

THE COMOVEMENTS ALONG THE TERM STRUCTURE OF OIL FORWARDS IN PERIODS OF HIGH AND LOW VOLATILITY: HOW TIGHT ARE THEY?

Massimiliano Marzo and Paolo Zagaglia*

This version: January 6, 2009

Preliminary: comments welcome

Abstract

We study the pattern of contagion in volatility along the term structure of oil forwards. We use measures of codependence of returns from quantile regressions to discriminate between integration of the markets for different maturities in the cases of low and high volatility of the returns. Our results provide evidence of decoupling: for most of the maturities we consider, the probability of contagion falls during periods of high volatility.

KEYWORDS: conditional quantiles, oil prices.

JEL CLASSIFICATION: C22, G15.

1 Introduction

A large body of literature studies the patterns of ‘contagion’ or spillovers of between different asset classes (see e.g. Forbes and Rigobon, 2002). This idea of contagions is founded on the observation that periods of large volatility in different assets tend to occur at the same time, or with a small time lag. The available papers typically concentrate on bond and stock markets. To knowledge, no contribution provides evidence on the presence of volatility spillovers across commodity markets.

In this paper, we focus on the maturity structure of oil forwards. We use a measure of contagion proposed by Cappiello, Gerard and Manganeli (2005). In particular, we investigate whether the probability of observing closer comovements between different

*Marzo: Università di Bologna, massimiliano.marzo@unibo.it; Zagaglia: Stockholm University, pzaga@ne.su.se. This paper was completed while Zagaglia was visiting the Research Unit of the Bank of Finland, whose warm hospitality is gratefully acknowledged.

maturities increases in bad times – i.e. in periods of large volatility – with respect to periods of stable forward prices.

The framework of Cappiello, Gerard and Manganelli (2005) is based on the computation of the probability of a variable falling below a threshold conditional on the same pattern for the other variable. Thresholds are obtained through quantile estimation. In this statistical model, a high conditional probability of comovement implies a strong codependence between the variables. A convenient way to visualize the relationship between quantiles and probabilities of comovement is provided by the so-called ‘comovement box’. We use this box to provide insights on the changes of codependence in periods of low and high volatility for the returns of oil forwards, thus shedding light on whether contagion exists across maturities. The results show that the probability of contagion falls during periods of high volatility. In other words, the maturities decouple from one another in times of market turbulence.

This paper is organized in the following way. Section 2 explains the details of the comovement box and discusses the formal tests of codependence. The results are presented in section 3. Section 4 proposes some concluding remarks.

2 The comovement box

Standard tests for comovements rely on the estimation of correlations between asset returns. These tests are however typically significant both to the presence of heteroskedasticity, and to departures from normality in the empirical distributions of two returns. The comovement box of Cappiello, Gerard and Manganelli (2005) relies on semiparametric methods to provide a robust method for analyzing comovements.

Let $\{r_{i,t}\}_{t=1}^T$ and $\{r_{j,t}\}_{t=1}^T$ denote the time series of returns on two different maturities of crude oil futures. Define by $q_{\theta,i}^{r_i}$ the θ -quantile of the conditional distribution of $r_{i,t}$ at time t . $F_t(r_i, r_j)$ denotes the conditional cumulative joint distribution of the two asset returns. Finally,

$$F_t^-(r_i|r_j) := \text{prob}(r_{i,t} \leq r_i | r_{j,t} \leq r_j) \quad (1)$$

$$F_t^+(r_i|r_j) := \text{prob}(r_{i,t} \geq r_i | r_{j,t} \geq r_j) \quad (2)$$

The conditional probability

$$p_t(\theta) := \begin{cases} F_t^-(q_{\theta,t}^{r_i} | q_{\theta,t}^{r_j}) & \text{if } \theta \leq 0.5 \\ F_t^+(q_{\theta,t}^{r_i} | q_{\theta,t}^{r_j}) & \text{if } \theta > 0.5. \end{cases} \quad (3)$$

can be used to represent the characteristics of $F_t(r_i, r_j)$. In fact, $p_t(\theta)$ measures the probability that the returns at maturity i are below its θ -quantile, conditional on the same event occurring at maturity j .

