European 'fear' indices – evidence before and during the financial crisis

Wolfgang Aussenegg[(a)], Lukas Goetz[(b)], and Ranko Jelic[(c)*]

(a) Institute of Management Sciences, Vienna University of Technology,
Address: Theresianumgasse 27, A-1040 Vienna, Austria,
E-mail: waussen@pop.tuwien.ac.at, Phone: +43 1 58801 33082
(b) UNIQA Capital Markets GmbH
Untere Donaustraße 21, A-1029 Vienna, Austria
E-mail: lukas.goetz@uniqa.at, Phone: +43 1 211 75 2012
(c) Department of Accounting and Finance, University of Birmingham,
Address: Birmingham, B15 2TT, United Kingdom,
E-mail: r.jelic@bham.ac.uk, Phone: +44 (0) 121 414 5990
*Corresponding author

This draft 5th May 2013

Acknowledgements: We thank participants at the 2013 International Conference on the Global Financial Crisis-European Financial Markets and Institutions in Southampton. Special thanks to Thomson Reuters Austria GmbH for providing data.

Abstract

We document a negative and asymmetric contemporaneous relation of European stock and implied volatility returns. The negative relation is significantly more pronounced at the highest quantile of the stock market return distribution (i.e. largest price decrease). The relation between stock returns and implied volatility exhibits differences consistent with European institutional and cultural clusters. For example, German stock market tends to be more responsive to changes in implied volatility compared to UK stock market. In addition, the volatility spread for these two markets persist for a longer period compared to other European volatility spreads. The degree of integration between the leading European (UK, Germany and France) volatility markets, however, is very high and shocks on the implied volatility spread die out within a few days. Our Markov switching model distinguishes three volatility regimes. Large changes in both, implied volatility and stock returns increase the probability that volatility enters a higher (from low to middle and from middle to high) volatility regime. Factor loadings obtained by principal component analysis (PCA) of volatility returns are also regime dependent. Compared to US, the changes in European implied volatility tend to be more driven by tilts and non-linear movements of the volatility term structure. Our findings lend support to the behavioral explanation of the stock return-implied volatility relation and have implications for risk management.

JEL classification: C32, G13, G15

Keywords**:** European volatility indices, Return-volatility relation, Markov switching, Quantile regression, Impulse response function

1. Introduction

Although Chicago Board Options Exchange (CBOE) volatility index (VIX) has been de facto benchmark for stock market volatility since early 1990s, gaining exposure to volatility was not straightforward for some time. This changed in 2003, when CBOE adopted a new methodology for calculation of the VIX that facilitated replication properties of the index.[1] Soon after, European stock exchanges, such as the Eurex and Euronext, created volatility indices for several European stock markets based on the same methodology. These indices are tradeable via swap, futures, options and exchange traded notes (ETN) which, thus, provide investors with easy access to strategies involving hedging of equity risk by taking positions in implied volatility.

Early studies (Fleming et al., 1995; Whale, 2000) report a significantly negative contemporaneous relationship between changes in implied volatility indices and underlying stock market returns. This result was echoed in subsequent US (Giot 2005; Carr and Wu, 2006) and international (Gonzalez and Novales, 2009; Siriopoulos and Fassas, 2009) studies. Recent empirical evidence suggests that the US stock returns-implied volatility relation tends to be driven by behavior of market participants (Low, 2004; Hibbert et al., 2008) rather than by leverage effect (Black, 1976) and changes in investors risk aversion due to a significant increase in aggregate volatility (Poterba and Summers, 1986; Campbell and Hentschel, 1992). Giot (2005) examines the casual observation that the returns-implied volatility relation could be conditional on the trading environment. He reports that the contemporaneous relationship between implied volatility (i.e. old VIX) and S&P index returns is much stronger in a low volatility trading environment. There is, however, no previous study on the returns-implied volatility relation for the entire European market.

The objective of this study is to analyze all official European volatility indices (VDAX (Germany), VCAC (France), VFTSE (UK), VSMI (Switzerland), VBEL (Belgium), VAEX (Netherlands) and VSTOXX (eurozone)) before and during the recent financial crisis. A regime switching model is used to capture recent abrupt changes in markets' behavior. We expect differences in distributions of volatility indices in different trading environments (i.e.

[1] The methodology is based on Carr and Madan (1998) and Demeterfi et al. (1999) work on pricing variance swaps. The methodology does not require selection of a specific stock price process but assumes market completeness and continuous trading. Another important advantage of the new VIX over VOX (i.e. old VIX), is that it uses option prices over a wide range of strike prices.

high vs. low volatility periods) and across European Union (EU) countries. EU countries share a common market, the same currency (with some exceptions), and harmonized regulations, thus, creating a similar macroeconomic environment for member states. However, important institutional, legal, and cultural differences still remain. For example, UK is often described as an 'outsider economy' with a large stock market, dispersed ownership, strong investors' rights and legal enforcement, and a low degree of uncertainty avoidance (see La Porta et al., 1997 and Hofstede, 2001). Germany, on the other hand, is often described as an 'insider economy' with a smaller stock market, weaker investors' rights and a high degree of uncertainty avoidance. Thus, we expect different investors' behavior across EU volatility markets especially during the financial crisis.

We make the following contributions to the implied volatility literature. First, we extend the empirical work on the return-implied volatility association by utilizing a set of all available official European volatility indices. Second, we apply quantile regressions in order to capture potential asymmetric relations between European stock returns and implied volatility before and during financial crisis. Third, we examine differences in volatility index distributions together with differences in the stock returns-implied volatility relation across institutional and cultural clusters. We also construct impulse response functions and examine persistence in spreads between leading European volatility markets. Fourth, we examine regime-dependent movements of the entire maturity spectrum of the eurozone's volatility index returns and compare it with the results for US volatility indices. Finally, by means of principal component analysis (PCA) we shed further light into the dynamics between European stock and volatility indices.

Our main findings are: (i) European stock and volatility markets exhibit a statistically significant contemporaneous negative relationship. The negative relationship is slightly less pronounced for European than for US indices; (ii) volatility and equity markets exhibit bi-directional causality; (iii) equity and volatility markets have an asymmetric relationship and this asymmetry is significantly more pronounced than indicated by traditional ordinary least squares (OLS) models; (iv) implied volatility influence stock returns at the quantile with highest market returns significantly less compared to the quantile with the lowest returns; (v) hedge ratios derived from quantile regressions perform better compared to their OLS counterparts; (vi) the returns-implied volatility relation and persistence in volatility spreads vary across institutional and cultural clusters identified in the previous literature. The degree of integration between the German, French and UK volatility indices, however, is very high and shocks on the spread die out within a few days; (vii) the dynamics of the volatility term structure are clearly regime dependent. Our Markov model depicts three (low, middle, high) volatility regimes; (viii) short maturities exhibit higher volatility of volatility than longer maturities; (ix) large movements (regardless of direction) in both, implied volatility and stock markets increase the probability that volatility enters a higher volatility regime (low to middle and middle to high); (x) in the high volatility regime, the first three principal components (level, slope, and curvature) of volatility index returns explain 97% of the eurozone's volatility term structure.

The remainder of this paper proceeds as follows: Section 2 motivates hypotheses and introduces methodology. Section 3 describes the main characteristics of our sample. Section 4 presents results for the association of returns and implied volatility. Results of testing for integration of European volatility indices are presented in section 5. Section 6 deals with dynamics of the volatility term structure. Robustness checks and further analysis are presented in section 7. Finally, section 8 concludes.

2. Hypotheses and methodology

2.1. Association of returns and implied volatility[2]

Previous literature formulated various hypotheses on the negative stock return-volatility relationship based either on firm fundamentals (leverage and feedback theories) or the (heuristic) behavior of market participants. The leverage hypothesis (Black, 1976; Christie, 1982; Schwert, 1989) attributes the negative relationship to increasing financial leverage of companies caused by decrease in stock prices. Consequently, the increase in leverage drives equity volatility and the risk of equity holders. The feedback hypothesis (French et al., 1987; Bekaert and Wu, 2000; Wu, 2001; Kim et al., 2004) postulates that any increase in volatility leads to an increase in future required rates of return on stocks which results in a simultaneous fall in stock prices. Similarly, an increase in aggregate volatility leads to a reduction in investor holdings of risky assets. Ultimately, this results in lower contemporaneous returns (Campbell

[2] In this section we refer only to the literature on official indices. For more on unofficial indices in various countries see Gongalez and Novales (2009) and Siriopoulos and Fassas (2009).

and Hentschel, 1992).[3] Both leverage and feedback theories suggest a long-run lagged association between return and volatility (or vice verse).[4]

More recently, Hibbert et al. (2008) observe that investors tend to view low risk and high return as attributes of good investments and use heuristics to make decisions. As a consequence, larger negative (positive) returns are normally linked with larger (smaller) volatility. Since implied volatility is a gauge for both market exuberance and fear, the response of stock market returns is likely to be higher at both tails than at the center of the stock market returns distribution. However, Giot (2005) reports that S&P 100's negative returns tend to be associated with greater proportional changes in VXO (old VIX) than are positive returns.

Giot (2005) also reports that the asymmetric relationship tends to differ in periods of low and high volatility. For example, the increase in implied volatility (when negative stock index returns occur) is lower in high-volatility periods than in low-volatility periods.[5] This may be due to stronger reaction of option traders to negative returns during low-volatility periods (Bakshri and Kapadia, 2003). An alternative explanation is a possible stronger impact of sharp volatility shocks on discount rates in low volatility regimes. For example, sharp volatility shocks in low volatility periods lead to proportionally higher discount factors in equity markets and thus lower prices (see Schwert, 1990).

Whilst evidence on the negative contemporaneous relationship between implied volatility and returns is conclusive, the evidence on the asymmetric relation is inconclusive. For example, Siriopoulos and Fassas (2009) and Whaley (2000) report lack of evidence for strong asymmetric relation between VIX, RVX, VNX and their respective stock market indices.[6] In Europe, Alexander (2008) and Siriopoulos and Fassas (2012) both report an asymmetric negative relation for VFTSE and FTSE whilst Gonzalez and Novales (2009) report lack of asymmetric negative relation between VDAX, VSMI, and their respective stock market indices.[7] Therefore, we test the following hypotheses:

[3] The feedback volatility hypothesis implies that volatility is incorporated in stock prices.
[4] The results of empirical studies, however, provide only weak support for this hypothesis (see Schwert, 1989; Campbell and Hentschel, 1992; Low, 2004; Bollerslev et al, 2006).
[5] Fleming et al. (1995) also report statistically significant asymmetric relation between old VIX and S&P returns. Simon (2003) report reports statistically significant asymmetric relation between VIX, VNX and their respective equity indices.
[6] Whaley (2000) examines VXO.
[7] Elsewhere, lack of the asymmetry in association between implied volatility and stock returns was reported for Canadian (Siriopoulos and Fassas, 2008) and Australian indices (Frijns et al., 2010; Dowling and Muthuswamy, 2005). Strong asymmetric association was reported for Korean (Ting, 2007) and Indian (Kumar, 2012) indices.

Hypothesis 1a: The contemporaneous relationship between the European market perception of volatility (i.e. implied volatility) and underlying stock returns is negative.

Hypothesis 1b: The contemporaneous relationship between the European market perception of volatility (i.e. implied volatility) and underlying stock returns is stronger at the ends than at the middle of the return distribution.

Hypothesis 1c: The contemporaneous relationship between the European market perception of volatility (i.e. implied volatility) and underlying stock returns is strongest in the part of distribution with lowest returns.

