some event may at least be partly explainable by a suitable return model. For example, if stochastic volatility relates to a market-wide time-varying risk premium (Merton (1980)), increased volatility may also coincide with a positive abnormal stock return as found e.g. by Golsten et al. (1993). When trading volume relates to a risk premium (cp. Gervais et al. (1998)), market participants require compensation for abnormal trading activity. Hence, by its implicit stationarity assumption, the standard model does not consider variation in the return dynamics around an event and therefore potentially yields biased estimates of abnormal returns.

Considering the second aim of the paper, an application of the model is presented not as a classical event study, but as an application to aftermarket IPO returns. The initial underpricing and the long-run price behavior of IPO’s has attracted the attention of financial economists for decades and also gave raise to a number of empirical studies of the German market including e.g. Schuster (1996) and Stehle et al. (2000). Recently, Aggarwal (2000) pointed out that there is evidence of a difference between aftermarket and otherwise regular return behavior for IPO’s in the US-market. The present paper addresses the issue of IPO aftermarket return premia for a sample of German Neuer Markt stocks. Thereby it accounts for the potential effects from the particular volume dynamics after an initial offering. The perspective is on the short term return aftermarket dynamics as compared to the return dynamics from a later estimation window. As we do not measure performance against some absolute standard (i.e. an asset pricing model), anomalies such as size are not accounted for and have an identical impact on our first versus second return window. The aim of our empirical application is to study differences in the return dynamics for aftermarket IPO and later market trading which one would consider as “normal”. This is in the spirit of the classical event study methodology.

A crucial issue in empirical market model fitting is the degree of fat-tailedness in the idiosyncratic return component, a feature that is well-documented in the empirical finance literature. We therefore do not assume a normal distribution for the idiosyncratic return component and provide general results on the stationarity conditions and the extremal behavior of the marginal return distribution of our market model. Based on earlier mathematical results one can show that the conditions for our model follow as a straightforward extension of those for the well-known GARCH(1,1)-process. In the empirical part of the paper we then carry out an estimation of the tail indices of our event window average return distributions. Similar estimation techniques were previously for example used by Krämer and Runde (1996) who, among other characteristics, study the tails of German stock returns.

The empirical results for our sample of Neuer Markt IPO's show that there is evidence of statistically significant abnormal performance within the first six months of aftermarket trading. Apart from a higher return expectation this coincides with positive skewness and a thinner lower tail of the return distribution. The results also show that caution is advisable in abnormal return measurement: Application of the proposed modified market model by conditioning aftermarket returns on aftermarket return variance yields much lower levels of statistical significance for abnormal performance than the standard approach.

The remainder of the paper is as follows. The model and its properties are outlined in Section 2. The empirical study on Neuer Markt IPO's is given in Section 3. The paper ends with a brief conclusion in Section 4.

2. The Market Model

This chapter outlines the standard and modified version of the market model. We discuss model assumptions and the conditions for the existence of a stationary marginal return distribution function as well as its tail behavior.

2.1. General Model Assumptions

Based on the financial time series P_t, $t = 0, 1, ..., T$, we model continuously compounded returns $R_t = \ln P_t - \ln P_{t-1}$. The raw returns $(R_t)_{1 \leq t \leq T}$ are assumed to follow a market model of the form

$$R_t - (\alpha + \beta F_t) = X_t, \tag{2.1}$$

with $\alpha, \beta \in \mathbb{R}$. The abnormal returns $(X_t)_{1 \leq t \leq T}$ are orthogonal to the observable market factor $(F_t)_{1 \leq t \leq T}$: $X_t \perp F_t$.[1] The market factor is normalized to have zero expectation, $\mathbf{E}F_t = 0$, has finite variance and is drawn from some stationary distribution.

2.2. The Unconditional Market Model

In the classical market model (2.1), the abnormal returns X_t's are typically assumed to be iid draws from some distribution function F_X with $\mathbf{E}X_t = 0$ and finite constant variance $\mathbf{E}X_t^2 < \infty$. Considering empirical results on financial returns, one may assume that F_X is fat-tailed.

2.3. The Conditional Market Model

In contrast to the classic market model, the modified market model does not assume that the abnormal returns X_t's in (2.1) are iid, but allows for a conditional distribution with time-varying expectation and variance.

2.3.1. Specification

Here we assume that the abnormal returns from equation (2.1) can be modeled as heteroskedastic innovations with time-varying mean which linearly relates to conditional variance

$$X_t = (\lambda \sigma_t + Z_t)\sigma_t, \tag{2.2.1}$$

or to conditional volatility (see Merton 1980):

$$X_t = (\lambda + Z_t)\sigma_t. \tag{2.2.2}$$

The constant $\lambda \in \mathbb{R}$ is a risk premium coefficient and σ_t^2 is the conditional abnormal return variance. The Z_t's are iid draws from some symmetric, possibly fat-tailed distribution function F_Z. Further assume a finite second moment and particularly let $\mathbf{E}Z_t = 0$, $\mathbf{E}Z_t^2 = 1$ and $Z_t \perp F_t$.

