# Testing Stationarity of Futures Hedge Ratios

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## Abstract

This paper re-investigates the stationarity of stock index futures hedge ratios. We show that the dynamic hedge ratios, calculated from time-varying variance-covariance matrices, are stationary over time. However, the examination of the evolution of spot and futures dynamics, provides evidence that the hedge ratios are better described as a combination of two different mean-reverting stationary processes which depend on the state of the market. Additionally, we analyse the dynamics of hedge ratios at intraday level, which display a complex picture, suggesting that intraday movements in the spread between spot asset and futures position are driven mainly by market participants with different perspectives of investment horizon.

**Keywords:** Diag-BEKK, Futures, Hedge Ratios, Intra-day Data, Multivariate Volatility Modelling, Regime-Switching, Stationarity, Unit Roots.

**JEL:** G13; G15; C32; C58.

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## 1. Introduction

Are futures hedge ratios stationary? This is a highly important question in the financial literature. The stationarity of the hedge ratios indicates a stable relationship between spot and futures prices. Since hedgers seek for reducing the risk of their investments, reliable dynamics of hedge ratios are expected. If not, futures markets may lose its usefulness to hedgers since the risk diversification can be hard to achieve. The property of stationarity motivates investors to use these strategies and can be utilised by policy makers to stabilize financial markets. This important question is also related to the performance of variances of spot and futures returns and their covariance. In this paper we pursue the answer to this question by analysing the properties of dynamic hedge ratios (HRs).

There are several techniques available for managing financial risk. One of the most widely used is hedging with futures contracts. A hedge is a spread between a spot asset and a futures position that reduces risk[1]. A considerable amount of research has focused on modelling the distribution of spot and futures prices and applies the results to estimate the optimal hedge ratio using various type of models such as OLS, GARCH, ECM and VECM models (see Chen *et al.*, 2003; Floros and Vougas, 2004; Salvador and Arago, 2014). The hedge ratio is defined as the number of futures contracts bought or sold divided by the number of spot contracts whose risk is being hedged.

Several studies have investigated the optimal hedge ratio using stock index futures under both a constant (static) and a time-varying (dynamic) setting. To estimate the optimal hedge ratios, early works used the slope of an OLS regression of the spot on the futures returns, while an improvement has been made by adopting a bivariate GARCH framework (see Park and Switzer, 1995). This last approach has become one of the most popular techniques since it allows the modelling of the empirical characteristics of the spot-futures distribution.

Although most of the previous studies are successful in capturing the time-varying covariance-variances, almost all of them focus only on the estimation of the

[1] In this paper we follow the traditional view of hedging, i.e. risk minimization. There are other alternative HRs, e.g. authors use other objectives such as (i) HR based on rates of returns situations where spot is fixed, (ii) HR for the case when trader wishes to maximize the ratio of the expected return on the hedged portfolio to its variance, or (iii) when there is marking to market and stochastic interest rates etc. These alternatives HRs involve both risk and return, but they are generally more complicated than the traditional minimisation of risk, and hence they are not considered in most empirical studies.

hedge ratios. The main purpose of this paper is to further examine and understand the stationarity of hedge ratios over time, as the literature provides limited information about it[2].

Previous studies such as Ederington (1979) and Anderson and Danthine (1981) assume that the optimal hedge ratio is constant when it can be obtained as a slope coefficient of an OLS regression. When the optimal hedge ratios depend on the conditional distributions of spot and futures price movements, then the hedge ratios vary over time as this distribution changes. Previous studies show the variability of the hedge ratios over time, and support the hypothesis that the optimal hedge ratios of commodities are time-varying and non-stationary (see Baillie and Myers, 1991). They report that the hedge ratios contain a unit root and therefore behave much like a random walk.

Grammatikos and Saunders (1983) were the first to examine the stability of hedge ratios. They concluded that the hedge ratio stability (stationarity) in currencies could not be rejected. Furthermore, Malliaris and Urrutia (1991) examined the random walk hypothesis and concluded that the hedge ratios of the selected indices and currencies follow a random walk. However, Ferguson and Leistikow (1998) report that futures hedge ratios are stationary using a simple OLS regression approach. They argue that the hedge ratios in previous studies follow a random walk due to a small sample size of data and hedge ratio calculation overlap. Furthermore, Lien *et al.* (2002) reject the null hypothesis that the optimal GARCH hedge ratios have a unit root. Recently, Lai and Sheu (2010) propose a new class of multivariate volatility models encompassing realized volatility (RV) estimates to obtain the risk-minimizing hedge ratios. Their results show that hedging improvement is substantial when switching from daily to intraday frequencies. They also report that the ADF test on the RV-based hedge ratios (intraday) is rejected, except for the results based on the (daily) OLS and the ECT-GARCH-CCC models for post-crisis period of 2008.

The contribution of this article is to examine whether the time-varying hedge ratios calculated from a set of European stock indices (German DAX30, British FTSE100, French CAC40 and Spanish IBEX35) are stationary over time. Testing for a unit root in futures and spot prices is tricky due to the propensity of such prices to jumps (Alexander, 2008). In order to overcome the predicament due to jumps, we

[2] There is to date no definite conclusion concerning the stationarity of the dynamic HRs, which may be used to improve hedging performance.

investigate the hedge ratios stationarity in low volatile periods and highly volatile periods based on the Regime-Switching Augmented Dickey Fuller (RS-ADF) unit root test introduced by Kanas and Genius (2005).

The paper provides empirical evidence that the time-varying hedge ratios are stationary over time. Thus, we confirm the stable relationship between futures and spot returns across time. However, if we take a closer look at the evolution of spot and futures dynamics, we find out that the hedge ratios are better described as a combination of two different mean-reverting stationary processes which depend on the state of the market. Although correlations follow a stable stationary process in both states, during periods of financial turmoil the correlations between spot and futures are different than during calm periods.

This result sheds light on the controversy caused by the evidence of greater hedging effectiveness using static hedge ratios than using simple dynamics ones, and why there have been several recent papers which both theoretically (Lien, 2010) and empirically (Alizadeh and Nomikos, 2008; Salvador and Arago, 2014) showed a greater effectiveness of regime-switching models. The intuition is that omitting the regime-switching specification leads to inefficient hedges compared not only to the ones considering this state-dependence but also to the static ones.

Moving one step beyond, we further analyse the dynamics of optimal hedge ratios at intraday level (we extend the study by Lai and Sheu, 2010). Since executing an intraday hedging strategy would be very expensive, we focus in providing new insights about the dynamics of the spot and futures markets at ultra-high frequency.

The results display a complex picture on the dynamics at ultra-high frequency, suggesting that intraday movements in the spread between spot asset and futures position are driven mainly by market participants with different perspectives of investment horizon. This is because there is very little hedging at short horizons (speculative actions are more than the investment actions), but at long horizons (speculative actions are less than the investment actions) there is more presence of hedging strategies.