We start the analysis by regressing daily returns of all sample stock indices on the corresponding volatility index returns:

$$\text{Index return}_{\text{t}} = c \;+\; \beta_1 \Delta IV_t + \varepsilon_t, \tag{1}$$

where *Index return*$_t$ is the daily stock index return, ΔIV_t the corresponding implied volatility index return, and ε_t represents a normally distributed error term. Since the early work of Whaley (1993) this regression is known as “fear gauge” regression with an expected positive intercept term (c) and a negative slope coefficient. Furthermore, we estimate a similar model to account for potentially asymmetric response:

$$\text{Index return}_{\text{t}} = c \;+\; \beta_1 \Delta IV_t^- + \beta_2 \Delta IV_t^+ +\; \varepsilon_t, \tag{2}$$

where the changes of the respective volatility index are split into negative ΔIV_t^- and positive ΔIV_t^+ volatility changes. A negative coefficient β_1, for example, shows the percentage increase in stock market returns associated with a 1% decrease in implied volatility. On the other hand, a negative coefficient β_2, reveals the percentage decrease in stock market returns associated with a 1% increase in implied volatility. If positive changes (i.e. increases) in volatility have a larger impact on stock returns than negative changes (i.e. decreases) of the same magnitude, β_2 is expected to be larger than β_1 (in absolute terms).

The above OLS approach, however, is highly sensitive to departures from normal distribution. An alternative approach is based on quantile regressions. The quantile regressions replace the least squares criterion by a least-absolute-distance estimation, thus, representing a natural extension of the OLS regression.[8] Quantile regressions are, therefore, more suitable for volatility indices which are often characterized by significant outliers and a leptokurtic distribution. They estimate rates of change across the whole distribution of a response variable and model conditional quantiles as a function of predictors. They also estimate several different regression curves corresponding to the τ^{th} quantile of the distribution and allow the slope coefficients to change accordingly. Estimates based on quantile regressions, therefore, allow us to test hypotheses 1b and 1c. Our quantile regression model has the following form:

$$Index\ return_t = c + \beta(\tau)\Delta IV_{\tau,t} + \varepsilon_{\tau,t}, \tag{3}$$

where the return of the stock index (*Index return$_t$*) depends on the quantile τ (τ = 0.1, … , 0.9) of the corresponding implied volatility index return $\Delta IV_{\tau,t}$. $\varepsilon_{\tau,t}$ is the quantile specific error term with an expected value of zero.

2.2. Integration of European volatility indices

Although the EU is probably one of the most advanced regional confederations in the World some important differences still remain. For example, the differences are associated with legal tradition, rule of law, and degree of protection of investors' rights.[9] Based on the above differences, distinct country clusters were identified and used in the previous literature (see Leuz et al. 2003; La Porta et al. 1997; La Porta et al. 2000; Ball et al. 2000).[10] For example, UK is described as 'outsider economy' with a large stock market, dispersed ownership, strong investors' rights, and strong legal enforcement. The large and diverse stock market, together with strong investors' rights, reduce investors' stress level and 'fear' of unknown future. Germany, on the other hand, is normally described as an 'insider economy' with relatively smaller stock markets, concentrated ownership, weak investors' rights, and strong legal enforcement. In

[8] Hibbert et al. (2008) report results for OLS in highest and lowest quantiles but do not use quantile regressions. To the best of our knowledge Kumar (2012) is the only study using quantile regressions in this context.

[9] UK, France and Germany would also have different legal origins. Based on the legal origin, Switzerland would normally be clustered together with Germany whilst Belgium and Netherlands would belong to the French legal cluster. (See for example, La Porte et al. 1997).

[10] For example, Leuz et al. (2003) show that strong and well-enforced investors rights mitigate managers' incentives to manage accounting earnings.

terms of investors' rights, France falls in between UK and Germany but with the weakest legal enforcement out of the three. France is also characterized by a relatively smaller stock market, and concentrated ownership.

In addition to the institutional and legal differences, there are also important cultural differences affecting investors' behavior. The cultural differences are a consequence of the fact that the EU bridges two major historical rifts (i.e. Latin vs. Germanic). The differences are normally associated with religion and the following cultural characteristics: power distance, uncertainty avoidance, individualism, masculinity, and long vs. short term orientation (Hofstede, 2001). For example, UK is characterized as a country with low uncertainty avoidance related to the level of stress in a society in the face of an unknown future.[11] Germany, on the other hand, is characterized as a country with very strong uncertainty avoidance. France falls in between UK and Germany. Netherlands and Switzerland exhibit similar cultural characteristics to Germany except that they both exhibit lower (and similar) degree of uncertainty avoidance (Hofstede, 2001). The consideration of cultural differences in financial studies is rare. Notable exception is Stulz and Williamson (2001) reporting that a country's principal religion helps to predict the cross-sectional variation in creditor rights better than a country's openness to international trade, its language, its income per capita, or the origin of its legal system.

Given the above differences, an important question is to what extent European volatility markets are integrated. If the volatility markets are indeed integrated, the differences between European volatility indices (i.e. spreads) are expected to be temporary otherwise investors could generate risk-adjusted returns through long exposure to undervalued implied volatility markets.[12] As long as the spreads between volatility indices are stationary and have constant means, supply and demand shocks only have a temporary effect with the spreads gradually moving towards the long-run relationship.

It is also plausible that the institutional and cultural differences affect investors' behavior in different markets. Specifically, we expect stronger "fear of crash" and stock market responsiveness to changes in volatility in 'insider' countries with a strong uncertainty avoidance

[11] Hofstede (2001) defines other cultural characteristics as follows: Long-term versus short-term orientation (LTO) is related to the choice of focus for people's efforts: the future or the present. Power distance (PDI) is related to the different solutions to the basic problem of human inequality. Individualism versus collectivism (IDV), which is related to the integration of individuals into primary groups. Masculinity versus femininity (MAS), is related to the division of emotional roles between men and women.
[12] It is important to note that the differences in spreads also reflect speed of arbitragers responding to profitable differentials in implied volatility.

(e.g. Germany) than in 'outsider' countries with a weak uncertainty avoidance (e.g. UK). Consequently we expect larger and more persistent spreads, following external shocks, between countries from different institutional and cultural clusters.[13] Thus our hypotheses are:

Hypothesis 2: European volatility indices are highly integrated.

Hypothesis 3: The market perception of volatility and the stock return-implied volatility relation differ across European countries.

The persistence of the spreads (following external shocks) is examined by the methodology of Cuddington and Wang (2006). The methodology is based on impulse response functions (IRF) and the use of autoregressive (AR) models robust to non-standard error distributions.[14] The dynamic effects on the spreads of one unit shock to the error term in the AR model are estimated using Monte Carlo simulations.

2.3. Regime dependent volatility term structure

Previous studies document time-varying properties of VIX (Mixon, 2002), VFTSE (Alexander, 2008), and variance swap markets (Allen et al., 2006). In this study, we examine the complete implied volatility term-structure for the eurozone (VSTOXX) and postulate that implied volatility varies over time in a systematic way. Thus,

Hypothesis 4: The term structure of eurozone's implied volatility has time-varying properties.

Regime switching (Markov) models are well suited to capture abrupt changes in stock market volatility. For example, regime switching models capture fat tails, time varying correlation, ARCH effects and other characteristics of many financial time series returns.[15] We identify

---

[13] The above differences in volatility markets would also be in line with the behavioral approach adopted in Hibbert et al. (2008).
[14] See also Goldberg and Verboven (2005) and Taylor (2001).
[15] For a detailed discussion of Markov switching models see Hamilton (1989). For an excellent survey on application of Markov switching models in finance, see Ang and Timmermann (2011).

different regimes using probabilities estimated by the following, first order, Markov switching model, with state-dependent volatility returns ($\Delta VSTOXX_t$):[16]

$$\Delta \mathrm{VSTOXX_t} = c_{St} + \varepsilon_t \tag{7}$$

with c_{st} being a state dependent constant term and ε_t represents the (state dependent) vector of disturbance terms, assumed to be normal with state-dependent variance $\sigma_{s,t}^2$. The unobservable state parameter s_t is assumed to follow a first-order, three-state Markov chain where the transition probabilities (i.e. probability to change from the current regime) are assumed to be constant.

We also estimate the likelihood of different regimes for any observation (based on the information available at that point in time) and examine the main drivers of regime switches. The following logit model relates the estimated state probability of being in a specified volatility regime to theoretical transition variables (i.e. drivers) that induce a regime shift.[17]

$$P_t = P[y_t = 1] = \frac{1}{1+e^{-(\alpha_0+\alpha_1 x_{t-1})}}, \tag{8}$$

where $P_t[y_t = 1]$ denotes the filtered probability of being in a higher volatility regime at time t and α_0 and α_1 represent regression coefficients. Binary variables are defined based on the estimated probabilities of the Markov switching model. They are equal to one when the probability is higher than one-half (i.e. upper volatility state) and equal zero if the probability value is equal to or lower than 0.5 (i.e. lower volatility state). Given bi-directional causality of implied volatility and returns, we expect that regime transitions are associated with the evolution of these variables. Therefore, lagged stock returns, square of lagged stock returns, lagged changes of the VSTOXX, and square of lagged changes of the VSTOXX are used as explanatory variables. Finally, we isolate common risk factors of the entire volatility structure in different regimes using principal component analysis (PCA).[18]

[16] This model specification allows us to back out the regime specific conditional mean levels of volatility returns and to detect in which regime the volatility is on a particular date t. The parameters are estimated by a maximum likelihood approach.
[17] The model is adopted from Clarida et al. (2006).
[18] PCA is based on eigen decomposition of the covariance matrix of the variables. The resulting principal components describe a series of orthogonal combinations that contain most of the variance.

3. Data

We examine all officially available volatility indices that are calculated and disseminated by Euronext and Eurex: VDAX, VCAC, VFTSE, VSMI, VBEL, VAEX and VSTOXX. All of the above indices are based on the same pricing methodology, which makes them directly comparable (Table 1). They also provide forecasts for the same period of 30 days. All sample indices are tradeable via swaps in OTC markets. VSTOXX is also traded via options, futures, and ETNs.

*** Insert Table 1 about here ***

Our sample includes 1,455 trading days during the period from January 1st, 2004 until July 31st , 2009. The sample descriptive statistics are presented in Table 2.

*** Insert Table 2 about here ***

Our sample is characterized by wide ranging levels of implied volatility (Panel A of Table 2). The highest single value of 87.5% was reached by VSTOXX, while the minimum of 8.6% was recorded for VBEL. The average (mean and median) level of implied volatility is highest in Germany and Netherlands followed by France, UK and Belgium. The median daily volatility returns are highest for VCAC (0.000%) and lowest for VAEX and VFTSE (-0.003%). Overall, the daily mean and median volatility log returns are close to zero, reflecting the absence of a deterministic growth trend in volatility.[19] We find significant positive skewness in all indices. Excess kurtosis is extremely high compared to the magnitude of skewness. Consequently, the Jarque-Bera statistics reject the hypothesis of a normal distribution in all cases at the 1% significance level, which implies a higher probability of extreme movements. Combined Kwiatkowski-Phillips-Schmidt-Shin (KPSS) and Augmented Dickey Fuller (ADF) test statistics indicate that volatility indices appear to be close to a random walk. To investigate a potential lead-lag relationship of implied volatility with the underlying stock markets, we run pair wise Granger causality tests. Apart from the Dutch market, where the equity market seems to lead the volatility market, the results for the European market are unambiguous in showing that causality runs in both ways. The negative relationship between equity and volatility markets are also confirmed by the correlation matrix presented in Panel B. All returns

[19] It has widely been accepted that volatility follows a mean-reverting process (see Allen et al., 2006).

for stock market and volatility indices are negatively correlated at the 1% level. The highest negative correlation (-0.74) was recorded between ESTOXX and VSTOXX. Among volatility indices, VSTOXX and VDAX exhibit the highest correlation (0.92).

Our sample clearly captures periods with different stock market conditions. As an illustration, we present in Figure 1 the evolution of eurozone's stock (EuroStoxx 50 (ESTOXX)) and the corresponding volatility index (VSTOXX). After a minor market correction in the first half of 2004 a tight range of volatility lasted until early 2006 when the closure of a majority of Ameriquest's branches heralded the imminent credit crises.[20] Although equity markets switch back to low levels of volatility for several months, eurozone's implied volatility jumped in Europe to 35% in the last quarter of 2007 (coinciding with news that some of Bear Stearns hedge funds are effectively bankrupt). The remainder of the sample period is characterized by the events of the subprime crisis, with implied volatility reaching levels not recorded since 1987.