The information about $p_t(\theta)$ is summarized in the so-called ‘comovement box’. This is a square with unit size where $p_t(\theta)$ is plotted against θ . Since the shape of $p_t(\theta)$ depends on the joint distribution of the two time series, it can be derived only by numerical simulation. Cappiello, Gerard and Manganelli (2005) point out that numerical simulations are not needed in three cases. When the futures returns at two maturities are independent, $p_t(\theta)$ is piecewise linear with a slope equal to one for $\theta \in (0, 0.5)$, and slope equal to minus one for $\theta \in (0.5, 1)$. With perfect positive correlation between $r_{i,t}$ and $r_{j,t}$, $p_t(\theta)$ is a flat line in correspondence of the value one. In this case, the futures markets for the two maturities shrink to one market. In the case of negative perfect correlation instead, $p_t(\theta)$ is equal to zero.

The framework of Cappiello, Gerard and Manganelli (2005) can also be used to test whether the dependence between two markets has changed over time. Given a cutoff date of a specific event, we can estimate the conditional probability of comovements in two different periods, and plot the estimated probabilities in a graph. Differences in the intensity of comovements can then be detected. This idea can be formalized in a simple way. Denote by $p^A(\theta) := A^{-1} \sum_{t < \tau} p_t(\theta)$ and $p^B(\theta) := B^{-1} \sum_{t < \tau} p_t(\theta)$ the average conditional probabilities before and after a certain event occurs at a threshold τ , with A and B the number of corresponding observations. Let $\Delta(\underline{\theta}, \bar{\theta})$ denote the area between $p^A(\theta)$ and $p^B(\theta)$. A measure of contagion or spillovers between the two markets can be introduced by noting that contagion increases if

$$\Delta(\underline{\theta}, \bar{\theta}) = \int_{\underline{\theta}}^{\bar{\theta}} [p^B(\theta) - p^A(\theta)] d\theta > 0. \quad (4)$$

We stress that, unlike the standard measures of correlation, $\Delta(\underline{\theta}, \bar{\theta})$ allows to study changes in codependence over specific quantiles of the distribution.

Several steps are followed to construct the comovement box and test for differences in conditional probabilities. First, we estimate univariate time-varying quantiles using the Conditional Autoregressive Value at Risk (CAViaR) model proposed by Engle and Manganelli (2004). For each series and each quantile, we create an indicator variable that takes the value one if the return is lower than this quantile, and zero otherwise. Then we regress the θ -quantile indicator variable on market j on the θ -quantile indicator on market i . The estimated regression coefficients provide a measure of conditional probabilities of comovements, and of their changes across regimes.

Cappiello, Gerard and Manganelli (2005) show that the average conditional probability $p(\theta)$ can be estimated from the regression

$$I_t^{r_i, r_j}(\hat{\beta}_\theta) = \alpha_\theta^1 + \alpha_\theta^2 D_t^T + \epsilon_t, \quad (5)$$

where hats denote estimated values, and

$$I_t^{r_i, r_j}(\hat{\beta}_\theta) := I\left(r_{i,t} \leq q_t^{r_i}(\hat{\beta}_{\theta, r_i})\right) \cdot I\left(r_{j,t} \leq q_t^{r_j}(\hat{\beta}_{\theta, r_j})\right) \quad (6)$$

for each θ -quantile, and D_t^T is a dummy variable for the test period $t > \tau$. The OLS estimators of the regression 5 are asymptotically-consistent estimators of the average conditional probability in the two periods:

$$\begin{aligned} \hat{\alpha}_\theta^1 &\xrightarrow{p} E[p_t(\theta)|\text{period A}] \equiv p^A(\theta) \\ \hat{\alpha}_\theta^1 + \hat{\alpha}_\theta^2 &\xrightarrow{p} E[p_t(\theta)|\text{period B}] \equiv p^B(\theta) \end{aligned} \quad (7)$$

where hats denote estimates. This results also suggests a way of testing for market integration:

$$\begin{aligned} \hat{\Delta}(\underline{\theta}, \bar{\theta}) &= (\#\theta)^{-1} \sum_{\theta \in [\underline{\theta}, \bar{\theta}]} [\hat{p}^B(\theta) - \hat{p}^A(\theta)] \\ &= (\#\theta)^{-1} \sum_{\theta \in [\underline{\theta}, \bar{\theta}]} \hat{\alpha}_\theta^2, \end{aligned} \quad (8)$$

where $\#\theta$ denotes the number of terms in the summation.

