# European 'fear' indices – evidence before and after the financial crisis

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## Abstract

European volatility markets exhibit differences consistent with institutional clusters identified in the previous literature. The degree of integration between leading markets, however, is very high and shocks on the implied volatility spread die out within few days. Our Markov switching model distinguishes three volatility regimes. In the high volatility regime, level, slope, and curvature factors explain 97% of the complete volatility term structure. A shock to the second principal component has regime dependent influence on the slope of the volatility term structure. Our findings lend support to the behaviour explanation of the return-implied volatility relation and have implications for risk management and option pricing.

***JEL classification:*** C32, G13, G15

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

## 1. Introduction

The VIX index, derived from S&P 100 options, is considered as the market's price for exposure to volatility over a specific period. It is, therefore, regarded as a market fear gauge to assess the vulnerability of financial markets. Although the VIX has become the de facto benchmark for equity market volatility, it remained highly illiquid 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 equity markets based on the same methodology.

Recent empirical evidence suggests that US returns-implied volatility relation tends to be driven by behavior of market participants (Low, 2004; Hibbert et al., 2008) rather than by leverage (Black, 1976) and changes in investors risk aversion due to significant increases in aggregate volatility (Poterba and Summers, 1986; Campbell and Hentschel, 1992). Giot (2005) examines casual observation that returns-implied volatility relation could be conditional on trading environment. He reports that conterprenous relationships between the implied volatility (i.e. VIX) and S&P index returns was much stronger in a low volatility trading environment. However, there was no previous study on returns-implied volatility relation for entire European market during the period of recent financial crisis.

The objective of this study is to analyze all European volatility indices before and after recent financial crisis. We expect differences in distributions of volatility indices across EU countries, conditional on trading environment (i.e. high vs. low volatility periods). Countries in European Union (EU) share common market, currency (with some exceptions), and harmonized regulation thus creating a similar macroeconomic environment for member states. Important institutional and cultural differences, however, still remain. The above differences are expected to affect investors' behavior and, therefore, should be also reflected in respective volatility markets.

We make following contributions to the implied volatility literature. First, we extend empirical work on return-implied volatility association by utilizing a set of all available European volatility indices and applying quantile regressions. Second, we examine differences in distri-

[1] The methodology was based on Carr and Madan (1998) work on pricing variance swaps. The methodology does not require selection of a specific stock price process but assumes market completeness and continuous trading.

bution of volatility indices, differences in returns-implied volatility relation across institutional and cultural clusters, and for how long the differences persist. Third, we examine the regime-dependent movements of the entire maturity spectrum of the Eurozone's volatility index and compare it within Europe and with the results for US volatility indices. Finally, by means of principal component analysis (PCA) we shed further light into the dynamics between European equity and volatility indices.

Our main findings are: (i) European equity and volatility markets exhibit a statistically significant negative relationship. The negative relationship is slightly less pronounced for the 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 returns at the lowest equity market return quantiles significantly more compared to the median quantile (but still less compared to the highest quantile). This result is consistent with the volatility smile and lends support to the behavioral explanation (see Hibbert et al., 2008) of the return-implied volatility relation; (v) hedge ratios derived from the quantile regressions produce better results compared to their OLS counterparts; (vi) characteristics of distributions of volatility indices vary across country 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; (vi) short maturities exhibit a higher volatility of volatility than longer maturities; (vii) the dynamics of the volatility term structure are clearly regime dependent; (viii) volatility of volatility is up to five times higher during periods of stress in financial markets; (ix) positive stock market returns tend to decrease the probability that volatility enters a higher volatility regime. Large movements (regardless of direction) in both, implied volatility and stock markets increase the probability that volatility enters a higher volatility regime; (x) in the high volatility regime, first three principal components (level, slope, and curvature) explain 97% of the complete European volatility term structure. A shock to the second principal component has regime dependent influence on the slope of the 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 of the models for the association of returns and implied volatility. The results of the tests for integration of European volatility indices are presented in section 5. Section 6 deals with dynamics of the volatility term structure. Results of the 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

Literature on association between implied volatility and returns is relatively scarce. In an early study, Whaley (2000) finds a significantly negative contemporaneous relationship between changes in implied volatility indices and underlying stock market returns. This result was echoed in subsequent international (Gonzalez and Novales, 2009; Skiadopoulos, 2004) and US (Giot 2005; Carr and Wu, 2006) studies.

Previous literature formulated various hypotheses on the negative return-volatility relationship based either on firm fundamentals (leverage and feedback theories) or (heuristic) behavior of market participants. The leverage hypothesis (Black, 1976) attributes the negative relationship to increasing financial leverage of companies caused by negative shocks to returns. Subsequently, the increase leverage drives up volatility of equity prices. The feedback hypothesis (French et al, 1987) postulates that any shock in volatility leads to a significant decrease in returns. Similarly, Campbell and Hentschel (1992) argue that increases in aggregate volatility leads to a reduction in investor holdings of risky assets. Ultimately, this results in lower contemporaneous returns. Both leverage and feedback theories suggest a long-run lagged association between return and volatility (or vice verse).[2] 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 higher at both tails than at the center of the equity market returns distribution. This, for example, explains why investors fear of future losses during market downturns and consequently bid up put option premiums. The increase in put option premiums leads to an increase in implied volatility leading to negative return-implied volatility relationship. Giot (2005), however, reports that S&P 100's negative returns tend to be associated with greater proportional changes in VXO (old VIX) than are positive returns. The result is consistent with the "fear of a crash" manifested with higher

[2] 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).

increase in implied volatility during bearish market than decrease in implied volatility observed during bullish market. Weaker impact of implied volatility on returns at the lower end of the distribution (i.e. increase in returns) is also consistent with volatility smile (skew) effect. We, therefore, test the following hypotheses:

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

*Hypothesis 2: The contemporaneous relationship between the European market perception of volatility (i.e. implied volatility) and underlying returns is stronger at the ends than at the middle of the return distribution.*

*Hypothesis 3: The contemporaneous relationship between the European market perception of volatility (i.e. implied volatility) and underlying returns is stronger in the highest (i.e. negative returns) than in the lowest (i.e. positive returns) quantile.*

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

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

Where $\text{Index return}_{\text{t}}$ is the daily return of the stock index, $\Delta\text{IV}_{\text{t}}$ the corresponding return of the respective implied volatility index, and $\varepsilon_t$ represents a normally distributed error term. Since the early work of Whaley (1993) this regression is known as “fear gauge” regression with expected positive (and statistically significant) intercept term and (a statistically significant) negative slope coefficient. We than estimate a similar model to account for potentially asymmetric response:

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

where the changes of the respective volatility index are split into negative $\Delta\text{IV}_t^-$ and positive $\Delta\text{IV}_{\text{t}}^+$ volatility changes. A negative β1, for example, shows a percentage of increase in the stock market returns associated with 1% decrease in the implied volatility. A negative β2, on the other hand, would show a percentage of decrease in the stock market returns associated with 1% increase in the implied volatility. If positive changes (i.e. increase) in volatility have a larger impact on stock returns than negative changes (i.e. decrease) of the same magnitude, $\beta_2$ is expected to be larger than $\beta_1$ (in absolute terms).

