Time-varying moments, idiosyncratic risk, and an application to hot-issue IPO aftermarket returns

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Abstract

This paper proposes time-varying idiosyncratic risk as a component driving conditional abnormal returns and outlines a corresponding Engle et al. [Econometrica 55 (1987) 391] ARCH-M market model. An application is given to initial public offering (IPO) aftermarket stock returns, where a positive relation between idiosyncratic risk and returns is consistent with young issues’ equity as a contingent claim on firm assets. The empirical results for an illustrative sample of German Neuer Markt stocks traded during the first two years after initial listing indicate pronounced skewness as well as a positive relation between conditional idiosyncratic risk and expected returns. Conditioning aftermarket performance on risk yields much lower levels of abnormal return significance than a standard approach. © 2004 Elsevier B.V. All rights reserved.

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Keywords: Abnormal returns; Idiosyncratic risk; Aftermarket stock returns

1. Introduction

The measurement of abnormal returns is essential to what financial economists conclude from studies on information processing in capital markets. One approach is measuring
market-adjusted excess returns, or—as a generalization of the latter—applying the so-called market model. The latter 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. For a survey on the methodology and related literature refer to MacKinlay (1997) and Campbell et al. (1997, Chapter 5), for example. Refining the standard approach, various modifications include Böhmer et al. (1991) who consider the effect of autoregressive conditional heteroskedasticity (ARCH) around an event. Franks et al. (1991) propose a multi-factor approach for measuring abnormal performance. So far, common agreement seems to be captured within the words of Campbell et al. (1997, p. 156) who note that: “In practice the gains from employing multifactor models for event studies are limited. The reason for this is that the explanatory power of additional factors beyond the market factor is small, and hence there is little reduction in the variance of the abnormal return”.¹

This paper presents a generalized method for measuring abnormal returns when time-varying idiosyncratic risk drives conditional abnormal returns. The methodological setting is given within an Engle et al. (1987) ARCH-M market model. An application is given to initial public offering (IPO) aftermarket stock returns. Young issues’ aftermarket returns are particularly suitable for a model application, since a relation between idiosyncratic risk and returns is consistent with the theory of young issues’ equity as a contingent claim on firm assets.

The modified ARCH-M market model takes fluctuations in volatility and trading volume into account, thereby referring back to suggestions by Engle et al. (1987) and Lamoureux and Lastrapes (1990). The model allows for time-varying conditional return variance where volume data are used to account for changes in the level of stochastic variance. A time-varying conditional risk premium for idiosyncratic risk is modeled as a function of conditional variance. The proposed model has two observable variables and one unobservable variable which determine conditional returns, namely the market factor, trading volume and conditional return variance. The 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 may prove 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 as in Merton (1980), increased volatility may also coincide with positive abnormal stock returns as found, e.g. by Golsten et al. (1993). Furthermore, even idiosyncratic risk may relate to a positive risk premium as recently documented by Goyal and Santa-Clara (2003).² Although the latter authors perform

¹ The market model has a long tradition in empirical finance, economics and accounting where it has found wide application in studies of stock return behavior. Needless to say, despite 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.
² Additional empirical evidence of a risk premium related to idiosyncratic risk is found by Campbell and Taksler (2003) in an investigation of corporate bond yield spreads.
robustness checks for their market-wide findings via controlling for volume, the results by Gervais et al. (2001) show that abnormal trading volume itself relates to a single-stock return premium. These findings indicate that market participants may require compensation for abnormal levels of idiosyncratic risk as well as corresponding trading activity. Hence, while the model suggested here captures both, the standard market model—by its implicit stationarity assumption—does not consider variation in the return dynamics. Of course, this may lead to deviating estimates of abnormal returns.

