Is Risk higher during Non-Trading Periods? The Risk Trade-Off for Intraday versus Overnight Market Returns*

Christoph Riedel†
Niklas Wagner‡

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†Department of Business and Economics, Passau University.

‡Corresponding author. Department of Business and Economics, Passau University, 94030 Passau, Germany. Phone: +49 851 509 3241, Fax: +49 851 509 3242, E-mail: nwagner@alum.calberkeley.org.

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Abstract

We study the magnitude of tail risk—particularly lower tail downside risk—that is present in intraday versus overnight market returns and thereby examine the nature of the respective market risk borne by market participants. Using the Generalized Pareto Distribution for the return innovations, we use a GARCH model for the conditional market return components of major stock markets covering the U.S., France, Germany and Japan. Testing for fat-tails and tail index equality, we find that overnight return innovations exhibit significant tail risk, while intraday innovations do not. We illustrate this volatility versus tail risk trade-off based on conditional Value-at-Risk calculations. Our results show that overnight downside market risk is composed of a moderate volatility risk component and a significant tail risk component. We conclude that market participants face different intraday versus overnight risk profiles and that a risk assessment based on volatility only will severely underestimate overnight downside risk.

Keywords: market risk, tail risk, downside risk, value-at-risk, intraday returns, overnight risk, stock markets, extreme returns, tail index;

JEL Classification: C13, C22, G10, G21;

1 Introduction

The nature of the risk inherent in the the books of financial institutions and other market participants once we consider intraday and overnight periods separately is not yet fully understood. Intraday and overnight returns break up the usually examined close-close returns into a component during trading periods (i.e. periods with high market functionality of major exchanges) and a component during non-trading periods, (i.e. overnight periods including weekends and holidays with reduced market functionality where less liquid alternative trading platforms may be available). While market risk measures today are uniquely set on a daily basis by banks and regulators, trading and risk sharing behavior in stock markets suggests that not all market participants typically maintain their risky positions for a full daily holding period. The existence of intraday traders has recently obtained renewed public attention with the emergence of high-speed intraday trading, also called "flash trading". Furthermore, the well-documented U-shape pattern of intraday volume—implying that market participants' trading activity is more pronounced at the beginning and at the end of the trading day, see e.g. Wood et al. (1985) and Admati and Pfleiderer (1988)—yields opportunities for market participants to open or close intraday or overnight positions at times of above average market liquidity. A natural question, which arises in this context, is how the risk sharing scheme looks like for investors who exit versus those how enter overnight. As return distributions are known to exhibit fat-tails, a related question is whether intraday and overnight returns can be described by the same magnitude not only of volatility but also of tail risk.[1]

[1] Numerous studies following Mandelbrot (1963) and Fama (1965) suggest that asset return distributions deviate from the normal distribution. Return distributions tend to exhibit fat-tails, which implies that the probability of extreme return realizations is greater than the one predicted by the normal. Oldfield and Rogalski (1980) suggest and test different combinations of diffusion and jump processes for intraday versus overnight stock returns. It is known that overnight returns are characterized by a lower per-period volatility, see e.g. French and Roll (1986), Stoll and Whaley (1990) and Barclay et al. (1990). Results in Ben-Zion and Wagner (2006) suggest higher levels of excess kurtosis for overnight stock market returns.

The present paper addresses the possible existence of a volatility versus tail risk trade-off for intraday versus overnight market returns. The focus is on differences in risk composition. Such differences may directly evolve from the operation of stock market exchanges. As such, the U.S. Securities and Exchange Commission, SEC (2000), identifies additional components of risk in after-hours trading, including a lack of liquidity, larger spreads, higher price volatility for stocks with low trading activity and a potential bias toward limit orders. The resulting differences in overnight price changes play a crucial role for several market participants including dealers, brokers, retail and institutional investors, but also for regulating authorities. For example, intraday traders are required to close their books by the end of the trading day. Holding a sub-optimal portfolio during a non-trading period may imply substantial costs to institutional investors. The identification of trading times that reduce the probability of large adverse market movements is also a crucial task in financial risk management.

Based on Bollerslev (1987), who considers fat-tailed innovations within the generalized autoregressive conditional heteroskedasticity (GARCH) model, we analyze the conditional return distributions of intraday and overnight returns for major stock market indices, covering the U.S., France, Germany and Japan. Our focus is on the conditional individual distributions as we are interested in capturing the tail risk, which is given beyond the time-varying conditional risk which is readily predicted by the time-series model. The magnitude of extreme downside risk exposure is thereby governed by the time-series model and its return innovations' distribution. We use extreme value theory (EVT) and thereby characterize independent and identically distributed (i.i.d.) return innovations by the classic limit results of extreme value theory (see for example Embrechts et al. (1997), Diebold et al. (1998), Lauridsen (2000), and McNeil and Frey (2000)). Conditional index returns follow the GARCH model (see Engle (1982), Bollerslev (1986) and Bollerslev (1987)), which accounts for volatility clustering. The threshold-GARCH (TGARCH or GJR-GARCH) specification of Glosten et al. (1993) and Zakoian (1994) allows us to capture the effect of asymmetric volatility, which is typically present in stock market returns. Relying on EVT results, the GARCH model innovations are modeled by the generalized Pareto distribution (GPD), whose central parameter is the so-called tail index. The GPD allows for an explicit individual modeling of the upper and lower tails, where the downside risk perspective implies a focus on the lower tail.[2]

The estimated GARCH processes offer a good approximation to the time series behavior of our respective market returns. This holds for the standard close-close as well as for the intraday and overnight conditional returns. Based on the models of conditional market returns, we demonstrate that conditional overnight market returns are subject to a significantly larger magnitude of unpredictable tail risk than those for intraday holding periods. Our results from maximum likelihood estimation, tests for fat-tailedness, and additional likelihood ratio tests for tail index equality reveal consistent and highly significant differences in tail behavior between intraday and overnight observations. Overnight downside tail risk is found to be most remarkable for the four markets under examination, i.e. strongest evidence for tail risk is given for overnight market losses.