As Z_t and σ_t^2 are assumed to be independent random variables, the time-varying conditional expectation of X_t is

$$\mu_t | (\sigma_t^2) = \lambda \sigma_t^2. \tag{2.3}$$

[1] This is equivalent to $Cov(X_t; F_t) = 0$. Note that raw returns are modeled which is suitable for daily returns. Alternatively one may define returns in excess of a risk-free period rate.

for (2.2.1) or

$$\mu_t|(\sigma_t^2) = \lambda\sigma_t. \tag{2.3}$$

for (2.2.2). This specification became known as 'ARCH-M' in the econometrics literature. Note that X_t in (2.2) has non-zero unconditional expectation. For $\lambda = 0$, a zero unconditional expectation as in the standard market model results.

The conditional variance of abnormal returns in equation (2.2) is modeled as

$$\begin{aligned}\sigma_t^2|(\sigma_{t-1}^2, Z_{t-1}, U_t) &= \omega_0 + \omega_1(X_{t-1} - \lambda\sigma_{t-1}^2)^2 + \omega_2\sigma_{t-1}^2 + \omega_3 U_t = \\ &= \omega_0 + \omega_1(Z_{t-1}\sigma_{t-1})^2 + \omega_2\sigma_{t-1}^2 + \omega_3 U_t, \end{aligned} \tag{2.4}$$

where $\omega_0 > 0,\ \omega_j \geq 0,\ j = 1, ..., 3$. Equation (2.4) is based on the definition of the conditional variance in the well-known GARCH(1,1)-process. As usual, the definition is based on suitable start random variables X_0 and σ_0. Additionally, a stationary series of contemporary non-negative random variables $(U_t)_{1\leq t\leq T}$ with $\mathbf{E}U_t < \infty$ enters the conditional variance equation. Note that requiring $U_t \perp F_t$ is sufficient in order to ensure the orthogonality condition $X_t \perp F_t$ in equation (2.1).

In the following section we ask under which conditions a stationary marginal distribution F_X' of the abnormal returns X_t follows.

2.3.2. Stationarity and Extremal Behavior of Abnormal Model Returns

The stationarity conditions and the extremal behavior of stochastic processes of the ARCH type have been widely studied in the literature. An overview of earlier mathematical results and related literature can be found for example in Nelson (1990), Embrechts et al. (1997, Chapter 8.4), and Mikosch and Stărică (2000).

It is well-known that the stationarity properties of GARCH(1,1)-models can be treated in the context of the general class of stochastic recurrence equations of the type $Y_t = A_t Y_{t-1} + B_t,\quad 1 \leq t \leq T$, with given start random variable Y_0 and iid pairs (A_t, B_t) independent of Y_{t-1}. Considering model (2.2), as Z_t and σ_t^2 are independent, the model yields a stationary distribution for X_t if and only if σ_t^2 given in (2.4) is stationary. The conditional variance equation (2.4) can be rewritten as

$$\sigma_t^2 = (\omega_1 Z_{t-1}^2 + \omega_2)\sigma_{t-1}^2 + \omega_0 + \omega_3 U_t. \tag{2.5}$$

Here, $A_t \equiv \omega_1 Z_{t-1}^2 + \omega_2$ and $B_t \equiv \omega_0 + \omega_3 U_t$ are assumed to be independent of σ_{t-1}^2.

Stationarity Based on (2.5), a theorem by Vervaat provides necessary and sufficient stationarity conditions for the marginal distribution of σ_t^2 and X_t^2; see e.g. Nelson (1990) and Mikosch and Stărică (2000). The conditions which ensure a stationary marginal distribution F'_X for the abnormal returns are

$$\mathbf{E}\ln^+ |\omega_0 + \omega_3 U_t| < \infty \quad \text{and} \quad \mathbf{E}\ln \left|\omega_1 Z_{t-1}^2 + \omega_2\right| < 0, \tag{2.6}$$

where $\ln^+(x) \equiv \max\{\ln x, 0\}$.

- A sufficient condition for $\mathbf{E}\ln^+ |\omega_0 + \omega_3 U_t| < \infty$ to hold is a finite expectation of the random variable U_t as required in Section 2.3.1.
  Proof: From $\mathbf{E}U_t < \infty$, where $U_t \geq 0$, we have $\mathbf{E}\,|U_t| < \infty$ and it follows for a linear transformation, $\mathbf{E}\,|\omega_0 + \omega_3 U_t| < \infty$. Hence, $\ln^+ \mathbf{E}\,|\omega_0 + \omega_3 U_t| < \infty$. By Jensen's inequality, $\mathbf{E}\ln^+ |\omega_0 + \omega_3 U_t| \leq \ln^+ \mathbf{E}\,|\omega_0 + \omega_3 U_t|$ for $|\omega_0 + \omega_3 U_t| > 1$ and $\mathbf{E}\ln^+ |\omega_0 + \omega_3 U_t| = 0$ for $|\omega_0 + \omega_3 U_t| \leq 1$ such that $\mathbf{E}\ln^+ |\omega_0 + \omega_3 U_t| < \infty$ as required.

- The second condition imposed on A_t in (2.6) is identical to the one for the standard GARCH(1,1)-model: $\mathbf{E}\ln \left|\omega_1 Z_{t-1}^2 + \omega_2\right| < 0$.