An illustrative model application is given in measuring the performance of IPOs. The initial underpricing and the long-run price behavior has attracted the attention of financial economists for decades; see, e.g. Ritter (1991) for evidence of long-run underperformance and Schultz (2003) who provides a methodological challenge to previous empirical findings. Recently, Aggarwal (2000) pointed out that there is evidence of a difference between aftermarket and otherwise regular return behavior for IPOs in the US-market. She discusses market-maker activities as a potential explanation. Based on the model proposed, the present study addresses the issue of IPO aftermarket returns for a sample of German Neuer Markt IPOs and thereby accounts for the volatility and volume dynamics after initial offering. The perspective is on the short-term return aftermarket dynamics as compared to the return dynamics from a later time window. As we do not measure performance against some absolute standard (i.e. an asset pricing model), cross-sectional pricing anomalies (such as size, for example) are not accounted for and have an identical impact on our first versus second return window. The aim 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 methodology as applied in previous studies of IPO performance.

The empirical findings given are based on an illustrative application of the model to a sample of German Neuer Markt stocks traded during the first two years after initial listing within the 1997–2000 hot-issue period. Young ventures’ aftermarket returns are particularly suitable for a model application since their payoff characteristics should imply a significant idiosyncratic risk premium in the spirit of Goyal and Santa-Clara (2003). Our results indeed indicate pronounced skewness as well as a positive relation between conditional idiosyncratic risk and expected returns. There is evidence of a statistically significant abnormal performance within the first six months of aftermarket trading which includes the lock-up period which restricts selling by initial shareholders. Apart from a higher return expectation this period coincides with pronounced positive skewness and a thinner lower tail of the return distribution. Application of the proposed market model by conditioning aftermarket returns on aftermarket return variance helps to explain the higher return expectation in the aftermarket trading period. Consequently, the model yields much lower levels of statistical significance for abnormal performance than a standard approach. An explanation for the documented positive relation between idiosyncratic risk and returns follows from the interpretation of equity and debt as contingent claims on the firm’s future assets. Increasing volatility in the firm’s assets which is reflected in stock volatility leads to a higher value of firm equity which represents a call option on the firm’s assets.

3 A study which focuses on such cross-sectional pricing anomalies is by Brav et al. (2000) who show that factor models can partly explain the “abnormal” performance of IPOs in their sample.
The remainder of the paper proposes the ARCH-M market model and adds to previous empirical studies of the German IPO market including Schuster (1996), Stehle et al. (2000) and Bessler and Kurth (2003). It is organized as follows. The model and its properties are outlined in Section 2. The application to Neuer Markt IPOs 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 the proposed modified version of the market model. As fat-tailedness in the idiosyncratic return component is a well-documented feature in the empirical finance literature (see, e.g. Bollerslev, 1987), we do not assume a normal distribution for the model innovations.

2.1. General model assumptions

Based on the financial time series $P_t$, $t = 0, 1, \ldots, T$, 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

$$R_t - (\alpha + \beta F_t) = X_t,$$

with $\alpha, \beta \in \mathbb{R}$. The abnormal returns $(X_t)_{1 \leq t \leq T}$ are orthogonal to the observable market factor $(F_t)_{1 \leq t \leq T}$: $X_t \perp F_t$. The market factor is normalized to have zero expectation, $E F_t = 0$, 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 $X_t$ are typically assumed to be i.i.d. draws from some distribution function $F_X$ with $E X_t = 0$ and finite constant variance $E X_t^2 < \infty$. Considering empirical results on financial returns, one may assume that $F_X$ has fat-tails.

2.3. The conditional market model

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

Assume that the abnormal returns from Eq. (2.1) can be modeled as heteroskedastic innovations with a time-varying mean which linearly relates to conditional variance

$$X_t = (\lambda \sigma_t + Z_t) \sigma_t,$$

with $\lambda, \sigma_t \in \mathbb{R}$. This is equivalent to $\text{Cov}(X_t; F_t) = 0$. 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.
or to conditional volatility:

\[ X_t = (\lambda + Z_t)\sigma_t. \]  
(2.2.2)

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

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

\[ \mu_t|\sigma_t^2 = \lambda \sigma_t^2. \]  
(2.3.1)

for (2.2.1) or

\[ \mu_t|\sigma_t^2 = \lambda \sigma_t. \]  
(2.3.2)

for (2.2.2). Following Engle et al. (1987), this specification became known as ‘ARCH-M’. 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.