The conditional GARCH framework allows us to break up market risk into two major components, namely in (i) conditional volatility and (ii) unconditional tail risk of the return innovations. Several papers have documented that overnight risk as measured by volatility, i.e. component (i), is lower than comparable intraday risk (see e.g. French and Roll (1986), Stoll and Whaley (1990)

[2]Our approach has been validated in detail by McNeil and Frey (2000) and Jalal and Rockinger (2008). EVT forms a powerful modeling framework for extreme market movements. Straetmans and Candelon (2013) test for structural change in the tail index and find that stationary tail behavior over long time spans can well be assumed for emerging as well as developed stock markets. Financial risk management applications based on tail index estimation methods include for example Bali and Neftci (2003), Danielsson and de Vries (2000), Galbraith and Zernov (2004), Kearns and Pagan (1997), Lauridsen (2000), Longin (2000), Wagner and Marsh (2005).

and Barclay et al. (1990).) While we confirm this finding, our results show that the picture is opposite for overnight tail risk, i.e. component (ii). Hence, while overnight volatility risk is typically remarkably lower, overnight returns are subject to significant innovation tail risk, which intraday returns are not at all. In other words, intraday fat-tailedness can be explained by time-varying GARCH volatility, while conditional overnight returns contain significant unexplained components of fat-tailedness. These latter components are obviously due to an overnight lack of market functionality and liquidity, which also manifests itself by a price jump in the market open. In a Value-at-Risk (VaR) setting, we demonstrate the implications of our findings and show that the tail risk component is of general relevancy for market downside risk. Overnight VaR calculations for the U.S. NASDAQ market illustrate how the risk components add to each other and that tail risk can become dominant for a high probability level. We conclude that overnight returns tend to exhibit fat-tailed innovations, while intraday returns do not. We therefore affirm that overnight market positions are subject to enhanced tail risk. A consideration of overnight volatilities only would severely underestimate overnight downside market risk. Market participants are therefore well advised to consider volatility as well as tail risk of their overnight market positions.

The remainder of this paper is organized as follows. Section 2 presents the GARCH model specification of conditional market returns. It also contains the methodological framework for tail index estimation based on threshold exceedances. The stock market sample and the empirical results are presented in Section 3, which also includes tail index test and VaR estimation results. Section 4 concludes.

2 Conditional Market Returns

Tail risk addresses tail events of an empirical distribution function, which are characterized by rare events that can hardly be modeled by traditional models (see e.g. Bhansali (2008)). Following Embrechts et al. (1997), Diebold et al. (1998), Lauridsen (2000), and McNeil and Frey (2000) one established approach is to model conditional returns first in a time series setting and then to characterize model innovations by EVT methods. As this method appears to be robust, we apply the two-step procedure as a starting point of our analysis.[3]

2.1 Market Return Model

The time series model of conditional market returns is composed of a conditional mean and a conditional variance equation. In order to account for autocorrelation in market index returns, the mean equation of the returns is given by a standard autoregressive model of order l, AR(l) in short. Given a differing impact of positive and negative innovations to variance, we choose the GARCH specification as introduced by Glosten et al. (1993) and Zakoian (1994) (TGARCH or GJR-GARCH model see also e.g. Taylor (2005)). In this setting, positive market return innovations $\epsilon_{t-1} > 0$, and negative innovations $\epsilon_{t-1} < 0$, have different effects on lagged conditional market return variance, σ_t^2, which is modeled by a threshold of order one. For lag order two, $l = 2$ for example, the AR(2)-TGARCH(1,1,1) model of conditional market returns reads as:

$$R_t = \mu + \rho_1 R_{t-1} + \rho_2 R_{t-2} + \epsilon_t, \tag{1}$$

[3] Jalal and Rockinger (2008) investigate the robustness of the McNeil and Frey (2000) approach under deviations from a return generating process as given by a GARCH model with normal innovations. They test several models, including processes with Student-t innovations, regime switching models and a stochastic volatility model with jumps, and conclude that the two-step procedure obtains accurate estimates also under such alternatives.

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \gamma\epsilon_{t-1}^2 I_{t-1} + \beta\sigma_{t-1}^2. \tag{2}$$

Here, $\epsilon_t = Z_t\sigma$ denotes an i.i.d. random variable with conditional variance σ_t^2, Z_t is an i.i.d. standardized draw from a stationary distribution, which is independent of σ_t^2, and I_t serves as an indicator function, i.e. $I_t = 1$ if $\epsilon_t < 0$ and $I_t = 0$ otherwise.

2.2 Market Return Components

Close-close market return observations R_t can be split up into the open-close intraday and the close-open overnight component. With index price levels $P_{t,\bullet}$ observed at the market open, O, or the market close, C, of day t and continuously compounded returns, we have

$$R_{t,\mathrm{CC}} = \ln P_{t,\mathrm{C}} - \ln P_{t-1,\mathrm{C}}, \tag{3}$$

$$R_{t,\mathrm{OC}} = \ln P_{t,\mathrm{C}} - \ln P_{t,\mathrm{O}}, \tag{4}$$

$$R_{t,\mathrm{CO}} = \ln P_{t,\mathrm{O}} - \ln P_{t-1,\mathrm{C}}, \tag{5}$$

and hence the equality

$$R_{t,\mathrm{CC}} = R_{t,\mathrm{OC}} + R_{t,\mathrm{CO}}, \tag{6}$$

holds. This result allows us to model not only the close-close market returns but also the open-close and the close-open components individually. While the distinct time series features of the three series may differ, the AR-TGARCH model allows us to capture the important linear and non-linear time series dependence effects for the observed returns.

2.3 Market Return Innovations

As the model residual is defined as $\epsilon_t = Z_t\sigma$ in equation (1) above, EVT can be applied to characterize the extreme behavior of the standardized i.i.d. innovations Z_t with $t = 1, ..., T$. The central result of EVT is that the only possible limiting distributions for standardized maxima or minima of a given distribution function—i.e. its upper tail or lower tail, respectively—are of the Gumbel, Fréchet or Weibull type of extreme value distribution families. Thereby, the Fréchet-type covers the case of the so-called fat-tailed distributions. In the following, we use the peaks over threshold approach, which is one of the most well-known implementations of EVT. It is based on the result that the extreme values of the i.i.d. innovations, $Z = Z_t$, can be modeled by the exceedances, $Y_1, ..., Y_i, ..., Y_{N_u}$, of a given high threshold $u > 0$, where N_u is the random number of exceedances. The conditional distribution function of the exceedances, $Y = Y_i$, is given as

$$F_u(y) = P(Z - u \leq y | Z > u) = P(Y \leq y | Z > u), \quad y \geq 0. \tag{7}$$

It can be shown that $F_u(y)$ can be approximated by the GPD, $G_{\xi,\beta}(y)$, with parameters $\xi \in \mathbb{R}$ and $\beta > 0$ (see e.g. Embrechts et al. (1997)), where the tail of the GPD, $1 - G_{\xi,\beta}(y)$, is

$$\bar{G}_{\xi,\beta}(y) = \begin{cases} \left(1 + \xi \frac{y}{\beta}\right)^{-\frac{1}{\xi}} & \text{if} \quad \xi \neq 0, \\ \mathrm{e}^{-\frac{y}{\beta}} & \text{if} \quad \xi = 0, \end{cases} \quad y \in D(\xi, \beta), \tag{8}$$

with

$$D(\xi, \beta) = \begin{cases} [0, \infty) & \text{if} \quad \xi \geq 0, \\ [0, -\beta/\xi] & \text{if} \quad \xi < 0. \end{cases} \tag{9}$$

Note that the GPD encompasses all three above mentioned types of extreme value distributions and is completely characterized by its parameters ξ and β. While the tail index ξ is invariant with respect to threshold choice, the parameter β is a linear function of the threshold.

