**CENTRE FOR APPLIED MACROECONOMIC ANALYSIS**

The Australian National University

---

**CAMA Working Paper Series** **September, 2009**

---

# DETECTING CONTAGION WITH CORRELATION: VOLATILITY AND TIMING MATTER

**Mardi Dungey**
University of Tasmania
University of Cambridge
Australian National University

**Abdullah Yalama**
Eskisehir Osmangazi University
University of Tasmania

---

CAMA Working Paper 23/2009
http://cama.anu.edu.au

# Detecting Contagion with Correlation: Volatility and Timing Matter[*]

Mardi DUNGEY[%&+], Abdullah YALAMA[#%]

[%]University of Tasmania
[&]CFAP, University of Cambridge
[+]CAMA, Australian National University
[#]Eskisehir Osmangazi University

June 2009

**Abstract**

We examine whether contagion tests are affected by controls for volatility clustering and the collection of synchronized data sets. Without controlling for volatility clustering synchronization does not apparently matter. Once volatility clustering is accounted for synchronized data dramatically changes results.

Keywords: Contagion, interdependence, timing, volatility spillover

JEL Classification: G01, C23.

---

[*] Yalama acknowledges support from an Eskisehir Osmangazi University Research Grant (200817046).

# 1 Introduction

Contagion between asset markets during financial crises is defined as the transmission of shocks via newly opened channels associated with crisis events. Many existing contagion tests rely in some form on detecting changes in correlation between asset returns when markets enter a crisis period, as surveyed in Dungey et al (2005). Contagion effects may be evidenced as increased correlation, such as in the theoretical models of Kodres and Pritsker (2002), or as lower correlation consistent with breaking linkages between financial institutions as proposed in network theory; see Allen and Babus (2008).

Detecting contagion effects relies upon two important determinants. The first is controlling for changes in volatility in common effects. Forbes and Rigobon (2002) (henceforth FR) suggest a correlation coefficient based test which adjusts for the increase in general market volatility during crisis periods. Without this adjustment unconditional correlation tests will be biased towards the detection of contagion effects. However, this test does not control for the well-known volatility clustering of financial market data. This paper considers whether controlling for volatility clustering results in different outcomes for tests of transmission between countries during times of financial crisis by comparing the results of the FR test with those of the Hong (2001) volatility spillover test.

The second potentially important determinant of contagion outcomes is in the timing of the collected data. Efficient market theories support that markets reflect news simultaneously, so that tests which compare data separated in time are likely to contain bias, as demonstrated by Martens and Poon (2001) for correlation coefficients. In contagion studies it is common to compare data from different time zones: Forbes and Rigobon (2002) use a two day moving average and Dungey et al (2005) lag North American markets by one day when comparing with Asian markets. Kleimeier, Lehnert and Verschoor (2008) address this issue using the FR test and find that although the calculated coefficients change, the result of no contagion between most markets was retained.

This paper examines the evidence for contagion from the US to European equity markets during the global financial crisis of 2007-2009. FR and Hong tests are applied to a non-synchronized dataset on closing market prices, and a synchronized dataset of

16:00GMT market prices. The results strongly indicate the importance of controlling for both volatility clustering and timing of the data. Changing from non-synchronized to synchronized data does not greatly affect the conclusions of the FR test. The Hong test finds more contagion than the FR test in both cases. In the non-synchronized dataset the Hong test regularly produces evidence of significant transmissions, while with synchronized data there is very little significant evidence for transmission.

