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Realized correlation analysis of contagion

Dimitrios I. Vortelinos *

Lincoln Business School, University of Lincoln, Lincoln, UK

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ABSTRACT

This paper investigates the cross-market contagion between spot and futures US stock markets by examining the significance and properties (textbook and lead-lag asymmetries) of realized correlation, testing the assumptions of the cost-of-carry model, as well as testing the in-sample predictive significance of heterogeneity and jumps to realized correlation. Evidence from the US stock market suggests realized correlation can be very helpful analyzing contagion. There is strong evidence of statistically significant cross-market contagion in the US stock markets, when realized correlation is used as conditional correlation, across all methods employed. To the best of my knowledge, this paper is the first to nonparametrically analyze contagion based on realized correlation.

1. Introduction

The approaches for estimating contagion vary with regard to its definition as a starting point. For an overview of literature see Periocoli and Sbracia (2003). A part of the contagion literature supports the so-called crisis-contagion theories arguing that propagation mechanisms change during a crisis. Forbes and Robinson (2002) estimate contagion by testing the significance of a conditional correlation estimate. This is implemented by *t*-testing equality between correlation in stable period and correlation in turmoil period. Another part of the contagion literature is that cross-market contagion concerns if prices from one market lead those of another market. Contagion literature splits into implied volatility contagion, sector-specific contagion, aggregate stock market contagion, credit default swap market contagion and commodity market contagion literature. The former was recently studied by Jiang, Konstantinidi, and Skiadopoulos (2012) and Kenourgios (2014); while, the second was examined by Baur (2012), Bekaert, Ehrmann, Fratzscher, and Mehl (2014) and Kenourgios and Dimitriou (2015). Aggregate stock market contagion was researched by Dimitriou, Kenourgios, and Simos (2013), Kenourgios and Padhi (2012) and Bekiros (2014). The credit default swap market contagion was studied by Wang and Moore (2012), among others. The commodity market contagion was studied by Chan, Treepongkaruna, Brooks, and Gray (2011), among others.

The present paper studies contagion by examining the significance and the properties (textbook and lead-lag asymmetries) of realized correlation as well as by testing the cost-of-carry model assumptions and also by testing the in-sample significance of the heterogeneity and jumps properties to correlation. In specific, the first way of examining contagion is to study the significance and properties of correlation between futures and spot equity indices. Correlation is systematically studied in finance literature for more than two decades.[1] Correlation literature pays a lot of attention to realized covariances and correlations since Andersen, Bollerslev,

* Tel.: +44 1522 835634.
E-mail address: dvortelinos@lincoln.ac.uk

[1] The mostly analyzed correlation estimation methods are: (i) multivariate GARCH (see Bauwens, Laurent, & Rombouts, 2006; Engle, Lilien, & Russell, 1987), (ii) Constant Conditional Correlation (CCC) model (see Bollerslev, 1990), (iii) Dynamic Conditional Correlation (DCC) model (Engle, 2002; Tse & Tsui, 2002 introduced it and Chiang, Jeon, & Li, 2007; Chou, Wu, & Liu, 2009; Guidolin & Timmermann, 2006; Kenourgios, Samitas, & Paltalidis, 2011; Long, Su, & Ullah, 2011; Pelletier, 2006 analyzed it), (iv) stochastic volatilities and correlations (see Han, 2007; Philipov & Gickman, 2006; Shephard, 2004, among others), (v) implied correlations

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Diebold, and Ebens (2001), Andersen, Bollerslev, Diebold, and Labys (2001) established realized correlations can be constructed by the realized covariation matrix and also these correlations can be modeled directly using standard time series techniques. Realized correlation measuring is the most convenient and powerful approach for efficiently incorporating intraday data to multivariate volatility estimation and forecasting.[2] Literature on estimating realized correlation in the presence of intraday microstructure noise includes, among others, Oomen (2006), Martens and van Dijk (2007), Voev and Lunde (2007), and Bandi, Russell, and Yang (2008).[3] The second is to examine the existence of textbook asymmetries between futures and spot stock indices. Farero and Giovazzi (2002) use VAR methodology to identify transmitted unexpected shocks across countries. Butler and Joaquin (2002) report that the contagion (change in correlation properties) differs depending on the direction of shocks. Dungey, Fry, and Martin (2003) analyze asymmetries as well. Thomakos and Wang (2003) are the first that analyzed textbook asymmetries in realized correlation. The third is whether the assumptions of the cost-of-carry model hold or not. In specific, the model assumes that (i) the volatility of returns in the spot markets equals volatility in futures markets and (ii) there are positive and almost perfect correlations between contemporaneous returns in spot markets and those in future markets (see Lafuente & Novales, 2003).[4] The fourth concerns the lead-lag asymmetries assumption of the cost-of-carry model (see Amira, Taamouti, & Tsafack, 2011; Lafuente & Novales, 2003). Fifth is if heterogeneity[5] and jumps[6] play a role in the cross-market correlation, via the introduction of two cost-of-carry heterogeneous autoregressive (COC) models. Both COC models take into account the heterogeneity between the two markets. Additionally, one takes into account the other market's jumps, and the other takes into account the other market's liquidity.