The rest of the paper is organised as follows. Section 2 provides a description of the database. Section 3 develops the model used to obtain the dynamic hedge ratios. Section 4 analyses the time-series stationarity of the estimated hedge ratios not only from a standard perspective but also from the regime-switching framework. In section 5 we take a closer look at the stationarity properties of hedge ratios using intraday data and section 6 concludes.

## 2. Data Description

The dataset is comprised by daily data (spot and futures closing prices) from the main stock indices and its corresponding futures contracts in Germany (DAX30), France (CAC40), United Kingdom (FTSE100) and Spain (IBEX35). The time horizon includes observations from May 2000[3] to November 2013. Within this sample period we have two different contexts, i.e. before (under several years of stability and sustained growth) and after the global financial crisis and the Eurozone debt problems started in 2008.

The stock markets analysed are the most traded European financial markets and all of them are traded on an electronic trading system. The time-series for the indices and their near-time delivery (nearby) futures contract[4] are provided by Datastream®.

[Insert Table 1 about here]

Table 1 presents the statistical properties of the price and returns series. The returns of spot and futures prices follow all stylized facts of financial time series such as leptokurtosis, volatility clustering, leverage effects, etc. (see Bollerslev *et al.*, 1994). Further, the log of prices are found to be I(1), i.e. the series are non-stationary, thus we model the log-returns for the time-series analysis[5]. We estimate time-varying hedge ratios using GARCH models which are very popular in the literature to capture the stylized facts of financial time series (see, for example, Degiannakis and Floros, 2010). In the next section we develop the empirical models to obtain dynamic hedge ratios and we describe their patterns.

## 3. Estimating Time-Varying Hedge Ratios

### 3.1. Methodology

[3] Since May of 2000 data is available for all the examined indices.
[4] Carchano and Pardo (2008) show that rolling over the futures series has no significant impact on the resultant series. Therefore, the least complex method can be used for the construction of the series to reach the same conclusions.
[5] These results are available upon request.

According to Lee (1999), given the time-varying nature of the covariance in financial markets, the OLS assumption is inappropriate when estimating optimal hedge ratios. In the GARCH model[6] the conditional variance of a time series depends upon the squared residuals of the process (Bollerslev, 1986). It also captures the tendency for volatility clustering in financial data, and utilises the information in one market own history (univariate GARCH) or uses information from more than one market history (multivariate GARCH). According to Conrad *et al.* (1991), multivariate GARCH models provide more precise estimates of the parameters because they utilise information in the entire variance-covariance matrix of the errors and allow the variance and covariance depend on the information set in a vector of the ARMA manner (Engle and Kroner, 1995).

In the more traditional hedge ratio estimation methodology, the covariance matrix of spot and futures prices (and therefore the hedge ratio) is constant through time. However, a large body of research has applied the GARCH framework to infer time-varying hedge ratios (Cecchetti *et al.*, 1988; Kroner and Sultan, 1993; Park and Switzer, 1995). Although GARCH models are useful for estimating time-varying optimal hedge ratios, a time-varying covariance matrix of spot and futures prices is not sufficient to establish that the optimal hedge ratio is time-varying[7].

In this study we use a bivariate model with GARCH errors, the Diag-BEKK(*p,q*) model, to estimate the dynamic variance-covariance matrix of spot and futures log-returns. The Diag-BEKK(*p,q*) framework of log-spot (*s*) and log-futures (*f*) is estimated in the form

$$\mathbf{y}_t = \begin{pmatrix} (1-L)\log(s_t) \\ (1-L)\log(f_t) \end{pmatrix} = \begin{pmatrix} a_0 \\ b_0 \end{pmatrix} + \begin{pmatrix} \varepsilon_{s,t} \\ \varepsilon_{f,t} \end{pmatrix}$$

$$\boldsymbol{\varepsilon}_t \equiv \begin{pmatrix} \varepsilon_{s,t} \\ \varepsilon_{f,t} \end{pmatrix} \mid \Psi_{t-1} \sim N(0, \mathbf{H}_t) \tag{1}$$

$$\mathbf{H}_t = \begin{pmatrix} \sigma^2_{s,t} & \sigma_{sf,t} \\ \sigma_{sf,t} & \sigma^2_{f,t} \end{pmatrix} = C_0 C_0' + \sum_{i=1}^{q} (\mathbf{A}_i \boldsymbol{\varepsilon}_{t-i} \boldsymbol{\varepsilon}'_{t-i} \mathbf{A}'_i) + \sum_{j=1}^{p} (\mathbf{B}_j \mathbf{H}_{t-j} \mathbf{B}'_j),$$

where $\Psi_{t-1}$ is the information at time $t-1$ and the variance-covariance matrix specification, $\mathbf{H}_t$, is the BEKK model of Baba *et al.* (1990). The matrices $\mathbf{A}_i$ and $\mathbf{B}_j$

[6] The advantage of the GARCH specification is that it is a model that allows for leptokurtosis in the distributions of price changes.

[7] Constancy of the HR refers to the ratio of the covariance (between the spot and futures price) to the variance of the futures price, which is constant (Moschini and Myers, 2002).

are restricted to be diagonal. The Diag-BEKK($p,q$) model is guaranteed to be positive definite and requires the estimation of fewer parameters compared to other multivariate models; i.e. Diag-VECH, BEKK, etc.

This multivariate specification allows us obtain time-varying hedge ratios through the conditional covariance matrix

$$HR_t = \frac{\sigma_{sf,t}}{\sigma_{f,t}^2}, \tag{2}$$

where the dynamic hedge ratios are computed as the quotient between the conditional spot-futures covariance and the futures variance.

### 3.2. Empirical Results

The estimation of the model is carried out using conditional quasi maximum likelihood estimation[8]. The $p$ and $q$ lag orders have been selected according to the Schwarz's (1978) Bayesian criterion. The results from the Diag-BEKK(1,1) model (eq.1) are presented in Table 2. The coefficients are all statistically significant and imply volatility clustering. Both spot and futures log-returns exhibit strong persistence in volatility but it is the futures market which shows the strongest persistence.

[Insert Table 2 about here]

Figure 1 shows the estimated variances over time for the DAX30, FTSE100, CAC40 and IBEX35 spot and futures indices. We observe several peaks in the volatility measures common to all markets; e.g. around 2003, in latest 2008 coinciding with global financial crisis, and one covering end 2011- beginnings 2012 with the worst part of the Eurozone debt problems which reflected in the stock markets. Also in Spain there is a peak during the beginnings of 2013 showing further problems with the stability of that market.