The above OLS approach, however, is highly sensitive to departures from normal distribution. Quantile regressions replace the least squares criterion with least-absolute-distance estimation, thus representing a natural extension of OLS regression.[3] This approach is, therefore, more suitable for volatility indices which are often characterized with significant outliers and leptokurtic distribution. Quantile regressions 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 $\tau^{\text{th}}$ quantile of the distribution and allow the slope coefficients to change accordingly. Estimates based on quantile regressions, therefore, allow us to test hypotheses 2 and 3. Our quantile regression model has the following form:

$$Index\ return_t = c + \Delta \mathrm{IV}_i \beta_\tau + \varepsilon_{\tau i} \tag{3}$$

where $Index\ return_t$ represents the return of the stock index and depends on the quantile of the corresponding returns of the implied volatility index $\Delta \mathrm{IV}_\mathrm{i}$. $\varepsilon_{\tau i}$ is a quantile specific error term with expected value of zero.

### 2.2 Return-volatility relation across Europe

Although EU is, by far, the most advanced regional confederation in the World, some important institutional and cultural differences still remain. For example, La Porta et al. (2000) show significant differences across countries (including EU) in terms of protection of investors' rights. The differences are associated by legal tradition, rule of law, and some other cul-

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[3] Following Mosteller and Tukey (1977) original insights, quantile regressions were introduced by Koenker and Bassett (1978). They have been employed in a variety of topics in finance: value at risk models (Taylor, 1999; Engle and Manganelli, 1999; Gourieroux and Jasiak, 2008), portfolio style analysis (Bassett and Chen, 2001), asset pricing (Barnes and Hughes, 2002), determinants of capital structure of listed companies (Fattouh, 2005), optimal portfolio construction (Ma and Pohlman, 2005), the structure of comovements in equity markets (Cappiello et al., 2005), the relationship between firm efficiency and leverage (Margaritis and Psillaki, 2007), forecasting the distribution of stock returns (Cenesizoglu and Timmermann, 2008), explaining hedge fund alphas (Zhong, 2008), the tail dependence of stock indices (Beine et al. 2008), home foreclosure rate differentials (Richter, 2008), the causal relation between stock returns and volume (Chuang et al., 2009), the performance of venture capital funds (Smith, 2009), and many others.

tural differences (e.g. religion). The cultural differences are consequence of the fact that EU bridges two major historical rifts (i.e. Latin vs. Germanic) and are associated with power distance, uncertainty avoidance, individualism, masculinity, and long vs. short term orientation (Hofstede, 2001).[4] For example, Stulz and Williamson (2001) examine importance of cultural differences and report that a country's principal religion helps 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.

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; Ball et al. 2000; Hofstede, 2001).[5] For example, UK is described as outsider economy with large stock market, dispersed ownership, strong investors' rights, and strong legal enforcement. The large and diverse stock market (i.e. high degree of market completeness), together with strong investors' rights and protection, reduces investors' levels of stress and 'fear' of unknown future. Thus UK is characterized as a country with low uncertainty avoidance. Germany, on the other hand, is normally described as insider economy with relatively smaller stock markets, concentrated ownership, weak investors' rights, strong legal enforcement, and strong uncertainty avoidance.[6] In terms of investors' rights, France falls in between UK and Germany but with weakest legal enforcement out of the three.[7] France is also characterized by relatively smaller stock market, concentrated ownership and strong certainty avoidance. Finally, southern European countries (e.g. Italy) would be clustered as insider economies with weak legal enforcement and strong uncertainty avoidance. It is plausible that the institutional and cultural differences affect behavior of market participants and result in differences across European countries. Specifically, we expect stronger "fear of crash" and stock market responsiveness to changes in volatility in insider (e.g. Germany) than outsider (e.g. UK) economies. The different behavior would also be in line with Hibbert et al. (2008) who identified behavioral factors as important determinants of implied volatility and return-implied volatility relation. Thus,

[4] Power distance (PDI) is related to the different solutions to the basic problem of human inequality.Uncertainty avoidance (UAI) is related to the level of stress in a society in the face of an unknown future. Individualism versus collectivisim (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. Long-term versus short-term orientation (LTO), is related to the choice of focus for people's efforts: the future or the present.

[5] For example, Ball et al. (2000) highlighted importance of different institutional factors for properties of accounting earnings. Leuz et al (2003) show that strong and well-enforced investors rights mitigate insiders' incentives to manage accounting earnings.

[6] Netherlands and Switzerland are very similar to Germany except that they both exhibit (similar) lower degree of uncertainty avoidance.

[7] Belgium is very similar to France.

*Hypothesis 4: The market perception of volatility and returns- implied volatility relation differ across European countries.*

**2.3 Integration of European volatility indices**

Previous studies for the European markets find evidence of a highly significant cointegration relationship between major stock market indices (Rousova, 2009; Syriopoulos, 2007), stock option markets (Nikkinen and Sahlström, 2004) and currency option markets (Krylova et al, 2008). Wagner and Szimayer (2004) investigate the behavior of implied volatility for the US and German market under a mean reversion model and find evidence that jumps spill-over. More recently, Äijö (2008) reports high correlation between German (VDax), Swiss (VSmi) and Eurozone (VStoxx) volatility indices. We expect similar results for other European volatility markets, in the long run.

One of the limitations of the above mentioned studies is that they are either based on the old (i.e. pre 2003) volatility index pricing methodology or historical volatility. They also deploy vector autoregressive modeling which cannot quantify lengths (i.e. persistence) of various shocks to related indices. To overcome these problems we follow the methodology of Cuddington and Wang (2006), which is based on impulse response functions and adopts popular autoregressive (AR) models robust to non-standard error distributions. The methodology is capable of determining the speed of adjustment (see Goldberg and Verboven, 2005; Taylor, 2001). The adjustment mechanism to the mean level $\bar{x}$ is formalized by the following equation:

$$x_t - \bar{x} = \lambda(x_{t-1} - \bar{x}) + \varepsilon_t \tag{4}$$

when such a stationary mean exists. Any deviation $x_t - \bar{x}$ at time $t$ is hypothesized to be a fraction $(0 \leq \lambda \leq 1)$ of the lagged deviation $(x_{t-1} - \bar{x})$, where $\lambda$ represents the persistence of the deviation and $\varepsilon_t$ is a random error term. Rearranging equation (4) yields an AR (1) specification of the form,

$$x_t = c + \lambda x_{t-1} + \varepsilon_t \tag{5}$$

$\lambda = 1$ implies that a shock to the spread would be permanent, thus $x_t$ would have a unit-root, hence it is non-stationary. Conversely, $\lambda = 0$ indicates perfect integration, implying that deviations are uncorrelated events. For serially correlated time-series, like the volatility spread, a higher order autoregressive process is needed to capture the dynamic behavior:

$$x_t = c + \lambda_1 x_{t-1} + \cdots + \lambda_q x_{t-q} + \varepsilon_t \tag{6}$$

in which case a long-run mean exists if $\sum \lambda_i < 1$ is fulfilled.