Extremal Behavior Referring to the previous section on stationarity, results on the extremal behavior of the stationary marginal distribution F'_X are given based on a set of theorems by Kesten, Goldie and Breiman; see e.g. Mikosch and Stărică (2000) for details.

The results for the variance process (2.5) are based on two conditions imposed on A_t and B_t

$$\mathbf{E}\,|\omega_0 + \omega_3 U_t|^p < \infty \quad \text{and} \quad \mathbf{E}\left|\omega_1 Z_{t-1}^2 + \omega_2\right|^p = 1, \tag{2.7}$$

for some $p > 0$. Together with additional technical regularity conditions, it follows that the stationary marginal distribution of the σ_t^2-process has a Pareto-type tail with tail index p and the σ_t-process has tail index $2p$.

Based on the assumption that the distribution function of the innovations Z_t has a Pareto-type tail with tail index larger than $2p$ (i.e. the innovations have a thinner tail), the stationary marginal distribution of $(Z_t\sigma_t)$ has a tail index $2p$ and F'_X shows Pareto-type tail behavoir with some tail index $\gamma > 0$, i.e.:

$$1 - F'_X(x) \sim cx^{-\gamma}, c > 0, \quad \text{as} \quad x \to \infty.$$

Conditions (2.7) imply in detail:

- B_t has to satisfy the moment condition: $\mathbf{E}\left|\omega_0 + \omega_3 U_t\right|^b < \infty$ for some $b > 0$. Setting $b = 1$ we have the condition, which was shown to ensure the existence of the stationary marginal distribution in (2.6) above. $\mathbf{E}\left|U_t\right|^p < \infty$, i.e. the existence of the pth moment is a condition which we have to impose on the distribution of U_t in order to allow for the existence of a tail index of the σ_t^2-process and hence of the the X_t-process.

- The condition on A_t is standard as in the GARCH(1,1) case. It requires: $\mathbf{E}\left|\omega_1 Z_{t-1}^2 + \omega_2\right|^p = 1$. The unique solution yields the tail index $p > 0$. For specification (2.2.2), $X_t = (\lambda + Z_t)\sigma_t$, it follows that $\gamma = 2p$, i.e. $F'_X(x)$ has tail index $2p$.

In summary, our model with time-varying risk premium and random U_t given in Section 2.1 provides a stationary marginal distribution F'_X for the abnormal returns X_t under fairly general conditions comparable to those for the standard GARCH(1,1)-model. Also, given a stationary distribution for the market factor F_t which is in the maximum domain of attraction of the Fréchet extreme value distribution and finite higher order moments of U_t, there exists a tail index γ for the tail of the marginal distribution of the abnormal returns X_t and also for the raw model returns R_t.

3. Application to IPO Aftermarket Returns

The empirical application addresses the issue of aftermarket return premia for a sample of ten Neuer Markt IPO's from the years 1997 and 1998. It includes the following companies given together with the date of their initial listing: Mobilcom (March 11, 1997), SER Systeme (July 14, 1997), SCM Microsystems (October 9, 1997), Aixtron (November 6, 1997), Singulus (November 25, 1997), Teles (June 30, 1998), Infomatec (July 8, 1998), Intershop (July 16, 1998), Heyde (September 14, 1998), and Brokat (September 17, 1998). This selection of the IPO's was driven by size and data availability. Although the study is therefore not intended to be comprehensive, it serves as an illustration of the modified market model and gives an empirical indication on abnormal aftermarket return behavior for a sample of important Neuer Markt IPO's during the early stage of initial offering.

Daily company i returns $r_{i,t} = \ln(P_{i,t} + D_{i,t}) - \ln(P_{i,t-1})$, where $D_{i,t}$ denote potential day t stock redistributions, and volume realizations $v_{i,t}$ were provided by the Datastream database. For each stock, we record the first 500 daily observations, $t = 1, ..., 500$, which correspond to a period of approximately two calendar years after the date of the IPO. Since the first day of trading is subject to the well-documented IPO underpricing phenomenon, it is not contained in the investigation of the aftermarket return sample. In our setting, this is equivalent to defining the first trading day t as day zero. Also, as returns are not observable prior to the IPO, market model estimation has to be carried out in an observation window after the IPO event. Throughout the investigation we split the sample in half: The aftermarket event window is 'window I', $t = 1, ..., 250$, and the estimation window is 'window II' with $t = 251, ..., 500$. Given this framework, the overall sample period from which data are obtained includes March 11th, 1997 to September 6th, 2000.

3.1. Average Window Returns

Before we turn to the calculation of abnormal returns, we first have a look at average window I and window II returns. These are given as simple "portfolio" averages from our sample, $\overline{r}_t = \frac{1}{10} \sum_{i=1}^{10} r_{i,t}$, $t = 1, ..., 500$.

Descriptive statistics on the $\overline{r}_t$'s are given in Table 3.1. Apart from sample mean and standard deviation, skewness and excess kurtosis are reported. The median is given as an alternative measure of location which is robust under positive excess kurtosis. The results from Table 3.1 give a first indication on differences in aftermarket versus later trading periods for our sample of IPO's. Obviously, the sample mean is larger for window II, where, of course, a relatively high sample variance in both windows makes a statement about statistical significance difficult. The results also indicate that positive sample skewness is larger in aftermarket trading returns, whereas sample kurtosis is lower. Considering these departures from normality, the sample median indicates a smaller, yet still substantial, difference in the location of the window return distributions. Also note that the sample standard deviation of average returns itself gives no indication of differences in return risk, whereas sample kurtosis is larger for window II.