[Insert Figure 1 about here]

Figure 2 shows the plot of time-varying hedge ratios obtained using eq.2. The DAX hedge ratios are quite volatile during the first part of the sample but they seem to stabilise after 2005. Despite the evident peaks in volatilities in all countries, the hedge ratios follow a smooth pattern along the sample period where they seem to

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[8] The conditional log-likelihood function for a single observation can be written as $L_t(\theta) = -(n/2)\log(2\pi) - (1/2)\log(|H_t(\theta)|) - (1/2)\varepsilon_t(\theta)' H_t^{-1}(\theta)\varepsilon_t(\theta)$, where $\theta$ represents a vector of parameters and $n$ is the sample size (for more details see Xekalaki and Degiannakis, 2010).

return always to a predetermined value. As, from visual description of the hedge ratios we cannot infer about their stationarity, next section provides a formal study of the hedge ratio stationarity and the implications for optimal hedging.

[Insert Figure 2 about here]

## 4. Analysing the (Non) Stationarity of the Hedge Ratios

### 4.1. Unit Root Theory

The Augmented Dickey Fuller (ADF) test assumes that the $y_t$ series follows an AR(*p*) process

$$\Delta y_t = a y_{t-1} + x_t^{'}\delta + \beta_1 \Delta y_{t-1} + ... + \beta_p \Delta y_{t-p} + u_t\,, \tag{3}$$

where $\Delta y_t$ defines the first difference of hedge ratios, and $u_t \sim N\left(0, \sigma_u^2\right)$, with $H_0 : a = 0$ and $H_1 : a < 0$.

Phillips and Perron (1998) propose a nonparametric method to control for serial correlation when testing for a unit root (this test is popular in the analysis of financial time series). The PP test estimates the test equation $\Delta y_t = a y_{t-1} + x_t^{'}\delta + u_t$, and modifies the *t*-ratio of the $a$ coefficient; hence, the serial correlation does not affect the asymptotic ditribution of the test statistic[9].

### 4.2. Regime-Switching ADF Test

Recent literature has questioned the asymptotic power and statistical properties of traditional ADF tests; e.g. Chortareas *et al.* (2002) and Solis *et al.* (2002). In this paper we are interested in the stationarity properties of hedge ratios conditioned to volatility levels in the markets (low and high volatility), i.e. if the hedge ratios are (non)stationary within high and low volatility periods independently of which is its stationarity in the long-run (assuming a single regime in the long-run).

This can be done by applying the methodology developed by Kanas and Genius (2005). They extend the ADF regression by allowing both the autoregressive parameters and the volatility of the hedge ratios to change over time following a first order Markov process. Hence, the regime-switching ADF, or RS-ADF, specification

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[9] The test corrects for any serial correlation and heteroskedasticity in the errors $u_t$ of the test regression.

test for the (non)stationarity of hedge ratios under different states of volatility is defined as:

$$\Delta y_t = a_{0,s_t} + \sum_{k=1}^{p} a_{k,s_t} \Delta y_{t-k} + b_{s_t} y_{t-1} + u_t \ , \ u_t \sim N\left(0, \sigma_{s_t}^2\right), \tag{4}$$

where $a_{0,s_t}, \ldots, a_{k,s_t}, b_{s_t}$ are regime-switching parameters, $s_t$ is the unobservable regime, and $u_t$ are normal innovations with state-dependent variances[10].

### 4.3. Empirical Results

Table 3 shows the results from the ADF and PP tests applied to the estimated hedge ratios under three cases: i) a simple AR(*p*) process, ii) a constant trend and iii) a time stationary trend. Tests when considering a specific trend show that the hedge ratio estimated from the Diag-BEKK model considering the returns of spot and futures prices are stationary, or I(0). This does not hold, however, when we do not specify a trend in the data which shows its importance when testing for stationarity in hedge ratios. Our results are in line with previous papers such as Ferguson and Leistikow, 1998 and Lien *et al.* 2002 who also found that time-varying hedge ratios are stationary over time.

[Insert Table 3 about here]

The implication of this result is that optimal hedges on stock indices tend to fluctuate around a mean-reverting value. This stable relationship between the correlations of spot and futures markets can be exploited by hedgers to reduce the risk of their investments. However, this adds further controversy on the debate about the superiority or not of dynamic hedge ratios against static strategies for minimising the risk of a hedged portfolio. Several authors found that more complex models do not provide a better performance than simple static ones (Lien *et al.*, 2002; Cotter and Hanley, 2012). The variability of the time-varying hedge ratios around this mean is what may cause a worse performance of this kind of dynamic models compared to the static ones. Nevertheless, this result of stationarity in the hedge ratios can be viewed as good news, since it implies a reliable relationship between the spot and futures prices and a confirmation that futures markets are useful for hedgers.

[10] The model is estimated by the maximum likelihood method using an algorithm where ex-ante and filtered probabilities are inferred in first place and then based on them standard maximisation of the likelihood function is performed (see Hamilton, 1994; Floros and Salvador, 2014).

Besides this first analysis, we also examine the stationarity of hedge ratios by looking at low and high volatile periods. The advantage of our approach is that we do not need to assume which periods correspond to low/high volatility states but it is the estimation procedure itself which makes this classification.

Table 4 shows the estimations of the RS-ADF model presented in eq.4. We observe that most of the coefficients representing a constant drift in the time-series are statistically significant, but if we look at the autoregressive coefficient just a few of them present significance. The most relevant coefficient in Table 4 is $b_{s_t}$ which represents the existence or not of a unit root in the state-dependent process. Some results are noteworthy.

[Insert Table 4 about here]

First, in both states the coefficients $b_{s_t}$ are negative and significant which implies stationarity within each state-dependent process. This confirms the results of stationarity (Francq and Zakoian, 2001; Timmerman, 2000; Yang, 2000) on time-varying hedge ratios previously obtained, but its interpretation is different. Here we have two different mean-reverting processes, one when the process is in low-volatility periods, and another one when the process is in high-volatility periods. Within each state the hedge ratios tend to fluctuate around different values instead of just one common value independent of the state.

Figure 3 shows the probability of being in a state of low volatility and complements Figure 2 which shows in shaded areas the observations that correspond to high volatility periods when compared to the estimated hedge ratios.

[Insert Figure 3 about here]

The hedge ratios process changes among regimes. The hedge ratios within each regime are stationary but the dynamics of the correlation in the different regimes are not the same. Thus, if we are interested in shorter horizons hedges the omission in considering different states can be a cause of a worse hedging performance.

In fact, this result sheds light to very recent evidence which shows both theoretically and empirically that hedge ratios obtained from regime switching models outperform the rest of strategies (both static and dynamic). Lien (2010) characterizes conditions under which the regime-switching hedge strategy performs better than the OLS hedge strategy and where the GARCH effects prevail. These conditions would allow the RS-GARCH hedge strategy to dominate both OLS and GARCH hedge strategies.

Recently, Alizadeh and Nomikos (2008) for commodities and Salvador and Arago (2014) for stock indices report a greater performance of regime-switching strategies than those obtained through single-regime models. Our results about this state-dependent stationarity of hedge ratios support this previous evidence. When analysing the performance of hedging strategies we usually look at shorter horizons and we tend to follow the false dynamics. So, not considering the switching of HRs' regimes causes a worse hedging effectiveness.