3 Results

This paper considers the forward prices of oil contracts with maturity of one, three, six and twelve months. We obtain the series from Platts. The dataset contains 4331 observations and spans from January 2 1990 to April 27 2007. We compute daily log-returns from the forward prices.

As suggested earlier, the first step of the empirical analysis consists in discriminating between observations at low and high volatility. In order to do this, we compute exponentially weighted moving averages (EWMA) ¹. Then we identify as high volatility the 10% observations with the highest volatility estimated from the EWMA, i.e. with a standard deviation above its 90th unconditional quantile. ² Figure 1 plots the the volatility regimes

¹We set the decay coefficient to 0.97.

²We also report the results for periods of high volatility identified with unconditional volatility in 5% of the observations. Further sensitivity analysis on the period of high volatility shows that no major changes emerge.

from the 10% criterion.

The time-varying quantiles of the returns are estimated using the CAViaR model of Engle and Manganelli (2004). The quantiles of the returns r_t are assumed to follow the autoregressive model

$$q_t(\beta_\theta) = \beta_{\theta,0} + \sum_{i=1}^q \beta_{\theta,i} q_{t-i} + \sum_{j=1}^p l(\beta_{\theta,j}, r_{t-j}, \Omega_t), \quad (9)$$

where Ω_t denotes the information set at time t . The autoregressive terms of the quantiles are meant to capture the clustering of volatility that is typical of financial variables. Including a predetermined information set allows instead to consider the interaction between the quantiles and the conditions of the market. Following Capiello, Gerard and Manganelli (2005), we estimate the time-varying quantiles using the following specification of the CAViaR:

$$q_t(\beta_\theta) = \beta_{\theta,0} + \beta_{\theta,1} d_t + \beta_{\theta,2} r_{t-1} + \beta_{\theta,3} q_{t-1}(\beta_\theta) - \beta_{\theta,2} \beta_{\theta,3} r_{t-2} + \beta_{\theta,4} |r_{t-1}|. \quad (10)$$

The dummy variable d_t ensures that the periods of high and low volatility have the same proportion of quantile exceedances.

In order to investigate the specification of the CAViaR model, we compute the DQ test of Engle and Manganelli (2004). This null of the DQ tests the hypothesis of no autocorrelation in the exceedances of the quantiles. Figure 2 reports the p-values for 99 conditional quantiles, together with the p-values for unconditional quantiles. The specification with unconditional quantiles is rejected over the entire domain.

Figure 3 plots the estimates of the conditional probabilities of comovements in periods with low and high volatility identified through the 10% criterion, whereas figure 4 displays the results for the 5% criterion. The comovement boxes depict the entire distribution of the returns. There are confidence bands of plus/minus twice the standard errors around the estimates of the probability for the high-volatility regime. When high volatility is defined as standard deviation in excess of the 99% unconditional quantile, the confidence bands become larger as the number of exceedances falls.

Two observations emerge. First, it is important to distinguish between comovements long the upper and lower tails of the bivariate distributions. In fact, one curve is never above or below the other over the entire domain. Whether the probability of comovements during periods of low volatility is higher or lower than the probability during the high-volatility regime depends on the spot of the distribution we consider. This stresses the value added of the quantile-based methodology considered here. Second, independently on

how the regimes are identified, for most of the maturities, periods of low volatility generate higher probabilities of comovements than periods of high volatility. In other words, when volatility is low, there is robust evidence of contagion across maturities. Instead, in periods of volatility, the comovement boxes suggest that a form of decoupling takes place. The only exception concerns the relation between the forwards at the sixth and the twelfth position, for which the measure of codependence surges in periods of high volatility.

Table 1 reports the results of the test for contagion for specific parts of the distribution outlined in section 2. Most of the test statistics are significant, with the exception of those on the joint distribution between the first and the first position, and the sixth and the twelfth position. For all the other maturities, the negative sign indicates a drop in comovements during periods of high volatility.