*** Insert Figure 1 about here ***

4. Association of returns and implied volatility

4.1. OLS

The results of OLS regressions (equation 1) are presented in Panel A of Table 3. They reveal strictly negative and significant coefficients for all volatility indices. The result is consistent with our hypothesis 1a. Contrary to theoretical predictions the intercept term is not statistically different from zero.[21]

Results for equation 2 are reported in Panel B of Table 2. All coefficients are significant and negative at the 1% level. For all indices, returns are less sensitive to declining volatility than to increasing volatility. If the implied volatility of the DAX, for example, decreases by 1%, the stock market will increase by 0.17%.[22] On the other hand, our findings suggest that for a

[20] Ameriquest was one of the largest mortgage lenders in North America.
[21] This is likely to be due to a significant drop in the major European stock market indices during the sample period.
[22] DAX $\text{return}_t = 0.0001 + -0.157*-0.01 = 0.00167 = 0.17\%$.

1% increase in implied volatility of the same magnitude the DAX responds stronger and falls by 0.20%.[23]

*** Insert Table 3 about here ***

Across sample countries, DAX returns exhibit the highest sensitivity to volatility changes, whereas this sensitivity is lowest in Belgium (see Panels A and B in Table 2). The results are in line with our hypothesis 3.

4.2. Quantile regression

Table 4 presents the quantile regression results. Contrary to the OLS model, quantile regressions reveal highly statistically significant constant terms. The constant terms are positive in lower quantiles ($\tau = 0.1$ to 0.5) and negative in higher quantiles ($\tau = 0.6$ to 0.9). Previous studies report lower betas (sensitivities) for increasing stock market returns.[24] Our results also suggest higher (absolute) betas in the highest ($\tau = 0.9$) quantile (i.e. lowest returns) than in the middle ($\tau = 0.5$) and lowest quantile ($\tau = 0.1$), for all sample volatility indices. Absolute values for betas in the lowest quantile ($\tau = 0.1$) are higher compared to the center of the conditional joint distribution ($\tau = 0.5$) in 4 out of 7 volatility indices. Notably, estimates obtained by OLS are more in line with the estimates for higher than for median quantiles.

*** Insert Table 4 here ***

The above results highlight asymmetric response of stock returns to volatility and lend support to our hypotheses 1b and 1c.[25] It is worth noting that both leverage and feedback hypotheses suggest models with lag terms. We, therefore, tried alternative specifications with lag terms for both stock index and the implied volatility index. Since none of the alternative spec-

---

[23] DAX return$_t$ = 0.0001 + -0.211*0.01 = -0.00201 = -0.20%.

[24] See Whaley (2000), Giot (2005) and Gonzalez and Novales (2009).

[25] Our results differ from the results reported for VIX, RVX (Russel 2000 volatility index), MVX (Montreal volatility index), and VXN (Nasdaq 2000 volatility index) (see Siriopoulos and Fassas, 2009), and Australian volatility market (see Dowling and Muthuswamy, 2005). Giot (2005) reports only weak asymmetric relationship between NASDAQ 100 and VXN. Our results, however, are consistent with the volatility smile (i.e. skew) commonly observed in options market.

ifications improved explanatory power and/or statistical significance we conclude that responses are indeed contemporaneous as in equation 3.

The cross country differences of quantile regression results reported in Table 4 are similar to those reported for OLS regressions in Table 3. Notably, absolute values of the regression coefficients for the DAX are highest in all quantiles across indices.[26] The results, therefore, suggest the most conservative attitude towards uncertainty in Germany and most relaxed attitude in the UK, with France in the middle. Compared to UK and France, Germany also exhibits the largest difference in absolute values for betas in the lowest and highest quantiles. The results for other European markets are mixed. While the Netherlands and Switzerland exhibit quite similar results, Belgium stock returns are least sensitive to changes in volatility (see Table 4). For example, the reaction of stock returns to volatility changes (in the lowest and highest volatility quantiles) in Belgium is 50-70% smaller than in Germany. The Belgium's volatility index also exhibits the lowest mean, median, and standard deviation during the investigation period (Panel A of Table 2). Overall, with the exception of Belgium, the results are in line with our hypothesis 3.

4.3. OLS vs. quantile regressions

We further compare OLS with quantile regressions using a Wald-test with the following null hypothesis (H_0):[27]

$$H_0: \beta(\tau_1) = \beta(\tau_2) = \ \dots \ = \beta(\tau_K). \tag{9}$$

$\tau_1 \dots \tau_K$ are the corresponding quantiles (i.e. $\tau_1 = 0.1, \dots \tau_9 = 0.9$). The test-statistic is asymptotically $\chi^2_{(p-1)(K-1)}$ distributed, where p reflects the number of regressors and K represents the number of quantiles (in our case 9), and can be considered as a robust alternative to traditional least-squares-based tests of heteroscedasticity. Results and p-values are presented in the last column of Table 4. The null hypothesis of equal coefficients can be rejected across the entire sample at the 1% significance level, with the exception of the Swiss market (5% signif-

[26] In case of the DAX, absolute values for respective betas are identical in lowest and medium quantiles.
[27] The test was introduced by Koenker and Bassett (1982).

icance level) and the French market (10% significance level). Quantile regressions, therefore, represent a more robust alternative to OLS estimates.

5. Integration of European volatility markets

First we analyze the distribution of volatility level differences (i.e. volatility spreads) in the three main markets: Germany (VDAX), France (VCAC), and UK (VFTSE). Table 5 reveals that the corresponding distributions significantly deviate from normality (with significant skewness and excess kurtosis). A formal cointegration test indicates that these three countries exhibit a significant long-term association of the volatility markets.[28]

*** Insert Table 5 about here ***

The combined results of ADF and KPSS tests indicate stationarity of the differences between implied volatility indices. Several autoregressive models with the optimal number of lags (chosen by information criteria) are fitted. The simulated impulse response functions for the spread between volatility indices (e.g. VDAX – VCAC) by a shock of one standard deviation are presented in Table 6.

*** Insert Table 6 about here ***

In general, a shock of one standard deviation in the spreads dies out monotonically and relatively quickly in all three volatility spreads. Following the initial spike in case of VDAX-VCAC and VFTSE-VCAC spreads, the majority of the shock vanishes during the first two days. A shock in the spread for the VDAX-VFTSE is more persistent, thus, convergence to the long-run mean level is slower.

We compare the different speed of adjustments by half life (HF) measure that is normally used in this context (see Cuddington and Wang, 2006) (Figure 2). HL measures the number of days it takes for one unit shock to shrink to half of its initial value. As expected, HL is longest

[28] To investigate potential lead-lag relationships we run bi-directional Granger-causality tests for French, German and UK markets. Unreported results indicate strong contemporaneous relationships and no significant lead or lag relation within implied volatility. Causality, therefore, runs in both ways.

for the VFTSE-DAX spread (around 3 days). The HL for the VFTSE-VCAC spread is just below 2 days. The shortest HL (just over 1 day) is recorded for the VDAC-VCAC spread. Overall, the above results lend support to our hypotheses 2 and 3.

*** Insert Figure 2 about here ***

6. European volatility indices in different market regimes

6.1. Regime dependent VSTOXX's returns

We analyze the term structure of the VSTOXX returns, comprising tenors of 1, 2, 3, 6, 9, 12, 18 and 24 months. The regime dependent VSTOXX returns term structure is presented in Table 7. As expected, the standard deviation of volatility returns is regime dependent (hypothesis 4). For example, for the shortest maturity the standard deviation of VSTOXX returns is approximately four to five times larger in the highest compared to lowest volatility regime (109.09% and 23.79%, respectively).[29] Furthermore, the standard deviation of VSTOXX returns is a decreasing function of maturity. For example during tranquil periods the volatility returns fluctuate with an annual standard deviation of 23.79% for one month contracts, compared to 6.91% for two year contracts, exhibiting a nearly monotonically decreasing function of maturity. The more pronounced changes of volatility returns in the short term tenors is due to better liquidity of short dated options compared to longer dated options that are mostly used by companies in need of long-term hedging.[30]

*** Insert Table 7 about here ***

6.2. Determinants of regime changes

Results of logit models for drivers of VSTOXX's regime changes are reported in Table 8. As expected, coefficients in the regression with lagged stock returns (see column 2) are negative while coefficients for the regressions with changes in volatility (see column 4) are positive.

[29] For the longest maturity, VSTOXX's returns are approximately two times larger in the higher volatility regime compared to lower volatility regime.
[30] See Allen et al. (2006).

The only exceptions are lagged stock returns in transition from low to middle regime. Results in the regressions with squared changes of the two explanatory variables indicate (with high significance) that large jumps in volatility and stock prices (irrespective of direction) tend to induce a shift to the next higher volatility regime.

*** Insert Table 8 about here ***

6.3. Regime dependent determinants of implied volatility

The results in Table 9 suggest that 72.3% of the total variation in VSTOXX's returns can be explained by the first common factor (see Table 9). The loadings for the first component are similar across indices, indicating that the majority of the movement of implied volatility is due to a common level shifting factor. Interestingly, French, German and UK markets exhibit very similar loadings for the first component (0.415, 0.388 and 0.398, respectively). The second component (i.e. changes in slope of the term structure) explains additional 8.8%. Negative second eigenvalues for French and Belgian markets suggest that they are subject to higher idiosyncratic regional risk.

*** Insert Table 9 about here ***

The regime-specific eigenvectors of the principal component representation, based on the covariance matrix of one-day changes of the entire term structure of the VSTOXX, are shown in Figure 3. In all three volatility regimes considerably more than 90% of the total variation of the term structure can be explained by only three factors.[31]

*** Insert Figure 3 about here ***

The first factor (level factor) is, based on the percentage of variation explained, much more important in the middle and high volatility regime than in the low volatility regime (80.5% and 78.6% versus 60.2%, respectively). At the same time the second and third factor (slope and curvature) explain much more in the low volatility regime (8.4% compared to 2.2% and 2.6%, respectively).

[31] Our results are consistent with Mixon (2002) and Fengler et al. (2002) who find that three PCA components describe the time-series movement across the US implied volatility term structure and option exercise prices.

For each regime, the loadings of the first factor nearly resemble the 'level' factor found previously by Litterman and Scheikman (1991).[32] The short-term volatilities, however, move significantly more than long-term volatilities. This is especially the case for the (very short) one month maturity and to some extent also the two and three month maturity in the high volatility regime (see PC1 in Figure 3). Factor loadings of the second PC are (with an exception for the very short 1 month maturity) negative in all three regimes, constant in the low volatility and upward sloping in the middle and high volatility regime. Thus, during the low volatility regime the second principal component behaves like a level-shifted first component (see Panel A of Figure 3).

The factor loadings of the third principal component tend to be U-shaped (curvature effect). This is especially the case for the low volatility regime. Interestingly, the loadings tend to be constant (low volatility regime) or declining (middle and high volatility regime) for maturities exceeding one year. Overall, Figure 3 reveals that the factor loading structure is regime dependent (especially concerning principal component 2 and principal component 3).

7. Robustness checks and further analysis

7.1. European vs. US volatility indices

We repeated our analysis for the following US volatility indices: the VNX, representing the Technology sector based on the Nasdaq 100 implied volatility; the RVX, based on option prices of the Russel 2000 (small cap sector); the VXD, inferred from options on the Dow Jones Industrial Average Index; and the VIX, derived from the implied volatility of S&P 500 (SPX) options (a broad stock market proxy). The results, presented in Table 10, suggest that the US small cap sector (RVX) exhibits the highest level of volatility (median value of 22.6%) (see Panel A of Table 10). The maximum single value of 87.6% for the RVX was reached on November, 20th 2008, following the bankruptcy of Lehman Brothers. All US volatility indices exhibit bi-directional causality with respective equity indices (see Panel A of Table 10).

[32] This level factor originates from the loadings of the eigenvectors that all have similar magnitude and the same size across all maturities.

