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PERSISTENCE IN THE RUSSIAN STOCK MARKET VOLATILITY INDICES

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Abstract

This paper applies a fractional integration framework to analyse the stochastic behaviour of two Russian stock market volatility índices (namely the originally created RTSVX and the new RVI that has replaced it), using daily data over the period 2010-2018. The empirical findings are consistent and imply in all cases that the two series are mean-reverting, i.e. they are not highly persistent and the effects of shocks disappear over time. This is true regardless of whether the errors are assumed to follow a white noise or autocorrelated process, it is confirmed by the rolling window estimation, and it holds for both subsamples, before and after the detected break. On the whole, it seems that shocks do not have permanent effects on investor sentiment in the Russian stock market.

Keywords: RTSVX, RVI, volatility, persistence, fractional integration, long memory

JEL Classification: C22, G12

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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 al., 2018), and as a stock market indicator/barometer (Iso-Markku, 2009; Fernandes et al., 2014).

In the existing literature only a few studies have examined in depth the statistical behaviour of the VIX; moreover, they have typically focused on the developed economies. By contrast, the present paper uses a fractional integration framework to shed light on long-range dependence, non-linearities and breaks in the case of the VIX in an emerging economy such as Russia; in particular, it analyses both the old and the new VIX constructed for the Russian stock market.

The layout of the paper is as follows. Section 2 provides background information on the Russian VIX, Section 3 outlines the empirical methodology, Section 4 describes the data and the empirical findings, Section 5 offers some concluding remarks.

2. The VIX in the Russian Stock Market

The idea of constructing a volatility index using option prices was first formulated at the time of the introduction of exchange trade index options in 1973. In subsequent years, the original methodology of Gastineau (1977), Cox and Rubinstein (1985) and others was considerably developed. The first implied volatility index, the VIX, was introduced by the Chicago Board Options Exchange (CBOE) in 1993 and was based on the S&P 100 index. It aimed to measure market expectations of the short-term volatility implied by stock index option prices. Subsequently, similar indices have been constructed for many developed and emerging markets.

Russia, one of the most important emerging economies, first introduced a volatility index, named RTSVX (Russian Trading System Volatility Index) on 7 December 2010. It is an aggregate indicator of the performance of futures and options in the Russian market based on the volatility of the nearby and next option series for the

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:

$$RVI = \left\{ 100 * \sqrt{\frac{T_{365}}{T_{30}} * \left| T_1 * \sigma_1^2 * \left(\frac{T_2 - T_{30}}{T_2 - T_1} \right) + T_2 * \sigma_2^2 * \left(\frac{T_{30} - T_1}{T_2 - T_1} \right) \right|} \right., \qquad (1)$$

where T_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; T_{30} and T_{365} stand for 30 and 365 days respectively, expressed as a fraction of a year; σ_1^2 and σ_2^2 are the variance of the nearby and next option series respectively.

There is only a limited number of studies on the Russian stock market, possibly because of the lack of long series of reliable data. As Mirkin and Lebedeva (2006) point out, Russian companies are more dependent on debt financing than equity financing 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 stock market returns (Mariničevaitė & Ražauskaitė, 2015); in general, 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 $u_t \approx I(0)$) 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 $x_t \approx I(d)$), if it can be represented as

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

with $x_t = 0$ for $t \leq 0$, and where 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:

$$(1-L)^d = \sum_{j=0}^{\infty} \psi_j L^j = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - d\,L + \frac{d\,(d-1)}{2} L^2 - \ldots,$$

and thus

$$(1-L)^d x_t = x_t - d\,x_{t-1} + \frac{d\,(d-1)}{2} x_{t-2} - \ldots .$$

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-Alana and Moreno, 2004; Abbritti et al., 2016; etc.), is that it is more general than standard models based on integer differentiation: it includes the stationary I(0) and nonstationary I(1) series as particular cases of interest when d = 0 and 1 respectively, but also nonstationary though mean-reverting processes if the differencing parameter is in the range [0.5, 1).

We estimate the fractional differencing parameter d along with the rest of the parameters in the model by using the Whittle function in the frequency domain (Dahlhaus, 1989; Robinson, 1994) under the assumption that the estimated errors are uncorrelated and autocorrelated in turn.