4 Conclusion

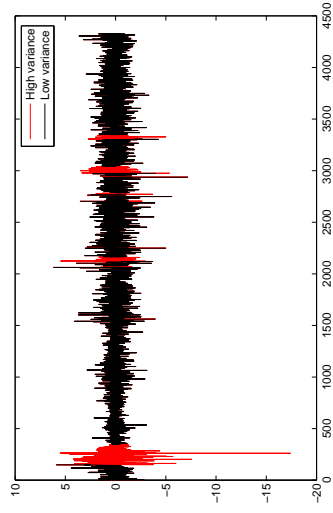
We use the comovement-box methodology of Cappiello, Gerard and Manganelli (2005) to study the codependence between maturities of oil forwards. We find strong evidence against the hypothesis of contagion. During periods of high volatility return comovements are lower than in periods of low volatility. This is consistent with what Cappiello, Gerard and Manganelli (2005) document with reference to other asset classes.

The results discussed here deserve scrutiny from a variety of additional dimensions. For instance, it would be interesting to consider how the role of sources of market volatility related only indirectly to oil products can play out. The first candidate would be exchange rate variability, in particular for the U.S. Dollar. We could also relate the pattern of fluctuations in volatility to the evolution of supply and demand factors for oil as a source of macroeconomic risk. Finally, the most compelling question has to do with the reason for oil forward maturities exhibit a low degree of contagion.

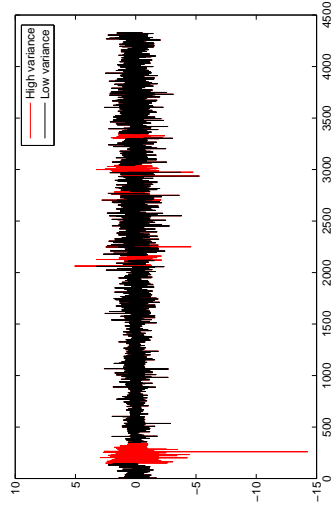
References

- Cappiello, Lorenzo, Bruno Gerard, and Simone Manganelli (2005), “Measuring comovements by regression quantiles,” *ECB Working Paper* 501.
- Engle, Robert, and Simone Manganelli (2004), ‘CAViaR: Conditional Autoregressive Value at Risk by regression quantiles,” *Journal of Business and Economic Statistics*, 22, 367–381.
- Forbes, Kristin J., and Roberto Rigobon (2002), ‘No contagion, only interdependence: Measuring stock market comovements,” *Journal of Finance*, 57, 2223–2261.