Insert Table 10 about here

The negative contemporaneous relation between equity returns and implied volatility is also confirmed in the US sample. The negative relation is slightly more pronounced in the US than in Europe. The US market is also highly integrated regarding implied volatility changes, with correlation coefficients in excess of 0.84 (see Panel B of Table 10). Furthermore, the average R^2 (51.5%) for the OLS model (equation 1), based on the four US indices, is higher than the average R^2 of the respective seven European indices (40.2%) (see Panel C of Table 10 and Panel A of Table 3). The results for equation 2 suggest that when VIX decreases by 1%, SPX increase by around 0.13% (see Panel D of Table 10). On the other hand, a 1% increase in VIX triggers the SPX to decrease by around 0.16%.[33]

The results for US quantile regressions are economically and statistically consistent with the results reported for European markets (Panel E of Table 10). For example, the constant terms are positive in lower quantiles and negative in higher quantiles. Coefficients in lowest and highest quantiles are higher than the coefficients in the middle quantile. Furthermore, coefficients in the lowest quantile are lower than those in the highest quantile, for all indices. The lower level of statistical significance for NDX/VNX's Wald test suggests lower degree of asymmetric relation for this index.[34]

The results of PCA analysis (see Panel F of Table 10) show that the first principal component explains 93.8% of the total variation of the term structure. This is higher than the 72.3% (see Table 9-Panel A) reported for European markets. The second component, related to the slope factor, explains only additional 3.2% (compared to 8.8% for European markets).

7.2. OLS vs. quantile regression hedge ratios

Recent growth in markets for volatility derivatives (e.g. index futures, variance swaps, and ETNs) facilitated the development of various strategies for gaining volatility exposure. Due to negative equity returns-volatility relationship, long positions in volatility can help to hedge

[33] SPX Return_t = 0.0000 + -0.129*-0.01 = 0.00129 = 0.13%; SPX Return_t = 0.0000 + -0.164*0.01 = -0.00164 = -0.16%. Similar results are reported in previous research focusing on the US market (See Giot, 2005; Simon, 2003; and Whaley, 2008).

[34] The results are consistent with Whiley (2000) and Siriopoulos and Fassas (2009).

against market risk. Given time-varying behavior of volatility and equity markets, determination of adequate hedge ratios becomes an important empirical question for investors. Figure 4 illustrates the difference in hedge ratios based on OLS and quantile regression coefficients (of the quantile with the lowest returns ($\tau = 0.9$)). The presented results are for DAX and SPX indices.[35]

*** Insert Figure 4 about here ***

DAX quantile regression hedge ratios are different from OLS estimates throughout the sample period, except during a very short period in late 2007. The results are consistent with the earlier reported (relative to other investigated indices) highest absolute values of DAX coefficients in the highest quantiles.[36]

For the SPX, however, quantile regression hedge ratios are not distinctively different from the OLS estimate until the late 2007. Given that the asymmetric weighting algorithm in quantile regressions asserts a higher penalty term to negative returns (i.e. $\tau > 0.5$), this suggest that US investors were not taking adequate downside protection before August 2007. This is consistent with evidence from other US market indicators during mortgage lending crisis. For example, US Libor-OIS spread was very small and nearly constant until August 2007 (Thornton, 2009).[37]

To further show the difference in hedge performance based on OLS and quantile regression, we select two events that lead many institutional asset managers to buy protection in the form of volatility indices. These two events are: (i) major banks' announcement of drastic write-downs in their assets (August 2007), and (ii) the Lehman Brothers bankruptcy filing (September 2008). We then estimate the performance of respective hedging strategies using all sample indices and assuming transaction costs equal to 0.5 vega (points). The results (for τ= 0.9) are presented in Table 11. Overall, the volatility indices provided a very good hedge against the

[35] For reasons of brevity we confine the discussion to the DAX and SPX indices. To show the evolution of the hedge ratios, regressions (1) and (3) are rolled over on the previous 500 observations for the DAX and SPX.
[36] Our unreported results also suggest better accuracy of quantile regression compared to OLS estimates. For example, the 90% prediction interval derived from equation 1 (OLS) for the DAX (SPX) conditional on a 1% increase in volatility is -1.89% to 1.56% (-1.75% to 1.42%). The equivalent prediction interval, derived from equation 3 (quantile regression), yields stock market returns of -1.55% to 1.22% (-1.50% to 1.09%).
[37] However, due to the variance risk premium, long positions in volatility derivatives are biased to generate a loss and considering them as part of strategic asset allocation may not be appropriate. Consequently market practitioners usually pursue an active approach and engage in long positions only over short time horizons, mostly on a discretionary basis when they expect turmoil in financial markets.

steep stock market decline during both selected events. For example, a stock market portfolio, with the DAX as underlying, worth € 1 million protected by a volatility index with one month tenor would have returned a gain of € 34,100 or 3.41% in August 2007. For comparison, a non-hedged portfolio would have resulted in a loss of 6.09%. Across the sample quantile regression based hedge ratios return higher overall pay-offs compared to OLS-based hedge ratios.[38]

*** Insert Table 11 about here ***

8. Conclusion

This study examines the dynamics of European volatility indices, between 1st January 2004 and 31st July 2009. Our results show that quantile regressions provide a more detailed and nuanced view on the conditional relationship between implied volatility and equity market returns. For example, results of our quantile regressions suggest a significantly more pronounced asymmetric volatility phenomenon than is inferred from ordinary least squares regression. Importantly, this asymmetry is not monotonically decreasing. Although the negative relation between European stock returns and implied volatility is significantly more pronounced at the highest quantiles (i.e. lowest returns) of the equity market return distribution, we also find increased sensitivity at the lowest quantiles (i.e. highest returns). Furthermore, hedge ratios derived from sample quantile regressions are economically superior to hedge ratios derived from sample OLS regressions both in European and US samples. The above results are of particular importance for investors given the increasing popularity of various hedging strategies based on exposure to volatility indices.

The main European volatility markets exhibit differences consistent with institutional and cultural clusters identified in the previous literature. For example, half life of the VFTSE-VDAX spread is twice as long as the half-life of the VCAC-VDAX spread. The leading markets (UK, France, Germany), however, are in bilateral equilibriums. Deviations, as a result of a shock in one of the indices, are temporary and die out within a few days.

[38] The only exception is a slightly (0.05%) better OLS performance for SMI in September 2008. Notably, quantile regressions are overhedged (except for the Nasaq index) due to different treatment of up and down-side deviations and unprecedented sell-off in equity markets following Lehman Brothers' bankruptcy, yielding extreme levels of volatility.

Our Markov switching model distinguishes three volatility regimes. In the high volatility regime, principal components, corresponding to level, slope and curvature, explain 97% of the eurozone's volatility term structure. Compared to US market, the larger proportion of the changes in volatility is related to tilts and non-linear movements in term structure. Overall, our findings lend support to the behavioral explanation of the stock return-implied volatility relation and have implications for risk management.

References

Äijö, J. (2008), Implied volatility term structure linkages between VDAX, VSMI and VSTOXX volatility indices, Global Finance Journal, Vol. 18, pp. 290 – 302.

Alexander, C. (2008), Market risk analysis, Volume 3: Pricing, hedging and trading financial instruments, John Wiley & Sons, Chichester.

Allen, P., Einchcomb, S. and Granger, N. (2006), Variance swaps, European Equity Derivatives Research, JP Morgan.

Ang, A. and Timmermann, A. (2011), Regime changes and financial markets, Netspar Discussion Paper, DP06, No. 68.

Bakshi, G. and Kapadia, N. (2003), Delta-hedging gains and the negative market volatility risk premium, Review of Financial Studies, Vol. 16, No. 2, pp.527-566.

Ball, R., Kothari, S., and Robin, A. (2000), The effect of international institutional factors on properties of accounting earnings, Journal of Accounting and Economics, Vol. 29, pp.1-23.

Bekaert, G. and Wu, G. 2000, Asymmetric volatilities and risk in equity markets, Review of Financial Studies, Vol. 13, No. 1, pp. 1-42.

Black, F. (1976), Studies of stock market volatility changes. Proceedings of the American Statistical Association, pp. 177-181.

Bollerslev, T., Litvinova, J. and Tauchen, G. (2006), Leverage and volatility feedback effects in high-frequency data, Journal of Financial Econometrics, Vol. 4, No. 3, pp. 353-384.

Campbell, J. and Hentschel, L. (1992), No news is good news: An asymmetric model of changing volatility in stock returns, Journal of Financial Economics, Vol. 10, No. 2, pp. 407-432.

Carr, P. and Madan, D. (1998), Towards a theory of totality trading, in: Jarrow, R. A. (Ed): Volatility estimation techniques for pricing derivatives, Risk Books, London.

Christie, A. (1982), The stochastic behavior of common stock variances: value, leverage and interest rate effects, Journal of Financial Economics, Vol. 10, pp. 407-432.

Clarida, R. H., Sarno, L., Taylor, M. P., and Valente, G. (2006), The role of asymmetries and regime shifts in the term structure of interest rates, Journal of Business, Vol. 79, No. 3, pp. 1193–1224.

Cuddington, J. and Wang, Z. (2006), Assessing the degree of spot market integration for US natural gas: evidence from daily price data, Journal of Regulatory Economics, Vol. 29, No. 2, pp. 195-210.

Demeterfi K., Derman E, Kamal M., and Zou J. (1999), More than you ever wanted to know about volatility swaps, Goldman Sachs Quantitative Strategies Research Notes.

Dowling, S. and Muthuswamy, J. (2005), The implied volatility of Australian index options, Review of Futures Markets, Vol. 14, No.1, pp. 117-155.

Fengler, M., Härdle, W. and Schmidt, P. (2002), Common factors governing VDAX movements and the maximum loss, Financial Markets and Portfolio Management, Vol. 16, No. 1, pp. 16-29.

French, K., Schwert, G. and Stambaugh, R. (1987), Expected stock returns and volatility, Journal of Financial Economics, Vol. 19, No. 1, pp. 3-29.

Frijns, B., Tallau, C., and Tourani-Rad, A. (2010), The information content of implied volatility: evidence from Australia, Journal of Futures Markets, Vol. 30, No.2, pp.134-155.

Giot, P. (2005), Relationships between implied volatility indexes and stock index returns, Journal of Portfolio Management, Vol. 31, pp. 133-154.

Goldberg, P., and Verboven, F. (2005), Market integration and convergence to the law of one price: Evidence from the European car market, Journal of International Economics, Vol. 65, No. 2, pp. 49-73.

Gonzalez, M. and Novales, A. (2009), Are volatility indices in international stock markets forward looking, Review Real Academia de Ciencias, Vol. 103, No. 2, pp. 339-352.

Hamilton, J. D. (1989), A new approach to the economic analysis of nonstationary time series and the business cycle, Econometrica, Vol. 57, No. 2, pp. 357-84.

Hibbert, A., Daigler, R. and Dupoyet, B. (2008), A behavioral explanation for the negative asymmetric return-volatility relation, Journal of Banking and Finance, Vol. 32, No. 1, pp. 2254-2266.

Hofstede, G. (2001), Culture's consequences, comparing values, behaviours, institutions, and organisations across nations, 2nd edition, Sage Publications.

Kim, C., Morley, J. And Nelson, C. (2004), Is there a positive relationship between stock market volatility and the equity premium? Journal of Money, Credit and Banking, Vol. 36, No.3, pp. 339-360.

Koenker, R. and Basset, G. (1982), Robust tests for heteroscedasticity based on regression quantiles, Econometrica, Vol. 50, No. 2, pp. 43-61.

Kumar, S.S.S. (2012), A first look at the properties of India's volatility index, International Journal of Emerging Markets, Vol. 7, No.2, pp.160-176.

La Porta R., Lopez-de-Silanes, F., Shleifer, A. and Vishny, R. (1997), Legal determinants of external finance, Journal of Finance, Vol. 52, pp. 1131-1150.

La Porta R., Shleifer, A. Lopez-de-Silanes, F. and Vishny, R. (2000), Investor protection and corporate governance, Journal of Financial Economics, Vol. 58, pp. 3-27.

Leuz C., D. Nanda, and P. D. Wysocki, P.D. (2003), Earnings management and investor protection: an international comparison, Journal of Financial Economics, Vol. 69, pp. 505-527.

Litterman, R. and Scheinkman, J. (1991), Common factors affecting bond returns, Journal of Fixed Income, Vol. 1, No. 1, pp. 54-61.