Turning to specification (2.2.1), the conditional variance of abnormal returns can be modeled as

\[ \sigma_t^2|\sigma_{t-1}^2, Z_{t-1}, U_t = \omega_0 + \omega_1 (X_{t-1} - \lambda \sigma_{t-1}^2)^2 + \omega_2 \sigma_{t-1}^2 + \omega_3 U_t \]

\[ = \omega_0 + \omega_1 (Z_{t-1} \sigma_{t-1})^2 + \omega_2 \sigma_{t-1}^2 + \omega_3 U_t, \]  
(2.4)

where \( \omega_0 > 0, \omega_j \geq 0, j = 1, \ldots, 3 \). Eq. (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 \( \sigma_0 \). Additionally, a stationary series of contemporary non-negative random variables \( (U_t)_{1 \leq t \leq T} \) with \( EU_t < \infty \) enters the conditional variance equation. Note that requiring \( U_t \perp \sigma_t \) is sufficient in order to ensure the orthogonality condition \( X_t \perp F_t \) in Eq. (2.1).

3. Application to IPO aftermarket returns

3.1. The data

The empirical application illustrates the issue of aftermarket return premia for a sample of 10 Neuer Markt IPOs 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 IPOs 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 IPOs during aftermarket trading.
Table 1
Descriptive sample statistics for average window returns $\bar{r}_t$

<table>
<thead>
<tr>
<th>Window</th>
<th>Mean</th>
<th>Median</th>
<th>Standard deviation</th>
<th>Skewness</th>
<th>Excess kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>0.0048</td>
<td>0.0035</td>
<td>0.016</td>
<td>0.40</td>
<td>0.17</td>
</tr>
<tr>
<td>II</td>
<td>0.0016</td>
<td>0.0017</td>
<td>0.015</td>
<td>0.25</td>
<td>0.74</td>
</tr>
</tbody>
</table>

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, $t = 1, \ldots, 500$, 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’, $t = 1, \ldots, 250$, and the estimation window is ‘window II’ with $t = 251, \ldots, 500$. Given this framework, the overall sample period from which data are obtained includes March 11, 1997 to September 6, 2000.

### 3.2. Average window returns

Before we turn to the calculation of abnormal returns, we first have a look at average windows I and II returns. These are given as simple “portfolio” averages from our sample, $\bar{r}_t = (1/10) \sum_{i=1}^{10} r_{i,t}$.

Descriptive statistics on the $\bar{r}_t$’s are given in Table 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 1 give a first indication on differences in aftermarket versus later trading periods for our sample of IPOs. Obviously, the sample mean is larger for window I, 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.

The above results on skewness and kurtosis find a graphical illustration in the quantile/quantile (QQ)-plots of Fig. 1. In comparison to the normal distribution, the upper distribution tail shows a comparable tendency for outliers in both windows, i.e. fat-tailedness, which is what we would typically expect from stock returns and stock return averages. However, the lower tail appears thin-tailed in window I and fat-tailed in window II. Hence,
particularly the lower tail of the average returns differs for aftermarket trading, yielding differences in the descriptive higher sample moments of Table 1.

Overall, the results on the sample return averages $\bar{r}_t$ 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.

3.3. 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:

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

(3.1)

3.3.1. 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, $t = 251, \ldots, 500$. Realizations of the market factor $F_t$ are modeled by CDAX index returns $f_t = \ln \text{CDA}X_t - \ln \text{CDA}X_{t-1}$.

5 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.
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 $\alpha$ and $\lambda$ capture unconditional and conditional abnormal returns with respect to the CDAX, respectively.