4. Data and Empirical Results

We analyse daily transaction level data for both the old (RTSVX) and new (RVI) volatility indices obtained from the Moscow exchange web database; the sample period goes from 7 December 2010 to 12 December 2014 and 6 January 2014 to 9 February 2018 respectively.

4a. The RTSVX index

As a first step we estimate the following model:

$$y_t = \alpha + \beta t + x_t, \qquad (1-L)^d x_t = u_t, \qquad t = 1, 2, ..., \qquad (3)$$

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 deterministic terms (i.e. α = β = 0 a priori in (3)); (ii) with an intercept (α is estimated and β = 0 a 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 results are displayed in Figure 1. Under the white noise assumption, the estimates of d (the degree of persistence) start around 0.9, then they decline in the subsample [301-800] and till the subample [621-1120]; then they increase again till the subsample [931-1430] and only start decreasing again in the final two subsamples, when the unit root null cannot be rejected.

[Insert Figure 1 about here]

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 sample; all of them are below 1, implying mean-reverting behaviour.

Next, we test for breaks using the approach suggested by Bai and Perron (2003) and then its extension to the fractional case by Gil-Alana (2008). The results (not reported) suggest in both cases that there is a single break occurring on 5 August 2011. We then split the sample in two subsamples accordingly. The results for the two cases of uncorrelated and autocorrelated errors are presented respectively in Tables 2 and 3. The estimates of d are significantly below 1 in both subsamples, with both white noise and autocorrelated errors, and for both the original and the logged data.

[Insert Tables 2 and 3 about here]

4b. The RVI index

Table 4 has the same structure as Table 1 (i.e., it displays the estimates of d for the three cases of no regressors, an intercept, and intercept with a linear trend, for both white noise and autocorrelated errors, and for both the original and the logged data) for the new RVI index. The results are fairly similar to the previous ones, with the estimates of d in all cases in the interval (0.5 , 1) and the unit root null hypothesis being rejected in all cases in favour of mean reversion ($d < 1$).

[Insert Table 4 and Figure 2 about here]

As in Figure 1, Figure 2 displays rolling estimates of d using a window with size 10 shifting over a subsample of 500 observations. A clear break is found around the 25^{th} subsample; the Bai and Perron (2003) and Gil-Alana (2008) tests detect a single break on 20 July 2016.

[Insert Tables 5 and 6 about here]

Tables 5 and 6 displays the estimates of d for each subsample under the assumption of white noise and autocorrelated errors respectively. As for the other index, the estimates of d are all statistically smaller than 1 (which implies mean reversion) and decline in the second subsample. Specifically, with uncorrelated errors, they are 0.91 (original series) and 0.89 (logged data) for the first subsample, and 0.60 and 0.63 for the second one; with autocorrelated errors, they shift from 0.72 and 0.85 in the first subsample to 0.55 and 0.61 in the second one.

5. Conclusions

This paper has applied a fractional integration framework to analyse the stochastic behaviour of two Russian stock market volatility indices, namely the originally created RTSVX and the new RVI that has replaced it (for both of which very limited evidence was previously available), using daily data over the period 2010-2018. The chosen approach is more general than those based on the I(0) v. I(1) dichotomy and provides useful information on the long-memory properties and degree of persistence of the series being analysed.

The empirical findings are consistent and imply in all cases that the two series are mean-reverting, i.e. their degree of persistence is limited and the effects of shocks disappear over time. This is true regardless of whether the errors are assumed to follow a white noise or autocorrelated process, and it holds for both subsamples, before and after the detected break. The rolling window estimation reveals the presence of some degree of time variation, but does not affect the general conclusion about the behaviour of the two series under examination. Since this type of volatility index can also be seen as a measure of market fear, the implication of our findings is that in the case of the Russian stock market shocks do not have permanent effects on investor sentiment.