If the underlying stock markets are significantly cointegrated, the differences in the level of implied volatility (defined as volatility spread) are expected to be mean-stationary. From an economic viewpoint the differences reflect the speed of traders, arbitrageurs and investors responding to profitable differentials in implied volatility. Whenever implied volatility trades at an unwarranted premium or discount, market practitioners try to exploit deviations from the long-term level by engaging in a trade that is short the supposedly expensive index and is long the undervalued index. These opportunities are the largest and hence most profitable in the days immediately following a shock. The differences are, therefore, expected to be temporary, otherwise investors can generate higher risk-adjusted returns by allocating investments to the undervalued market (i.e. market with a higher ratio of expected returns to market expected volatility). As long as the spread between two volatility indices is stationary and has a constant mean, supply and demand shocks should only have a temporal effect with the spreads gradually moving toward the long-run relationship. Thus,

*Hypothesis 5: European volatility indices are highly integrated.*

### 2.4 Regime dependent volatility term structure

Mixon (2002) and Fengler et al. (2002) apply PCA and identify that three components are sufficient to describe the time-series movement across the implied volatility term structure and option exercise prices. Previous studies also documented time-varying properties of volatility (Schwert, 1989; Derman, 1999). More recently, Allen et al. (2006) identify three unique (low, mid and exploding) phases of implied volatility for variance swap markets. In this study, we examine the complete term-structure of the implied volatility for Eurozone (VStoxx) and postulate that implied volatility varies over time in a systematic way. Thus, *Hypothesis 6: The term structure of Eurozone's implied volatility has time-varying dynamics.*

We identify different regimes using probabilities estimated by the following Markov switching model, with state-dependent volatility of volatility: [8]

$$\Delta \mathrm{VStoxx}_{\mathrm{k,t}} = c_{S,k,0} + \varepsilon_{S,k,t}, \qquad (7)$$

with $c_{S,k,j}$ being the explanatory coefficient, which is dependent on the state parameter $s$ and $\varepsilon_{S,k,t}$ represents the vector of disturbance terms, assumed to be normal with state-dependent variance $\sigma^2_{S,k,t}$. The unobservable state parameter $s_t$ is assumed to follow a first-order, three-state Markov chain where the transition probabilities are assumed to be constant. The above model allows us to back out the regime specific conditional mean levels of volatility. We then isolate common risk factors, of the entire volatility structure in different regimes, using PCA.

## 3. Data

We examine all officially available volatility indices that are calculated and disseminated by Euronext and Eurex: VDax (Germany), VCac (France), VFtse (UK), VSmi (Switzerland), VBel (Belgium), VAex (Netherlands) and VStoxx (proxy for the Eurozone). All of the above indices are based on the same pricing methodology, which makes them directly comparable. Our sample includes 1,455 trading days during the period from January 1st, 2004 until July 31st, 2009. The sample descriptive statistics is presented in Table 1.

*** Insert Table 1 about here ***

Our sample is characterized by wide ranging levels of implied volatility (Panel A). 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 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 determin-

[8] For a detailed discussion of Markov switching models see Hamilton (1989).

istic growth trend in volatility.[9] 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. Both KPSS and Augmented Dickey Fuller (ADF) test statistics indicates, 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 a correlation matrix presented in Panel B. All returns for stock market and volatility indices are negatively correlated at the 1% level. The highest correlation (-0.74) was recorded between EuroStoxx and VStoxx. Among volatility indices, VStoxx and VDax exhibit the highest correlation (0.92).

Our sample captures periods with different stock market conditions. As an illustration, in Figure 1, we present the evolution of the European equity (EuroStoxx) and corresponding volatility index (VStoxx), during the sample period. 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.[10] Although equity markets switch back to low levels of volatility for several months, in the last quarter of 2007 implied volatility in Europe jumped to 35% (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 the OLS regressions (equation 1) are presented in Panel A of Table 2. They reveal strictly negative and significant coefficients for all volatility indices. Contrary to theo-

[9] It has widely been accepted that volatility follows a mean-reverting process. See e.g. Allen et al. (2006).
[10] Ameriquest was one of the largest mortgage lenders in North America.

retical predictions the intercept term is not statistically different from zero.[11] 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%.[12] On the other hand, our findings suggest that for a 1% increase in implied volatility of the same magnitude the DAX responds stronger and falls by 0.20%.[13]

*** Insert Table 2 about here ***

Across sample countries, we observer higher sensitivity of DAX returns compared to the sensitivity of FTSE returns. The coefficients for CAC are always in between the coefficients reported for FTSE and DAX (Panels A and B). The results are in line with our hypothesis 6.

**4.2 Quantile regression**

We tried alternative specifications of equation 3 with lag terms for both stock index and the implied volatility index. Since none of the alternative specifications improved explanatory power and/or statistical significance we conclude that responses are indeed contemporaneous as in equation 3.[14] Table 3 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 (sensitivity) for increase in stock market returns.[15] Our results also suggest higher (absolute) betas in highest ($\tau$=0.9) quantile (i.e. decrease in 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 ($\tau = 0.5$), for 4 out of 7 volatility indices.

The above results highlight asymmetric response of stock returns to volatility and lend support to our hypotheses 2 and 3. Our results are also consistent with the volatility smile (i.e.

[11] This is likely to be due to a significant drop in the major European stock market indices during the sample period.
[12] $DAXreturn_t = 0.0001 + -0.157*-0.01 = 0.00167 = 0.17\%$.
[13] $DAXreturn_t = 0.0001 + -0.211*0.01 = -0.00201 = -0.20\%$.
[14] It is worth noting that both leverage and feedback hypotheses suggest models with the lag terms.
[15] See e.g. Whaley (2000), Giot (2005), and Gonzalez and Novales (2009).

skew) commonly observed in options market. Notably, estimates obtained by OLS are more in line with the estimates for higher than for median quantiles. In above the median quantiles, however, the magnitude of the response is underestimated by OLS models.

*** Insert Table 3 here ***

The cross country differences remain similar to those reported in Table 2. Notably, absolute values of coefficients for DAX are highest in the sample, in all quantiles. In case of DAX, absolute values for respective betas are identical in lowest and medium quantiles. In the lowest and highest quantiles, the absolute values for DAX betas are followed by betas for AEX, SMI, CAC, FTSE, and BEL. The results are, therefore, consistent with country clustering suggesting the most conservative attitude towards uncertainty in Germany and most relaxed attitude in the UK, with France in the middle. DAX also exhibits largest difference in absolute values for the betas in the lowest and highest quantiles. The results for smaller European markets are mixed. While Netherlands and Switzerland exhibit similar results to Germany (as expected), the results for Belgium are surprising. Belgium, for example, exhibits lowest mean, median, and standard deviation of volatility index (Table 1). In addition, BEL returns are least sensitive to changes in volatility (Tables 2 and 3). Overall, with the exception of Belgium, the results are in line with the countries' differences identified in previous literature.