The estimators of ξ and β can be determined via maximization of the following log-likelihood function:

$$\ell((\xi, \beta); y_i) = -N_u \ln\beta - \left(1 + \frac{1}{\xi}\right) \sum_{t=i}^{N_u} \ln\left(1 + \frac{\xi}{\beta} y_i\right). \tag{10}$$

The method of parameter estimation for the GPD via maximum likelihood is valid for $\xi > -0.5$ and the estimators exhibit the usual asymptotic properties of consistency and asymptotic efficiency (see Smith (1985)). The selection process of an optimal threshold u implies a bias-variance trade-off in estimation, as a low threshold results in too many exceedances that may violate the limiting results of EVT, whereas a very high threshold may induce an insufficient number of exceedances, which in turn results in high estimation error (see e.g. Embrechts et al. (1997)). We will address this issue in the empirical analysis in more detail.

3 Empirical Analysis

3.1 Market Returns Summary Description

Before we proceed with our estimation results, the empirical summary characteristics of the intraday and overnight returns are given in this section. Our dataset consists of four major stock market indices covering the U.S., France, Germany and Japan. The chosen indices include the NASDAQ Composite, the CAC 40, and the DAX 30 with observations ranging from September 1, 1988 to July 30, 2010. The Japanese TOPIX is added with observations from August 1, 1990 to July 30, 2010. The choice of the data set is governed by the representativeness of the respective indices and a given consistent long term availability of open as well as close index quotes. The daily close-close market observations are split up into the open-close intraday trading period and the close-open overnight non-trading period. Summary statistics for the resulting 5716 daily continuously compounded returns are presented in Table 1 for the NASDAQ and the TOPIX (with 5217 daily return observations) and in Table 2 for the CAC and the DAX. The tables include the standard close-close returns, R_{CC}, as well as overnight and intraday returns, i.e. R_{CO} and R_{OC} for the respective markets.

(Table 1 and 2 about here)

Tables 1 and 2 confirm that the null hypothesis of normality has to be rejected by the Jarque-Bera statistic, and the Ljung-Box statistics for lags of 5, 10 and 15 trading days indicate significant linear dependence. This holds for all the market return series of our sample. Turning to the volatility estimates, we observe that overnight estimates are lower than those obtained from the intraday returns, where overnight volatility of the markets on average is less than about 60 percent of intraday volatility. Given that differing time spans are considered, the effect is even more remarkable as the overnight period is about twice as long as the intraday trading period. This finding is in line with previous empirical results of lower volatility during non-trading periods (see e.g. French and Roll (1986), Stoll and Whaley (1990) and Barclay et al. (1990)). In an information flow setting, it has been argued that less market wide information is embedded into prices during overnight periods, i.e. when stock exchanges are closed. However, this picture from the second moment is different when we look at the forth moment of the return distributions. As to be expected, all return series exhibit high degrees of sample kurtosis. At the same time, the statistics indicate remarkably high degrees of sample kurtosis for NASDAQ, CAC and DAX overnight periods, where the highest estimate is given for DAX overnight returns. Sample skewness is negative for all market close-close returns. As with kurtosis, negative sample skewness is especially remarkable for NASDAQ, CAC and DAX overnight periods, where the highest estimate again is given for DAX overnight returns. These sample kurtosis and skewness results jointly yield a first suggestion that downside risk is most remarkable for overnight returns, where evidence for the TOPIX is weak but remarkable for the other three markets. Higher moment sample estimates are know to be relatively unstable. Based on the presented EVT approach, we examine our return sample in more detail in the following sections.

3.2 Conditional Market Returns and Innovations

Our time series model as given by equations (1) and (2) above describes conditional market returns, which are predictable, and the unpredictable innovations, which drive the return series. By modeling conditional returns we embed all conventional knowledge on the market return dynamics via the model and then focus on the tail risk, which remains in the distribution function of the model innovations. This approach allows us to focus on the unpredictable downside risk component.

Estimation of the AR(l)-TGARCH(1,1,1) model via quasi maximum likelihood yields the coefficients presented in Table 3 and Table 4, where $l = 2$ was chosen as one reasonable choice for the lag order, which is confirmed with the results in the following paragraph. Inspection of the tables indicates that the estimated parameters of the variance equation of the GARCH specification are highly significant in all but one case, whereas the parameters of the mean equation are in several cases turn out to be insignificant. Given equation (6), where intraday and overnight continuously compounded returns add up to close-to-close returns, we may expect very distinct time series features of the three series. Surprisingly, the results in the tables do indeed confirm very similar linear (i.e. AR) as well as nonlinear (i.e. GARCH) time series properties. As such, the AR-terms do not show remarkable differences in their significance. Unreported TGARCH volatility persistence measures, $\alpha + 1/2\gamma + \beta$, are of similar order.

Also, the maximized log-likelihood values and adjusted R-squared measures do not indicate differences in model fit. The only notable observation appears to be that estimates of the α-parameter for the overnight returns of all markets tend to be about three times higher than those for regular close-close as well as intraday observations. This observation suggests that predictable overnight market volatility is particularly induced by the previous overnight return innovation.

(Table 3 and 4 about here)

Summary statistics of the resulting standardized innovations, $\hat{Z}_t = \hat{\epsilon}_t / \hat{\sigma}_t$, as well as corresponding Ljung-Box statistics are presented in Table 5 and Table 6. The Ljung-Box results demonstrate that the null hypothesis of uncorrelated innovations cannot be rejected at conventional levels. Interestingly, overnight return innovations exhibit the highest levels of sample kurtosis and negative sample skewness for all markets. Kurtosis and skewness results jointly suggest that unpredictable downside risk stemming from the return innovations is most remarkable for overnight returns for all four markets. Overall, the AR-TGARCH model captures important linear and non-linear time series dependence effects for the distinct observed market returns. This allows us to proceed with our EVT analysis.

(Table 5 and 6 about here)

3.3 GPD Tail Index Estimation

Our next step is the estimation of the tail indices and an analysis of their potential differences given intraday and overnight returns. To this aim, the GPD peaks over threshold model is estimated for the exceedances of the standardized market return innovations given a high threshold. As mentioned above, the threshold parameter u has to be chosen with care. In the literature several sophisticated adaptive approaches for threshold selection were presented (see e.g. Wagner and Marsh (2005) for an overview on the small sample bias-variance trade-off). An alternative pragmatic approach, which is chosen here is to determine the threshold in a way such that a fixed percentage of returns lies above the chosen threshold level. Based on a Monte Carlo simulation study, McNeil and Frey (2000) find that a fixed number of exceedances of approximately ten percent of the return observations yields adequate results for GPD parameter estimation. Following Embrechts et al. (1997), it is advisable to augment such procedure by visual approaches, where one assures that the threshold is chosen such that it is chosen from a region where the estimator of the tail index is stable. As an example, Figure 1 demonstrates the choice of the appropriate threshold for the overnight returns of the NASDAQ. The tail index estimate remains stable in the region of approximately 450 to 550 exceedances, and a choice of 540 exceedances corresponds to a fraction of about 9.5 percent of the given return innovations. Overall, applying this procedure to the upper and lower tail regions of our four markets, results in choices that amount to between seven and ten percent of the return innovations.

