Department of
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1. Introduction

Financial market instabilities have become more frequent and pronounced in the era of globalisation (Bordo et al., 2001), and have sparked concerns over the benefits of traditional portfolio diversification strategies. Those involving instruments based on the VIX volatility index (which is negatively correlated to equity returns) are thought to be particularly effective during periods of market turmoil for tail risk hedging (Whaley, 1993). The VIX is especially attractive to investors with a high skewness preference (Barberis and Huang, 2008). Unlike credit derivative instruments, the liquidity of VIX derivatives improves during periods of markets turmoil, when investors are in search of hedging instruments (Bahaji and Aberkane, 2016). The existing literature also shows the diversification benefits of VIX exposures in institutional investment portfolios (Szado, 2009). In particular, a VIX short future exposure in a benchmark portfolio triggers a positive expansion of the efficient frontier (Chen et al., 2011); moreover, the addition of VIX futures to pension fund equity portfolios can significantly improve their in-sample performance, whilst incorporating VIX instruments into long-only equity portfolios significantly enhances Value-at-Risk optimisation (Briere et al., 2010).

A number of empirical papers have examined the features of the VIX, specifically its information content (Canina and Figlewski, 1993; Fleming, 1998; Christensen and Prabhala, 1998; Koopman et al, 2005; Becker, et al., 2009, Smales, 2014), importance and effectiveness (Whaley, 1993; Barberis and Huang, 2008; Bahaji and Aberkane, 2016; Szado, 2009; Briere et al, 2010), statistical properties (Lee and Ree, 2005), dynamic association and regime switching behaviour (Baba and Sakurai, 2011), as well as the presence of a day-of-the week effect (Qadan, 2013), and its usefulness as a measure of investor sentiment (Brown and Cliff, 2004; Bandopadhyaya and Jones, 2008) and/or risk aversion and market fear (Bekaert et al., 2013; Caporale et

RTS (Russian Trading System) Index futures (for further details see the Moscow Exchange website, *https://www.moex.com*). However, in late 2013, the Moscow Exchange decided to replace the RTSVX with a new Russian Volatility Index (RVI) taking into account the latest international financial industry standards as well as feedback from market participants; this was launched on 16 April 2014. It also decided to keep calculating the RTSVX until futures contracts on the index expired and to discontinue it from 12 December 2016 (RTSVX futures are not traded anymore, with RVI futures having being available instead to trade from June 2014).

The new RVI measures market expectation of the 30-day volatility on the basis of real prices of nearby and next RTS Index option series. In the previous RTSVX volatility index, a parameterised volatility smile was used to construct continuous, theoretical Black-Scholes prices of the nearby and next RTS Index option series. The RVI is calculated in real time during both day and evening sessions (first values 19:00 – 23:50 MSK and then 10:00 – 18:45 MSK), and differs from the RTSVX in three main respects, i.e. it is discrete, it uses actual option prices over 15 strikes, and calculates the 30-day volatility. Specifically, it is defined as follows:

(1)

where ${}_1$ and T_2 are the time to expiration expressed as a fraction of a year consisting of 365 days for the nearby and far option series respectively ${}_{30}$ and since only about 6 percent of listed companies are traded in the largest Russian exchange; ownership in the equity market is highly concentrated; the Russian bond and equity markets are easily accessible to international investors and the corporate bond market has proven to be highly profitable without any defaults. Russian financial markets are rather stable and integrated in terms of international capital flows (Peresetsky and Ivanter, 2000); the degree of financial liberalisation in Russia determines the strength of its international integration (Hayo and Kutan, 2005); since the Russian stock market is not cointegrated with the US one investors should focus on the Russian VIX for predicting Russian sto

they have become more knowledgeable about the effects of the VIX on stock price indices for developed and emerging economies (Natarajan et al., 2014).