We further compare OLS with quantile regressions using Wald-test with the following null hypothesis ($H_0$):[16]

$$H_0: \beta_\tau(\tau_1) = \beta_\tau(\tau_2) = \ldots = \beta_\tau(\tau_K) \quad (8)$$

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 $\tau$ quantiles, 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 3. The null hypothesis of equal coefficients can be rejected across the entire distribution. The test for Swiss and French indices is statistically significant at the 5% and the 10% level, respectively. For all other indices the test is statistically

[16] The test was introduced by Koenker and Bassett (1982).

significant at the 1% level. The quantile regressions, therefore, present a more robust alternative to OLS estimates.

## 5. Integration of European volatility indices

The descriptive statistics of the spread between the level of implied volatility indices of Germany, France and the UK in Table 4, reveal non-normal and skewed distributions. Spreads exhibit high excess kurtosis. A formal cointegration test reveals that these three countries exhibit a long-term association of the stock markets at the 5% level of significance. [17]

*** Insert Table 4 about here ***

After confirming that the differences between implied volatility indices of these countries are stationary, autoregressive models with the optimal number of lags (chosen by information criteria) are fitted. The evolution of the impulse response functions, after shocking the volatility spread between the volatility indices (e.g. VDax – VCac) by one standard deviation, is presented in Table 5.

*** Insert Table 5 about here ***

The effects of a one standard deviation shock die out relatively quickly in all three volatility spreads. Following an initial spike in the case of VDax-VCac and VFtse-VCac spreads, the majority of the shock vanishes at the second day. A shock in the spread for the VDax-VFtse is slightly more persistent, thus convergence to the long-run mean level is slower. Generally, after the third day (in all three cases) the effects die out monotonically (Figure 2). The results, therefore, lend support to our hypotheses 4 and 5.

*** Insert Figure 2 about here ***

[17] 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, underlining the outcome of the PCA, but no significant lead or lag relation within implied volatility. Causality, therefore, runs in both ways.

## 6. Dynamics of the volatility term structure

### 6.1 Regime dependent VStoxx's volatility

We analyze the term structure of the VStoxx, comprising tenors of 1, 2, 3, 6, 9, 12, 18 and 24 months. Regime dependent VStoxx's volatility term structure is presented in Table 6. As expected, volatility of VStoxx is decreasing function of maturity. The more pronounced movement of short maturities is due to liquidity considerations, because short dated options are actively traded by financial professionals.[18] In contrast longer dated options are foremost used by companies in need of long-term hedges and strategic investors and are less frequently traded. This is also reflected in volatility of volatility across the whole maturity spectrum. During tranquil periods the level of implied volatility fluctuates by 21.79% for one month contracts, compared to 6.91% for two year contracts, hence it exhibits a nearly monotonically decreasing function of maturity as shown in Table 6. Volatility of volatility is clearly regime dependent. For example, for the shortest maturity VStoxx's volatility is approximately four times higher in the low volatility regime compared to high volatility regime (109.09% and 23.79% respectively).[19]

*** Insert Table 6 about here ***

The more pronounced movement of short maturities 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.[20] This is reflected in volatility of volatility across the whole maturity spectrum. For example, during tranquil periods the level of implied volatility fluctuates by 21.79% for one month contracts, compared to 6.91% for two year contracts, hence it exhibits a nearly monotonically decreasing function of maturity.

We also examine causality between explanatory variables and regime switches. We estimate a logit model relating the estimated state probability of being in a specified volatility regime to theoretical transition variables that induce a regime shift.[21] 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 to zero if the probabil-

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[18] See Allen et al. (2006).

[19] For the longest maturity, VStoxx's volatility is approximately two times higher in the low volatility regime compared to high volatility regime.

[20] See e.g. Allen et al. (2006).

[21] The model is adopted from Clarida et al. (2006).

ity value is equal to or lower than 0.5 (i.e. lower volatility state).[22] The model has the following form:

$$P_t = P[y_t = 1] = \frac{1}{1 + e^{-(\alpha_0 + \alpha_1 x_{t-1})}} \tag{9}$$

where $P_t[y_t = 1]$ denotes the filtered probability of being in a higher volatility regime at time $t$ and $\alpha_0$ and $\alpha_1$ represent regression coefficients.

Given bi-directional causality of implied volatility and returns, we expect that regime transitions are also associated with the evolution of these variables. The first two explanatory variables are the lagged stock returns and the lagged changes of the VStoxx. Results of the logit models are reported in Table 7. As expected, coefficients for stock returns are negative while coefficients for changes in volatility are positive. The coefficients, however, are not statistically significant. The only exceptions are lagged stock returns in the model for the transition from low to middle regime. The results 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 market regime.

*** Insert Table 7 about here ***

### 6.2 Regime dependent PCA representation

By means of PCA we are able to shed further light into the co-dynamics between equity and volatility indices. The first two eigenvectors are reported in Table 8. For the entire European market, 72.3% of the total variation can be explained by the first common factor. 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 explains additional 8.8%. The negative 2nd eigenfactor values for French and Belgian markets suggest that they are subject to higher idiosyncratic regional risk.

[22] This formulation is possible because a switch only occurs from regime 1 to regime 2 and form regime 2 to regime 3 and the other way around. There is no switch from regime 1 to regime 3 or vice versa.

*** Insert Table 8 about here ***

The regime-specific eigenvectors of the principal component representation, based on the covariance matrix of the one-day changes of the entire term structure of the VStoxx term structure, 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.

*** Insert Figure 3 about here ***

For each regime, the loadings of the first factor nearly resemble the 'level' factor found previously by Litterman and Scheikman (1991). The short-term volatilities, however, move significantly more than long-term volatilities. This level factor originates from the loadings of the eigenvectors that all have similar magnitude and the same size across all maturities. The loadings of the eigenvectors for the second factor (i.e. sloe) are an increasing function of maturity. A shock to the second common factor has regime-dependent influence on the slope of the implied volatility term structure. During tranquil periods (low volatility regime) the second principal component behaves like a level-shifted first component. In times of increased volatility (middle and high volatility regime), the second principal component changes the slope of the implied volatility term structure. The third component (i.e. curvature factor) brings more concavity during high volatility regime. However, it has similar eigenvector loadings at the very short and long maturities but different for the tenors with three to twelve months. It, therefore, has only marginal influence on term structure movements. Since upward sloping volatility term structure typically inverts during stock market declines, our findings imply that the slope of the term structure hardly changes in tranquil periods (i.e. movements are mostly parallel across all tenors). Significant changes in the slope of the complete maturity spectrum take place almost exclusively during times of financial turmoil (i.e. in the middle and high regime).

## 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, of the Technology sector based on the implied volatility of the Nasdaq 100 index; 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; the VIX is derived from the implied volatility of S&P 500 (SPX) options representing a broad stock market proxy. The results, presented in Table 9, suggest that the US small cap sector (Rvx) exhibits the highest level of volatility (median value of 22.6%) (Panel A). The maximum single value of 87.5% 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 indices.