(Figure 1 about here)

Maximum likelihood estimation of the parameters ξ and β of the GPD according to (10) yields the estimates reported in Table 7. Inspection of the table demonstrates that the estimated β-parameters of the distributions do not vary remarkably, while the tail indices, which govern extreme behavior, show remarkable variation. The reported estimation results in Table 7 allow us to test the null hypothesis $H_0 : \xi = 0$ of a zero tail index, which states that the innovation tails are moderate. Based on the asymptotic normality results of the GPD estimator, the critical value for a double-sided test at the 5 percent level is: $\pm 1.96\hat{\sigma}$. The table also reports the number of threshold exceedances and the corresponding sample fraction that is used. Estimation is carried out for the upper and lower tails of all three returns in each of the four markets, i.e. for 24 cases altogether.

(Table 7 about here)

As it turns out, the null hypothesis of a zero tail index cannot be rejected in 13 out of 24 cases (see Table 7).[4] These cases encompass all of the *intraday* returns, except the upper tail of the TOPIX intraday returns, which yield a tail index estimate slightly above the critical value. In these cases, a conditionally normal innovation distribution suffices in explaining the observable fat-tails in unconditional returns. In other words, the TGARCH time-varying conditional volatility indeed explains intraday fat-tailedness. Overnight returns in contrast reveal fat-tailed innovations as a source of unpredictable tail risk, which is beyond that produced by the TGARCH model. As such, the null hypothesis has to be rejected in 7 out of 24 cases with the conclusion that fat-tails are present in the respective *overnight* innovations. The rejections concern the upper as well as lower tails of all overnight returns, except the upper overnight tail of the CAC, which yields a tail index estimate slightly below the critical value. Further, in 2 out of 24 cases evidence of fat-tailed innovations is given for lower tail CAC and DAX standard close-close returns. In the case of the close-close NASDAQ upper tail return innovations the null is interestingly rejected in favor of the thin-tailed Weibull alternative. For the lower tail return NASDAQ innovations the null is not rejected. Hence, the conclusion applies that GARCH time-varying volatility explains fat-tailedness of NASDAQ unconditional close-close returns. These results on close-close returns also underline the tendency for higher tail risk in lower versus upper innovation tails. While the results for the TOPIX are insignificant,

[4]In these cases we observe moderate tail behavior without evidence of fat-tailedness. The innovation distribution (as for example the normal distribution) belongs to the maximum domain of attraction of the Gumbel extreme value distribution class; see e.g. Embrechts et al. (1997).

Table 7 reports evidence that lower tail return innovations not only exhibit larger tail index point estimates, but also that they follow an extreme value distribution class, which encompasses higher degrees of fat-tailedness.[5] Considering the particular significance of downside tail risk or lower tail risk in Table 7, it has to be noted that the only category which shows significant fat-tailedness for all four markets is the overnight lower tail. Overnight market losses are particularly subject to tail risk as the null hypothesis of a zero tail index uniquely has to be rejected for all markets with the alternative always being the Fréchet extreme value distribution.

In sum, we can conclude that conditional overnight returns tend to exhibit fat-tailed unpredictable innovations, while intraday returns do not. Also, we note that the lower tails of the market return distributions tend to be fatter than the upper tails. The strongest evidence for fat-tails and hence tail risk is given for overnight market losses.

3.4 Testing for Tail Index Equality

A simple comparison of the point estimates of the two GPD parameters for intraday and overnight periods may lead to inaccurate conclusions. As a robustness test of our results above, we therefore proceed with the application of a likelihood ratio (LR) test of the null hypothesis of equal GPD parameters (see e.g. Greene (2008)). The LR test statistic, $2(L_R - L_U)$, is based on the difference between the value of the log-likelihood of the unconstrained GPD, L_U, and the value of the log-likelihood which is obtained under the restricted GPD, L_R. Its limiting distribution is a chi-squared with degrees of freedom equal to the number of restrictions imposed. Testing the equality of the ξ-parameter, the likelihood ratio

[5] This result is in line with findings by Hartmann et al. (2001) who observe a larger tail index of the lower tail for stock index returns with a Hill-estimator based t-test. In contrast, Jondeau and Rockinger (2003) find no significant difference in the lower and the upper tail indices for a large set of stock indices using a likelihood ratio test.

test statistic is therefore χ_1^2-distributed.

The likelihood ratio test is performed under the null hypothesis of equal tail indices for the market return innovations. Hence, the tail index for intraday innovations, ξ_{OC}, supposedly equals the one for overnight innovations, ξ_{CO}, and $H_0 : \xi_{\mathrm{OC}} = \xi_{\mathrm{CO}}$. Table 8 further reports likelihood ratio test statistics based on standard close-close returns, i.e. $H_0 : \xi_{\mathrm{CO}} = \xi_{\mathrm{CC}}$ and $H_0 : \xi_{\mathrm{OC}} = \xi_{\mathrm{CC}}$. As the GPD estimation can be restricted by conditioning on each of the pairs' individually obtained unrestricted ξ-parameter estimate, Table 8 reports six LR-test-statistics for the three hypotheses above.

(Table 8 about here)

The results in the last two columns of Table 8 show that the null of equal intraday and overnight tail index parameters has to be rejected at the 1 percent level. Hence, a highly significant difference of the tail indices is found. This result underlines our findings from the previous section and holds for the lower as well as the upper tails. The overall magnitude of the difference is large. One exception represents the comparison for the upper tail of CAC index innovations, which allows for a rejection of the null only at the 10 percent level. Similar results are found for the comparison of the tail indices with the standard close-close returns. Considering overnight innovations, ξ_{CO}, and close-close innovations, ξ_{CC}, tail index equality is rejected at the 5 percent level for the upper as well as lower tails of all markets. An exception is given by CAC index lower tail innovations, which allow for a rejection of the null only at the 10 percent level (see columns two and three of Table 8).

This overall finding underlines that conditional overnight returns in all markets exhibit significantly higher levels of unpredictable tail risk as compared to intraday as well as standard close-close returns. In contrast to this, the remaining results confirm that intraday innovation tail indices and close-close innovation tail indices do not significantly differ from each other (see columns four and five in Table 8).[6]

3.5 Downside Risk Implications

The risk implications of our results are straightforward to point out in a conditional Value-at-Risk (VaR) setting. Based on our tail index estimation results for overnight and intraday lower tail return innovations, $-Z$, we can illustrate downside market risk via VaR for a set of suitable parameter assumptions.