[Insert Table 5 about here]

In Table 5 we repeat the estimations of the RS-ADF model, but in this case we do not consider a drift in the model. Here we obtain a surprising result. The coefficient $b_{s_t}$ in the low volatility state is negative and significant providing evidence of stationarity of hedge ratios during this low volatility state. However, if we look at high volatility states it seems that the process followed by optimal hedge ratios is nonstationary. This result highlights the importance of modelling properly the trend of the time-series (similar results when using standard unit-root tests) since its wrong-specification could lead to wrong conclusions about the stationarity of hedge ratios.

## 5. Hedge Ratio Stationarity for Intraday Data

Dynamic hedging is usually expensive to implement since it involves transaction costs any time the hedged portfolio is re-balanced. Therefore, hedging is more rational at low frequencies. However, if the hedging is conducted only by investors, the hedge dynamics will not differ across different sampling frequencies. On the other hand, if the hedging is conducted by investors and traders (i.e. swap trading between futures and spot for speculation), then the hedge dynamics will differ across different sampling frequencies. In this section, we try to unmask this hypothesis by looking at the stationarity patterns of intraday hedge ratios both from standard and regime-switching techniques. Given the costs associated with a hedging strategy at intraday level we do not associate any of these results with hedging effectiveness.

The dataset is comprised by hourly observations of the DAX index and its corresponding future contract from 3rd of January, 2000 to 30th of December, 2010

(25138 observations)[11]. As in the previous datasets, we first compute the dynamic hedge ratios based on eqs.1 and 2. A plot of the estimated intraday hedge ratios is displayed in Figure 4. The hedge ratios seem to follow a smooth pattern although it is not possible to draw any conclusion about its stationarity from this figure. Therefore, we run the standard and regime-switching stationarity tests to provide new insights.

[Insert Figure 4 about here]

Panel A in Table 6 displays the standard unit-root tests for the German intraday hedge ratios. Similar to the results above, we reject the null hypothesis of a unit root in the intraday hedge ratio series. However, if we consider the regime-switching approach and distinguish between high and low volatility regimes (panel B Table 6) we cannot reject the unit root in any of the regimes.

[Insert Table 6 about here]

This result draws a complex picture for the distributions of spot and futures returns at ultra-high frequency. Although when looking at longer horizons the spot-future correlations seem to follow a stationary process, when looking at intra-day horizons the dynamics of the spreads between these two markets follow unpredictable dynamics. Taken this result together with the ones reported in previous sections, we conclude that the dynamics of hedge ratios vary across different sampling frequencies. Given these results and according to our hypothesis, the agents driving the spread of these markets at intraday level are mainly speculators. In other words, our results support that, at the ultra-high frequency, investors who hedge their strategies are dominated by speculators. This is due to the fact that market participants have different perspectives of their investment horizon. On the one hand, we have the investors who prevail at the daily frequency, and on the other hand, we have the speculators who prevail at the intra-day frequency.

The implied transaction cost when rebalancing the optimal hedge position can be the reason to discourage the hedgers to operate at this ultra-high frequency. Also, the unstable dynamics followed by the correlations of spot and futures markets at this ultra-high frequency can make difficult for hedgers to achieve the desired risk reduction in their investments.

On the other hand, day trading or speculation in securities is conducted not only by financial firms and professional speculators (i.e. equity investment and fund

[11] The hourly sampling frequency has been selected in order to minimize the effect of microstructure noise, see Degiannakis and Floros (2013).

management specialists) but, thanks to electronic trading and margin trading, it has become increasingly popular among at-home traders as well[12]. This is increasingly giving to this kind of market participants a very important role when defining the dynamics of the spot-futures markets at this ultra-high frequency. Our results are in line with Tse and Williams (2013) who support that any future efforts studying speculation in the futures markets must be done using high frequency intraday data.

## 6. Conclusion

Static and dynamic models of various forms have been well accepted to calculate hedge ratios. However, there is to date no definite conclusion concerning the stationarity of the dynamic hedge ratios. We focus on the characteristics of optimal hedge ratios for the DAX30 (Germany), FTSE100 (UK), CAC40 (France), and IBEX35 (Spain) indices over the period 2000-2013. We examine the stationarity of hedge ratios by employing standard econometric methods of unit root tests and a new state-dependent approach following the RS-ADF test. Dynamic hedge ratios are estimated by a bivariate GARCH-type model.

We find that dynamic hedge ratios are stationary over time when the entire sample is considered. This result implies a stable relationship in the spot-futures correlations that can be used for hedgers to reduce the risk in their investments. However, when we consider shorter horizons and distinguish between volatility states (i.e. high and low volatile periods), we show that the dynamic hedge ratios follow different stationary processes during periods of calm and periods of financial turmoil. These results support evidence from previous studies which report a greater hedging performance of dynamic strategies using regime-switching models.

The different processes followed by the hedge ratios for volatile periods are associated with changes in the variances and the covariance between spot and future returns. This has important implications for hedgers. First, financial analysts and hedgers must determine the effect of this unexpected change in the risk on their position. Second, they should determine the factors causing this shifted stationarity.

[12] Speculators are more active at intraday level since they profit from their intraday investments in information. Moreover, a speculative activity is important for intraday markets. Speculators make markets more liquid and efficient, while they benefit from the high price volatility. We argue that without speculation at intraday level, markets would be less complete in that there would be fewer opportunities for other market participants.

The results for the dynamic hedge ratios at intraday level draw a complex picture suggesting that the spreads are mainly driven by short-term market participants. We argue that we have investors who prevail at the daily frequency and speculators who prevail at the intra-day frequency in the spot-futures stock markets.

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# Tables

**Table 1.**Summary statistics for prices and log-returns of spot and futures on the selected European indices

**Panel A.- Summary statistics for log-returns**

| | *Germany* | | *United Kingdom* | | *France* | | *Spain* | |
|---|---|---|---|---|---|---|---|---|
| | ***Spot*** | ***Futures*** | ***Spot*** | ***Futures*** | ***Spot*** | ***Futures*** | ***Spot*** | ***Futures*** |
| *Mean* | *2.37 e-05* | *2.26e-05* | *4.98e-06* | *2.55e-06* | *-1.45e-04* | *-1.45e-04* | *-9.98e-05* | *-1.04e-04* |
| *Standard deviation* | *0.0159* | *0.0158* | *0.0127* | *0.0126* | *0.0154* | *0.0153* | *0.0155* | *0.0158* |
| *Minimum* | *-0.0887* | *-0.1481* | *-0.0926* | *-0.0969* | *-0.0947* | *-0.0882* | *-0.0959* | *-0.0988* |
| *Maximum* | *0.1080* | *0.1208* | *0.0938* | *0.0958* | *0.1059* | *0.1028* | *0.1348* | *0.1383* |
| *Skewness* | *0.0000* | *-0.1527* | *-0.1490* | *-0.1674* | *0.0427* | *0.0120* | *0.1204* | *0.0706* |
| *Kurtosis (excess)* | *1.4142* | *3.6816* | *3.2337* | *3.6535* | *1.7892* | *16396* | *1.9989* | *1.8315* |
| *JB test* | *2767.97* | *6356.89* | *5534.01* | *6306.22* | *3259.47* | *3058.11* | *3558.34* | *3319.15* |