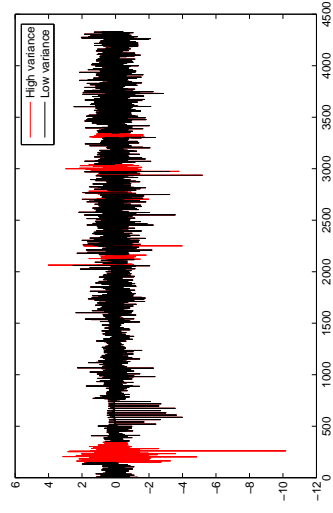
Figure 1: Forward returns



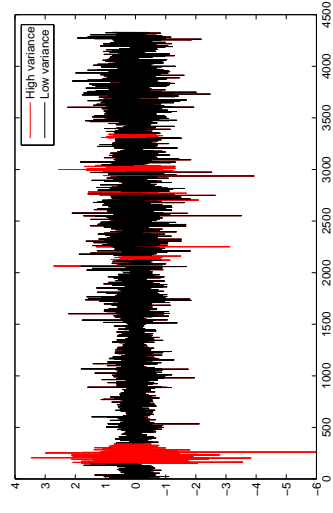
(a) One-month forward returns



(b) Three-month forward returns



(c) Six-month forward returns



(d) Twelve-month forward returns

Figure 2: p -values of the dynamic quantile test

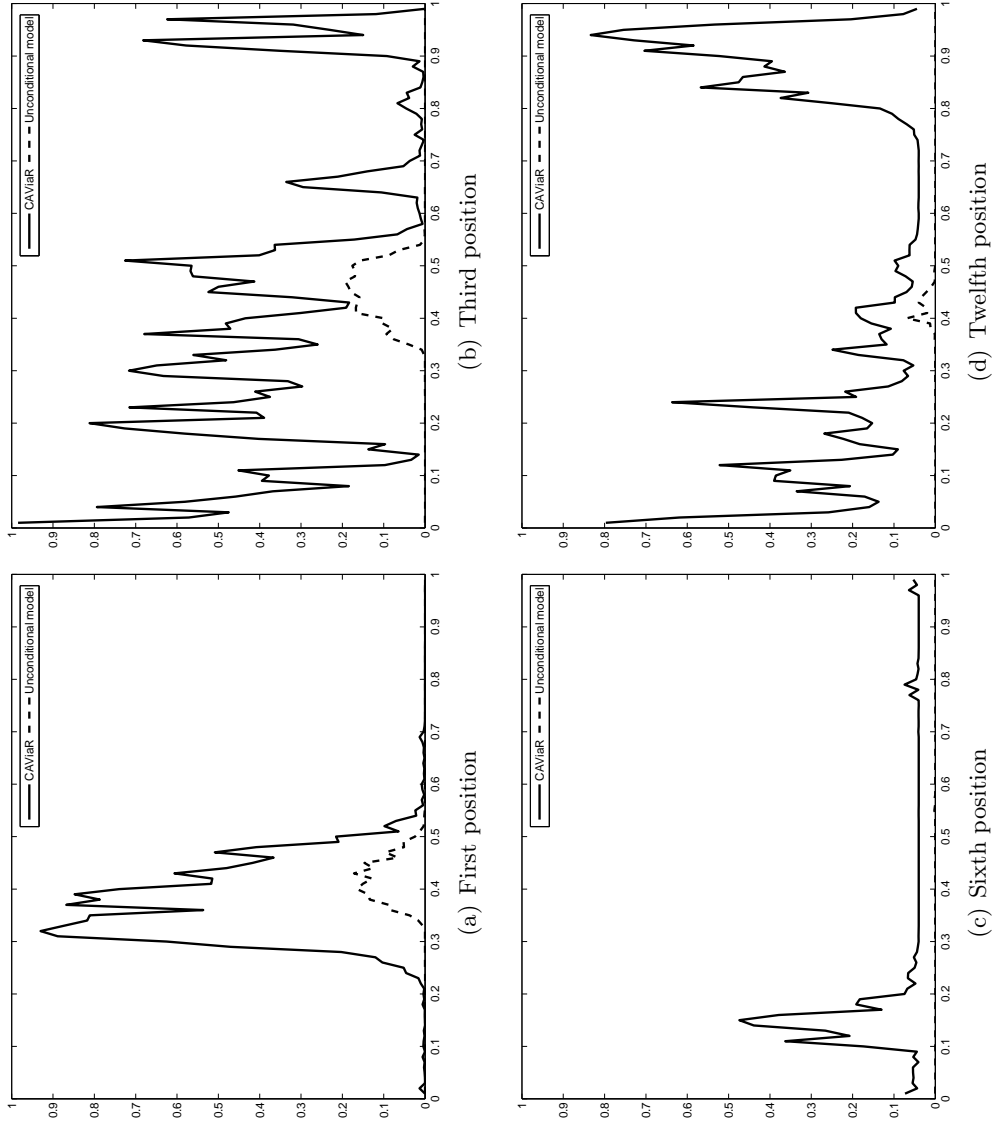


Figure 3: Estimated tail codependence with 10% in EWMA

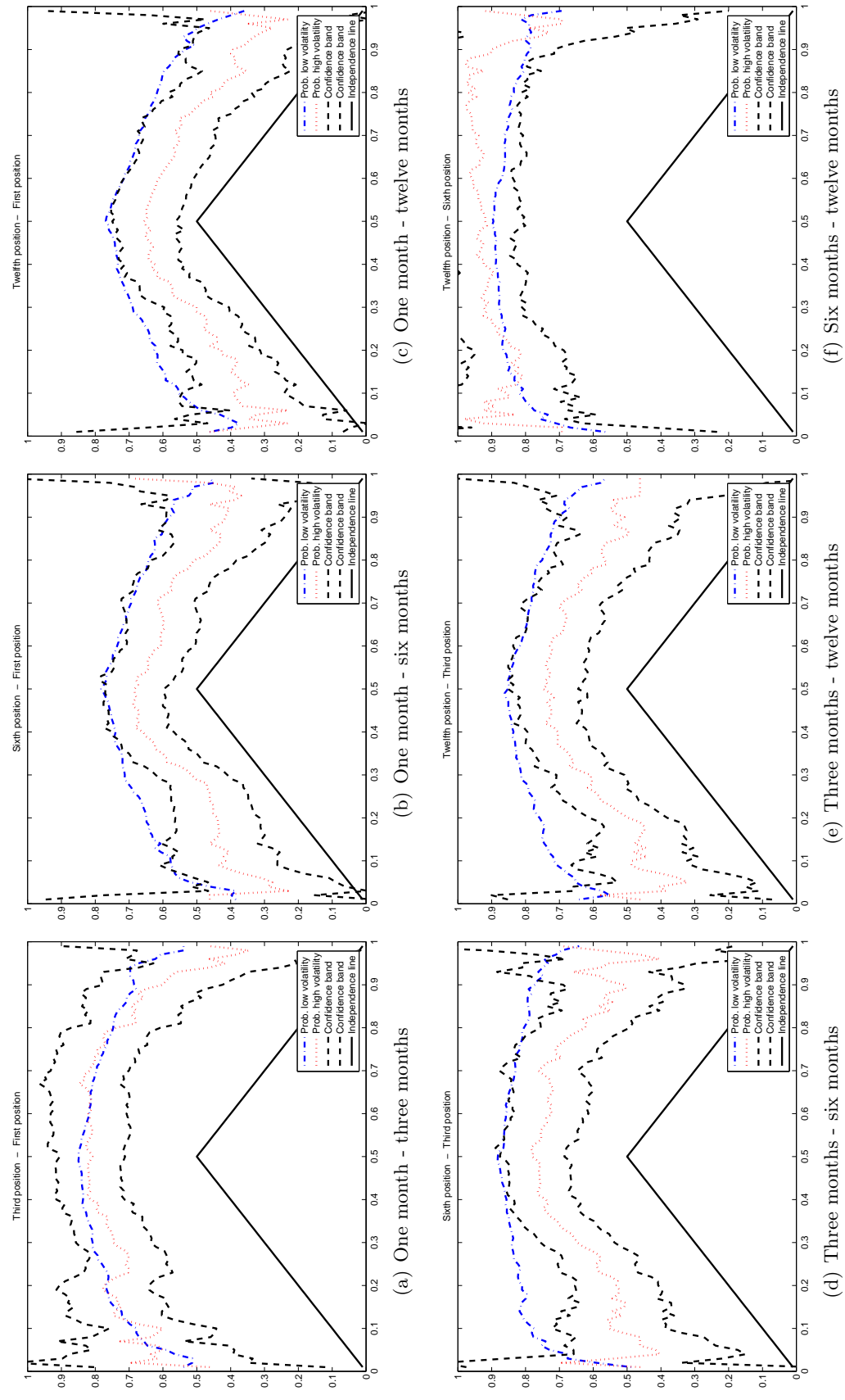


Figure 4: Estimated tail codependence with 5% in EWMA