Low, C. (2004), The fear and exuberance from implied volatility of S&P 100 index options, Journal of Business, Vol .77, pp. 527-546.

Mixon, S. (2002), The implied volatility term structure of stock index options. Journal of Empirical Finance, Vol. 14, No. 2, pp. 333-354.

Poterba, J.M. and Summers, L.H. (1986), The persistence of volatility and stock market fluctuations, American Economic Review, Vol. 76, pp. 1142-1151.

Schwert, G.W. (1989), Why does stock market volatility change over time?, Journal of Finance, Vol. 44, No. 5, pp. 1115-1153.

Schwert, G.W. (1990), Stock volatility and the Crash of ’87, Review of Financial Studies, Vol. 3, pp. 77-102.

Simon, D. (2003), The Nasdaq volatility index during and after the bubble, Journal of Derivatives, Vol. 11, No. 2, pp. 9-24.

Siriopoulos, C. and Fassas, A. (2012), The information content of VFTSE, Working paper, University of Patras.

Siriopoulos, C. and Fassas, A. (2009), Implied volatility indices – a review, Working paper, University of Patras.

Stulz, R.M. and Williamson, R. (2001), Culture, openness, and finance, NBER Working paper, 8222, http://www.nber.org/papers/w8222.

Taylor, A. (2001), Potential pitfalls for the purchasing-power-parity puzzle? Sampling and specification biases in mean-reversion tests to the law of one price, Econometrica, Vol. 69, No. 2, pp. 473-498.

Ting, C. (2007), Fear in the Korea stock market, Review of Futures Markets, Vol. 16; No 1, pp.106-140.

Whaley, R.E. (2000), The investor fear gauge, Journal of Portfolio Management, Vol. 26; No. 3, pp. 12-17.

Wu, G. (2001), The determinants of asymmetric volatility, Review of Financial Studies, Vol. 14, pp. 837-859.

Table 1: Sample volatility indices

This table presents characteristics of European official volatility indices. Sources: Eurex and Euronext various websites and publications.

Index/Country	Underlying stock index	Introduced	Exchange/Provider	Forecast period	Tradeable instruments			
					Futures	Options	Exchange-traded notes	Variance and volatility swaps
VSTOXX/Eurozone	DJ Euro Stoxx 50 (ESTOXX)	2005	Eurex/ STOXX Limited	30 days	FVS (mini-futures, since June 2009); FVSX (delisted in July 2009),	Yes (since March 2010)	iPath VSTOXX Short-Term Exchange Traded Note (Barclays)	Yes
VSMI/Switzerland	SMI	2005	Eurex/SIX Swiss Exchange AG	30 days	FVSM (delisted in July 2009)	n.a.	n.a.	Yes
VDAX/Germany	DAX	1994, (re-launched in 2005)	Eurex/Deutsche Borse AG	30 days	FVDX (delisted in July 2009)	n.a.	n.a.	Yes
VFTSE/UK	FTSE 100	2008	Euronext/Euronext	30 days	n.a.	n.a.	n.a.	Yes
VCAC/France	CAC 40	1997, (re-launched in 2007)	Euronext/Euronext	30 days	n.a.	n.a.	n.a.	Yes
VBEL/Belgium	BEL 20	2007	Euronext/Euronext	30 days	n.a.	n.a.	n.a.	Yes
VAEX/Netherlands	AEX	2007	Euronext/Euronext	30 days	n.a.	n.a.	n.a.	Yes

Table 2: Sample volatility and equity market indices

Panel A: Descriptive statistics of volatility indices

Level and log return (Δ) statistics for the respective volatility index from January 1st, 2004 until July 31st, 2009 (1,455 daily observations for each index). All series are represented in volatility points (percentage points /100 p.a.). The mean and median are given in the first two columns. The columns labeled maximum and minimum report the highest and lowest level as well as daily log changes (see the Δ-rows) over the scrutinized period, respectively. Higher moments are reported in the adjacent three columns, followed by the values of a test of normality. The Jarque-Bera test statistic is highly significant, rejecting the hypothesis of a normal distribution for each time-series. ADF-statistics and LM-statistics for the KPSS test are for combined test for unit-roots and stationarity. The last two columns present the p-values of Granger-causality tests to address the question of a potential lead-lag relation between the stock and the corresponding volatility indices of Germany (DAX / VDAX), France (CAC / VCAC), United Kingdom (FTSE / VFTSE), Switzerland (SMI / VSMI), Belgium (BEL / VBEL), the Netherlands (AEX / VAEX), and the Eurozone (ESTOXX / VSTOXX). ** denotes significance at the 1% level.

	Mean	**Median**	**Maximum**	**Minimum**	**Std. Dev**	**Skewness**	**Excess Kurtosis**	**Jarque-Bera**	**ADF Statistic**	**KPSS (LM-stat)**	**H_0: volatility does not Granger-cause stock index (p-value)**	**H_0: Stock index does not Granger-cause volatility (p-value)**
VSTOXX	0.224	0.185	0.875	0.116	0.112	2.14**	5.21**	2746**	-2.29	2.41**	-	-
VFTSE	0.198	0.153	0.755	0.091	0.108	2.00**	4.71**	2300**	-2.36	2.82**	-	-
VDAX	0.225	0.193	0.832	0.117	0.107	2.33**	6.54**	3891**	-2.34	2.12**	-	-
VSMI	0.193	0.155	0.849	0.092	0.102	2.29**	6.53**	3831**	-2.28	2.48**	-	-
VCAC	0.214	0.180	0.781	0.092	0.103	2.11**	5.34**	2797**	-2.57	2.52**	-	-
VBEL	0.187	0.148	0.695	0.086	0.100	1.84**	3.71**	1647**	-2.20	2.75**	-	-
VAEX	0.225	0.186	0.812	0.101	0.120	2.06**	4.36**	2176**	-2.10	2.18**	-	-
ΔVSTOXX	0.000	-0.003	0.328	-0.198	0.056	0.89**	6.39**	889**	-40.29**	0.06	0.000	0.042
ΔVFTSE	0.000	-0.003	0.372	-0.268	0.060	0.65**	6.04**	664**	-43.12**	0.04	0.000	0.007
ΔVDAX	0.000	-0.002	0.306	-0.212	0.051	0.73**	6.32**	797**	-37.94**	0.06	0.000	0.000
ΔVSMI	0.000	-0.001	0.250	-0.249	0.047	0.53**	7.11**	1092**	-37.06**	0.05	0.001	0.002
ΔVCAC	0.000	0.000	0.487	-0.372	0.062	0.45**	8.16**	1665**	-42.25**	0.05	0.000	0.001
ΔVBEL	0.000	-0.001	0.322	-0.311	0.055	0.14*	6.99**	971**	-41.69**	0.04	0.037	0.000
ΔVAEX	0.000	-0.003	0.333	-0.227	0.055	0.55**	5.56**	472**	-40.59**	0.06	0.111	0.001

Panel B: Correlation matrix of volatility and stock indices

Pearson's correlation matrix of EU volatility and stock index returns from January 1st, 2004 until July 31st, 2009, including 1,456 trading days. All values are significant at the 1% level.

	Volatility Indices							Stock Indices						
	VSTOXX	**VFTSE**	**VDAX**	**VSMI**	**VCAC**	**VBEL**	**VAEX**	**ESTOXX**	**FTSE**	**DAX**	**SMI**	**CAC**	**BEL**	**AEX**
VSTOXX	1.00													
VFTSE	0.79	1.00												
VDAX	0.92	0.76	1.00											
VSMI	0.74	0.67	0.76	1.00										
VCAC	0.76	0.70	0.76	0.63	1.00									
VBEL	0.61	0.60	0.62	0.56	0.62	1.00								
VAEX	0.83	0.78	0.82	0.71	0.75	0.67	1.00							
ESTOXX	-0.74	-0.64	-0.70	-0.54	-0.63	-0.55	-0.66	1.00						
FTSE	-0.70	-0.66	-0.65	-0.52	-0.60	-0.53	-0.62	0.92	1.00					
DAX	-0.72	-0.63	-0.68	-0.52	-0.60	-0.52	-0.63	0.96	0.86	1.00				
SMI	-0.66	-0.57	-0.61	-0.55	-0.55	-0.50	-0.58	0.87	0.86	0.82	1.00			
CAC	-0.74	-0.63	-0.69	-0.55	-0.63	-0.54	-0.65	0.98	0.93	0.92	0.87	1.00		
BEL	-0.65	-0.56	-0.64	-0.54	-0.56	-0.53	-0.60	0.86	0.84	0.80	0.81	0.87	1.00	
AEX	-0.70	-0.61	-0.67	-0.55	-0.59	-0.53	-0.65	0.94	0.91	0.89	0.84	0.95	0.87	1.00

Table 3: OLS regression results

This table presents results of OLS regressions of stock market indices returns on returns of their respective volatility indices. Panel A exhibit results for equation 1 and Panel B for equation 2. ΔIV represents changes (returns) in implied volatility of the corresponding index. ΔIV^+ and ΔIV^- represent positive and negative volatility changes. T-statistics are reported in parentheses. A Newey-West consistent estimate of the covariance matrix to control for autocorrelation and heteroscedasticity is used. AIC and SC represent Akaike Information Criterion and Schwarz Bayesian Information Criterion, respectively. ** and * denote significance at the 1% and 5% level, respectively.

Panel A: Stock return – implied volatility relationship

	ESTOXX	FTSE	DAX	SMI	CAC	BEL	AEX
Intercept	-0.0002	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000
	(-0.92)	(0.29)	(1.04)	(0.38)	(0.38)	(0.03)	(0.36)
ΔIV	-0.182**	-0.144**	-0.186**	-0.144**	-0.146**	-0.127**	-0.175**
	(-12.69)	(-11.63)	(-13.83)	(-10.13)	(-12.31)	(-13.91)	(-13.40)
adj. R^2	0.541	0.433	0.448	0.291	0.406	0.282	0.419
AIC	-6.46	-6.40	-6.28	-6.30	-6.23	-6.16	-6.12
SC	-6.45	-6.39	-6.27	-6.29	-6.22	-6.15	-6.12

Panel B: Asymmetric response model

	ESTOXX	FTSE	DAX	SMI	CAC	BEL	AEX
Intercept	0.0000	0.0004	0.0001	0.0003	0.0006	0.0007	0.0008
	(0.12)	(1.31)	(1.17)	(1.21)	(1.42)	(1.84)	(1.77)
ΔIV^+	-0.189**	-0.162**	-0.211**	-0.163**	-0.160**	-0.146**	-0.196**
	(-10.75)	(-10.75)	(-13.17)	(-8.72)	(-11.27)	(-10.29)	(-10.45)
ΔIV^-	-0.177**	-0.119**	-0.157**	-0.117**	-0.131**	-0.107**	-0.148**
	(-8.12)	(-7.50)	(-10.17)	(-7.82)	(-8.61)	(-11.31)	(-8.87)
adj. R^2	0.550	0.440	0.468	0.305	0.409	0.297	0.429
AIC	-6.50	-6.47	-6.39	-6.31	-6.24	-6.20	-6.13
SC	-6.49	-6.46	-6.38	-6.30	-6.23	-6.19	-6.12

Table 4: Quantile regression results

This table presents results of regressing stock index returns on returns of their respective volatility indices. Quantile regression coefficients for the τ^{th} quantile of the equity market distribution with corresponding t-statistics (in parentheses). We use bootstrap estimation of the covariance matrix for the calculation of robust standard errors. The last column contains X^2-statistics of a Wald test (with p-values in parentheses), testing the equality of the slope coefficients across the whole distribution (H_0: equal slope coefficients in all quantiles τ). ** and * denote significance at the 1% and 5% level, respectively.