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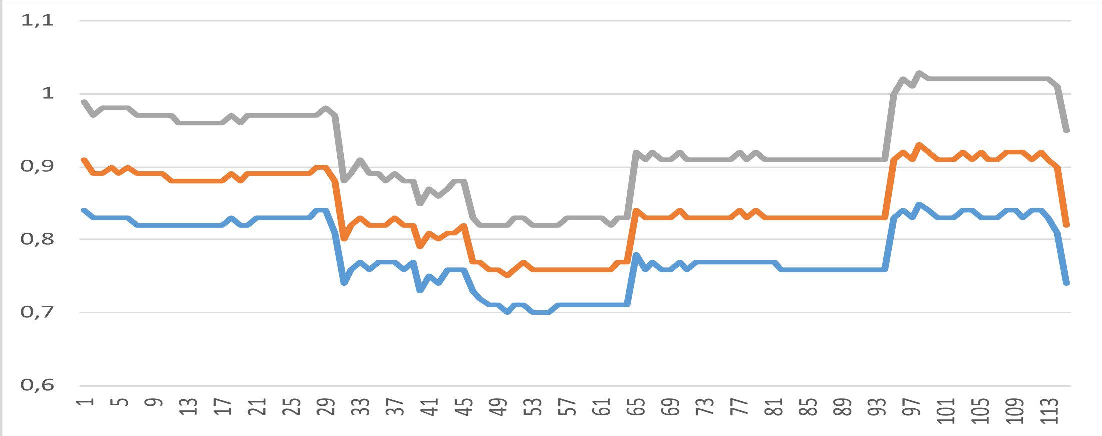
Table 1: Estimated coefficients of d and 95% confidence bands, RTSVX

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)
Bloomfield	0.80 (0.74, 0.85)	**0.76 (0.71, 0.82)**	0.76 (0.72, 0.82)
ii) Log-transformed data (Log RTSVX)			
	No terms	An intercept	A linear time trend
White noise	0.97 (0.93, 1.01)	**0.88 (0.84, 0.92)**	0.88 (0.84, 0.92)
Bloomfield	0.96 (0.90, 1.01)	**0.81 (0.76, 0.87)**	0.81 (0.76, 0.87)

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

Figure 1: Rolling window estimates of d and 95% confidence bands, RTSVX

i) Uncorrelated errors



ii) Autocorrelated errors

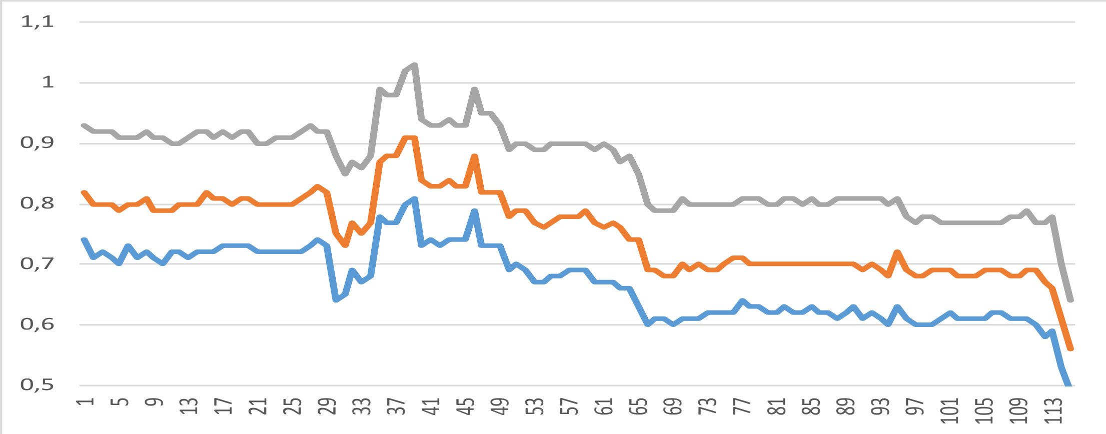


Table 2: Results for the two subsamples using white noise errors, RTSVX

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)**	0.81 (0.76, 0.88)