## 1.1 The tests

The FR test is applied to returns on two assets, $\{r_{1,t}, r_{2,t}\}$ which have been filtered via a VAR(1). Under the null hypothesis of no contagion, the correlation coefficients of these returns from the VAR(1) do not change between crisis and noncrisis period, that is $\mathrm{H}_0 = p_{nc} = v_c$ where $p_{nc}$ is the non-crisis period correlation coefficient and $v_c$ represents the crisis period correlation coefficient adjusted for heteroskedasticity

$$v_c = \frac{\hat{p}c}{\sqrt{1 + (\frac{s_c^2 - s_{nc}^2}{s_{nc}^2})(1 - \hat{p}_c)^2}} \tag{1}$$

where $\mathrm{p}_c$ is the crisis sample correlation coefficient, and $\mathrm{s}^2$ denotes the appropriate sample variances. Under the null hypothesis the FR statistic is

$$FR = \frac{\frac{1}{2}\ln\left(\frac{1+\hat{v}_c}{1-\hat{v}_c}\right) - \frac{1}{2}\ln\left(\frac{\hat{p}_{nc}}{1-\hat{p}_{nc}}\right)}{\sqrt{\frac{1}{T_c - 3} + \frac{1}{T_{nc} - 3}}}\,{}^{\sim}N(0,1) \tag{2}$$

where $\mathrm{T}_c$ and $\mathrm{T}_{nc}$ are the number of observations in the crisis and non-crisis periods respectively.

The Hong (2001) test is an extension of the Cheung and Ng (1996) test for causality in variance, based on cross correlations of conditional variances obtained from univariate GARCH processes. It involves lagged mean effects from other markets, and can be viewed as being parallel to the FR test while controlling for volatility clustering. An advantage of the Hong test is that it does not rely on a priori exogeneity assumptions, as required in the FR test, but determines the direction of transmission.

The test procedure involves estimating univariate GARCH(p,q) models including one-lagged returns from other markets and testing the correlations between the resulting standardized conditional variances. Defining $\mathrm{r}_{i,t}$ as the return series of interest, with $r_{j,t}$ as the other market under consideration

$$r_{i,t} = \phi_0 + \phi_1 D_t + \phi_2 r_{i,t-1} + \phi_3 D r_{i,t-1} + \phi_4 r j_{,t-1} + \phi_5 D r_{j,t-1} + z_t \tag{3}$$

$$h_{i,t} = \kappa_0 + \sum_{s=1}^{p} \alpha_s h_{t-s} + \sum_{s=1}^{q} \beta_s \varepsilon^2_{t-s}$$

where $\varepsilon_{i,t} \sim$ idd(0, $h_t$), and $D_t$ is a dummy variable taking the value 1 during the exogenously defined crisis period and 0 otherwise. Let , $I_{it}$, i=1,2 be the information set defined as $I_{it} = \{R_{ij}, j \succeq 0\}$, $I_t = I_{1t} \cup I_{2t}$ so that $E(\varepsilon_{it} \,|I_{it-1}) = 0$ and $E(\varepsilon^2_{it} \,|I_{it-1}) = 1$ The Hong (2001) null hypothesis for no causality in time varying conditional variances can be written as:

$$H_0 : \ \mathrm{Var}(\varepsilon_{1t} \,|I_{1t-1}) = \mathrm{Var}(\varepsilon_{1t} \,|I_{t-1})$$

The one-sided test statistic proposed by Hong is given as:

$$Q = \frac{\{T \sum w^2(k/M) p^2_{uv}(k) - c(w)\}}{(2D(w))^{1/2}} \,\tilde{}\, N(0,1) \tag{4}$$

$$C(w) : \ \sum_{k=1}^{T-1} (1 - k/T) w^2(k/M)$$

$$D(w) : \ \sum_{k=1}^{T-1} (1 - k/T)[1 - (j+1)/T] w^4(k/M)$$

where $\hat{\mu}_t = \hat{\varepsilon}^2_{1t} / \hat{h}_{1t}$ and $\hat{\nu}_t = \hat{\varepsilon}^2_{2t} / \hat{h}_{2t}$ are the centered squared standardized residuals from the GARCH (p,q) estimates on a sample size of T, with a sample cross-correlation at lag k, given by