	τ	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**Wald-Test**
ESTOXX	**Intercept**	0.009**	0.005**	0.003**	0.001**	0.000	-0.002**	-0.003**	-0.005**	-0.009**	22.960
		(17.03)	(17.51)	(12.69)	(6.64)	(-0.675)	(-8.29)	(-14.98)	(-19.56)	(-20.38)	(0.003)
	Beta	-0.174**	-0.164**	-0.161**	-0.161**	-0.163**	-0.166**	-0.167**	-0.173**	-0.188**	
		(-26.76)	(-32.59)	(-30.15)	(-27.8)	(-29.64)	(-30.6)	(-28.70)	(-27.42)	(-29.25)	
FTSE	**Intercept**	0.008**	0.005**	0.003**	0.001**	0.000	-0.001**	-0.003**	-0.005**	-0.008**	25.900
		(16.54)	(18.97)	(13.76)	(6.59)	(0.00)	(-7.42)	(-13.39)	(-17.94)	(-17.83)	(0.001)
	Beta	-0.141**	-0.129**	-0.125**	-0.125**	-0.126**	-0.129**	-0.131**	-0.138**	-0.159**	
		(-19.00)	(-26.39)	(-27.99)	(-27.75)	(-25.71)	(-24.14)	(-25.48)	(-24.19)	(-20.63)	
DAX	**Intercept**	0.009**	0.006**	0.003**	0.001**	0.000	-0.002**	-0.003**	-0.005**	-0.009**	20.172
		(19.48)	(20.13)	(13.96)	(6.67)	(0.00)	(-7.48)	(-13.70)	(-17.89)	(-21.74)	(0.009)
	Beta	-0.174**	-0.165**	-0.166**	-0.170**	-0.174**	-0.173**	-0.176**	-0.186**	-0.202**	
		(-22.71)	(-20.33)	(-24.64)	(-27.31)	(-26.26)	(-28.05)	(-29.08)	(-25.45)	(-27.25)	
SMI	**Intercept**	0.009**	0.005**	0.003**	0.001**	0.000	-0.001**	-0.003**	-0.005**	-0.009**	17.676
		(22.39)	(19.63)	(13.66)	(7.35)	(0.00)	(-6.78)	(-13.82)	(-18.51)	(-17.68)	(0.023)
	Beta	-0.146**	-0.146**	-0.148**	-0.142**	-0.140**	-0.151**	-0.156**	-0.159**	-0.171**	
		(-17.47)	(-19.20)	(-27.03)	(-23.96)	(-22.49)	(-21.07)	(-32.00)	(-28.81)	(-19.76)	
CAC	**Intercept**	0.009**	0.005**	0.003**	0.002**	0.000	-0.001**	-0.003**	-0.005**	-0.008**	14.031
		(20.09)	(19.34)	(14.25)	(8.37)	(0.96)	(-45.2)	(-11.48)	(-16.97)	(-17.19)	(0.081)
	Beta	-0.142**	-0.135**	-0.142**	-0.142**	-0.147**	-0.146**	-0.147**	-0.157**	-0.159**	
		(-24.34)	(-28.06)	(-28.35)	(-28.97)	(-29.82)	(-28.75)	(-20.80)	(-19.93)	(-22.69)	
BEL	**Intercept**	0.010**	0.006**	0.003**	0.002**	0.000	-0.001**	-0.002**	-0.005**	-0.010**	30.140
		(19.55)	(18.75)	(14.83)	(8.99)	(1.829)	(-4.95)	(-11.07)	(-15.18)	(-14.98)	(0.000)
	Beta	-0.106**	-0.125**	-0.133**	-0.134**	-0.136**	-0.138**	-0.139**	-0.146**	-0.138**	
		(-15.77)	(-16.5)	(-24.36)	(-25.55)	(-25.29)	(-23.18)	(-17.81)	(-23.08)	(-16.50)	
AEX	**Intercept**	0.009**	0.005**	0.003**	0.001**	0.000	-0.001**	-0.003**	-0.006**	-0.010**	29.618
		(19.47)	(19.93)	(13.94)	(6.66)	(0)	(-6.70)	(-13.16)	(-18.20)	(-17.37)	(0.000)
	Beta	-0.149**	-0.146**	-0.143**	-0.143**	-0.139**	-0.145**	-0.149**	-0.157**	-0.183**	
		(-21.43)	(-25.45)	(-27.97)	(-25.28)	(-23.98)	(-22.91)	(-27.70)	(-26.59)	(-22.70)	

Table 5: Difference in the level of implied volatility in main European markets

Statistics for the respective volatility spreads of pairwise combinations of Germany, France and the UK, defined as the difference in the level of implied volatility between the VDAX, VFTSE and VCAC. All series are represented in volatility points. The ADF (augmented Dickey Fuller) test is used to test for unit root in the time series. The KPSS (Kwiatkowski-Phillips-Schmidt-Shin) test is used to test for stationarity (critical values of 0.739 and 0.463 for the 1% and 5% level of significance, respectively). ** denotes significance at the 1% level.

	VDAX-VCAC	**VDAX-VFTSE**	**VFTSE - VCAC**
Mean	0.010	0.027	-0.017
Median	0.010	0.029	-0.018
Maximum	0.263	0.219	0.144
Minimum	-0.140	-0.127	-0.179
Std. Dev	0.021	0.030	0.022
Skewness	1.56**	-0.25**	0.24**
Excess Kurtosis	27.12**	7.04**	11.60**
Jarque Bera	35891**	1006**	4504**
ADF	-4.60**	-3.50**	-3.92**
KPSS	0.26	0.31	0.30

Table 6: Integration of the leading European volatility markets

Evolution of the impulse response function by a standardized unit shock to the implied volatility spread with the respective Monte Carlo standard errors.

Period	VDAX-VFTSE	Std. Err.	VDAX-VCAC	Std. Err.	VFTSE-VCAC	Std. Err.
1	1.0000	0.0186	1.0000	0.0185	1.0000	0.0185
2	0.6496	0.0281	0.4855	0.0277	0.5273	0.0279
3	0.5683	0.0277	0.4813	0.0292	0.4199	0.0300
4	0.4642	0.0327	0.4414	0.0229	0.3836	0.0244
5	0.4223	0.0338	0.3755	0.0251	0.3079	0.0256
6	0.4064	0.0216	0.3333	0.0267	0.2535	0.0262
7	0.3683	0.0224	0.2931	0.0279	0.2109	0.0263
8	0.3288	0.0238	0.2574	0.0284	0.1741	0.0254
9	0.3155	0.0270	0.2264	0.0286	0.1439	0.0242
10	0.2578	0.0289	0.1991	0.0283	0.1190	0.0226
11	0.2431	0.0294	0.1750	0.0277	0.0984	0.0209
12	0.2209	0.0301	0.1539	0.0268	0.0813	0.0191
13	0.1959	0.0313	0.1353	0.0258	0.0672	0.0173
14	0.1745	0.0323	0.1190	0.0246	0.0556	0.0155
15	0.1538	0.0335	0.1046	0.0234	0.0460	0.0139
16	0.1344	0.0346	0.0920	0.0220	0.0380	0.0123
17	0.1132	0.0355	0.0809	0.0207	0.0314	0.0109
18	0.0946	0.0364	0.0711	0.0194	0.0260	0.0096
19	0.0873	0.0372	0.0625	0.0181	0.0215	0.0084
20	0.0770	0.0379	0.0550	0.0168	0.0178	0.0074
21	0.0647	0.0386	0.0484	0.0156	0.0147	0.0064
22	0.0546	0.0392	0.0425	0.0144	0.0121	0.0056
23	0.0476	0.0398	0.0374	0.0133	0.0100	0.0048
24	0.0424	0.0402	0.0329	0.0122	0.0083	0.0042
25	0.0358	0.0407	0.0289	0.0112	0.0069	0.0036

Table 7: VSTOXX's regime dependent volatility

Regime-dependent standard deviation of VSTOXX's returns (in annualized percentages) of the entire maturity spectrum. The prevailing regimes are based on the smoothed probabilities from the Markov switching model.

Maturity	**1 month**	**2 months**	**3 months**	**6 months**	**9 months**	**12 months**	**18 months**	**24 months**
Low regime	23.79%	9.32%	8.83%	6.52%	6.58%	8.48%	7.90%	6.91%
Middle regime	43.72%	17.06%	14.50%	10.26%	7.70%	8.11%	5.92%	5.37%
High regime	109.09%	50.79%	38.34%	24.70%	18.87%	21.86%	16.65%	11.54%

Table 8: Logit model for determinants of regime changes

This table presents the α_1 coefficients from logit regressions (see equation 8) with t-statistics (in parentheses) and R^2 [in brackets]. We use a Huber-White consistent estimate of the covariance matrix to control for autocorrelation and heteroscedasticity. Determinants of the regime changes are: Stock return_{t-1} (lagged daily returns on the ESTOXX); Stock return^2_{t-1} (square of the lagged stock return); $\Delta VSTOXX_{t-1}$ (lagged returns on the VSTOXX), and $\Delta VSTOXX^2{}_{t-1}$ (square of lagged returns on the VSTOXX). ** and * denote significance at the 1% and 5% level, respectively.

Regime changes	**Stock return_{t-1}**	**Stock return^2_{t-1}**	**$\Delta VSTOXX_{t-1}$**	**$\Delta VSTOXX^2_{t-1}$**
From low to middle	-20.590*	5758.7**	0.0825	0.5679**
	(-2.0829)	(6.9531)	(0.8466)	(4.1132)
	[0.0011]	[0.062916]	[0.00905]	[0.0789]
From middle to high	-3.4153	2816.2**	0.0016	0.1995**
	(-0.9023)	(5.8813)	(0.6272)	(4.5436)
	[0.0085]	[0.1154]	[0.00368]	[0.1075]

Table 9: Principal component analysis of European volatility indices

Panel A reports the total variation of VSTOXX that can be explained by the first two principal components (PC1 and PC2). Panel B reveals loadings for the first two principal components of respective indices.

	PC 1	PC 2
Panel A: Explained variation		
VSTOXX - Cumulative % explained	72.30%	81.10%
Panel B: Factor loadings		
VSTOXX	0.437	0.284
VFTSE	0.398	0.200
VDAX	0.388	0.194
VSMI	0.273	0.259
VCAC	0.415	-0.837
VBEL	0.305	-0.192
VAEX	0.379	0.193

Table 10: US volatility indices

Results for Standard and Poors 500 (SPX/VIX), Dow Jones International Average (DJIA/VXD), Russel 2000 (RUS/RVX), and the Nasdaq 100 (NDX/VNX) indices, from January 1st, 2004 until July 31st, 2009 (1,455 daily observations for each index). The presented results are comparable with the results for European indices in: Table 2 (Panel A and Panel B), Table 3 (Panels C and D), Table 4 (Panel E), Table 9 (Panel F).

Panel A: Descriptive statistics

The presented results are comparable to the results for European indices presented in Table 2 (Panel A). Level and log return (Δ) statistics for the respective US volatility index. All series are represented in volatility points (percentage points /100 p.a.). The mean and median are given in the first two columns. The columns labeled maximum and minimum report the highest and lowest level as well as daily log changes (see the Δ-rows) over the scrutinized period, respectively. Higher moments are reported in the adjacent three columns, followed by the values of a test of normality. The Jarque-Bera test statistic is highly significant, rejecting the hypothesis of a normal distribution for each time-series. ADF-statistics and LM-statistics for the KPSS test are for combined test for unit-roots and stationarity. The last two columns present the p-values of Granger-causality tests to address the question of a potential lead-lag relation between the stock and the corresponding volatility indices. ** denotes significance at the 1% level.

	Mean	Median	Maximum	Minimum	Std. Dev	Skewness	Excess Kurtosis	Jarque-Bera	ADF Statistic	KPSS (LM-stat)	H_0: volatility does not Granger-cause stock index	H_0: Stock index does not Granger-cause volatility
VIX	0.202	0.154	0.809	0.099	0.120	2.16**	4.89**	2562**	-1.98	2.38**	-	-
VNX	0.240	0.209	0.806	0.126	0.107	2.23**	5.77**	3200**	-2.38	2.04**	-	-
VXD	0.186	0.144	0.746	0.093	0.107	2.20**	5.19**	2786**	-1.97	2.37**	-	-
RVX	0.267	0.226	0.876	0.144	0.122	2.12**	4.55**	2329**	-2.39	2.21**	-	-
ΔVIX	0.000	-0.003	0.496	-0.300	0.064	0.61**	7.92**	1557**	-32.37**	0.07	0.000	0.037
ΔVNX	0.000	-0.002	0.363	-0.223	0.052	0.52**	6.64**	870**	-31.56**	0.06	0.001	0.029
ΔVXD	0.000	-0.001	0.528	-0.334	0.064	0.55**	8.11**	1656**	-32.08**	0.07	0.000	0.000
ΔRVX	0.000	0.000	0.333	-0.226	0.051	0.61**	6.35**	771**	-42.17**	0.05	0.059	0.091

Panel B: Correlation matrix of volatility and stock indices

The presented results are comparable to the results for European indices presented in Table 2 (Panel B). All values are significant at the 1% level.