***Insert Table 9 about here***

The negative 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. Also, the US market is highly integrated regarding implied volatility changes, with correlation coefficients in excess of 0.84 (Panel B). Average $R^2$ (51.5%) for the OLS model (equation 1), fitted with US data, is higher than for the respective European model (40.2%) (Panel C). The results for equation 2 suggest that when VIX decreases by 1%, SPX increase by around 0.13% (Panel D). On the other hand, the 1% increase in VIX triggers SPX's fall by around 0.16%.[23]

The results for US quantile regressions are economically and statistically consistent with the results reported for European markets (Panel E). For example, the constant terms are positive in lower quantiles and negative in higher quantiles. Beta values in lowest and highest quantiles are higher than betas in the middle quantile. Betas in the lowest quantile are higher compared to beta values in the middle quantile but lower than betas in the highest quantile for all indices. The results of PCA analysis (Panel F) show that the first principal component explains 93.8% of the total variation of the term structure. This is higher than 72.3% reported for European markets. The second component, related to specific risks, explains only additional 3.2% (compared to 8.8% for European markets).

[23] SPXreturnt = 0.0000 + -0.129*-0.01 = 0.00129 = 0.13%; SPXreturnt = 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).

## 7.2 OLS vs. quantile regression hedge ratios

Figure 4 illustrates the difference in hedge ratios based on OLS and quantile regression coefficients.[24] The presented results for quantile regressions are for the highest quantile (τ=0.9) associated with decrease in returns.

*** Insert Figure 4 about here ***

On average the DAX (SPX) sensitivity derived from OLS is 12.1% (7.3%) lower and this divergence becomes particularly apparent during the events that lead to the bankruptcy of Lehman Brothers in autumn of 2008. 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 earlier reported highest absolute values for DAX betas in the highest quantiles and most conservative attitude towards uncertainty in Germany.[25]

In the US market, however, quantile regression hedge ratios were not distinctively different from the OLS estimate until the late 2007. This result reaffirms the less pronounced asymmetry in the US market. Given that asymmetric weighting algorithm in quantile regressions asserts a higher penalty term to negative returns (τ>0.5), this suggest that US investors were not taking adequate downside protection before August 2007.[26] However, due to the variance risk premium, long positions in volatility derivatives are biased to make a loss and considering them as part of strategic asset allocation may not be appropriate. [27]

To further show the difference in hedge performance based on OLS and quantile regression, we selected two events that lead many institutional asset managers to buy protection in the

[24] 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.

[25] Our unreported results also suggest better accuracy of quantile regression compared to OLS estimates. For example, the 90% prediction interval derived from equation (1) 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, yields stock market returns of -1.55% to 1.22% (-1.50% to 1.09%).

[26] 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).

[27] 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.

form of volatility indices. These two events are: i) major banks' announcement of drastic write-downs in their assets (August 2007); ii) Lehman Brothers bankruptcy filing (September 2008). We then estimate the performance of respective hedging strategies using all sample indices.[28] The results are presented in Table 10. Overall, the volatility indices provided a very good hedge against the 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 € 34,500 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.[29]

*** Insert Table 10 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 more detailed and nuanced view on the conditional relationship between implied volatility and equity market returns. For example, results of our quantile regressions suggest significantly more pronounced asymmetric volatility phenomenon than is inferred from ordinary least squares regression. Importantly, this asymmetry is not monotonically decreasing. We also find increased sensitivity at the lowest quantiles, $(\tau = 0.1)$ of the conditional joint distribution of stock returns and changes in implied volatility, compared to the median. Furthermore, hedge ratios derived from sample quantile regressions are economically superior to hedge ratios derived from sample OLS regressions. Our results are robust in both European and US samples.

The main European volatility markets exhibit differences consistent with institutional and cultural clusters identified in the previous literature. For example, FTSE returns tend to be less sensitive to volatility changes compared to DAX and CAC returns. The leading markets

[28] Calculations take into account transaction costs (0.5 vegas). For quantile regressions, we present calculations for $\tau = 0.9$.

[29] 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.

(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 two days.

Our Markov switching model distinguishes three volatility regimes. In turbulent regimes, principal components, corresponding to level, slope and curvature, explain 97% of the complete European volatility term structure. A shock to the second principal component has regime dependent influence on the slope of the implied volatility term structure. Our findings lend support to the behavior explanation of the return-implied volatility relation and have implications for risk management and option pricing.

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**TABLE 1: 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 sector). 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. In the course of a confirmatory data analysis ADF-statistics and LM-statistics for the KPSS test are reported. 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 (EuroStoxx / 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 equity indices**

Pearson's correlation matrix of EU volatility and equity 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 | | | | | | | |
| **EuroStoxx** | -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 |

**FIGURE 1: Evolution of the EuroStoxx index and the derived implied volatility index VStoxx**

The development of the EuroStoxx (dotted line and left scale in point) and the volatility index VStoxx (solid line and right scale in percent per year) from January, 1st 2004 to July, 31st 2009.