The conditional day-t VaR, given as a positive-valued market return loss quantile that is not exceeded with a high probability $0 < p < 1$, is

$$\mathrm{VaR}_{t,p} = \mu_t + \sigma_t \, q_p, \tag{11}$$

where μ_t follows from the conditional return equation (1), the conditional market variance σ_t is given by equation (2), and q_p is the p-quantile of the distribution of the i.i.d. innovations (Z_t). Based on the GPD, we have (see e.g. Embrechts et al. (1997)):

$$q_p = u + \frac{\beta}{\xi}\left(\left(\frac{1-p}{N_u/T}\right)^{-\xi} - 1\right). \tag{12}$$

Using our estimation results for the NASDAQ market, we make the following parameter assumptions in Table 9. The conditional intraday, overnight and close-close market return variances are set equal to their unconditional values. In model (2), unconditional market return variance is given by: $\sigma^2 = \omega/(1 - \alpha - \frac{1}{2}\gamma - \beta)$. Based on the point estimates of Table 3, the corresponding market volatility estimates are reported in Table 9. Targeting downside risk, we set the conditional return in (11) equal to zero, as conditional daily returns are very

[6] An exception is given for the lower tail of the CAC index innovations, where the equality hypothesis cannot be maintained as lower tail CAC close-close innovations are significantly fat-tailed (see also Table 7).

small, and address the EVT distribution of the lower tail innovations. Table 7 above delivers the GPD (ξ, β)-point estimates for the intraday and for the overnight return innovations. It also reports the corresponding chosen thresholds and the empirical threshold exceedance probabilities. According to equation (10) and (11), Table 9 presents the resulting GPD-quantiles, q_p and the VaR_p estimates for five different probability levels p. Note for example that a p-value of 0.999 relates to one event in 1000 trading days, i.e. the worst day within about four years.

(Table 9 about here)

Table 9 reports NASDAQ downside risk VaR results. The observation of higher intraday as compared to overnight market volatility confirms the discussion above. Daily NASDAQ overnight unconditional market return volatility amounts to about 80 percent of the intraday level.[7] Why is it then that some trader appear to try to avoid overnight exposure when overnight volatility is remarkably lower than intraday volatility? The answer is that, despite this observation, the given overnight tail risk yields substantially higher quantile estimates especially for the higher probability levels including the 99.9, the 99.5 and the 97.5 percent levels.[8] This observation underlines that, given a location μ_t level, conditional VaR breaks up into two multiplicative components in equation (11), namely the volatility and the innovation component. Intraday returns are subject to a larger volatility and smaller innovation component. The situation is reverse for overnight returns, where tail risk emerges. For example, given its tail risk component, NASDAQ overnight VaR turns out to be higher than intraday VaR at the 99.9 percent level as tail risk dominates the lower overnight volatility

[7] See also Section 2.1 and the summary statistics of Table 1, where the overnight sample volatility is about 55 percent of the intraday level.

[8] The GPD-quantiles are also substantially higher than those of the standard normal distribution, which are additionally given in column one of Table 9.

level. Overall, downside VaR is equal or lower for the overnight period due to the fact that overnight volatility is low. Still, even for a mature stock market such as the NASDAQ, it can be concluded that overnight tail risk may matter for at least some (cautious) market participants. The results for the other markets underline that overnight downside tail risk impacts overnight VaR for the French, German and Japanese markets as well. This can be seen from the ratios of overnight to intraday quantiles for our markets under study. Given the 99.9 percent VaR level, the quantile-ratios for NASDAQ, TOPIX, CAC and DAX are 1.33, 1.27, 1.33, and 1.38, respectively. Given the 99 percent level, the quantile-ratios still are 1.07, 1.03, 1.05, and 1.02, respectively. Hence, while overnight volatility is only between 40 to about 80 percent of intraday volatility in our sample, higher tail risk results in higher downside risk exposure. Therefore, a consideration of volatilities only would severely underestimate overnight downside market risk.

4 Conclusion

Is the risk on the books of a financial institution higher during non-trading periods? The present paper shows that this question generally cannot be simply affirmed or rejected. Previous research has shown that volatility per time period is lower during overnight non-trading hours. However, we demonstrate that conditional overnight market returns are subject to a significantly larger magnitude of tail risk than intraday market returns. As such our test results obtained from maximum likelihood estimation as well as likelihood ratio tests show consistent and highly significant differences in tail behavior. This finding underlines that the features of intraday versus overnight market returns are fundamentally different. While intraday fat-tailedness can be explained by time-varying volatility, overnight non-trading period returns contain significant components of fat-tailedness. These latter components are obviously due to an overnight lack of market functionality and liquidity, which manifests itself by a price jump in the market open. This tail risk component has relevancy in an overall market downside risk setting and we illustrate that overnight tail risk should be considered in market participants' risk assessment. Further research may address the underlying risk sources in more detail, examine additional components of overnight non-trading risk or address the market dynamics in more detail.

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A 1. Tables (Descriptive Statistics)

	NASDAQ RETURN CC	**NASDAQ RETURN CO**	**NASDAQ RETURN OC**	**TOPIX RETURN CC**	**TOPIX RETURN CO**	**TOPIX RETURN OC**
Mean	0.000315	0.000419	-0.000104	-0.000186	0.000208	-0.000394
Median	0.000645	0.00064	0.0006	0.00000	0.00029	-0.00035
Maximum	0.13255	0.05051	0.14896	0.12865	0.05822	0.11256
Minimum	-0.10168	-0.07166	-0.09384	-0.10007	-0.0391	-0.08436
Std. Dev.	0.015006	0.007454	0.013196	0.01335	0.005219	0.011594
Skewness	-0.056376	-0.651311	-0.032309	-0.018264	0.065502	0.107713
Kurtosis	9.61182	13.57892	11.33438	8.888116	9.314936	9.655946
Jarque-Bera	10414.76	27058.19	16544.51	7536.661	8672.3	9640.152
Probability	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	5716	5716	5716	5217	5217	5217
lag	Q-Stat	Q-Stat	Q-Stat	Q-Stat	Q-Stat	Q-Stat
5	6.863	61.019	8.4942	35.701	12.716	51.316
	(0.231)	(0.000)	(0.131)	(0.000)	(0.026)	(0.000)
10	11.252	78.729	14.175	49.214	20.481	67.062
	(0.338)	(0.000)	(0.165)	(0.000)	(0.025)	(0.000)
15	47.788	134.91	30.528	53.843	34.109	72.287
	(0.000)	(0.000)	(0.010)	(0.000)	(0.003)	(0.000)

Table 1: Summary statistics and Ljung-Box statistics for lags 5, 10 and 15 of daily NASDAQ returns from 09/01/1988 to 07/30/2010 and daily TOPIX returns from 08/01/1990 to 07/30/2010: CC: close-close returns, CO: close-open returns and OC: open-close returns. p-values in parentheses.