	Volatility Indices				Stock Indices			
	VIX	**VNX**	**VXD**	**RVX**	**SPX**	**NDX**	**DJIA**	**RUS**
VIX	1.00							
VNX	0.87	1.00						
VXD	0.95	0.86	1.00					
RVX	0.85	0.84	0.84	1.00				
SPX	-0.73	-0.69	-0.72	-0.68	1.00			
NDX	-0.71	-0.72	-0.71	-0.67	0.92	1.00		
DJIA	-0.72	-0.67	-0.72	-0.67	0.98	0.89	1.00	
RUS	-0.70	-0.66	-0.69	-0.70	0.92	0.88	0.89	1.00

Panel C: Stock return – implied volatility

The presented results are comparable to the results for European indices presented in Table 3 (Panel A). T-statistics are reported in parentheses. A Newey-West consistent estimate of the covariance matrix to control for autocorrelation and heteroscedasticity is used. AIC and SC represent Akaike Information Criterion and Schwarz Bayesian Information Criterion, respectively. ** and * denote significance at the 1% and 5% level, respectively.

	SPX	**NDX**	**DJIA**	**RUS**
Intercept	0.0000	0.0000	0.0000	0.0000
	(-0.42)	(0.26)	(-0.23)	(0.14)
ΔIV	-0.161**	-0.208**	-0.144**	-0.246**
	(-12.29)	(-12.04)	(-11.63)	(-10.12)
adj. R^2	0.537	0.511	0.518	0.494
AIC	-6.44	-6.28	-6.57	-5.91
SC	-6.44	-6.27	-6.57	-5.90

Panel D: Asymmetric response model

The presented results are comparable to the results for European indices presented in Table 3 (Panel B). ΔIV represents changes (returns) in implied volatility of the corresponding index. ΔIV+ and ΔIV- represent positive and negative volatility changes. T-statistics are reported in parentheses. A Newey-West consistent estimate of the covariance matrix to control for autocorrelation and heteroscedasticity is used. AIC and SC represent Akaike Information Criterion and Schwarz Bayesian Information Criterion, respectively. ** and * denote significance at the 1% and 5% level, respectively.

	SPX	**NDX**	**DJIA**	**RUS**
Intercept	0.0000	-0.0002	-0.0002	-0.0003
	(0.12)	(-0.45)	(-0.55)	(-0.88)
ΔIV^{+}	-0.164**	-0.220**	-0.150**	-0.257**
	(-9.77)	(-10.51)	(-10.63)	(-13.58)
ΔIV^{-}	-0.129**	-0.192**	-0.128**	-0.236**
	(-9.41)	(-11.93)	(-8.72)	(-11.47)
adj. R^2	0.541	0.518	0.529	0.506
AIC	-6.45	-6.32	-6.70	-5.98
SC	-6.44	-6.31	-6.69	-5.97

Panel E: Quantile regression results

The presented results are comparable to the results for European indices presented in Table 4. Quantile regression coefficients for the τth quantile of the equity market distribution with corresponding t-statistics (in parentheses). We use bootstrap estimation of the covariance matrix for the calculation of robust standard errors. The last column contains χ^2-statistics of a Wald test (with p-values in parentheses), testing the equality of the slope coefficients across the whole distribution (H0: equal slope coefficients in all quantiles). ** and * denote significance at the 1% and 5% level, respectively.

	τ	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**Wald-Test**
SPX	**Intercept**	0.008**	0.004**	0.002**	0.001**	0.000	-0.001**	-0.002**	-0.004**	-0.008**	60.013
		(16.84)	(15.60)	(11.63)	(6.06)	(0)	(-6.72)	(-12.63)	(-18.16)	(-15.06)	(0.000)
	Beta	-0.139**	-0.130**	-0.122**	-0.121**	-0.121**	-0.125**	-0.136**	-0.139**	-0.166**	
		(-26.79)	(-22.64)	(-25.32)	(-30.20)	(-30.75)	(-26.35)	(-27.62)	(-26.28)	(-21.20)	
NDX	**Intercept**	0.011**	0.007**	0.004**	0.002**	0.000	-0.002**	-0.004**	-0.007**	-0.011**	13.632
		(24.02)	(19.24)	(12.81)	(6.62)	(0)	(-7.07)	(-12.74)	(-17.49)	(-24.40)	(0.091)
	Beta	-0.197**	-0.194**	-0.186**	-0.184**	-0.183**	-0.184**	-0.193**	-0.202**	-0.210**	
		(-23.29)	(-24.45)	(-23.45)	(-24.37)	(-25.86)	(-26.50)	(-23.81)	(-20.77)	(-24.73)	
DJIA	**Intercept**	0.008**	0.004**	0.003**	0.001**	0.000	-0.001**	-0.003**	-0.005**	-0.008**	39.719
		(20.00)	(17.00)	(12.14)	(6.58)	(0)	(-6.61)	(-12.46)	(-18.89)	(-16.55)	(0.000)
	Beta	-0.131**	-0.124**	-0.117**	-0.114**	-0.113**	-0.115**	-0.117**	-0.125**	-0.142**	
		(-23.39)	(-24.59)	(-25.47)	(-26.05)	(-24.24)	(-24.26)	(-27.37)	(-27.25)	(-21.34)	
RUS	**Intercept**	0.012**	0.006**	0.003**	0.002**	0.000	-0.002**	-0.004**	-0.007**	-0.011**	28.434
		(20.63)	(16.50)	(11.72)	(6.81)	(0)	(-6.74)	(-12.19)	(-17.23)	(-18.22)	(0.000)
	Beta	-0.224**	-0.219**	-0.216**	-0.215**	-0.215**	-0.218**	-0.235**	-0.246**	-0.258**	
		(-20.28)	(-22.90)	(-24.53)	(-35.38)	(-36.38)	(-31.64)	(-25.73)	(-29.12)	(-22.38)	

Panel F: Principal component analysis of US volatility indices

The presented results are comparable to the results for European indices presented in Table 9 (Panel A).Panel A reports the total variation of volatility indices that can be explained by the first two principal components (PC1 and PC2). Panel B reveals loadings for the first two principal components of respective indices.

	PCA 1	**PCA 2**
Panel A: Explained variation		
VIX - Cumulative % explained	93.8%	97.0%
Panel B: Factor loadings		
VIX	0.544	0.291
VNX	0.473	-0.069
VXD	0.491	0.533
RVX	0.489	-0.792

Table 11: Hedging performance – OLS vs. quantile regression

Overall pay-off comparison of the performance of OLS and quantile regression based hedge ratios. The presented results are for the $\tau = 0.9$ quantile, on respective dates (assuming transaction costs equal to 0.5 vega points).

	August 2007		September 2008	
	OLS	**Quantile Regression**	**OLS**	**Quantile Regression**
Europe				
STOXX	0.38%	0.68%	7.41%	8.36%
FTSE	3.40%	3.45%	9.30%	9.70%
DAX	3.30%	3.41%	1.90%	2.74%
SMI	2.15%	3.51%	6.79%	6.74%
CAC	-0.37%	-0.26%	7.32%	8.03%
BEL	-1.49%	-0.79%	8.70%	9.80%
AEX	0.06%	0.60%	1.86%	3.13%
US				
SPX	0.09%	0.19%	5.41%	6.05%
NDX	0.38%	0.55%	-0.67%	-0.61%
DJIA	-0.60%	-0.51%	5.29%	5.54%
RUS	-1.06%	-0.92%	11.93%	12.42%

Figure 1: Evolution of the ESTOXX and VSTOXX indices

The development of the ESTOXX (Euro Stoxx 50) (dotted line and left scale in points) and the volatility index VSTOXX (solid line and right scale in percent per year) from January, 1st 2004 to July, 31st 2009.

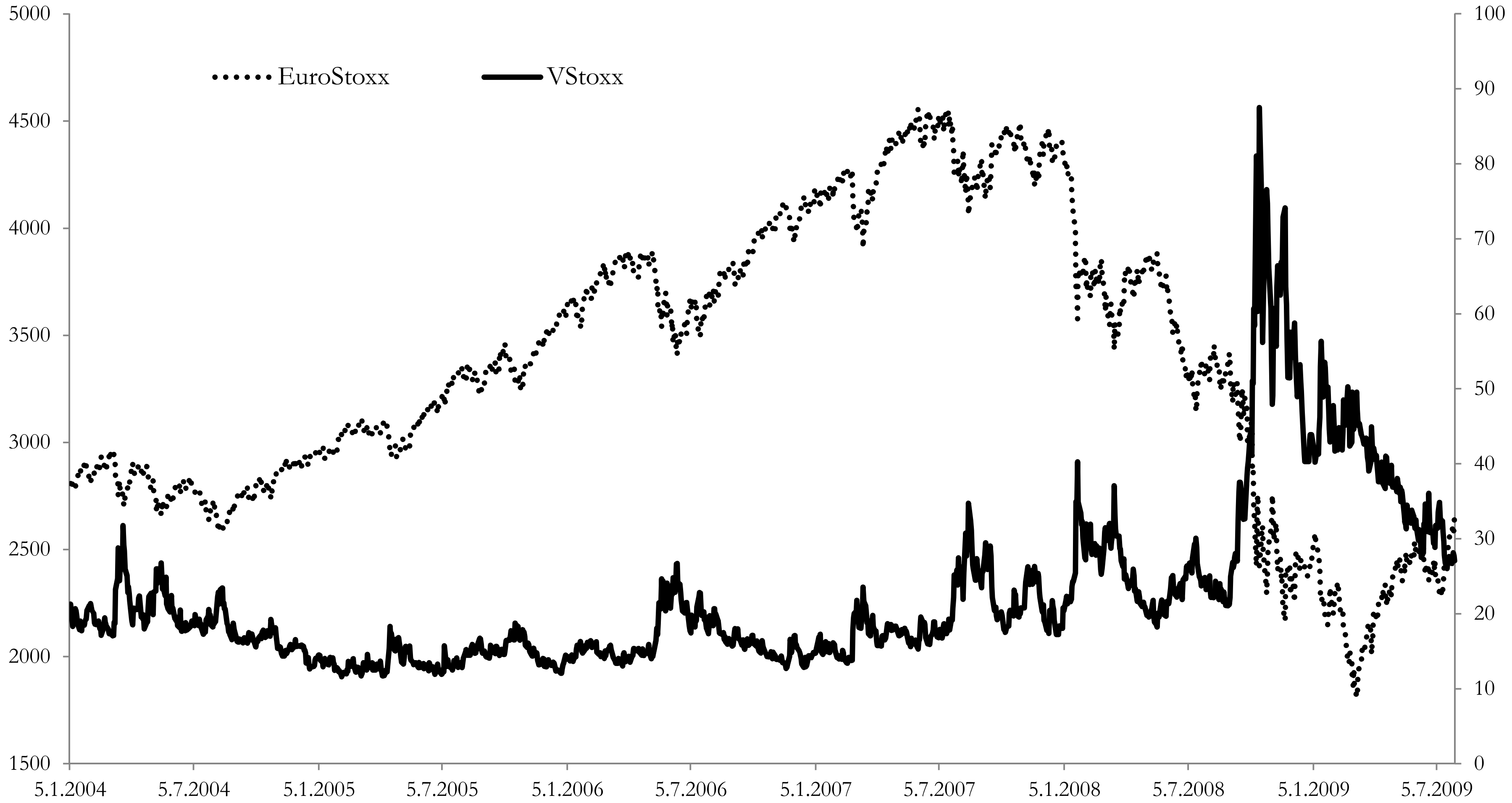


Figure 2: Impulse response function (IRF) for spreads in European volatility indices

The thick bold solid line represents the IRF for the VDAX-VFTSE spread, the thin solid line represents the IRF for the VFTSE-VCAC spread, and the dashed line represents the IRF for the VDAX-VCAC spread. Half life (HL) measures the number of days it takes for one unit shock to shrink to half of its initial value. HLs are depicted by arrows indicating intercept points between the respective IRFs and the 0.5 gridline.