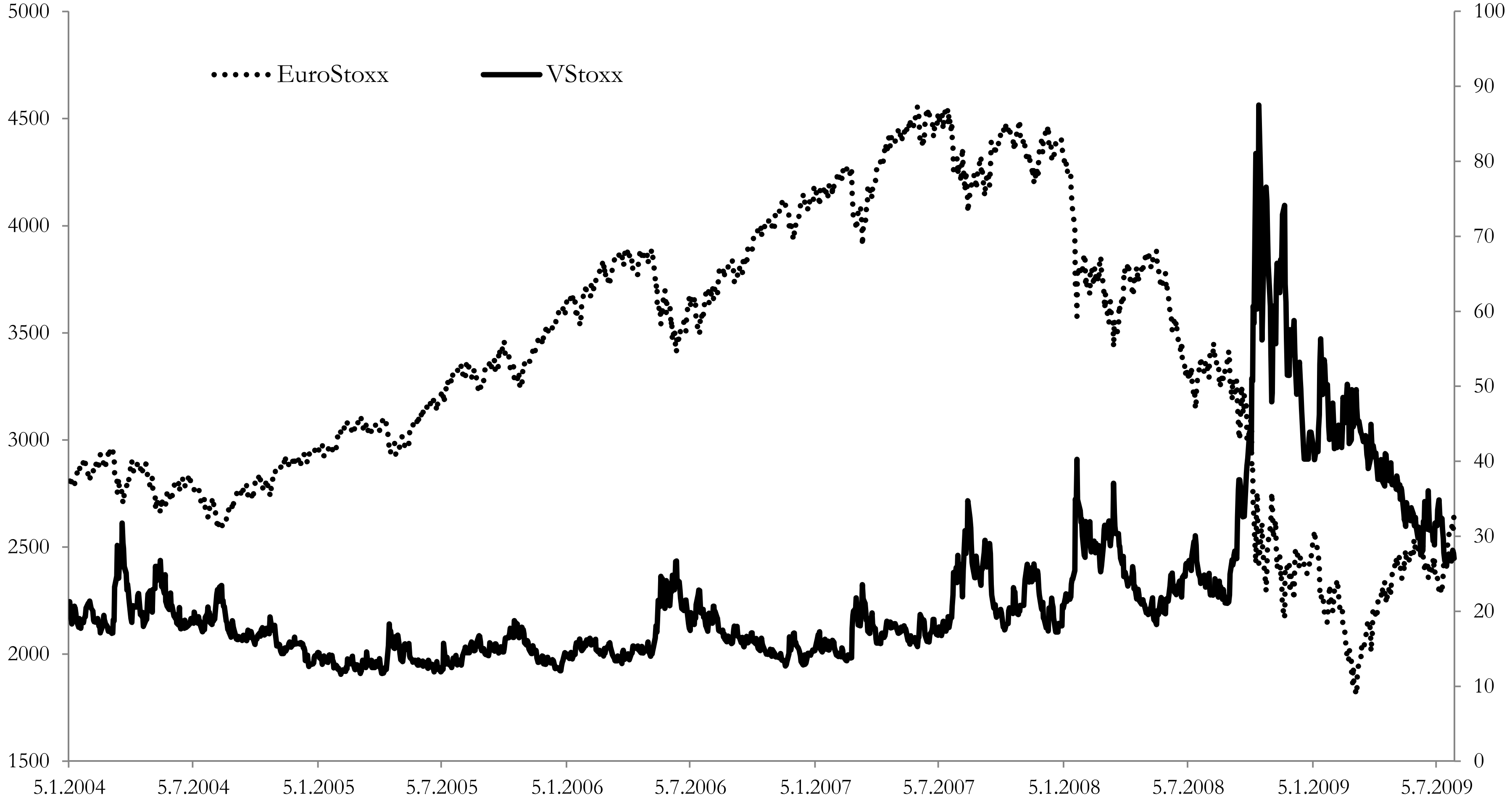


**TABLE 2: Ordinary Least Squares regression results of regressing equity market indices on their respective volatility index**

Panel A presents results for equation 1. Panel B presents results for equation 2. T-statistics reported in parentheses. We use a Newey-West consistent estimate of the covariance matrix to control for autocorrelation and heteroscedasticity. 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:**

| | **EuroStoxx** | **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) |
| **IV** | -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:**

| | **EuroStoxx** | **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) |
| **$IV^+$** | -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) |
| **$IV^-$** | -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 3: Quantile regression results**

Results of regressing stock index returns on changes of their respective volatility index. Quantile regression coefficients for the $\tau$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 equality of the slope coefficients across the whole distribution ($H_0$ : equal slope coefficients in all quantiles $\tau$ ). ** and * denote significance at the 1% and 5% level, respectively.

| | $\tau$ | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | Wald-Test |
|---|---|---|---|---|---|---|---|---|---|---|---|
| EuroStoxx | 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 4: Descriptive statistics of the spread of VDax, VCac and VFtse**

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. Critical values for the KPSS test are 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 5: Evolution of the impulse response function**

Evolution of the impulse response function by a standardized unit shock to the implied volatility spread (difference in the level of implied volatility between the VDax, VFtse and VCac) 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 |

**FIGURE 2: Evolution of the impulse response function**

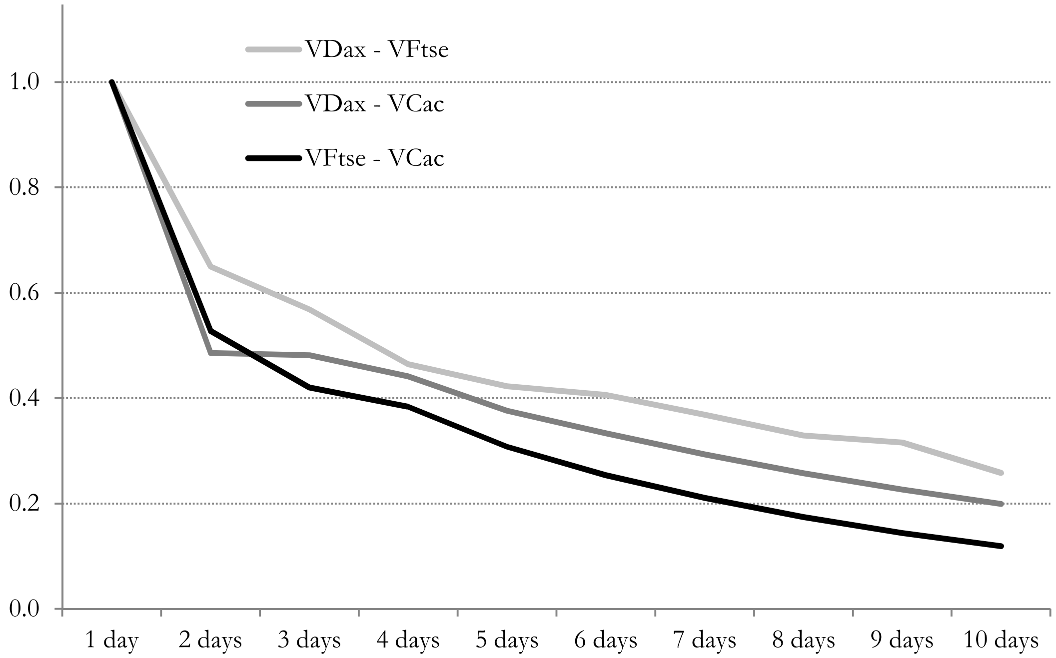


**TABLE 6: VStoxx regime dependent volatility**

Regime-dependent volatility of volatility (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 7: Logit models for determinants of regime changes**

This table presents the α1 coefficients from the logit regressions (see equation 9) with t-statistics (in parentheses) and R2 [in brackets]. We use a Huber-White consistent estimate of the covariance matrix to control for autocorrelation and heteroscedasticity. Determinants driving the regime changes are: Stock returnt-1 represents the lagged daily return of the EuroStoxx 50; Stock return2t-1 is the square of the lagged stock return; ΔVStoxxt-1 is the lagged change in the VStoxx volatility index, and ΔVStoxx2 t-1 denotes the square of the lagged change in the VStoxx volatility index. ** and * denote significance at the 1% and 5% level, respectively.

| **Regime changes** | **Stock return$_{t-1}$** | **Stock return$^2_{t-1}$** | **ΔVStoxx$_{t-1}$** | **ΔVStoxx$^2_{t-1}$** |
|---|---|---|---|---|
| **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] |