**Panel B- Stationarity test for log-returns**

| | *Germany* | | *United Kingdom* | | *France* | | *Spain* | *Germany* |
|---|---|---|---|---|---|---|---|---|
| | ***Spot*** | ***Futures*** | ***Spot*** | ***Futures*** | ***Spot*** | ***Futures*** | ***Spot*** | ***Futures*** |
| *Dickey-Fuller* | *-59.512*$^{***}$ | *-58.843*$^{***}$ | *-61.585*$^{***}$ | *-60.731*$^{***}$ | *-60.600*$^{***}$ | *-60.494*$^{***}$ | *-58.429*$^{***}$ | *-58.875*$^{***}$ |
| *Phillips-Perron* | *-59.512*$^{***}$ | *-58.843*$^{***}$ | *-61.585*$^{***}$ | *-60.731*$^{***}$ | *-60.600*$^{***}$ | *-60.494*$^{***}$ | *-58.429*$^{***}$ | *-58.875*$^{***}$ |

**Panel C.- Summary statistics prices**

| | *Germany* | | *United Kingdom* | | *France* | | *Spain* | |
|---|---|---|---|---|---|---|---|---|
| | ***Spot*** | ***Futures*** | ***Spot*** | ***Futures*** | ***Spot*** | ***Futures*** | ***Spot*** | ***Futures*** |
| *Mean* | *5688.36* | *5710.46* | *5366.68* | *5361.56* | *4190.81* | *4189.39* | *9726.12* | *9701.97* |
| *Standard deviation* | *1439.34* | *1445.12* | *797.90* | *802.45* | *969.41* | *976.41* | *2365.61* | *2370.29* |
| *Minimum* | *2202.96* | *2214.00* | *3287.04* | *3262.00* | *2403.04* | *2397.00* | *5364.50* | *5362.00* |
| *Maximum* | *8530.89* | *8530.00* | *6840.27* | *6902.00* | *6922.33* | *6956.50* | *15945.70* | *15981.00* |
| *Skewness* | *-0.2335* | *-0.2323* | *-0.3758* | *-0.3653* | *0.7019* | *0.7089* | *0.6500* | *0.6618* |
| *Kurtosis (levels)* | *-0.8637* | *-0.8688* | *-0.8745* | *-0.8486* | *-0.4280* | *-0.4153* | *-0.1908* | *-0.1777* |
| *JB test* | *139.81* | *140.76* | *192.74* | *181.79* | *312.00* | *316.22* | *250.05* | *258.27* |

**Panel D- Stationarity test prices**

| | *Germany* | | *United Kingdom* | | *France* | | *Spain* | *Germany* |
|---|---|---|---|---|---|---|---|---|
| | ***Spot*** | ***Futures*** | ***Spot*** | ***Futures*** | ***Spot*** | ***Futures*** | ***Spot*** | ***Futures*** |
| *Dickey-Fuller* | *-0.2262* | *-0.2330* | *-0.3067* | *-0.3208* | *-1.3078* | *-1.3006* | *-0.8342* | *-0.8546* |
| *Phillips-Perron* | *-0.2262* | *-0.2330* | *-0.3067* | *-0.3208* | *-1.3078* | *-1.3006* | *-0.8342* | *-0.8546* |

The Table shows summary statistics and stationarity tests for prices $(s_t, f_t)$ and returns $[(1-L)\log(s_t),(1-L)\log(f_t)]$ of the 4 European stock indices (German DAX30, the British FTSE100, the French CAC40 and the Spanish IBEX35) in the spot and futures market. Panels A and C show the descriptive statistics and the Jarque-Bera normality test for spot and futures markets, respectively. Panels B and D show the stationary tests on the price and returns series, respectively ($^{***}$, $^{**}$ and $^{*}$ represents rejection of the null hypothesis at 1%, 5% and 10% levels of significance, respectively).

**Table 2**. Parameters estimations of the Diag-BEKK(1,1) model.

| | DAX30 | FTSE100 | CAC40 | IBEX35 |
|---|---|---|---|---|
| $a_0$ | 0.0632*** | 0.0384** | 0.0416*** | 0.0468*** |
| | *(0.0185)* | *(0.0153)* | *(0.0125)* | *(0.0188)* |
| $b_0$ | 0.0648*** | 0.0374** | 0.0394*** | 0.0455*** |
| | *(0.0181)* | *(0.0153)* | *(0.0127)* | *(0.0192)* |
| $c_{11}$ | 0.1974*** | 0.0936** | 0.2182*** | 0.1507*** |
| | *(0.0254)* | *(0.0376)* | *(0.0367)* | *(0.0108)* |
| $c_{12}$ | 0.1938*** | 0.0895*** | 0.2428*** | 0.1676*** |
| | *(0.0271)* | *(0.0307)* | *(0.0450)* | *(0.0123)* |
| $c_{22}$ | 0.0368*** | 0.0231*** | 0.0307*** | 0.0236*** |
| | *(0.0086)* | *(0.0056)* | *(0.0141)* | *(0.0027)* |
| $a_{11}$ | 0.3319*** | 0.2294*** | 0.2827*** | 0.2425*** |
| | *(0.0320)* | *(0.0377)* | *(0.0201)* | *(0.0061)* |
| $a_{22}$ | 0.3520*** | 0.2237*** | 0.2969*** | 0.2544*** |
| | *(0.0427)* | *(0.0292)* | *(0.0228)* | *(0.0070)* |
| $b_{11}$ | 0.9382*** | 0.9694*** | 0.9438*** | 0.9632*** |
| | *(0.0095)* | *(0.0123)* | *(0.0096)* | *(0.0014)* |
| $b_{22}$ | 0.9322*** | 0.9708*** | 0.9353*** | 0.9587*** |
| | *(0.0130)* | *(0.0094)* | *(0.0126)* | *(0.0019)* |

The Table shows the estimated parameters for the model in eq.1 for the log-returns on the spot and futures markets for the DAX30, FTSE100, CAC40 and IBEX35 indices. Standard errors are computed using Bollerslev-Wooldridge (1992) specification correcting for heteroskedasticity (***, ** and * represents statistical significance at 1%, 5% and 10% levels of significance, respectively).