	CAC RETURN CC	**CAC RETURN CO**	**CAC RETURN OC**	**DAX RETURN CC**	**DAX RETURN CO**	**DAX RETURN CO**
Mean	0.000183	0.000137	4.60E-05	0.000293	0.000307	-1.43E-05
Median	0	0.00031	0.000305	0.000445	0.00036	0.000395
Maximum	0.10595	0.06567	0.07282	0.10797	0.04936	0.11141
Minimum	-0.09472	-0.11105	-0.0832	-0.1371	-0.09641	-0.09103
Std. Dev.	0.013723	0.008329	0.01145	0.014414	0.006785	0.012189
Skewness	-0.039565	-0.571993	-0.116498	-0.266568	-1.307942	-0.007889
Kurtosis	8.30314	18.11913	7.37387	9.612046	22.09131	10.44406
Jarque-Bera	6699.523	54753.77	4569.234	10480.14	88436.31	13197.83
Probability	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	5716	5716	5716	5716	5716	5716
lag	Q-Stat	Q-Stat	Q-Stat	Q-Stat	Q-Stat	Q-Stat
5	41.251	109.47	14.621	16.013	22.507	10.700
	(0.000)	(0.000)	(0.012)	(0.007)	(0.000)	(0.058)
10	48.276	142.13	16.369	23.469	37.001	18.717
	(0.000)	(0.000)	(0.090)	(0.009)	(0.000)	(0.044)
15	52.320	148.87	27.765	28.320	43.703	23.591
	(0.000)	(0.000)	(0.023)	(0.020)	(0.000)	(0.072)

Table 2: Summary statistics and Ljung-Box statistics for lags 5, 10 and 15 of daily CAC and DAX returns from 09/01/1988 to 07/30/2010: CC: close-close returns, CO: close-open returns and OC: open-close returns. p-values in parentheses.

A 2. Tables (Estimation Results)

	u/extremes	percentage	ξ	β	Log-Lik.
CAC					
CAC Return CC +	1.31/490	8.57%	-0.0341461	0.4767916	110.3261
			(0.0400512)	(0.0287779)	
CAC Return CC -	-1.47/420	7.30%	0.1145443	0.4913094	168.7772
			(0.0460857)*	(0.0329025)	
CAC Return CO +	1.15/540	9.45%	0.0821976	0.4873992	196.2765
			(0.0439784)	(0.0299412)	
CAC Return CO -	-1.33/460	8.05%	0.1845792	0.5478399	268.0186
			(0.0516954)*	(0.0378425)	
CAC Return OC +	1.41/420	7.35%	0.0071848	0.4472973	85.11401
			(0.0414818)	(0.0286454)	
CAC Return OC -	-1.34/510	8.92%	-0.0489179	0.6066345	230.1258
			(0.0421126)	(0.0370448)	
DAX					
DAX Return CC +	1.19/570	9.97%	0.0109114	0.4662172	141.2375
			(0.0349722)	(0.0254382)	
DAX Return CC -	-1.31/520	9.10%	0.1309496	0.5230063	251.0345
			(0.0396891)*	(0.030784)	
DAX Return CO +	1.23/430	7.53%	0.18719	0.3939646	110.1919
			(0.0548471)*	(0.0285369)	
DAX Return CO -	-1.14/520	9.10%	0.2960368	0.5272615	341.1378
			(0.0538204)*	(0.0359572)	
DAX Return OC +	1.21/540	9.45%	-0.0392117	0.5003368	144.9182
			(0.0377418)	(0.0286225)	
DAX Return OC -	-1.27/570	9.97%	0.0687089	0.5888206	307.2375
			(0.0371184)	(0.0329109)	
NASDAQ					
NASDAQ Return CC +	1.26/500	8.75%	-0.1114749	0.5125322	110.0516
			(0.0331988)*	(0.0284326)	
NASDAQ Return CC -	-1.38/500	8.75%	0.0715503	0.56323	248.7781
			(0.041988)	(0.0345031)	
NASDAQ Return CO +	1.07/540	9.45%	0.1301555	0.5031926	239.4371
			(0.0497709)*	(0.032986)	
NASDAQ Return CO -	-1.08/560	9.80%	0.183618	0.6519693	423.3155
			(0.0442855)*	(0.0395874)	
NASDAQ Return OC +	1.16/560	9.80%	-0.0340114	0.4789272	128.6695
			(0.0415302)	(0.0283661)	
NASDAQ Return OC -	-1.33/530	9.27%	0.0441602	0.5989791	281.8018
			(0.0382567)	(0.034653)	
TOPIX					
TOPIX Return CC +	1.30/450	8.63%	0.0888369	0.4976145	175.8766
			(0.0524847)	(0.0350424)	
TOPIX Return CC -	-1.25/500	9.59%	0.00000202	0.5959771	241.7206
			(0.0421525)	(0.0366082)	
TOPIX Return CO +	1.21/430	8.25%	0.2926287	0.3652684	123.0677
			(0.0555027)*	(0.0263454)	
TOPIX Return CO -	-1.18/490	9.39%	0.2235528	0.5002013	260.1422
			(0.0473179)*	(0.0323307)	
TOPIX Return OC +	1.35/400	7.67%	0.1249602	0.4860228	161.3419
			(0.0568701)*	(0.0366768)	
TOPIX Return OC -	-1.23/500	9.59%	0.0377058	0.5600874	229.4663
			(0.0447266)	(0.035396)	

Table 7: Maximum likelihood estimates for the parameters ξ and β of the GPD distribution. Standard errors in parentheses. - and + correspond to the lower and the upper tail of the market return innovations Z_t. CC: close-close returns, CO: close-open returns and OC: open-close returns. Superscript * denotes significance at the 5% level.