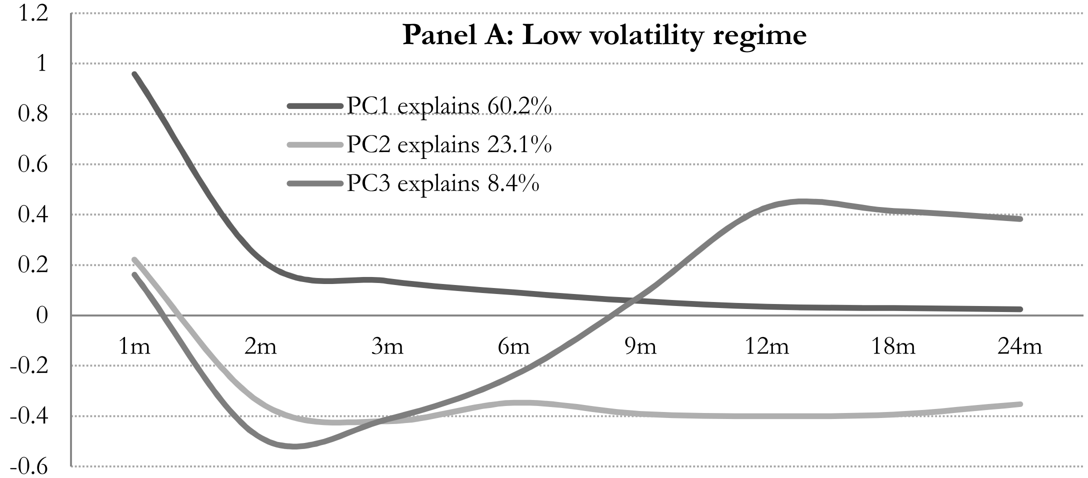
**TABLE 8: Principal component analysis of European volatility indices**

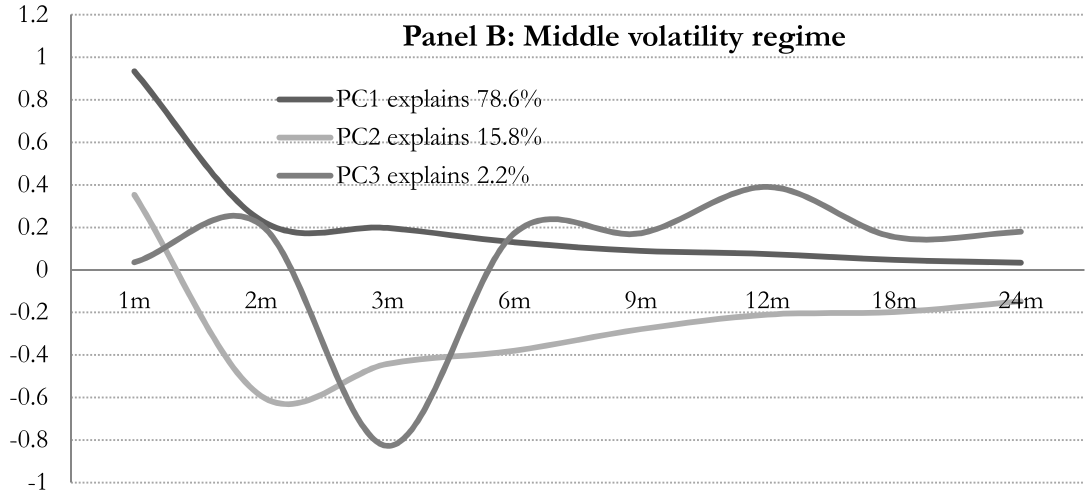
Panel A, reports the total variation of VStoxx that can be explained by the first two principal components (PCA1 and PCA2). Panel B, reports loadings for the first two principal components of respective indices.

| | **PC 1** | **PC 2** |
|---|---|---|
| **Panel A:** | | |
| **VStoxx - Cumulative % explained** | 72.30% | 81.10% |
| | | |
| **Panel B:** | | |
| **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 |

**FIGURE 3: Regime-dependent dynamics of the VStoxx term structure**

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. Data points are connected by cubic splines interpolation. Percentage figures indicate the marginal contribution to explaining the complete term structure by the respective principal component.




Panel B: Middle volatility regime
PC1 explains 78.6%
PC2 explains 15.8%
PC3 explains 2.2%
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
1m
2m
3m
6m
9m
12m
18m
24m

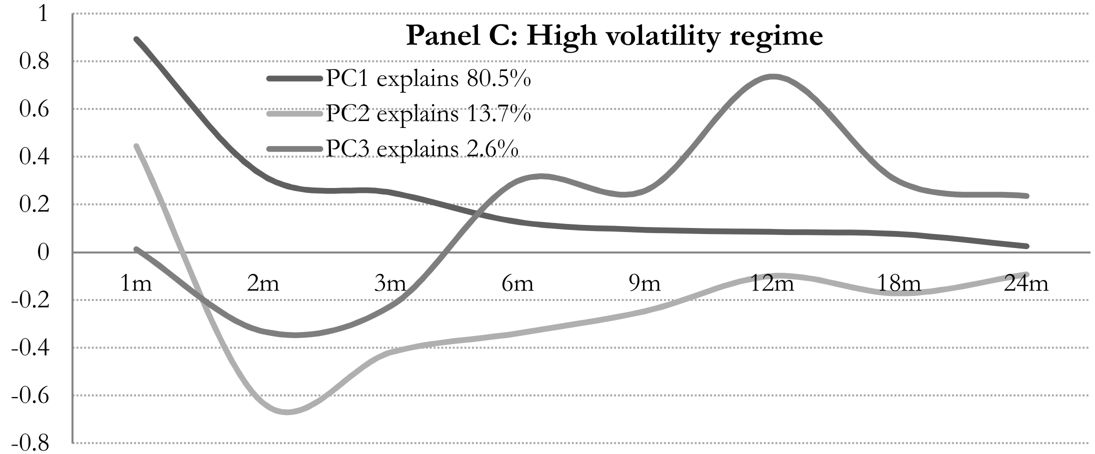

Panel C: High volatility regime
PC1 explains 80.5%
PC2 explains 13.7%
PC3 explains 2.6%
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
1m
2m
3m
6m
9m
12m
18m
24m

**TABLE 9: US volatility indices**

Results for Standard & Poors Composite Index (SPX/Vix), Dow Jones International Average (DJIA/Vxd), Russel 2000 (RUS/Rvx), and the Nasdaq 100 (NDX/Vnx), January 1st, 2004 until July 31st, 2009. T-statistics reported in parentheses. ** denotes significance at the 1% level.

