Economic Modelling 44 (2015) 283–293

Contents lists available at ScienceDirect

Economic Modelling

journal homepage: www.elsevier.com/locate/ecmod

Contagion of the Global Financial Crisis and the real economy: A regional analysis

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ARTICLE INFO

Article history:
Accepted 29 October 2014
Available online 19 November 2014

Keywords:
Global Financial Crisis
Contagion
Regions
Real economy sectors
FIAPARCH–DCC model

ABSTRACT

This paper investigates the contagion effects of the Global Financial Crisis (2007–2009) by examining ten sectors in six developed and emerging regions during different phases of the crisis. The analysis tests different channels of financial contagion across regions and real economy sectors by utilizing dynamic conditional correlation from the multivariate Fractionally Integrated Asymmetric Power ARCH (FIAPARCH) model. Evidence shows that the GFC can be characterized by contagion effects across regional stock markets and regional financial and non-financial sectors.

However, Developed Pacific region and some sectors in particular Consumer Goods, Healthcare and Technology across all regions seem to be less affected by the crisis, while the most vulnerable sectors are observed in the emerging Asian and European regions. Further, the analysis on a crisis phase level indicates that the most severe contagion effects exist after the failure of Lehman Brothers limiting the effectiveness of portfolio diversification.

1. Introduction

The Global Financial Crisis (GFC hereafter) of 2007–2009, triggered by the USA subprime crisis in August 2007, was one of the most unanticipated and tumultuous economic events in the recent history. Its severity affected both financial activities and macroeconomic conditions around the globe. This global scale and magnitude characterized it as the worst financial crisis since the Great Depression of the 1930s.

There is a large body of literature which investigates financial contagion, however most of these studies analyze aggregate equity market indices in different countries (see, among others, Forbes and Rigobon, 2002; Bekaert et al., 2005; Boyer et al., 2006; Kenourgios et al., 2011; Kenourgios and Padhi, 2012; Dimitriou et al., 2013; Ahmad et al., 2013; Hwang et al., 2013). Contagion, however, is possible in any set of financial and non-financial ("real economy") sectors across countries and regions. Studies that test for contagion based on non-aggregate stock market indices are still rare. Bekaert et al. (2011) investigate the contagion of the GFC across 55 countries and 415 country-sector equity portfolios and find that contagion mainly occurred through domestic channels. Recently, Baur (2012) studies contagion for twenty five major stock markets and their real economy sectors during the GFC and finds that no country and sector were immune to the adverse effects of the crisis, while some sectors were less severely affected.

This paper empirically investigates financial contagion during different phases of the GFC from a regional perspective, rather than considering individual markets, by using aggregate stock indices and sector stock indices for six developed and emerging regions and ten sectors. The analysis of stock prices grouped into regional sector indices will shed light on the impact of the global crisis on the real economy of regions, since regional sector indices are indicators of the economic activities of a region.[1] To identify the length of the crisis and its phases, we use both timelines provided by official data sources (Federal Reserve Bank of Saint Louis and Bank for International Settlements) and regimes of excess stock market volatility. We test various transmission channels: (i) contagion of regional aggregate stock markets, (ii) contagion of the financial sector across regions, (iii) contagion of the real economy sectors across regions, and (iv) contagion of the real economy sectors within a region.

Following other studies in the literature (Bekaert et al., 2005; Boyer et al., 2006; Forbes and Rigobon, 2002), we adopt an equivalently strict definition of contagion as a significant increase in correlation between stock returns in different markets/regions during a crisis episode, beyond the linkages in fundamentals. This form of contagion relates to shifts in investors' appetite for or aversion to risk. When investors' appetite for risk rises, demand for risky assets is increasing and their value rises simultaneously. When investors' appetite for risk falls during risk-off episodes, they immediately reduce their exposure to risky assets

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[1] Although several studies investigate the relationships among equity markets across regions, only few papers use regional aggregate stock market indices (see for example Ratanapakorn and Sharma, 2002 and Guesmi and Nguyen, 2011).

http://dx.doi.org/10.1016/j.econmod.2014.10.048
0264-9993/

and consequently fall in value together. This leads to an increased co-movement between asset returns in different markets establishing contagion. This type of contagion has been called "pure contagion", since it runs along the lines of risk and ignores fundamentals, trade and exchange rate arrangements (Kumar and Persaud, 2002).[2]

Our analysis across regional equity markets and sectors during different phases of the GFC is important for several reasons. First, since the seminal study of Heston and Rouwenhorst (1994), a large body of portfolio diversification literature examined the importance of country and industry factors in driving the variation of international stock returns. Although Heston and Rouwenhorst (1994, 1995) find that country risks are more important than sector risks, other empirical studies in recent years show that global sector factors dominate country specific factors, due to the globalization of the world economy (Baca et al, 2000; Cavaglia et al., 2000; Phylaktis and Xia, 2006).[3] This implies the increasing role of sectors as a transmitting channel of global shocks. The analysis will be informative for global investors and portfolio managers with respect to whether potential gains from international portfolio diversification are more likely to be achieved by diversifying across regional markets or sectors in times of turmoil. The regional insight will also provide important information to global policymakers given the intensive globalization of national capital markets and the growing number of regional economic agreements (EU, ASEAN, NAFTA, MERCOSUR, BRICS, etc.).