**Table 3.** Unit-root tests for HRs series

*Panel A. AR process*

$$H_0 : y_t = y_{t-1} + u_t$$
$$H_1 : y_t = ay_{t-1} + u_t \text{, where } a < 1$$

| | | DAX30 | FTSE100 | CAC40 | IBEX35 |
|---|---|---|---|---|---|
| ADF test | Statistic | -0.7062 | -0.3965 | -0.3642 | -0.3155 |
| | Critical Value | -1.9416 | -1.9416 | -1.9416 | -1.9416 |
| | Result | Cannot reject | Cannot reject | Cannot reject | Cannot reject |
| PP test | Statistic | -0.7935 | -0.3953 | -0.3833 | -0.2915 |
| | Critical Value | -1.9416 | -1.9416 | -1.9416 | -1.9416 |
| | Result | Cannot reject | Cannot reject | Cannot reject | Cannot reject |

*Panel B. AR with drift*

$$H_0 : y_t = y_{t-1} + u_t$$
$$H_1 : y_t = c + ay_{t-1} + u_t \text{, where } a < 1 \text{ and drift coefficient } c$$

| | | DAX30 | FTSE100 | CAC40 | IBEX35 |
|---|---|---|---|---|---|
| ADF test | Statistic | -12.3014 | -8.7212 | -12.7170- | -9.0966 |
| | Critical Value | -2.8638 | -2.8638 | -2.8638 | -2.8638 |
| | Result | Reject | Reject | Reject | Reject |
| PP test | Statistic | -13.3642 | -8.8844 | -13.2070 | -9.5918 |
| | Critical Value | -2.8638 | -2.8638 | -2.8638 | -2.8638 |
| | Result | Reject | Reject | Reject | Reject |

*Panel C. Trend-stationary*

$$H_0 : y_t = y_{t-1} + u_t$$
$$H_1 : y_t = c + dt + ay_{t-1} + u_t \text{, where } a < 1 \text{, drift coefficient and deterministic coefficient } d$$

| | | DAX30 | FTSE100 | CAC40 | IBEX35 |
|---|---|---|---|---|---|
| ADF test | Statistic | -12.3111 | -8.7223 | -12.8570 | -9.5937 |
| | Critical Value | -3.4139 | -3.4139 | -3.4139 | -3.4139 |
| | Result | Reject | Reject | Reject | Reject |
| PP test | Statistic | -13.3758 | -13.3441 | -8.8861 | -10.1352 |
| | Critical Value | -3.4139 | -3.4139 | -3.4139 | -3.4139 |
| | Result | Reject | Reject | Reject | Reject |

The Table shows the ADF and PP tests on the estimated HRs using eq.2 for the spots and futures returns on the DAX30, FTSE100, CAC40 and IBEX35 indices (sample period: May 2000-November 2013). Each panel shows a variation of the test in terms of the drift coefficient considered.

**Table 4.** RS-ADF test with drift

$$\Delta y_t = a_{0,s_t} + \sum_{k=1}^{p} a_{k,s_t} \Delta y_{t-k} + b_{s_t} y_{t-1} + u_t \ , \ u_t \sim N\left(0, \sigma^2_{s_t}\right),$$

| | | Hedge ratios | | | |
|---|---|---|---|---|---|
| *Parameters* | *State* | *Germany* | *UK* | *France* | *Spain* |
| $b_{s_t}$ | $S_t$ =1 | -0.1548*** | -0.1259*** | -0.2191*** | -0.1364*** |
| | | *(-5.3643)* | *(-4.7192)* | *(-5.3463)* | *(-6.3804)* |
| | $S_t$ =2 | -0.0467*** | -0.0158*** | -0.0429*** | -0.0199*** |
| | | *(-12.8277)* | *(-7.2695)* | *(-6.8347)* | *(-7.2798)* |
| $a_{0,s_t}$ | $S_t$ =1 | 0.1546*** | 0.1195*** | 0.2226*** | 0.1428*** |
| | | *(5.5581)* | *(4.6624)* | *(5.5059)* | *(6.5421)* |
| | $S_t$ =2 | 0.0414*** | 7.7625 | 0.0408*** | 0.0181*** |
| | | *(11.4636)* | *(0.0162)* | *(6.2814)* | *(6.5505)* |
| $a_{1,s_t}$ | $S_t$ =1 | 0.0894* | 0.2626** | 0.2242* | -0.1106 |
| | | *(1.6749)* | *(2.1778)* | *(1.8681)* | *(-1.5960)* |
| | $S_t$ =2 | -0.0078 | -0.0090 | -0.0114 | 0.0011 |
| | | *(-0.8433)* | *(-0.7209)* | *(-1.0612)* | *(0.1492)* |
| $a_{2,s_t}$ | $S_t$ =1 | -0.0437 | -0.0598 | 0.1055** | 0.0018 |
| | | *(-0.8081)* | *(-0.8644)* | *(2.0320)* | *(0.0368)* |
| | $S_t$ =2 | 0.0040 | 0.0022 | -0.0110 | 0.0015 |
| | | *(0.5623)* | *(0.2931)* | *(-0.9783)* | *(0.1703)* |
| $\sigma^2_{s_t}$ | $S_t$ =1 | 0.0018*** | 4.28 e-04*** | 9.02 e-04** | 3.52 e-04*** |
| | | *(4.6984)* | *(4.0308)* | *(2.4834)* | *(6.6941)* |
| | $S_t$ =2 | 0.0003*** | 1.27e-05*** | 2.42 e-05*** | 1.13 e-05*** |
| | | *(5.0392)* | *(5.4779)* | *(4.4565)* | *(9.1923)* |
| *P* | - | 0.4458*** | 0.3778*** | 0.1736*** | 0.2840*** |
| | | *(12.6924)* | *(8.5676)* | *(4.0981)* | *(9.3152)* |
| *Q* | - | 0.7037*** | 0.7752*** | 0.8276*** | 0.7558*** |
| | | *(21.3647)* | *(24.5056)* | *(18.1814)* | *(32.2734)* |

The Table shows the estimated parameters for the RS-ADF test presented in eq.4. Dependent variables in each column represent the estimated HRs using eq.2 for the spots and futures returns on the DAX30, FTSE100, CAC40 and IBEX35 indices (sample period May 2000-November 2013). Standard errors are computed using Bollerslev-Wooldridge (1992) specification correcting for heteroskedasticity (***, ** and * represents statistical significance at 1%, 5% and 10% levels of significance, respectively).