In order to examine the tail behavior of the average returns $\overline{r}_t$ in more detail, a tail index estimation is carried out by the Hill estimator which is discussed in detail in Embrechts et al. (1997). Here we apply it to estimate the tail index of the average of our assumedly stationary marginal return distributions. Note that this is done from a pure exploratory standpoint assuming that the average

Table 3.1

Descriptive sample statistics and Hill estimates of the tail index for average window returns $\overline{r}_t$. In parenthesis: Asymptotic standard errors of the Hill bootstrap estimator (BS) and number of tail observations, k, resulting from the MSE-bootstrap (5000 runs). MOT denotes estimator derived from the maximum occupation time criterion.

		window I	window II
$\overline{r}_t$			
mean		0.0048	0.0016
median		0.0035	0.0017
standard deviation		0.016	0.015
skewness		0.40	0.25
excess kurtosis		0.17	0.74
tail index estimated from both tails	BS:	5.55	5.40
		(1.48)	(1.44)
		(k=14)	(k=14)
	MOT:	4.55	5.32
tail index estimated for the upper tail	BS:	5.30	3.80
		(1.68)	(1.02)
		(k=10)	(k=14)
	MOT:	4.06	5.23
tail index estimated for the lower tail	BS:	6.19	2.47
		(2.06)	(0.66)
		(k=9)	(k=14)
	MOT:	5.99	3.35

returns are again in the maximum domain of attraction of a Fréchet law.[2] As the estimation procedure is based on the asymptotic tail shape of the underlying distribution, one has to determine the number of largest/smallest observations used in the calculation of the Hill estimator, thereby controlling for estimation bias and variance. Facing this problem, apart from graphical methods, various adaptive, data-driven criteria have been proposed in the literature. We use a mean squared error based bootstrap approach and alternatively a maximum occupation time estimator, the latter being an algorithmic version of graphical approaches. For applications and further literature refer e.g. to Krämer and Runde (1996), Lux (2000) and Wagner and Marsh (2000).

Turning again to Table 3.1, the results on the tail indices for upper, lower and both tails of the distribution indicate that particularly the lower tail of the average returns differs for aftermarket trading: While, in contrast to the other estimation results, the lower tail is relatively thin in window I, it turns out to be relatively fat for window II. The latter observation is what we would typically expect from stock return averages. A graphical illustration of the findings is also given by the quantile/quantile (QQ)-plots of Figure 3.1: While, as compared to the normal distribution, the upper distribution tail shows a comparable tendency for outliers in both windows, the lower tail appears thin-tailed in window I and fat-tailed in window II.

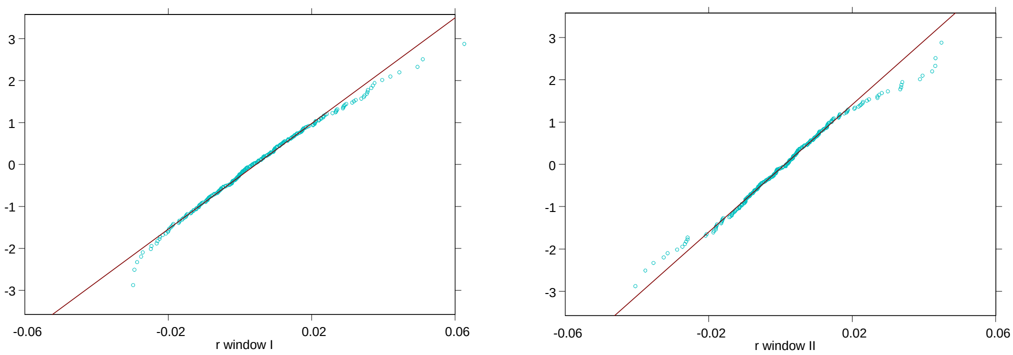

Figure 3.1: QQ-plots for window I (left) and window II (right) average returns $\overline{r}_t$ each against the normal distribution.

[2]An alternative would be to derive estimates of the tail index γ for each single return distribution and judge differences for each single case.

Overall, the results on the sample return averages $\overline{r}_t$ indicate differences not only in expected window returns but particularly also in the skewness of the return distributions. The finding of stronger positive sample skewness in aftermarket returns coincides with a relatively thin lower distribution tail. Whereas aftermarket returns on average exhibit strong positive skewness, average "mature returns" in window II exhibit larger sample kurtosis and particularly higher downside risk.