$$p_{uv}(k) = \frac{c_{uv}(k)}{\sqrt{T - 2 \sum_{t=1}^{T} \hat{\mu}^2_t \sum_{t=1}^{T} \hat{\nu}^2_t}} \tag{5}$$

with sample covariances

$$c_{uv}(k) = T^{-1} \sum_{k=1+1}^{T-1} \hat{\mu}_t \hat{\nu}_{t-k}, k \geq 0$$

and

$$c_{uv}(k) = T^{-1} \sum_{k=1+1}^{T-1} \hat{\mu}_t \hat{\nu}_{t+k}, k < 0$$

M is the number of cross correlations included. We report results with M=10 and the Daniell kernel as the weighting function,w(.), given the better properties for this combination reported in Hong (2001). Qualitative results are unchanged with differing values of M or alternative kernels.

## 2 Data

Stock market returns for the US S&P500, the UK FTSE100, and seven European indices are obtained from Thompson Datastream for local closing times (the CP dataset) and for 16:00 GMT times (the $4^{pm}$ dataset). The European indices considered are for the markets located in Austria, France, Germany, Italy, Netherlands and Switzerland a well as the EU wide index. Compound daily returns are calculated as log differences of the stock prices.[1]

The data sample begins on July 29, 2004, and ends on March 20, 2009. To implement the tests the period is divided into non-crisis and crisis samples, delineated by the start of the crisis period on July 17, 2007 which corresponds to the announcement by Bear Stearns of the collapse of its two hedge funds. Although not reported here, the sample covariances rise for each asset pair between the non-crisis and crisis periods.

## 3 Empirical Findings

Table 1 presents the p-values for FR test results for the test of no contagion from the US to the other markets using the CP and 4pm data. The tests find no evidence of significant contagion from the US to other countries in either the CP or $4^{pm}$ data sets.[2]

The p-values for the one sided test results from the Hong tests on standardized residuals from univariate GARCH(p,q) models are reported in Table 2. For brevity we omit the estimated GARCH results, but they are available on request; most are

---

[1] The Datastream codes for the indices at 4pm (Closing prices) are: Austria: AME0E16 (AMSTEOE), EU: DJES516 (DJES50I), France: CAC4016 (FRCAC40), Germany: DAXIN16 (DAXINDX), Italy: ITM3016 (ITMIB30), Netherlands: AME0E16 (AMSTEOE), Swiss: SWIMK16 (SWISSMI), UK: FTSE100 (FTSE100), US: SPCMP16 (S&PCOMP). Daily returns in all series are found to be stationary.

[2] Note that we largely solve the endogeneity problem inherent in these pairwise tests by denoting the US and the UK as source countries for the potentially contagious shocks. However, Table 4 does include a result for both US to UK and UK to US based tests, which strictly speaking violate the exogeneity assumption required for these tests. They are advanced here as illustration.

GARCH(1,1) models selected using AIC criteria.

Table 2 presents the results for the null hypothesis of no causality in variance from the US to the European countries, for both the CP and $4^{pm}$ data. During the non-crisis period there is no evidence of rejection of this hypothesis. The second column presents the results for the null hypothesis of no causality from European countries to the US, and again there is no evidence of rejection of that hypothesis in the non-crisis period.

During the crisis period the non-synchronized data strongly reject the hypothesis of no causality from the US to Europe, but not from the European countries to the US. This is consistent with contagion effects from the US to Europe. However, when the synchronized $4^{pm}$ data set are used, there is no evidence of significant rejections of the null of no causality in either direction. The use of non-synchronised data will give misleading results.

## 4 Conclusions

This paper has shown how controlling for volatility clustering, and synchronization of data sets can effect test results for the existence of crisis transmission effects, that is contagion. The FR test suggests the absence of contagion between all markets in the study, regardless of the synchronicity of the datasets. However, when volatility clustering is accounted for the Hong test suggests significant transmissions between markets, particularly if the data are asynchronous. When synchronicity was accounted for the findings of significant causality from the US to Europe, consistent with contagion effects, are overruled. This suggests that care is needed in data set construction as after accounting for volatility effects, data timing may drive results.