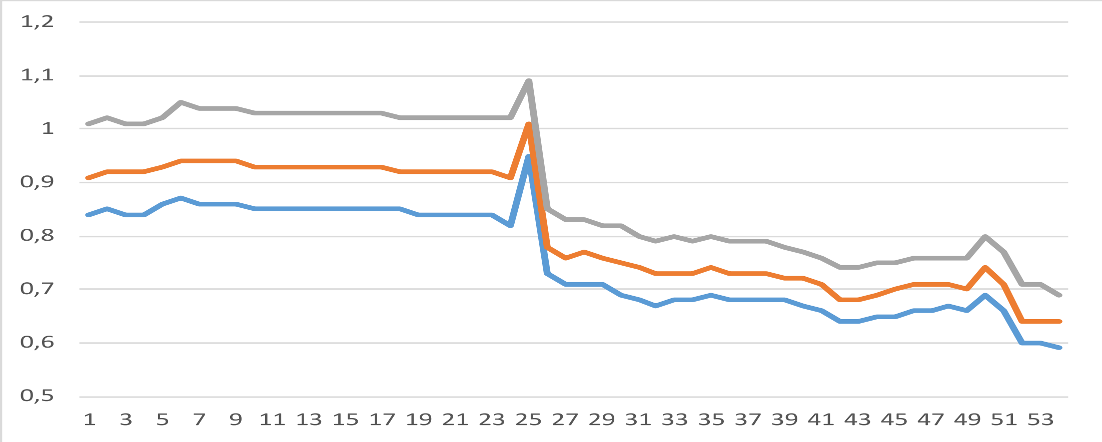
Table 4: Estimated coefficients of d and 95% confidence bands, RVI

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

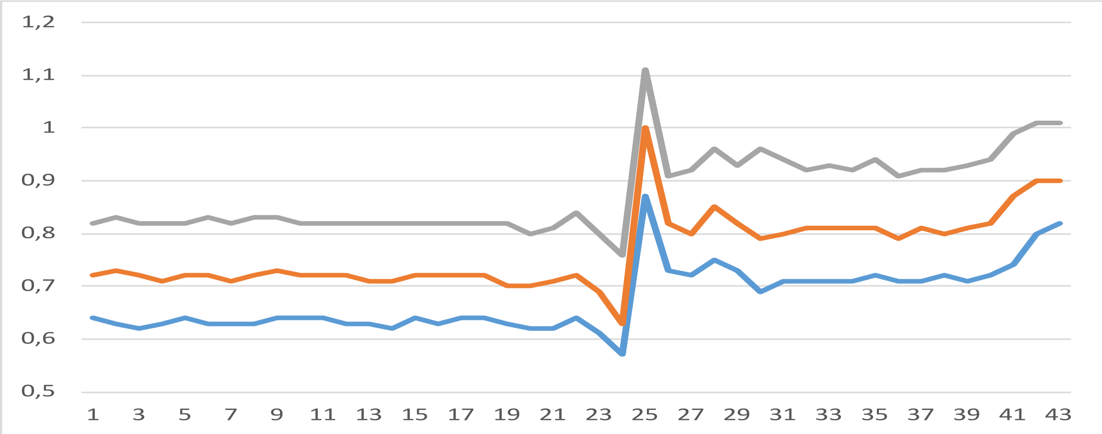


Table 5: Results for the two subsamples using white noise errors, RVI

Original data	No terms	An intercept	A línear time trend
First subsample	0.90 (0.84, 0.98)	**0.91 (0.84, 0.99)**	0.91 (0.84, 0.99)
Second subsample	0.90 (0.84, 0.97)	0.62 (0.57, 0.68)	**0.60 (0.54, 0.68)**
Logged data	No terms	An intercept	A línear time trend
First subsample	0.94 (0.90, 1.00)	**0.89 (0.84, 0.95)**	0.89 (0.84, 0.95)
Second subsample	0.98 (0.92, 1.06)	0.64 (0.59, 0.71)	**0.63 (0.57, 0.70)**

Table 6: Results for two subsamples with autocorrelated errors, Log RVI

Original data	No terms	An intercept	A línear time trend
First subsample	0.77 (0.70, 0.85)	**0.72 (0.65, 0.82)**	0.72 (0.65, 0.82)
Second subsample	0.92 (0.84, 1.04)	0.61 (0.54, 0.70)	**0.55 (0.46, 0.68)**
Logged data	No terms	An intercept	A línear time trend
First subsample	0.97 (0.90, 1.06)	**0.85 (0.77, 0.96)**	0.85 (0.77, 0.96)
Second subsample	0.98 (0.88, 1.10)	0.63 (0.57, 0.73)	**0.61 (0.52, 0.72)**