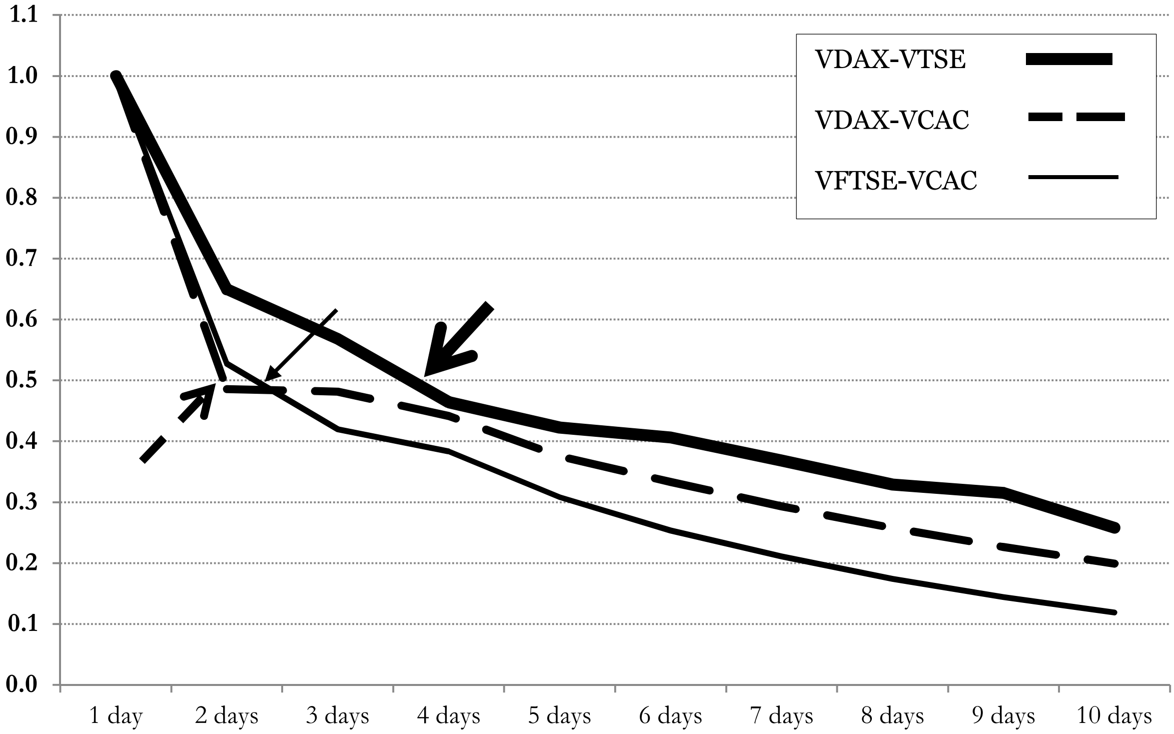
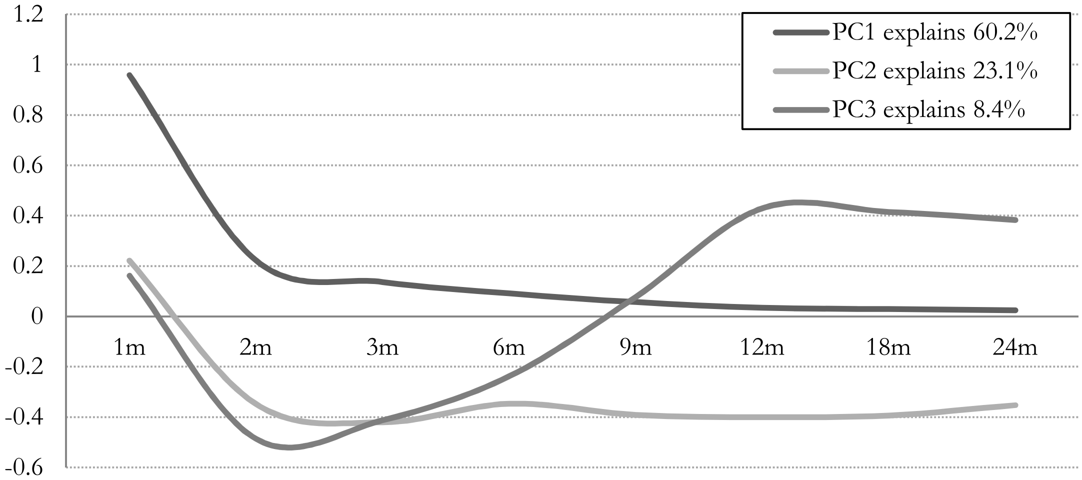


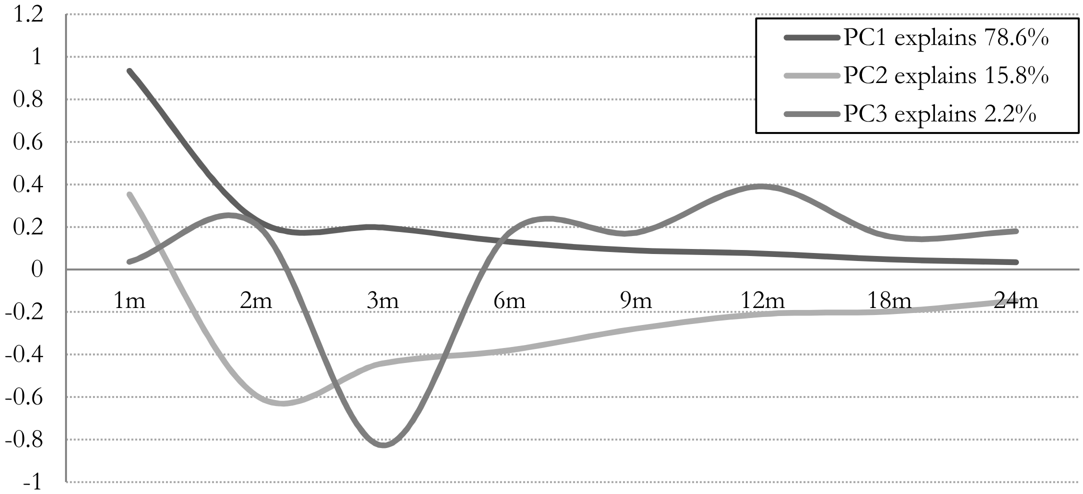
Figure 3: Factor loadings in different market regimes

Factor loadings of the respective principal components, measured as the eigenvectors (on the y-axis) of the entire maturity spectrum of the VSTOXX term structure, derived by a principal component analysis (PCA). Calculations are based on the covariance matrix of the daily changes in VSTOXX. Data points are connected via cubic spline interpolation. Percentage figures indicate the marginal contribution explaining the complete volatility term structure by the respective principal component.

Panel A: Low volatility regime



Panel B: Middle volatility regime



Panel C: High volatility regime

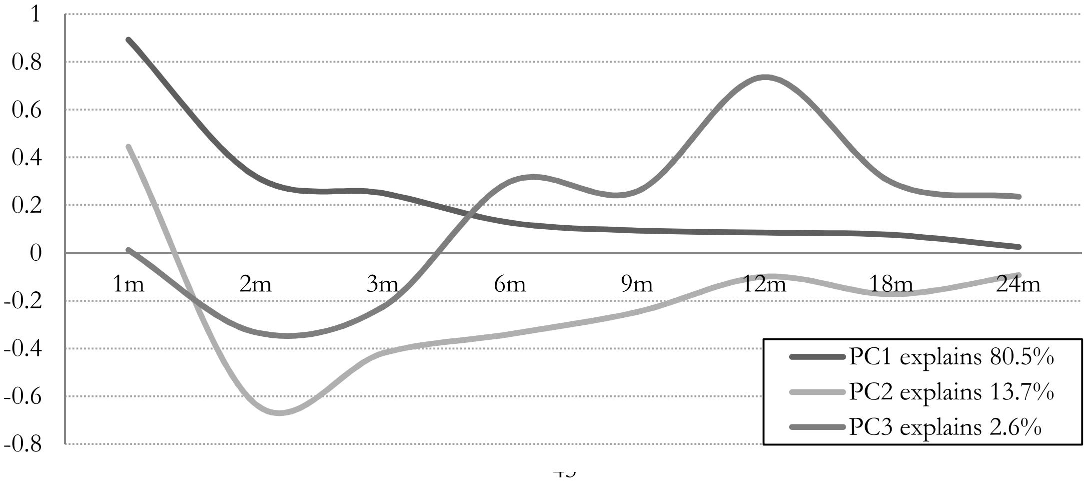
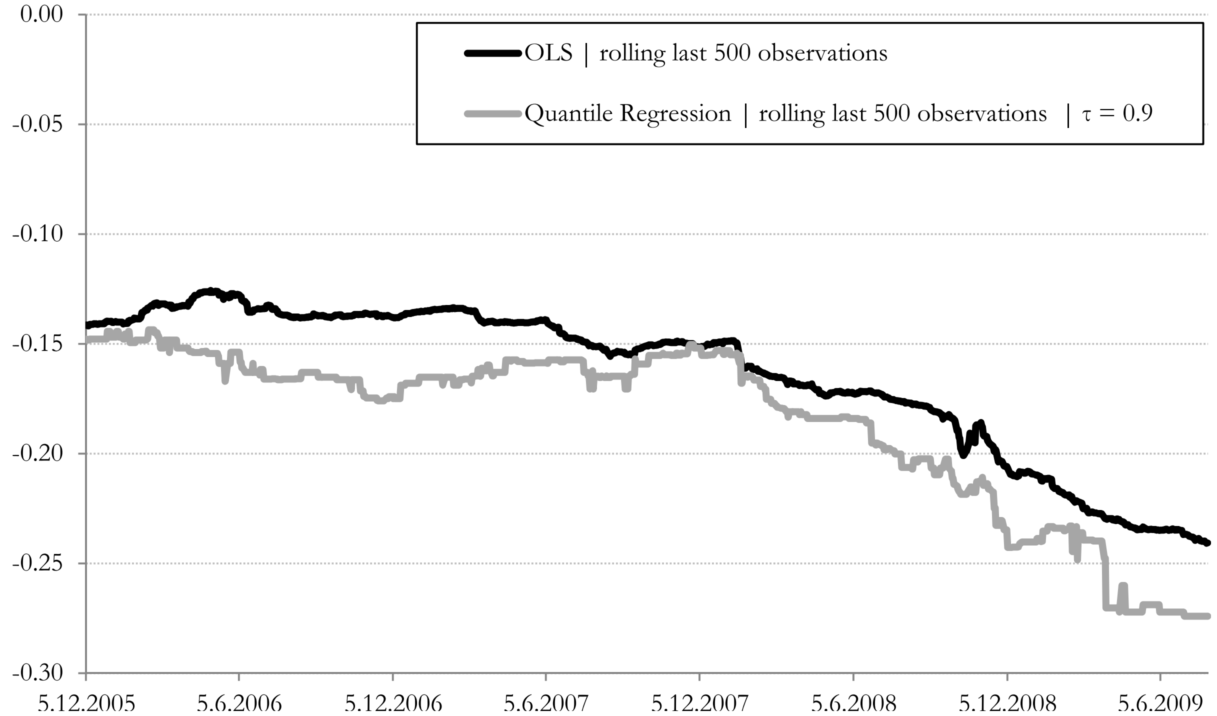


Figure 4: Evolution and comparison of hedge ratios

OLS and quantile regression based hedge ratios obtained by regressing the returns of the DAX (Panel A) and SPX (Panel B) on changes in their respective volatility indices. The black line represents hedge ratios based on OLS regressions. The grey line represents hedge ratios based on quantile regressions (for quantiles with the lowest returns (τ = 0.9)).

Panel A: DAX



Panel B: SPX