The present paper provides evidence in favor of the use of realized correlation measure in relation to the cost of carry theory for explaining contagion between spot and futures US stock markets. In specific, the cost-of-carry model assumption that volatility of returns in the spot markets equals volatility in futures markets is rejected. The second assumption of significant contemporaneous correlations is rejected only in an intraday (hourly) frequency. Moreover, there is strong evidence in favor of the existence of textbook correlation asymmetries between futures and spot stock indices as indicated by leverage and volatility feedback effects. Also, the lead-lag asymmetries assumption of the cost-of-carry model does not hold in most of the cases. Furthermore, the properties of heterogeneity and jumps are significant in a cost-of-carry heterogeneous autoregressive (COC) model. Liquidity is important in an intraday frequency. These results add to cost-of-carry and market efficiency literature. The implications of such results concentrate on the research of the cost-of-carry theory. There is evidence both in favor of and against the assumptions of the cost-of-carry theory. This reveals that the spot and futures stock markets are not entirely either efficient or inefficient. Moreover, in few cases there are significant lead-lag asymmetries. The cost-of-carry relation can be significantly explained by market imperfections, such as heterogeneity, jumps and liquidity. Such evidence should be taken into account and be incorporated in the cost-of-carry theory.

The paper is structured as follows. In Section 2 there is a description of data used. In Section 3, I describe the unrestricted realized volatility estimator used to estimate volatilities, covariances and correlations across the paper. In Section 4, the cost-of-carry theory assumptions are tested. Section 5 looks the significance of textbook correlation asymmetries. Section 6 analyzes the lead-lag correlation asymmetries with Section 7 examining the cost-of-carry heterogeneous autoregressive models. Section 8 provides concluding remarks.

2. Data

The present paper uses 1-min data. The dataset includes five futures stock indices and their underlying spot stock indices. The futures stock indices are: (i) E-Mini S&P 500 Continuous Contract (ES), (ii) E-Mini Nasdaq 100 Continuous Contract (NQ), (iii) Mini-sized Dow Futures Continuous Contract (YM), (iv) Mini Russell 2000 Continuous Contract (TF), and (v) E-Mini S&P MidCap 400 Continuous Contract (EMD). The underlying stock spot indices are: (i) Dow Jones Industrial Average (INDU), (ii) Nasdaq 100 Index (NDX), (iii) S&P 500 Index (INX), (iv) Russell 2000 Index (RUT), and (vi) S&P 400 Midcap Index (IDX). The dataset begins on April 5, 2002 and ends on October 14, 2011 with a total of 2,400 trading days. All data are capped to 6 1/2 trading hours per day; from 9:30 to 16:00 US Eastern time.[7] So, the number of 1-min intraday prices per day is 390.

Returns for either futures or spot equity indices are defined as $R_{f_x,t_i} = 100 \cdot \ln(f_{x,t_i}/f_{x,t_{i-1}})$ and $R_{s_x,t_i} = 100 \cdot \ln(s_{x,t_i}/s_{x,t_{i-1}})$ where f_{x,t_i} is the futures index price, and s_{x,t_i} is the futures index price with x being the symbol of either the futures or spot equity index, t_i the time with t days and i intraday interval. The daily returns are not distributed normally (according to the Cramœr–von Mises normality test) for any either futures or spot stock index, as evident in Table 1. Ljung-Box autocorrelation test rejects the null in either levels or squares of daily returns. Daily returns seem to have strong serial autocorrelation and the squared ones also have strong autocorrelation indicating volatility clustering. So, daily returns probably follow a standard Geometric Brownian motion. The daily returns of spot indices are in average much higher than those of the corresponding futures indices. Standard deviations, however, are almost equal. This is quite interesting result and drives this study to examine contagion and cross-market contagion in returns and volatility between futures and spot US stock markets across the next sections.

3. Volatility, covariance and correlation estimation

Before answer cross-market contagion, there is an analysis of the nonparametric unrestricted realized volatility estimator that is used in estimating volatilities, covariances and correlations throughout the paper. The currently accepted prototype of a realized volatility estimator comes from the work of Andersen,

(correlations in options estimated by the implied volatilities; see Walter & Lopez, 2000, among others), (vi) neural networks (see Chen & Leung, 2005), (vii) dynamic copulas with and without regime-switching (see Okimoto, 2008; Patton, 2006), (viii) semiparametric multivariate volatility models (see Hafner & Rombouts, 2007), (ix) structural conditional correlation (see Weber, 2010), (x) Bayesian modeling (see Wu & Lee, 2011), and (xi) a new model, named multivariate Student's t Generalized Autoregressive Score (GAS) model (with similarities to DCC), for estimating and forecasting both volatilities and correlations is introduced by Creal, Koopman, and Lucas (2011).

[2] Another interesting suggestion, regarding realized correlations, come from Andersen, Bollerslev, Diebold, and Labys (2003), where they suggest inferring covariances from variances of different cross-rates or portfolios through properly defined arbitrage conditions.

[3] In their very influential paper, they evaluate fourteen "best-in-class" realized volatility estimators in a univariate ARFIMA forecasting exercise and an options' profit-based ranking.

[4] Zhong, Darrat, and Otero (2004) test the hypotheses that changes in futures prices can predict short-term (temporary) or long-term (persistent) changes in spot prices, by using a Vector Error Correction model with EGARCH specifications.

[5] See Corsi (2009) and Andersen, Bollerslev, and Diebold (2007).

[6] Jumps ate detected by the jump detection scheme introduced by Andersen et al. (2007).

[7] The hours in which most US spot equity indices are traded. This trading period is known as American trading-time zone.