3.2. Average Abnormal Event Window Returns

Comparable to the classical event study methodology, the calculation of the abnormal returns in our aftermarket trading window is based on a fit of the market models in the estimation window. Referring back to Section 2, the standard market model (SMM) and the modified version of the market model (MMM) are both represented within the nested specification:

$$\begin{aligned} R_t &= \alpha + \beta F_t + (\lambda\sigma_t + Z_t)\sigma_t, \\ \sigma_t^2 &= \omega_0 + \omega_1(Z_{t-1}\sigma_{t-1})^2 + \omega_2\sigma_{t-1}^2 + \omega_3 U_t. \end{aligned} \tag{3.1}$$

The Estimation Procedure In estimating abnormal event window returns, consider the following points:

- The SMM and the MMM are fitted to the IPO returns $r_{i,t}$ in window II, $t = 251, ..., 500$. Realizations of the market factor F_t are modeled by CDAX index returns $f_t = \ln CDAX_t - \ln CDAX_{t-1}$.[3]
- Model (3.1) is used for an event study-type time-series comparison of returns. This is not a test of cross-sectional asset pricing and hence we do not consider potential return anomaly problems in choosing the CDAX as a broad proxy for the market factor. The model parameters α and λ capture unconditional and conditional abnormal returns with respect to the CDAX, respectively.
- Using the CDAX instead of the alternative of using the NEMAX as a proxy for F_t circumvents a statistical problem: The orthogonality condition $X_t \perp$

[3] Alternatively, one may additionally consider shorter event periods after the IPO. A quite long event period was chosen such that a stricter separation of aftermarket and later trading is given. Note also that the alternative proxy for the market factor, namely the NEMAX, was first calculated beginning with 1998.

F_t in model (2.1)/(3.1) is violated if the factor F_t contains the stock return R_t under consideration which would be the case as most of the stocks of our investigation are part of the NEMAX index universe. Orthogonality violations result in potentially biased parameter estimates.

- For the variable U_t in the MMM, we use the natural logarithm of reported trading volume $u_{i,t} = \ln v_{i,t}$ as the empirical specification. Note that logarithmic volume is typically approximately normally distributed (i.e. volume is approximately lognormally distributed).

- Estimation of the SMM is done by standard least squares regression yielding the estimate $(\widehat{\alpha}, \widehat{\beta})$.

- We do not account for a potential asynchronous trading problem for the index versus the modelled stock; given our data, unreported results on a correction methodology by Cohen et al. (1983) do not show a substantial impact on the parameter estimates of the SMM.

- Estimation of the MMM is done by a quasi maximum likelihood approach following Bollerslev and Wooldridge (1992): The derivation of the simultaneous estimates $(\widehat{\alpha}, \widehat{\beta}, \widehat{\lambda}, \widehat{\omega}_0, \widehat{\omega}_1, \widehat{\omega}_2, \widehat{\omega}_3)$ is based on fitting potentially fat-tailed return data to a jointly normal log-likelihood function where deviations from normality are accounted for in the estimates' standard errors.

- Finally, out-of-sample event window abnormal returns are calculated. For the SMM, abnormal returns are calculated as

$$a_{i,t} = r_{i,t} - (\widehat{\alpha}_i + \widehat{\beta}_i f_t), \quad t = 1, ..., \ 250. \tag{3.2}$$

  For the MMM, calculation of the event window abnormal returns is based on an estimation of the conditional return variance for the event window. Abnormal returns, conditional on estimated variance, are then calculated as

$$a_{i,t}|\widehat{\sigma}^2_{i,t} = r_{i,t} - (\widehat{\alpha}_i + \widehat{\beta}_i f_t + \widehat{\lambda}_i \widehat{\sigma}^2_{i,t}), \quad t = 1, ..., \ 250. \tag{3.3}$$

- Average abnormal event window returns are calculated as simple averages $\overline{a}_t = \frac{1}{N} \sum_{i=1}^{N} a_{i,t}$, $t = 1, ..., \ 250$. Standard asymptotic properties for cumulative average abnormal returns $\overline{c}_\tau = \sum_{t=1}^{\tau} \overline{a}_t$, $\tau = 1, ..., \ 250$, then follow based on the assumption that the abnormal event window returns are stochastically independent (time-series wise and cross-sectionally).[4] Under zero expected abnormal event window returns and sufficiently large N and τ, a normal distributional limit is obtained:

$$\bar{c}_\tau/(\sigma_{\bar{a}}\sqrt{\tau}) \xrightarrow{d} N(0;1). \tag{3.4}$$

In-sample Fit of the Market Models Considering in-sample fit, our results indicate that the MMM specification provides overall improvements in modeling estimation window returns. The results for the models SMM and MMM are given in Table 3.2. Apart from the coefficient of determination and the Akaike information criterion (AIC), t-statistics for the MMM parameters λ and ω_3 are given.

For all stocks, a smaller AIC in Table 3.2 indicates a better fit of the empirical observations to the modified market model specification. Considering the coefficients of determination, the market factor explains between 8 and 32 percent of the variation in sample IPO returns. The MMM explains a larger portion of the return variance for six out of ten stocks. In two of the cases where the coefficient of determination cannot be improved by the MMM, the risk premium coefficient λ is not significantly different from zero. The volume coefficient in the conditional variance equation turns out to be significant and positive for all stock return series.

Table 3.3 contains autocorrelation statistics on the model residuals which indicate linear dependence in Aixtron residuals for both models. For Mobilcom and Brokat, significant dependence at lag one only arises when the SMM is fitted.

Abnormal Event Window Returns Within our event study methodology, abnormal event window returns $a_{t,i}$ are out-of-sample estimates of aftermarket abnormal returns calculated according to equation (3.2) for the SMM and according to (3.3) for the MMM.