Using the CDAX instead of the alternative of using the NEMA as a proxy for $F_t$ circumvents a statistical problem: the orthogonality condition $X_t \perp F_t$ 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 NEMA 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 $u_{t,i} = \ln v_{t,i}$ 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 $(\hat{\alpha}, \hat{\beta})$.

We do not account for a potential asynchronous trading problem for the index versus the modeled 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 $(\hat{\alpha}, \hat{\beta}, \hat{\lambda}, \hat{\omega}_0, \hat{\omega}_1, \hat{\omega}_2, \hat{\omega}_3)$ 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

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

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

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

Average abnormal event window returns are calculated as simple averages $\bar{\tilde{a}}_t = (1/N) \sum_{i=1}^N a_{t,i}, t = 1, \ldots, 250$. Standard asymptotic properties for cumulative average abnormal returns $\tilde{c}_t = \sum_{\tau=1}^t \bar{\tilde{a}}_\tau, t = 1, \ldots, 250$, then follow based on the simplifying assumption that the abnormal event window returns are stochastically independent (time-series wise and cross-sectionally).\(^6\) Under zero expected abnormal event window returns and sufficiently large $N$ and $\tau$, a normal distributional limit is obtained:

$$\frac{\tilde{c}_\tau - d}{\sigma_{\bar{a}} \sqrt{\tau}} \overset{d}{\to} N(0; 1). \quad (3.4)$$

\(^6\) Also, all return variances have to exist as was assumed in the preceding discussions. 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 2
Sample statistics on the fitted market models SMM and MMM

<table>
<thead>
<tr>
<th>IPO</th>
<th>SMM</th>
<th>MMM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$R^2$</td>
<td>AIC</td>
</tr>
<tr>
<td>Mobilcom</td>
<td>0.20</td>
<td>−3.16</td>
</tr>
<tr>
<td>SER Systeme</td>
<td>0.31</td>
<td>−3.90</td>
</tr>
<tr>
<td>SCM Microsystems</td>
<td>0.14</td>
<td>−3.53</td>
</tr>
<tr>
<td>Aixtron</td>
<td>0.20</td>
<td>−4.20</td>
</tr>
<tr>
<td>Singulus</td>
<td>0.20</td>
<td>−4.12</td>
</tr>
<tr>
<td>Teles</td>
<td>0.08</td>
<td>−3.30</td>
</tr>
<tr>
<td>Infomatec</td>
<td>0.17</td>
<td>−3.48</td>
</tr>
<tr>
<td>Intershop</td>
<td>0.32</td>
<td>−3.35</td>
</tr>
<tr>
<td>Heyde</td>
<td>0.20</td>
<td>−3.53</td>
</tr>
<tr>
<td>Brokat</td>
<td>0.26</td>
<td>−3.15</td>
</tr>
</tbody>
</table>

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 and Wooldridge (1992). More detailed estimation results are available from the author upon request.

3.3.2. 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 2. Apart from the coefficient of determination and the Akaike information criterion (AIC), $t$-statistics for the MMM parameters $\lambda$ and $\omega_3$ are given.

For all stocks, a smaller AIC in Table 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 6 out of 10 stocks. In two of the cases where the coefficient of determination cannot be improved by the MMM, the risk premium coefficient $\lambda$ 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 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.

3.3.3. Abnormal event window returns

Within our event study methodology, abnormal event window returns $a_{it}$ are out-of-sample estimates of aftermarket abnormal returns calculated according to Eq. (3.2) for the SMM and according to (3.3) for the MMM.