	NASDAQ RETURN CC	**NASDAQ RETURN CO**	**NASDAQ RETURN OC**	**TOPIX RETURN CC**	**TOPIX RETURN CO**	**TOPIX RETURN OC**
Mean Equation	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
C	0.00042	0.00033	0.00022	-0.00017	0.000216	-0.000427
	(0.000132)**	(7.03E-05)**	(0.000111)*	(0.000147)	(4.61E-05)**	(0.000125)**
RETURN(-1)	0.07465	-0.059727	0.062871	0.072119	0.024097	0.088367
	(0.014605)**	(0.013969)**	(0.014086)**	(0.015157)**	(0.014584)	(0.014355)**
RETURN(-2)	0.001517	-0.009634	0.009628	-0.006186	-0.022614	0.009426
	(0.013265)	(0.013024)	(0.013741)	(0.014268)	(0.015324)	(0.014534)
Variance Equation						
ω	1.18E-06	5.75E-07	7.71E-07	3.48E-06	5.34E-07	2.46E-06
	(1.17E-07)**	(3.03E-08)**	(6.71E-08)**	(3.67E-07)**	(2.22E-08)**	(2.84E-07)**
α	0.028908	0.088583	0.034381	0.028738	0.109025	0.041777
	(0.005052)**	(0.006161)**	(0.006104)**	(0.005063)**	(0.005356)**	(0.005639)**
γ	0.075461	-0.002546	0.072942	0.111047	0.024976	0.118561
	(0.006393)**	(0.006136)	(0.007084)**	(0.008246)**	(0.008485)**	(0.009126)**
β	0.925707	0.904882	0.922265	0.896485	0.865693	0.883559
	(0.004523)**	(0.004185)**	(0.004518)**	(0.006283)**	(0.004169)**	(0.006665)**
Adjusted R-squared	-0.006731	0.008003	-0.005911	0.002196	0.001096	0.005041
Log likelihood	17477.97	21411.38	18311.68	15791.27	20937.55	16583.61

Table 3: Coefficients of the fitted AR(2)-TGARCH(1,1,1) model with normal innovations to daily NASDAQ returns from 09/01/1988 to 07/30/2010 and TOPIX returns from 08/01/1990 to 07/30/2010: CC: close-close returns, CO: close-open returns and OC: open-close returns. Standard errors in parentheses. Superscripts * and ** denote significance at the 5% and 1% level, respectively.

	CAC RETURN CC	**CAC RETURN CO**	**CAC RETURN OC**	**DAX RETURN CC**	**DAX RETURN CO**	**DAX RETURN OC**
Mean Equation	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
C	0.000189	5.92E-05	0.000238	0.000386	0.00014	0.000103
	(0.000147)	(8.05E-05)	(0.000116)*	(0.000151)*	(5.14E-05)**	(9.52E-05)
RETURN(-1)	0.008079	-0.044133	-0.019125	0.00535	-0.01792	-0.003376
	(0.014484)	(0.013841)**	(0.013349)	(0.015253)	(0.011372)	(0.014185)
RETURN(-2)	-0.002514	-0.023121	0.015593	0.003743	-0.004124	0.017131
	(0.014073)	(0.012502)	(0.013792)	(0.014151)	(0.014569)	(0.013821)
Variance Equation						
ω	3.36E-06	2.58E-06	1.65E-06	4.14E-06	2.44E-07	7.21E-07
	(2.99E-07)**	(1.82E-07)**	(2.04E-07)**	(2.98E-07)**	(1.60E-08)**	(7.68E-08)**
α	0.015687	0.090165	0.0281	0.025319	0.158835	0.061197
	(0.005301)**	(0.008439)**	(0.005558)**	(0.005468)**	(0.006713)**	(0.007143)**
γ	0.105657	0.209924	0.093357	0.118601	-0.033319	0.070799
	(0.007571)**	(0.011135)**	(0.008177)**	(0.006435)**	(0.006751)**	(0.007278)**
β	0.91021	0.784887	0.910827	0.892309	0.879917	0.900308
	(0.00558)**	(0.007371)**	(0.005494)**	(0.005373)**	(0.003489)**	(0.005126)**
Adjusted R-squared	-0.000443	0.009126	0.000276	-0.000816	0.000599	-0.000435
Log likelihood	17273.05	20293.31	18335.88	17118.44	21732.83	18890.39

Table 4: Coefficients of the fitted AR(2)-TGARCH(1,1,1) model with normal innovations to daily CAC and DAX returns from 09/01/1988 to 07/30/2010: CC: close-close returns, CO: close-open returns and OC: open-close returns. Standard errors in parentheses. Superscripts * and ** denote significance at the 5% and 1% level, respectively.

	NASDAQ RETURN CC	**NASDAQ RETURN CO**	**NASDAQ RETURN OC**	**TOPIX RETURN CC**	**TOPIX RETURN CO**	**TOPIX RETURN OC**
Mean	-0.006102	0.012641	-0.019037	-0.004962	-0.005671	-0.003228
Median	0.029086	0.070364	0.0373	0.007981	0.025318	0.002788
Maximum	4.178733	6.366367	4.028226	5.527212	11.51249	6.383851
Minimum	-6.382058	-14.01476	-7.393554	-4.916854	-10.74518	-5.358293
Std. Dev.	0.999904	0.999643	0.99965	1.000081	0.999937	1.000105
Skewness	-0.472655	-1.4633	-0.467934	-0.056761	-0.256411	-0.038804
Kurtosis	4.708034	19.97602	4.750266	4.587095	15.38001	4.756058
Jarque-Bera	907.3336	70651.29	937.8773	550.1296	33360.27	671.3796
Probability	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	5714	5714	5714	5215	5215	5215
lag	Q-Stat	Q-Stat	Q-Stat	Q-Stat	Q-Stat	Q-Stat
5	0.5132	4.2363	3.1684	1.3293	0.9484	2.1323
	(0.992)	(0.516)	(0.674)	(0.932)	(0.967)	(0.831)
10	2.3122	12.124	4.7015	6.1271	8.3026	6.7019
	(0.993)	(0.277)	(0.910)	(0.804)	(0.599)	(0.753)
15	20.434	44.884	11.565	8.007	23.538	8.7327
	(0.156)	(0.000)	(0.712)	(0.924)	(0.073)	(0.891)

Table 5: Summary statistics and Ljung-Box statistics for lags 5, 10 and 15 of the standardized innovations of the AR(2)-TGARCH(1,1,1) model with normal innovations to daily NASDAQ returns from 09/01/1988 to 07/30/2010 and daily TOPIX returns from 08/01/1990 to 07/30/2010: CC: close-close returns, CO: close-open returns and OC: open-close returns. p-values in parentheses.

	CAC RETURN CC	**CAC RETURN CO**	**CAC RETURN OC**	**DAX RETURN CC**	**DAX RETURN CO**	**DAX RETURN OC**
Mean	-0.001457	-0.00274	-0.010264	-0.006053	0.010978	-0.008269
Median	-0.011256	0.048562	0.004856	0.001827	0.054179	0.034223
Maximum	4.693604	5.698637	5.964306	5.113797	6.055912	4.551597
Minimum	-10.24667	-10.20945	-4.975239	-13.14378	-18.62735	-9.851412
Std. Dev.	1.000503	1.000114	1.000178	1.000265	0.999889	1.000287
Skewness	-0.407393	-0.633105	-0.162827	-0.844427	-2.118548	-0.507985
Kurtosis	5.808332	8.314439	3.835016	11.81438	33.05862	5.901979
Jarque-Bera	2035.756	7105.967	191.2527	19176.53	219387.5	2250.764
Probability	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	5714	5714	5714	5714	5714	5714
lag	Q-Stat	Q-Stat	Q-Stat	Q-Stat	Q-Stat	Q-Stat
5	12.756	2.288	4.0086	4.9473	0.7112	2.248
	(0.026)	(0.808)	(0.548)	(0.422)	(0.982)	(0.814)
10	18.381	13.295	6.2712	13.258	4.9634	8.6813
	(0.049)	(0.208)	(0.792)	(0.210)	(0.894)	(0.563)
15	24.142	18.661	13.667	21.273	12.954	13.4
	(0.063)	(0.229)	(0.551)	(0.128)	(0.606)	(0.571)

Table 6: Summary statistics and Ljung-Box statistics for lags 5, 10 and 15 of the standardized innovations of the AR(2)-TGARCH(1,1,1) model with normal innovations to daily CAC and DAX returns from 09/01/1988 to 07/30/2010: CC: close-close returns, CO: close-open returns and OC: open-close returns. p-values in parentheses.