[4]Also, all return variances have to exist as was assumed in the preceding. Campbell et al. (1997) present a procedure that correctly accounts for cross-sectional dependence in abnormal returns based on the assumption of joint normality.

Table 3.2

Sample statistics on the fitted market models SMM and MMM. MMM results were obtained using alternative start solutions. AIC denotes the Akaike information criterion derived from the fitted log-likelihood. t-statistics given according to Bollerslev/Wooldridge (1992). More detailed estimation results are available from the author upon request.

Model	SMM		MMM			
IPO:	R^2	AIC	R^2	AIC	t($\widehat{\lambda}$)	t($\widehat{\omega}_3$)
Mobilcom	0.20	–3.16	0.23	–3.48	2.16	6.07
SER Systeme	0.31	–3.90	0.25	–3.94	2.37	5.86
SCM Microsystems	0.14	–3.53	0.14	–3.81	2.19	7.12
Aixtron	0.20	–4.20	0.24	–4.39	3.73	4.28
Singulus	0.20	–4.12	0.26	–4.38	5.64	4.51
Teles	0.08	–3.30	0.08	–3.46	–0.077	3.84
Infomatec	0.17	–3.48	0.21	–3.56	2.22	2.04
Intershop	0.32	–3.35	0.32	–3.43	0.82	2.75
Heyde	0.20	–3.53	0.21	–3.71	5.55	9.11
Brokat	0.26	–3.15	0.27	–3.27	2.10	4.70

Table 3.3

Autocorrelation statistics on the fitted market model residuals. Note that asymptotically, (assuming finite second moments), $STD(\widehat{\rho}) = 1/\sqrt{250}$, where '*' denotes significance at the 95% level.

Model	SMM		MMM	
IPO:	$\widehat{\rho}(X_t; X_{t-1})$	$\widehat{\rho}(X_t; X_{t-2})$	$\widehat{\rho}(Z_t; Z_{t-1})$	$\widehat{\rho}(Z_t; Z_{t-2})$
Mobilcom	0.18*	–0.078	0.079	–0.091
SER Systeme	–0.026	0.062	–0.080	0.094
SCM Microsystems	0.027	0.021	–0.009	0.023
Aixtron	–0.26*	–0.033	–0.26*	–0.032
Singulus	–0.072	0.003	–0.041	–0.004
Teles	0.010	0.043	0.001	0.071
Infomatec	0.12	–0.025	0.083	–0.039
Intershop	–0.049	–0.062	–0.035	–0.079
Heyde	–0.067	0.051	–0.059	0.060
Brokat	0.18*	–0.011	0.076	–0.002

Table 3.4

Descriptive sample statistics for average estimated abnormal aftermarket returns $\overline{a}_t$ according to the SMM and the MMM.

	SMM	MMM
$\overline{a}_t$	Equation (3.2)	Equation (3.3)
mean	0.0032	0.0003
median	0.0025	–0.0008
standard deviation	0.015	0.015
skewness	0.61	0.38
excess kurtosis	1.78	1.28

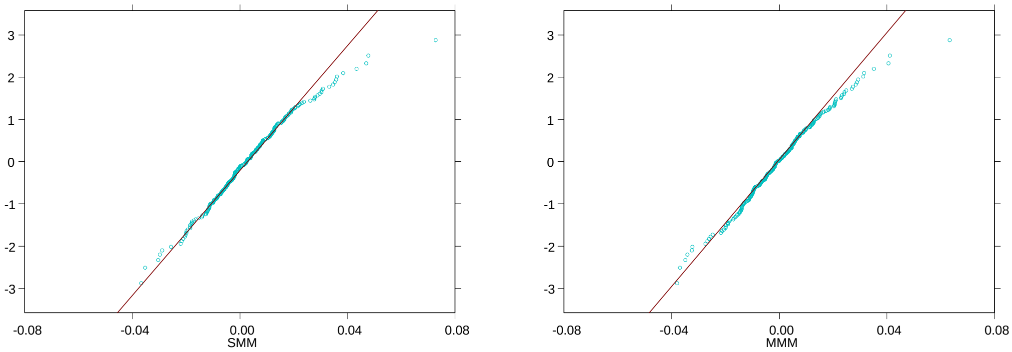

Figure 3.2: QQ-plots for SMM (left) and MMM (right) average aftermarket abnormal returns $\overline{a}_t$ each against the normal distribution.

Based on the cross-sectional independence assumption for the $a_{t,i}$'s and N being sufficiently large, average window returns $\overline{a}_t$ should approach a normal distribution. The empirical results for our sample indicate that the normal limit is not yet fully obtained for the cross-sectional averages $\overline{a}_t$; corresponding descriptive sample statistics are given in Table 3.4. Sample skewness and excess kurtosis suggest deviations from normality, which appear to be stronger for the standard market model. Figure 3.2 plots quantiles of the SMM and MMM $\overline{a}_t$'s each against quantiles of the normal distribution. The graphs indicate that normality is an approximation to the lower but not to the upper tail of the distribution of average abnormal returns. When compared to Figure 3.1, the quantile plots show that some of the thin-tailedness of average window I returns is explainable by both market model specifications.