Based on the cross-sectional independence assumption for the $a_{it}$’s and $N$ being sufficiently large, average window returns $\bar{a}_t$ 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 $\bar{a}_t$; corresponding descriptive sample statistics are given in Table 4.
Table 3
Autocorrelation statistics on the fitted market model residuals

<table>
<thead>
<tr>
<th>IPO</th>
<th>SMM</th>
<th>MMM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( \hat{\rho}(X_t; X_{t-1}) )</td>
<td>( \hat{\rho}(X_t; X_{t-2}) )</td>
</tr>
<tr>
<td>Mobilcom</td>
<td>0.18*</td>
<td>-0.078</td>
</tr>
<tr>
<td>SER Systems</td>
<td>-0.026</td>
<td>0.062</td>
</tr>
<tr>
<td>SCM Microsystems</td>
<td>0.027</td>
<td>0.021</td>
</tr>
<tr>
<td>Aixtron</td>
<td>-0.26*</td>
<td>-0.033</td>
</tr>
<tr>
<td>Singulus</td>
<td>-0.072</td>
<td>0.003</td>
</tr>
<tr>
<td>Teles</td>
<td>0.010</td>
<td>0.043</td>
</tr>
<tr>
<td>Infomatec</td>
<td>0.12</td>
<td>-0.025</td>
</tr>
<tr>
<td>Intershop</td>
<td>-0.049</td>
<td>-0.062</td>
</tr>
<tr>
<td>Heyde</td>
<td>-0.067</td>
<td>0.051</td>
</tr>
<tr>
<td>Brokat</td>
<td>0.18*</td>
<td>-0.011</td>
</tr>
</tbody>
</table>

Note that asymptotically (assuming finite second moments), \( \text{STD}(\hat{\rho}) = 1/\sqrt{250} \), where * denotes significance at the 95% level.

Sample skewness and excess kurtosis suggest deviations from normality, which appear to be stronger for the standard market model. Fig. 2 plots quantiles of the SMM and MMM \( \tilde{a}_t \)'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 Fig. 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 \( \tilde{c}_t \) are calculated as time series aggregations of the \( \tilde{a}_t \)'s. A graphical illustration of the SMM and the MMM cumulative abnormal return series in the aftermarket trading window is given in Fig. 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; note that this is approximately the length of the so-called lockup period which initially prevents insiders from selling their shares. Whereas the SMM indicates neutral performance thereafter, the results form the MMM indicate negative abnormal performance. Over the total 250 trading days

Table 4
Descriptive sample statistics for average estimated abnormal aftermarket returns \( \tilde{a}_t \) according to the SMM and the MMM

<table>
<thead>
<tr>
<th>( \tilde{a}_t )</th>
<th>SMM (Eq. (3.2))</th>
<th>MMM (Eq. (3.3))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.0032</td>
<td>0.0003</td>
</tr>
<tr>
<td>Median</td>
<td>0.0025</td>
<td>-0.0008</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>0.015</td>
<td>0.015</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.61</td>
<td>0.38</td>
</tr>
<tr>
<td>Excess kurtosis</td>
<td>1.78</td>
<td>1.28</td>
</tr>
</tbody>
</table>
event window period, the SSM produces a positive cumulative abnormal return, whereas the MMM yields an average close to zero.

Before drawing further conclusions from the data, consider the distributional properties of the abnormal returns, which, with sufficiently large $N$ and $\tau$, should approach the normal limit according to (3.4). Sample autocorrelation statistics for the event window returns $\bar{a}_t$ indicate insignificant linear time series dependence: $\hat{\rho}(\bar{a}_t; \bar{a}_{t-1}) = 0.10$ and $\hat{\rho}(\bar{a}_t; \bar{a}_{t-2}) = 0.003$ for the SMM and $\hat{\rho}(\bar{a}_t; \bar{a}_{t-1}) = 0.024$ and $\hat{\rho}(\bar{a}_t; \bar{a}_{t-2}) = -0.074$ 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 $\bar{c}_t$: For each $t = 1, \ldots, \tau$, a cross-sectional average $\bar{a}_t^*$ is calculated by drawing $N = 10$ random samples $i$ from the empirical distribution of the $a_{i,t}$’s. Aggregating average returns $\bar{a}_t^*$ over $\tau$ trading days then yields a bootstrap cumulative

![Fig. 2. QQ-plots for SMM (left) and MMM (right) average aftermarket abnormal returns $\bar{a}_t$ each against the normal distribution.](image)

![Fig. 3. Cumulative abnormal SMM and MMM aftermarket returns in the event window, $\bar{c}_t$, $t = 1, \ldots, 250$.](image)
abnormal return $\tilde{e}_\tau^\ast$, Fig. 4 plots the histograms under 10,000 repetitions of the procedure for $\tau$ equal to 60 and 250 trading days, respectively.