A 3. Figures

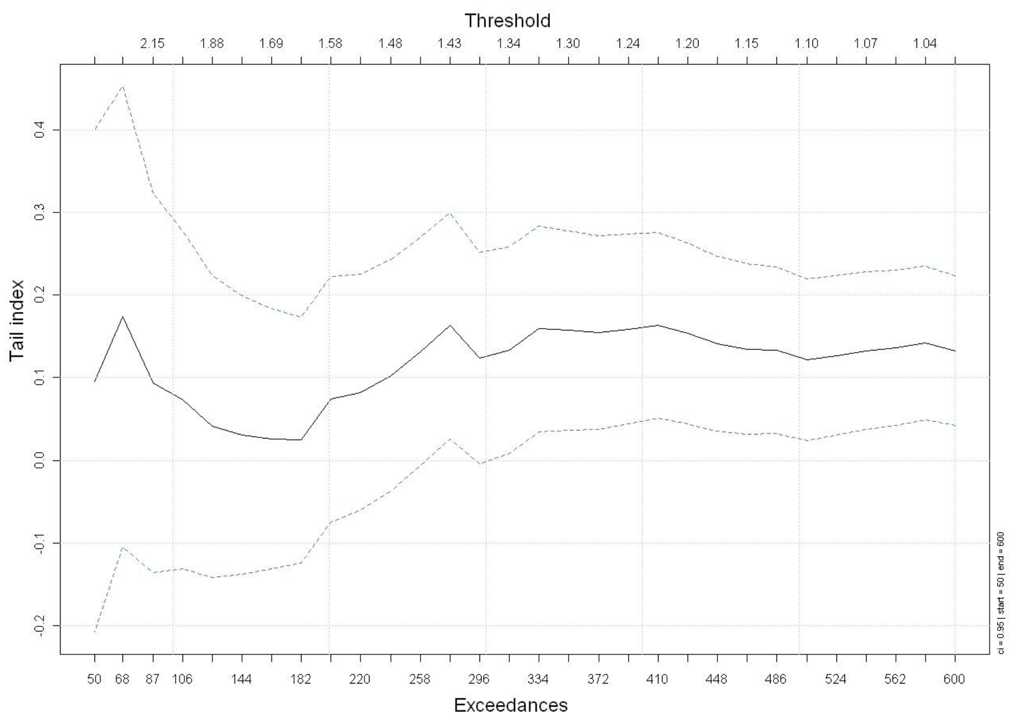

Figure 1: Tail index plot for the upper tail of the standardized daily NASDAQ overnight innovations. Dashed lines indicate upper and lower levels of the 95 percent confidence interval.

	LRT $\xi_{CC} = \xi_{CO}$	**LRT** $\xi_{CO} = \xi_{CC}$	**LRT** $\xi_{CC} = \xi_{OC}$	**LRT** $\xi_{OC} = \xi_{CC}$	**LRT** $\xi_{CO} = \xi_{OC}$	**LRT** $\xi_{OC} = \xi_{CO}$
CAC Return +	10.1716 (0.001)	6.8848 (0.009)	1.46818 (0.226)	1.6474 (0.199)	2.75196 (0.097)	4.117 (0.042)
CAC Return -	2.8596 (0.091)	4.527 (0.033)	11.7974 (0.001)	34.0936 (0.000)	20.5428 (0.000)	46.336 (0.000)
DAX Return +	17.8802 (0.000)	16.3198 (0.000)	2.0866 (0.149)	2.5386 (0.111)	21.6222 (0.000)	34.3762 (0.000)
DAX Return -	13.4836 (0.000)	11.5336 (0.001)	2.3966 (0.122)	3.2658 (0.071)	22.063 (0.000)	30.8178 (0.000)
NASDAQ Return +	26.0156 (0.000)	26.0156 (0.000)	4.469 (0.035)	4.080 (0.043)	11.0242 (0.001)	16.4588 (0.000)
NASDAQ Return -	8.7754 (0.003)	6.1584 (0.013)	4.1856 (0.041)	1.0508 (0.305)	13.2726 (0.000)	15.0132 (0.000)
TOPIX Return +	23.585 (0.000)	10.8644 (0.001)	0.6782 (0.410)	0.4584 (0.498)	6.9174 (0.009)	15.014 (0.000)
TOPIX Return -	43.4688 (0.000)	19.555 (0.000)	1.7572 (0.185)	1.7936 (0.180)	13.3418 (0.000)	26.5216 (0.000)

Table 8: Likelihood ratio test of the null hypothesis of equal tail indices ξ of upper tail (+) as well as lower tail (-) intraday, overnight and close-close market return innovations. p-values of the likelihood ratio test statistic (LRT) in parentheses. CC: close-close returns, CO: close-open returns and OC: open-close returns.

	NASDAQ Return - OC		**NASDAQ Return - CO**		**NASDAQ Return - CC**	
σ in %	1.058		0.858		1.242	
	q_p	**VaR** in %	q_p	**VaR** in %	q_p	**VaR** in %
$p = 0.999$ ($q_N = 3.09$)	4.333	4.586	5.769	4.951	4.348	5.399
$p = 0.995$ ($q_N = 2.58$)	3.197	3.383	3.661	3.142	3.169	3.935
$p = 0.99$ ($q_N = 2.33$)	2.732	2.891	2.928	2.513	2.702	3.354
$p = 0.975$ ($q_N = 1.96$)	2.138	2.263	2.092	1.796	2.118	2.630
$p = 0.95$ ($q_N = 1.64$)	1.705	1.804	1.547	1.328	1.702	2.113

Table 9: NASDAQ downside risk for intraday and overnight negative returns with additional information on close-close returns. The table reports unconditional GARCH model volatilities σ for intraday, overnight, and close-close returns in percent per day. Lower tail innovations yield estimated GPD-quantiles according to equation (11). VaR estimates are derived according to equation (10) with conditional expectations set to zero and conditional market volatility set to its unconditional levels σ. Probabilities p are given with corresponding p-quantiles of the standard Normal distribution as an additional reference. OC: open-close returns, CO: close-open returns and CC: close-close returns.