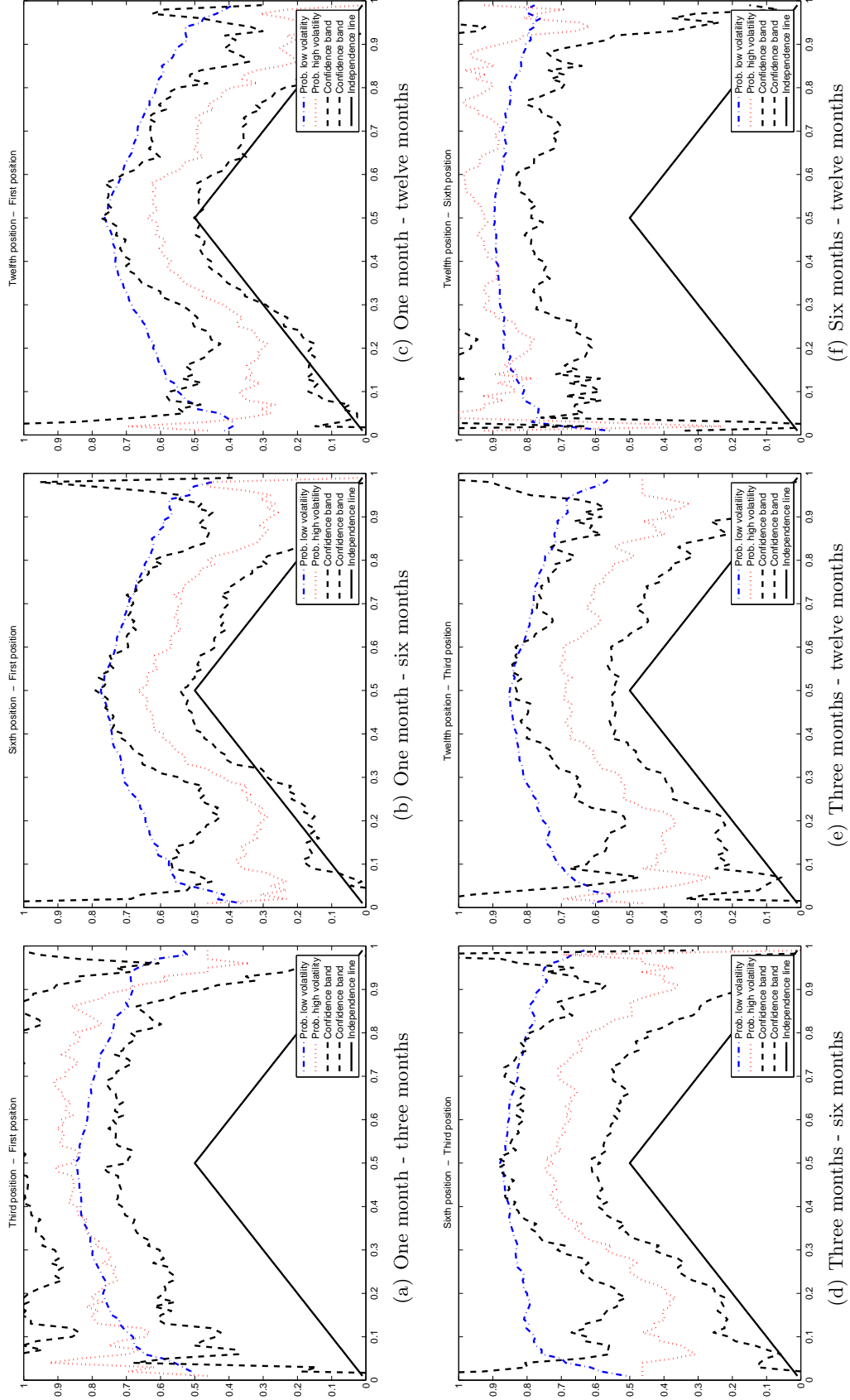


Table 1: Test of difference in tail co-incidences between periods of high and low volatility

	Lower tail: $\theta \leq 0.5$		Higher tail: $\theta \geq 0.5$	
	$\hat{\delta}(0, 0.5)$		$\hat{\delta}(0.5, 1)$	
	Stat.	s.e.	Stat.	s.e.
	10% in EWMA			
First-third position	-1.2467	2.5189	-1.9033	2.6948
First-sixth position	-7.4171	2.3475	-5.8103	2.5474
First-twelfth position	-7.5053	2.2309	-6.7975	2.4291
Third-sixth position	-9.6929	2.5607	-7.2847	2.8277
Third-twelfth position	-9.7091	2.3576	-6.9353	2.7672
Sixth-twelfth position	1.9382	2.7541	3.9507	3.3173
	5% in EWMA			
First-third position	3.2589	4.4634	-0.3050	4.1027
First-sixth position	-9.4300	3.4945	-9.9313	3.5604
First-twelfth position	-7.7397	3.4155	-11.6710	3.2084
Third-sixth position	-11.6103	3.8093	-10.9344	4.0820
Third-twelfth position	-10.0148	3.5568	-11.4071	3.7845
Sixth-twelfth position	4.4123	4.5273	1.4492	5.0315