**Table 5.** RS-ADF test with no drift

$$\Delta y_t = b_{s_t} y_{t-1} + \sum_{k=1}^{p} a_{k,s_t} \Delta y_{t-k} + u_t \ , \ u_t \sim N\left(0, \sigma_{s_t}^2\right),$$

| | | Hedge ratios | | | |
|---|---|---|---|---|---|
| *Parameters* | *State* | *Germany* | *UK* | *France* | *Spain* |
| $b_{s_t}$ | $S_t$ =1 | 0.0067*** | 9.02 e-04*** | 0.0076*** | 0.0054*** |
| | | *(3.9945)* | *(8.4932)* | *(7.1746)* | *(7.0819)* |
| | $S_t$ =2 | -0.0039*** | -0.0027*** | -0.0018*** | -0.0019*** |
| | | *(-15.2984)* | *(-3.0045)* | *(-5.1232)* | *(-16.3492)* |
| $a_{1,s_t}$ | $S_t$ =1 | -0.0012 | 0.2122** | 0.0199 | -0.2041*** |
| | | *(-0.0206)* | *(2.0078)* | *(0.2262)* | *(-2.8188)* |
| | $S_t$ =2 | -0.0241** | -0.0173 | -0.0152 | -0.0069 |
| | | *(-2.2556)* | *(-1.4901)* | *(-1.3763)* | *(-0.9274)* |
| $a_{2,s_t}$ | $S_t$ =1 | -0.1185** | -0.0934 | -0.0555 | -0.0612 |
| | | *(-2.3243)* | *(-1.069)* | *(-1.2342)* | *(-1.2678)* |
| | $S_t$ =2 | -0.0172 | -0.0097 | -0.0192 | -0.0063 |
| | | *(-1.2256)* | *(-1.2411)* | *(-1.6027)* | *(-0.6967)* |
| $\sigma_{s_t}^2$ | $S_t$ =1 | 0.0020*** | 4.64 e-04*** | 9.33 e-04*** | 3.74 e-04*** |
| | | *(4.9637)* | *(3.7786)* | *(2.8121)* | *(6.9448)* |
| | $S_t$ =2 | 4.54 e-05*** | 1.37e-05*** | 2.4117*** | 1.16e-05*** |
| | | *(5.7429)* | *(5.1356)* | *(4.8599)* | *(9.3970)* |
| *P* | - | 0.4471*** | 0.3663*** | 0.2076*** | 0.2846*** |
| | | *(12.2439)* | *(8.1832)* | *(5.0682)* | *(9.2134)* |
| *Q* | - | 0.7167*** | 0.7803*** | 0.8244*** | 0.7573*** |
| | | *(25.2484)* | *(22.3735)* | *(20.7753)* | *(34.0556)* |

The Table shows the estimated parameters for the RS-ADF test presented in eq.4 but omitting the drift component. Dependent variables in each column represent the estimated HRs using eq.2 for the spots and futures returns on the DAX30, FTSE100, CAC40 and IBEX35 indices (sample period May 2000-November 2013). Standard errors have been corrected for heteroskedasticity (***, ** and * represents statistical significance at 1%, 5% and 10% levels of significance, respectively).

**Table 6.** RS-ADF test with drift

Panel A. - Standard unit-root tests

| Hedge ratios (intraday data): Germany | | | | |
|---|---|---|---|---|
| | | AR | AR with drift | Trend stationary |
| ADF test | Statistic | -0.4907 | -20.0372 | -20.6146 |
| | Critical Value | -1.9416 | -2.8610 | -3.4123 |
| | Result | Cannot reject | Reject | Reject |
| PP test | Statistic | -0.4907 | -20.0372 | -20.6146 |
| | Critical Value | -1.9416 | -2.8638 | -3.4123 |
| | Result | Cannot reject | Reject | Reject |

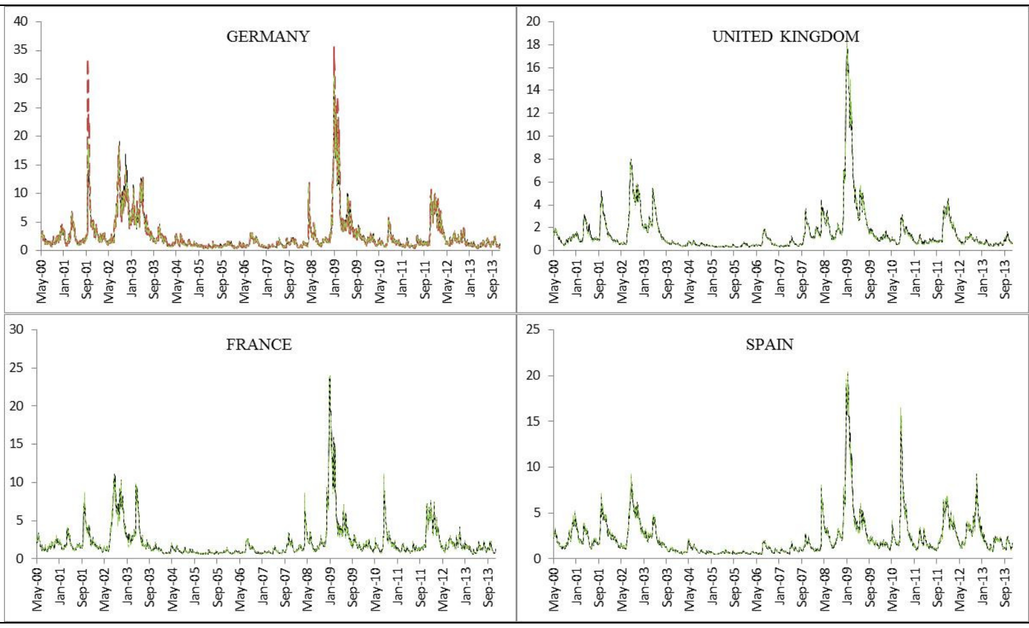
Panel B. - RS-ADF Test

| *Parameters* | Hedge ratios (intraday data) *Germany* | |
|---|---|---|
| | $S_t=1$ | $S_t=2$ |
| $b_{s_t}$ | -0.0106 *(0.0180)* | -0.0071 *(2.4421)* |
| $a_{0,s_t}$ | 0.0151 *(0.0193)* | 0.0621 *(2.4855)* |
| $a_{1,s_t}$ | 0.0286 *(0.0247)* | -0.0541 *(2.1608)* |
| $a_{2,s_t}$ | 0.0194 *(0.0213)* | -0.0553 *(1.5695)* |
| $a_{3,s_t}$ | 0.0355 *(0.0252)* | 0.0669 *(5.4937)* |
| $\sigma^2_{s_t}$ | *3.84e-05****** *(1.02e-05)* | 2.85 e-04*** *(8.86e-05)* |
| *P* | 0.9809*** *(0.0020)* | |
| *Q* | 0.9791*** *(0.0030)* | |

Panel A shows the statistics for the ADF and the PP tests on the estimated HRs using eq.2 for the spots and futures returns on the hourly DAX30 index. Each panel shows a variation of the test in terms of the drift coefficient considered. Panel B shows the estimated parameters for the RS-ADF test presented in eq.4 (sample period January 2000-Decemeber 2010). Standard errors have been corrected for heteroskedasticity (***, ** and * represents statistical significance at 1%, 5% and 10% levels of significance, respectively).