The cumulative average aftermarket returns $\overline{c}_\tau$ are calculated as time series aggregations of the $\overline{a}_t$'s. A graphical illustration of the SMM and the MMM cumulative abnormal return series in the aftermarket trading window is given in Figure 3.3. It is obvious from the figure, that the level of cumulative abnormal returns heavily depends on the model chosen. For our sample, MMM cumulative abnormal returns turn out to be substantially lower than those for the standard market model. Still, both series show increasing cumulative abnormal performance up to approximately 100 days of aftermarket trading. Whereas the SMM indicates neutral performance thereafter, the results form the MMM indicate negative abnormal performance. Over the total 250 trading days event window period, the SSM produces a positive cumulative abnormal return, whereas the MMM yields an average close to zero.

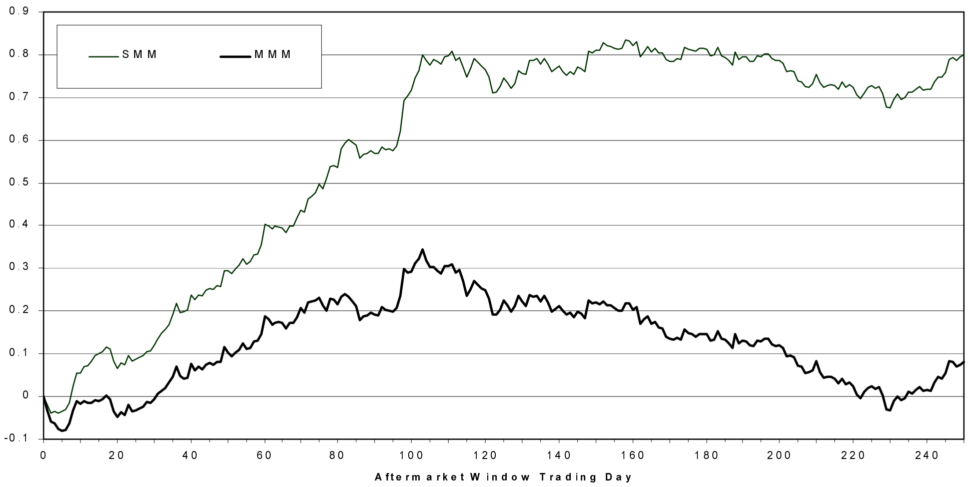

Figure 3.3: Cumulative abnormal SMM and MMM aftermarket returns in the event window, $\overline{c}_\tau$, $\tau = 1, ..., 250$.

Before drawing final conclusions from the data, consider the distributional properties of the abnormal returns, which, with sufficiently large N and τ, should approach the normal limit according to (3.4). Sample autocorrelation statistics for the event window returns $\overline{a}_t$ indicate insignificant linear time series dependence: $\widehat{\rho}(\overline{a}_t; \overline{a}_{t-1}) = 0.10$ and $\widehat{\rho}(\overline{a}_t; \overline{a}_{t-2}) = 0.003$ for the SMM and $\widehat{\rho}(\overline{a}_t; \overline{a}_{t-1}) = 0.024$ and $\widehat{\rho}(\overline{a}_t; \overline{a}_{t-1}) = -0.074$ for the MMM. Next, under the assumption of time series independence, a bootstrap resampling procedure is performed in order to examine to what extent (3.4) may serve as a distributional approximation for the cumulative abnormal returns $\overline{c}_\tau$: For each $t = 1, ..., \tau$, a cross-sectional average $\overline{a}_t^*$ is calculated by drawing $N = 10$ random samples i from the empirical distribution of the $a_{t,i}$'s. Aggregating average returns $\overline{a}_t^*$ over τ trading days then yields a bootstrap cumulative abnormal return $\overline{c}_\tau^*$. Figure 3.4 plots the histograms under 10.000 repetitions of the procedure for τ equal to 60 and 250 trading days, respectively.