Second, the contagion analysis at sector level may reveal that some sectors are more vulnerable to external shocks than others within a country or region.[4] This asymmetric sector contagion may be useful for portfolio managers, since it implies that there are sectors which can reap the benefits of international diversification during crises despite the prevailing contagion at the country/regional level. Third, the industrial structure varies across global markets and regions. Developed/mature markets/regions are comprised of more diversified sectors than emerging, less mature markets/regions. Further, the importance of a sector for a country's or region's economy can be quite different. An example which illustrates the disentangling of country factors from market composition is the Energy sector. The sector is 9% of MSCI world market capitalization. However, it accounts for only 1.2% of the Japanese market and is completely absent in Germany's market. On the other hand, energy accounts for 57% of Russia's total market capitalization (Kotok, 2014). Thus, it would be interesting to identify which sectors across regions with similar and/or different industrial composition are more prone to contagion.

To provide a robust analysis of financial contagion, time-varying dynamic conditional correlations (DCCs) are estimated into a multivariate autoregressive Fractionally Integrated Asymmetric Power ARCH (FIAPARCH) framework. This process is well suited to investigate financial contagion since it focuses on the second order moment dynamics of financial time-series and overcomes the heteroskedasticity problem when measuring correlations raised by Forbes and Rigobon (2002).[5] In addition, the FIAPARCH model is appropriate for financial data containing long memory and asymmetries.

The empirical results show that the GFC can be characterized by contagion effects across regional stock markets and regional financial and non-financial sectors. However, Developed Pacific region and some sectors across all regions (Consumer Goods, Healthcare and Technology) are less affected by the crisis, while the most vulnerable sectors are appeared in the emerging regions of Asia and Europe. Finally, most regions and sectors are immune to the shocks associated with the early phase of the crisis, while the period after the collapse of Lehman Brothers exhibits the highest infection rate limiting the portfolio diversification benefits.

The remainder of the paper is structured as follows. Section 2 introduces the methodology framework including a description of the multivariate AR(1)–FIAPARCH–DCC specification, the crisis period identification, the channels of contagion and the testing hypotheses. Section 3 presents the dataset, while Section 4 produces the empirical estimation results and robustness tests. Finally, Section 5 summarizes the findings and concludes.

2. Methodology framework

2.1. The empirical model

This section presents the multivariate AR(1)–FIAPARCH–DCC specification. The model is designed to allow for two-stage estimation of the conditional covariance matrix. In the first stage, univariate GARCH models are fit for each of the stock market returns. In our analysis, the estimates of $\sqrt{h_{iit}}$ are obtained from a univariate AR(1)–FIAPARCH (1,d,1) model. Stock returns r_t are assumed to be generated by an autoregressive AR(1) process as follows:

$$(1-\mu L)r_t = \omega + \varepsilon_t,\ \ t\in\mathbb{N}\ \text{ with }\ \varepsilon_t = e_t\sqrt{h_t} \tag{1}$$

where $\omega \in [0, \infty)$, $|\mu| < 1$, and $\{e_t\}$ are i.i.d. random variables and h_t is positive with probability one. The speed that market information is reflected in stock prices is captured by the autoregressive AR(1) term.The FIAPARCH specification of Tse (1998) can be expressed as follows:

$$(1-\zeta L)\left(h_t^{\delta/2}-c\right) = \left[(1-\zeta L)-(1-\lambda L)(1-L)^d\right](1+\gamma s_t)|\varepsilon_t|^{\delta} \tag{2}$$

where $c \in (0, \infty)$, $|\zeta| < 1$, $|\lambda| < 1$, $0 \le d \le 1$, $s_t = 1$ if $\varepsilon_t < 0$ and 0 otherwise, the parameter for the power term δ is a Box–Cox transformation of h_t that takes finite positive values, γ is the leverage coefficient and $(1 - L)^d$ is the financial differencing operator (see Conrad et al., 2011 for an application of this model to stock market volatility). When $\gamma > 0$, negative shocks have more impact on volatility than positive shocks.[6]

In the second stage, stock-return residuals are transformed by their estimated standard deviations from the first stage and then are used to estimate the parameters of the conditional correlations using the DCC model of Tse and Tsui (2002). The multivariate conditional variance is specified as:

$$H_t = D_t C_t D_t \tag{3}$$

where $D_t = diag\ (h_{11t}^{1/2} \ldots \ldots h_{NNt}^{1/2})$, h_{iit} is defined as the conditional variance obtained from the AR(1)–FIAPARCH model of the first stage and $C_t = (1 - \theta_1 - \theta_2)C + \theta_1\Psi_{t-1} + \theta_2 C_{t-1}$.[7] Moreover, θ_1 and θ_2 are assumed to be the non-negative parameters satisfying $\theta_1 + \theta_2 < 1$, $C = \{\rho_{ij}\}$ is a time-invariant symmetric $N \times N$ positive definite parameter

[2] Pure contagion is distinguished from other types appeared in the literature (e.g., the wake-up call contagion, the "shift" contagion). See Pericoli and Sbracia (2003) and Chiang et al. (2007) for a discussion of each contagion type.

[3] The advent of EMU has also weakened the importance of countries relative to regional market risk and EMU sector risks, suggesting that sector diversification could be more effective or at least complementary to geographical diversification (see Eiling et al., 2012).

[4] Forbes (2002) shows that sectors with extensive international trade (e.g., trade goods sectors) tend to be more prone to crises than sectors with less international trade (e.g., non-trade goods sectors).

[5] See Dungey et al. (2005) and Kenourgios et al. (2011) for a review of conventional and advanced econometric approaches used in the analysis of financial contagion.

[6] The FIAPARCH model increases the flexibility of the conditional variance specification by allowing an asymmetric response of volatility to positive and negative shocks and long-range volatility dependence. Furthermore, it allows the data to determine the power of returns for which the predictable structure in the volatility pattern is the strongest, while provides superior forecasts relative to other GARCH family models (Conrad et al., 2011).

[7] Engle (2002) proposed a different form of the DCC model. For an application of this model on contagion among equity markets, see Chiang et al. (2007), Celic (2012) and Hwang et al. (2013).