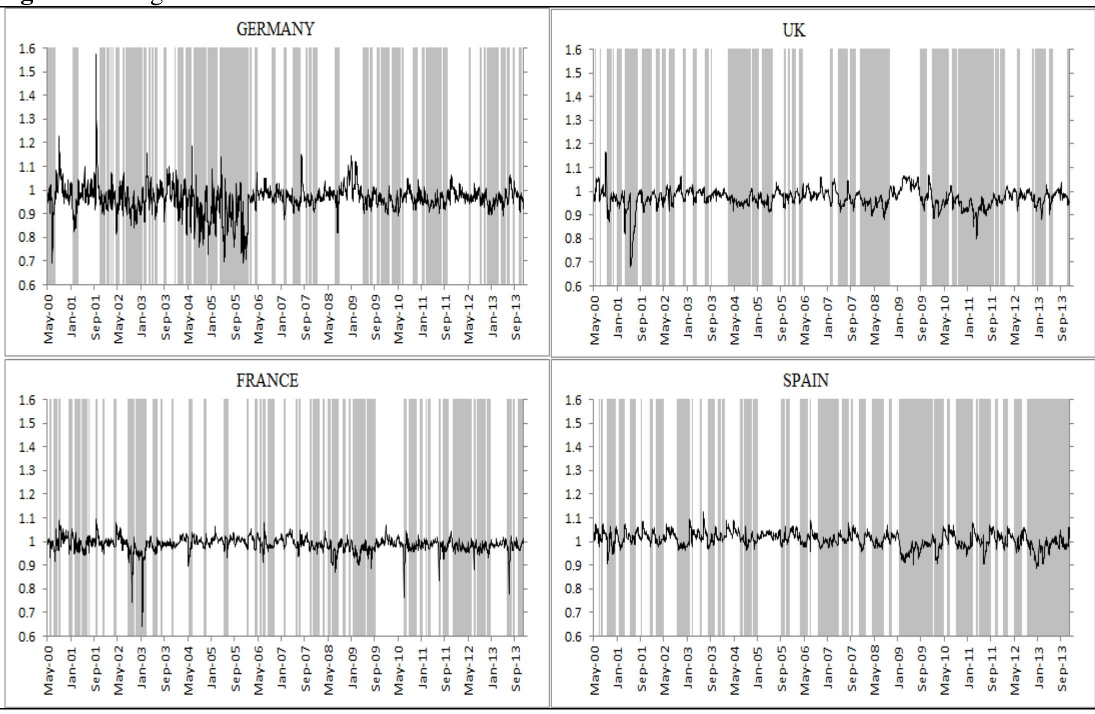
# Figures

**Figure 1.** Conditional variances



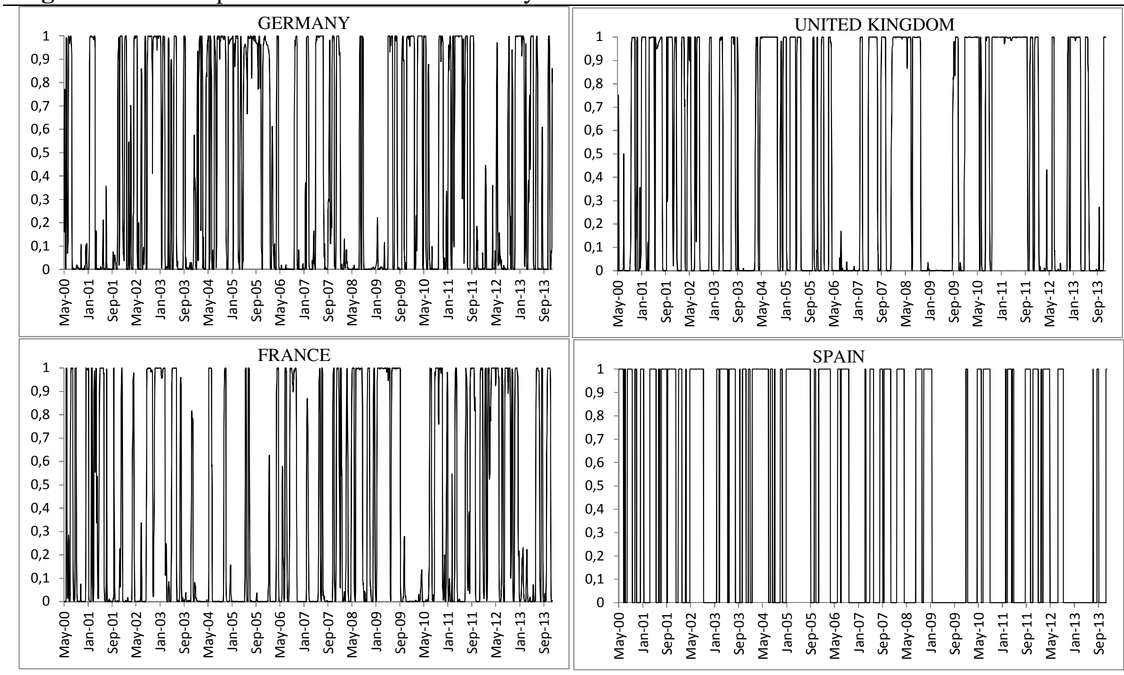

This Figure plots the conditional spot ( $\sigma^2_{s,t}$ ) (black line) and futures ( $\sigma^2_{f,t}$ ) variances (green line) for the log-returns of the DAX30, FTSE100, CAC40 and IBEX35 indices (sample period May 2000-November 2013).

**Figure 2.** Hedge ratios



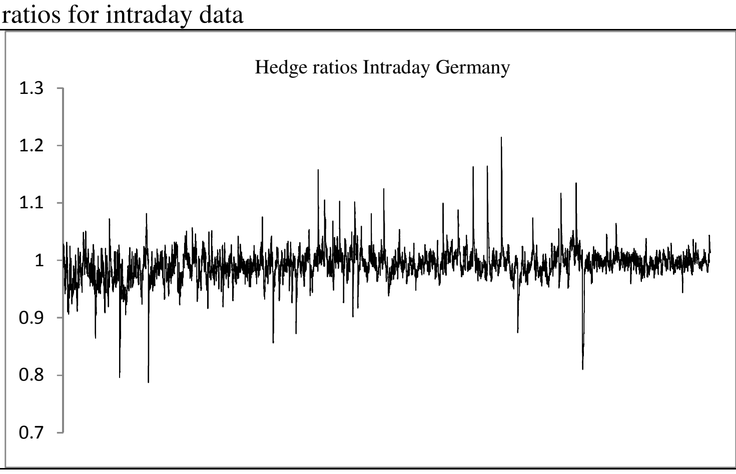

This Figure plots the estimated HRs according to eq.2 for the spot and futures stock indices in Germany, United Kingdom, France and Spain. Shaded areas correspond to periods of high volatility based on the filtered probabilities of eq.4.

**Figure 3.** Filtered probabilities for low volatility states




This Figure plots the probability of being in a low volatility state [$P(S_t=1|\Psi_{t-1})$] for the RS-ADF test of eq.4. In these plots we use the estimated HRs from eq.2 using the returns on the spot and futures stock indices in Germany, United Kingdom, France and Spain as the main input for the regime-switching stationarity test.

**Figure 4.** Hedge ratios for intraday data




This Figure plots the estimated HRs according to eq.2 using the intraday (hourly) returns on the spot and futures stock indices in Germany.