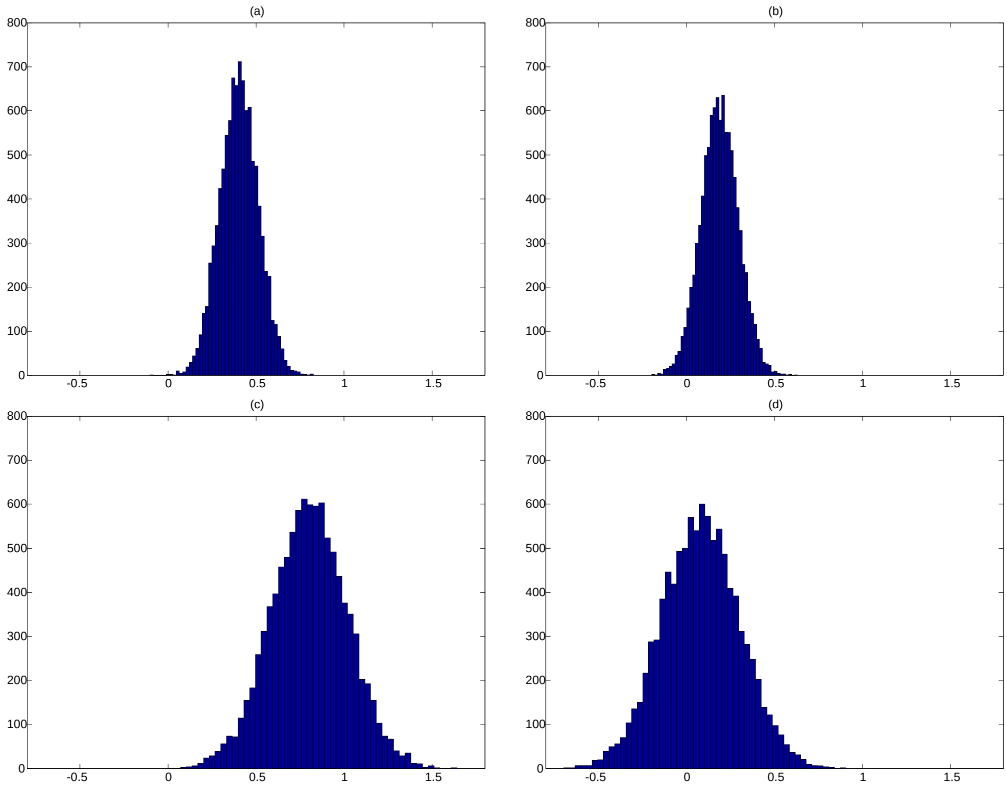

Figure 3.4: Histograms of resampled cumulative abnormal aftermarket returns, 10.000 draws; (a) SMM-$\overline{c}_{60}$, (b) MMM-$\overline{c}_{60}$, (c) SMM-$\overline{c}_{250}$, (d) MMM-$\overline{c}_{250}$.

The graphical results of Figure 3.4 give a first indication that the normality assumption may serve as a valid approximation of the distribution of cumulative abnormal returns.[5] From the resampled distributions, t-statistics $t^*(\overline{c}_\tau)$ and quantiles q^* follow. Table 3.5 gives cumulative abnormal event window returns $\overline{c}_\tau$ for the SMM and the MMM together with their asymptotic and resampled t-statistics $t(\overline{c}_\tau)$ and $t^*(\overline{c}_\tau)$, respectively. For τ periods of 60, 80, 100, 120 and 250 trading days are chosen. Asymptotic t-values under the assumption of normality as well as the quantiles from resampled distribution the both indicate that the modified market model cumulative abnormal returns are substantially lower and show lower significance levels than those from the standard approach. However, even the modified model yields significant positive cumulative abnormal returns

[5]Unreported descriptive statistics indicate only weak deviations from normality.

Table 3.5

Cumulative period τ aftermarket returns $\overline{c}_\tau$ for the SMM and the MMM together with their t-statistics. '$^+$' and '*' denote significance at the 95% level of rejecting the null 'H_0: $\overline{c}_\tau \leq 0$' against 'H_1: $\overline{c}_\tau > 0$' based on the asymptotic limit (3.4) and based on the resampled quantile $q^*_{5\%}$, respectively.

	SMM				MMM			
τ:	$\overline{c}_\tau$	$t(\overline{c}_\tau)$	$t^*(\overline{c}_\tau)$	$q^*_{5\%}$	$\overline{c}_\tau$	$t(\overline{c}_\tau)$	$t^*(\overline{c}_\tau)$	$q^*_{5\%}$
60	0.402^{+*}	3.55	3.68	0.22	0.188^{+*}	1.65	1.77	0.014
80	0.537^{+*}	4.25	4.01	0.32	0.215^{+}	1.69	1.58	–0.0072
100	0.717^{+*}	4.55	4.59	0.46	0.291^{+*}	1.91	1.82	0.029
120	0.766^{+*}	4.33	4.52	0.49	0.248	1.45	1.44	–0.036
250	0.800^{+*}	3.36	3.69	0.45	0.080	0.36	0.36	–0.28

for periods up to 100 trading days.

4. Conclusion

How abnormal are abnormal returns after an IPO? From our empirical study of Neuer Markt IPO aftermarket returns we can draw two main conclusions: (i) aftermarket return distributions differ from more mature stock return distributions thereby offering abnormal return expectation and positive skewness while, (ii) measuring abnormal returns may highly depend on the chosen equilibrium model specification for what is considered as "normal" return behavior.

The descriptive return statistics on average returns demonstrate that the empirical return distributions for the first and the second year after the IPO differ: Larger positive mean and positive skewness characterize IPO aftermarket returns in our sample. The results further indicate that these features do not come at the cost of larger risk in the lower distribution tail. In contrast, the empirical results even point out a thinner lower tail. Estimating both market models, where the overall aftermarket sample period covers March 11, 1997 to September 15, 1999, yields positive abnormal returns particularly in the first two quarters of aftermarket trading. As young issues in their first two quarters of aftermarket trading made up a large portion of the NEMAX index composition during the first two years of index calculation (January 1998 to December 1999), one may conclude tentatively that high average returns for the NEMAX were partly attributable to a one-time effect, namely the documented abnormal aftermarket returns. Of course, a question for further research that arises is where the abnormal return features come from: Is it market making activities after an IPO, is it due to strong call option-like payoff characteristics of new issues, or just investor psychology during "hot issue" periods?

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