3. Methodology

For the purpose of this paper we use fractional integration models suitable to analyse long memory, namely the large degree of dependence between observations that are far apart in time. These models were originally proposed by Granger (1980, 1981) and Granger and Joyeux (1980) and Hosking (1981) and allow the differencing parameter required to make a series stationary I(0) to be fractional as well. More precisely, assuming that u_t is an I(0) process (denoted as u_t with a positive spectral density function positive which is bounded at all frequencies, x_t is said to be integrated of order d, and denoted as x_t , if it can be represented as

$$(1 - L)^d x_t = u_t, \quad t = 0, \pm 1, \ldots, \qquad (2)$$

with x_t L is the lag-operator ($Lx_t = x_{t-1}$) and d can be any real value and is a measure of the persistence of the series. In such a case, one can use the following Binomial expansion for the polynomial on the left hand side of (2) for all real d:

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and thus

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The main advantage of this model, which became popular in the late 1990s and early 2000s (see Baillie, 1996; Gil-Alana and Robinson, 1997; Michelacci and Zaffaroni, 2000; Gil-

4a. The RTSVX index

As a first step we estimate the following model:

(3)

where y_t is the series of interest, in this case the original volatility index and the log-transformed data. Three specifications are considered, namely i) without determinististic

priori in (3)); (ii) with

priori), and iii) with an intercept and a linear time trend (as in equation (3)), and assuming that the errors are uncorrelated (white noise) and autocorrelated (Bloomfield, 1973) in turn.

[Insert Table 1 about here]

Table 1 show the estimated values of d with their 95% confidence intervals. These results support the specification with an intercept; the estimates are slightly higher in the case of uncorrelated errors, and in all cases favour fractional integration over the I(0) stationarity and the I(1) nonstationary hypotheses; being below 1, they imply mean reversion, with the effects of shocks disappearing in the long run.

Next, we check if the differencing parameter has remained constant across the sample period, and for this purpose we compute rolling estimates of d with a window of size 10 shifting over a subsample of 500 observations. The resulteg6(oJ(e)-10c2(i)-6(e-4(co)-4Do -4(

Under the assumption of autocorrelation, the estimates of d are initially around 0.8, and then decrease from the subample [381-880] till the end of the sa

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Table 1: Estimated coefficients of d and 95% confidence bands, RTSVX

i) Original data (RTSVX)			
	No terms	An intercept	A linear time trend
White noise	0.89 (0.85, 0.93)	**0.86 (0.82, 0.90)**	0.86 (0.82, 0.90)

Table 2: Results for the two subsamples using white noise errors, RTSVX

Original data	No terms	An intercept	A línear time trend
First subsample	1.06 (0.97, 1.17)	**0.87 (0.79, 0.98)**	0.88 (0.80, 0.98)
Second subsample	0.89 (0.85, 0.95)	**0.82 (0.78, 0.86)**	0.82 (0.78, 0.86)
Logged data	No terms	An intercept	A línear time trend
First subsample	1.02 (0.94, 1.12)	**0.82 (0.74, 0.93)**	0.82 (0.75, 0.93)
Second subsample	0.99 (0.95, 1.03)	**0.85 (0.81, 0.89)**	0.85 (0.81, 0.89)

Table 3: Results for two subsamples with autocorrelated errors, Log RTSVX data

Original data	No terms	An intercept	A línear time trend
First subsample	0.98 (0.83, 1.21)	0.80 (0.67, 1.00)	**0.82 (0.71, 1.00)**
Second subsample	0.78 (0.72, 0.82)	**0.74 (0.69, 0.81)**	0.74 (0.70, 0.81)
Logged data	No terms	An intercept	A línear time trend
First subsample	0.98 (0.85, 1.15)	0.73 (0.61, 0.89)	**0.75 (0.64, 0.89)**
Second subsample	0.93 (0.88, 0.99)	**0.81 (0.76, 0.88)**	

Table 4: Estimated coefficients of d and 95% confidence bands, RVI

i) Original data (RVI)			
	No terms	An intercept	A linear time trend
White noise	0.90 (0.86, 0.96)	**0.89 (0.84, 0.95)**	0.89 (0.84, 0.95)
Bloomfield	0.80 (0.73, 0.86)	**0.74 (0.68, 0.81)**	0.74 (0.68, 0.81)
ii) Log-transformed data (Log RVI)			
	No terms	An intercept	A linear time trend
White noise	0.97 (0.93, 1.01)	**0.84 (0.80, 0.88)**	0.84 (0.80, 0.88)
Bloomfield	0.99 (0.93, 1.06)	**0.82 (0.77, 0.89)**	0.82 (0.77, 0.89)

In bold, the selected model according to the deterministic termss.

Figure 2: Rolling window estimates of d and 95% confidence band, RVI

i) Uncorrelated errors

ii) Autocorrelated errors

Table 5