## References

[1] Allen, F. and Babus, A., 2008, Networks in Finance, Wharton Financial Institutions Center Working Paper 08-07.

[2] Cheung, Y-W. and Ng, L.K., 1996, A Causality-in Variance Test and Its Applications to Financial Market Prices, *Journal of Econometrics*, 72, 33-48.

[3] Dungey M., Fry, F., Gonzalez-Hermosillo. B., and Martin V. L., 2005, Empirical Modeling of Contagion: A Review of Methodologies, *Quantitative Finance*, 5, 1, 9-24.

[4] Forbes, K. and Rigobon, R., 2002, No Contagion, only Interdependence: Measuring Stock Market Co-movements, *Journal of Finance*, 57, 5, 2223-61.

[5] Hong, Y., 2001, A Test for Volatility Spillover with Application to Exchange Rates, *Journal of Econometrics*, 103, 1-2, 183-224.

[6] Kleimeier, S., Lehnert, T. and Verschoor, W.F.C., 2008, Measuring Financial Contagion Using Time Aligned Data: The Importance of the Speed of Transmission of Shocks, *Oxford Bulletin of Economics and Statistics*, 70, 493-508.

[7] Kodres, L.E. and Pritsker, M., 2002, A Rational Expectations Model of Financial Contagion, *Journal of Finance*, 57, 2, 768-99.

[8] Martens, M. and Poon, S-H., 2001, Returns Synchronization and Daily Correlation Dynamics Between International Stock Markets, *Journal of Banking and Finance*, 25, 1805-1827.

Table 1:
Results of Forbes and Rigobon test (p-values)

| Contagion to | Contagion from US | |
|---|---|---|
| | CP | $4^{pm}$ |
| AUSTRIA | 0.627 | 0.767 |
| EU | 0.948 | 0.994 |
| FRANCE | 0.480 | 0.673 |
| GERMANY | 0.579 | 0.349 |
| ITALY | 0.573 | 0.767 |
| NETH. | 0.720 | 0.782 |
| SWITH. | 0.618 | 0.835 |
| UK | 0.778 | 0.901 |

Table 2:
Results of Hong test (p-values)

| | **Pre-Crisis Period** | | | | **Crisis Period** | | | |
|---|---|---|---|---|---|---|---|---|
| **Country** | US$\nrightarrow R_{it}$ | | $R_{it} \nrightarrow US$ | | US$\nrightarrow R_{it}$ | | $R_{it} \nrightarrow US$ | |
| | CP | $4^{pm}$ | CP | $4^{pm}$ | CP | $4^{pm}$ | CP | $4^{pm}$ |
| AUSTRIA | 0.787 | 0.864 | 0.911 | 0.849 | **0.000** | 0.871 | 0.656 | 0.737 |
| EU | 0.808 | 0.797 | 0.936 | 0.756 | **0.000** | 0.872 | 0.842 | 0.620 |
| FRANCE | 0.916 | 0.886 | 0.934 | 0.670 | **0.000** | 0.849 | 0.799 | 0.670 |
| GERMANY | 0.939 | 0.575 | 0.915 | 0.519 | **0.000** | 0.890 | 0.893 | 0.309 |
| ITALY | 0.927 | 0.906 | 0.277 | 0.391 | **0.000** | 0.812 | 0.708 | 0.708 |
| NETH. | 0.178 | 0.811 | 0.924 | 0.853 | **0.000** | 0.760 | 0.776 | **0.077** |
| SWITH. | 0.867 | 0.866 | 0.214 | 0.452 | **0.000** | 0.673 | 0.413 | 0.537 |
| UK | 0.629 | 0.814 | 0.147 | 0.659 | **0.000** | 0.798 | 0.712 | 0.842 |