**Panel A: Level and log return (Δ) statistics for the respective volatility indices.** All series are represented in volatility points (percentage points p.a.). The Jarque-Bera test statistic, ADF-statistics and LM-statistics for the KPSS test are also reported. 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.

| | 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: Pearson' s correlation matrix of major US volatility and equity index returns**

| | 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: Results of OLS regressions of stock index returns on changes of their respective volatility index (equation 1).** Newey-West consistent estimates in Panels C and D. AIC and SC represent Akaike Information Criterion and Schwarz Bayesian Information Criterion, respectively.

| | SPX | NDX | DJIA | RUS |
|---|---|---|---|---|
| **Intercept** | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| | (-0.42) | (0.26) | (-0.23) | (0.14) |
| **Slope** | -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: Results of OLS regressions of stock index returns on changes of their respective volatility index (equation 2).** Newey-West consistent estimates in Panels C and D. AIC and SC represent Akaike Information Criterion and Schwarz Bayesian Information Criterion, respectively.

| | SPX | NDX | DJIA | RUS |
|---|---|---|---|---|
| **Intercept** | 0.0000 | -0.0002 | -0.0002 | -0.0003 |
| | (0.12) | (-0.45) | (-0.55) | (-0.88) |
| **$IV^+$** | -0.164** | -0.220** | -0.150** | -0.257** |
| | (-9.77) | (-10.51) | (-10.63) | (-13.58) |
| **$IV^-$** | -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: Results of regressing US stock index returns on changes of their respective volatility index**. Quantile regression coefficients for the $\tau$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 equality of the slope coefficients across the whole distribution ($H_0$ : equal slope coefficients in all quantiles $\tau$ ).

| | $\tau$ | **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) | |

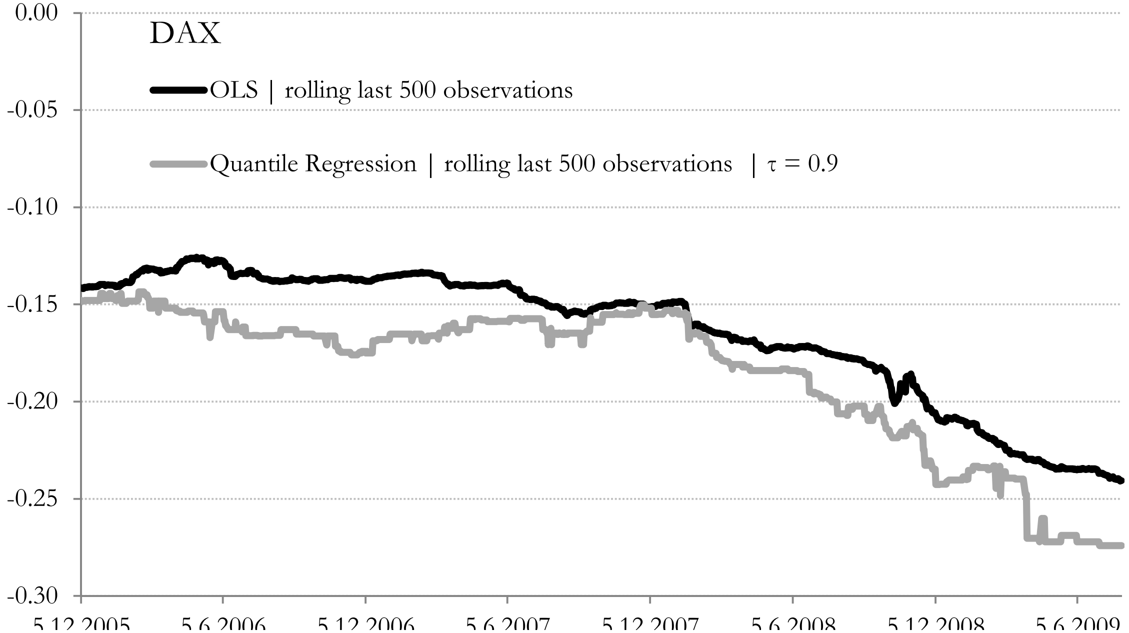
**Panel F: Principal Component Analysis for US volatility indices**.
Total variation that can be explained by the first two principal components (Row 1) and loadings for the first two principal components of respective indices.

| | **PCA 1** | **PCA 2** |
|---|---|---|
| **Vix - Cumulative % explained** | 93.8% | 97.0% |
| **Vix** | 0.544 | 0.291 |
| **Vnx** | 0.473 | -0.069 |
| **Vxd** | 0.491 | 0.533 |
| **Rvx** | 0.489 | -0.792 |

**FIGURE 4**: **Evolution and comparison of hedge ratios**

Ordinary least squares and quantile regression based hedge ratios in direct comparison obtained by regressing the returns of the DAX (Panel A) and SPX (Panel B) on the changes of their respective volatility index.

**Panel A:**



**Panel B:**

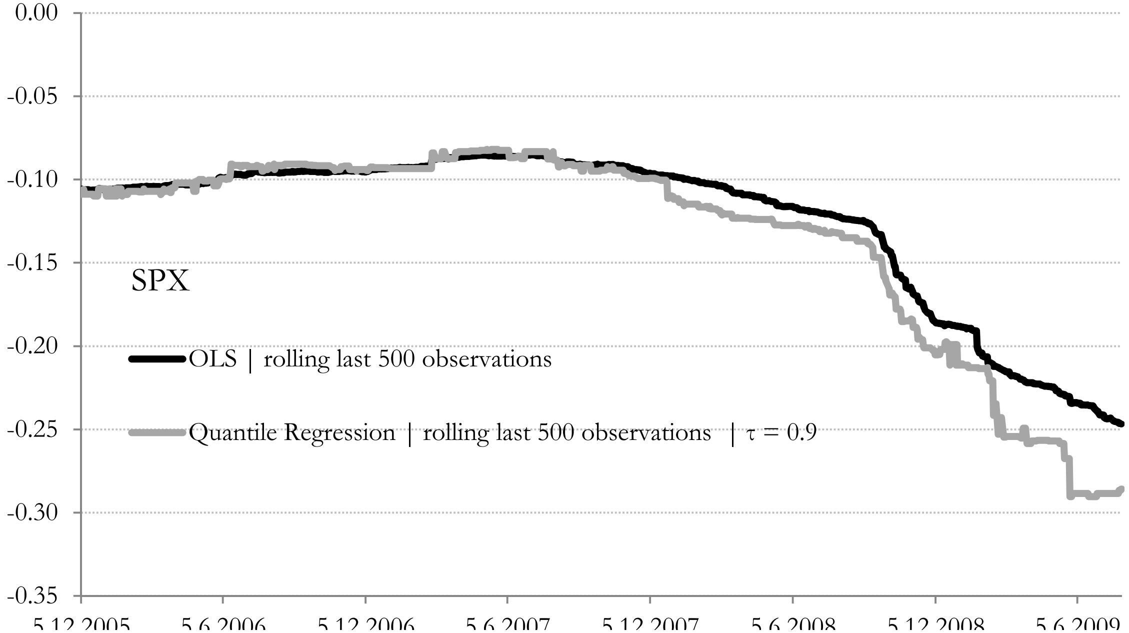

0.00
-0.05
-0.10
-0.15
-0.20
-0.25
-0.30
-0.35
SPX
OLS | rolling last 500 observations
Quantile Regression | rolling last 500 observations | τ = 0.9
5.12.2005
5.6.2006
5.12.2006
5.6.2007
5.12.2007
5.6.2008
5.12.2008
5.6.2009

**TABLE 10: Hedging performance – OLS vs. quantile regression**

Overall pay-off comparison of OLS-based hedge ratios and quantile regression ($\tau = 0.9$) derived hedge ratios, during respective months.

| | August 2007 | | September 2008 | |
|---|---|---|---|---|
| | **OLS** | **Quantile Regression** | **OLS** | **Quantile Regression** |
| **EUROPE** | | | | |
| **EuroStoxx** | 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% |
| **UNITED STATES** | | | | |
| **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% |