The graphical results of Fig. 4 give a first indication that the normality assumption may serve as a valid approximation of the distribution of cumulative abnormal returns; also, unreported descriptive statistics indicate only weak deviations from normality. From the resampled distributions, $t$-statistics $t^*(\tilde{e}_\tau)$ and quantiles $q^*$ follow.

Table 5 gives cumulative abnormal event window returns $\tilde{e}_\tau$ for the SMM and the MMM together with their asymptotic and resampled $t$-statistics, $t(\tilde{e}_\tau)$ and $t^*(\tilde{e}_\tau)$, respectively. For $\tau$ periods of 60, 80, 100, 120 and 250 trading days are chosen. Both asymptotic $t$-values under the assumption of normality as well as the quantiles from resampled distribution indicate that the modified market model cumulative abnormal returns are substantially lower and show lower significance levels than those from the standard approach.\(^7\) However, even the

\(^7\) As young issues in their first two quarters of aftermarket trading made up a large portion of the NEMAX index composition during the first 2 years of index calculation (January 1998 to December 1999), one may conclude that high average returns for the index were largely attributable to a one-time effect, namely the documented abnormal aftermarket returns.
Table 5
Cumulative period \( \tau \) aftermarket returns \( \bar{c}_\tau \) for the SMM and the MMM together with their \( t \)-statistics

<table>
<thead>
<tr>
<th>( \tau )</th>
<th>SMM</th>
<th>MMM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( \bar{c}_\tau )</td>
<td>( t(\bar{c}_\tau) )</td>
</tr>
<tr>
<td>60</td>
<td>0.402***</td>
<td>3.55</td>
</tr>
<tr>
<td>80</td>
<td>0.537***</td>
<td>4.25</td>
</tr>
<tr>
<td>100</td>
<td>0.717***</td>
<td>4.55</td>
</tr>
<tr>
<td>120</td>
<td>0.766***</td>
<td>4.33</td>
</tr>
<tr>
<td>250</td>
<td>0.800***</td>
<td>3.36</td>
</tr>
</tbody>
</table>

*** and ** denote significance at the 95% level of rejecting the null 'H\( \bar{0} \): \( \bar{c}_\tau \leq 0 \)' against 'H\( \bar{1} \): \( \bar{c}_\tau > 0 \)' based on the asymptotic limit (3.4) and based on the resampled quantile \( q_{5\%}^* \), respectively.

The modified model yields significant positive cumulative abnormal returns for periods up to 100 trading days.

4. Conclusion

How abnormal are abnormal returns after an IPO? First results from our empirical study on German Neuer Markt IPO aftermarket returns during the hot issue period 1997–2000 give the following indications. Aftermarket return distributions differ from more mature stock return distributions, thereby offering abnormal return expectation, pronounced positive skewness and a relatively thin lower tail of the return distribution. Abnormal return expectation is partly explainable by a positive relation between conditional idiosyncratic risk and expected return. This finding in turn implies that measuring abnormal return may highly depend on the chosen equilibrium model. Of course, a question that arises is where the abnormal return features come from. Is it market making and particularly stabilization activities after an IPO, is it due to strong option-like payoff characteristics of new issues, or irrational investor behavior during hot-issue periods? The empirical findings provided here support the interpretation of newly issued equity as an out-of-the-money call on the venture’s future assets. Future work in the area is needed to provide broader empirical evidence.

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