Asian Journal of Economics and Business
Volume 4; Number 2; 2023 : pp. 293-304
https://DOI:10.47509/AJEB.2023.v04i02.07

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Financial Stress Testing: Evidence of Asia, Euro Zone and the United States

Nadhem Selmi

Department of Quantitative Methods; Faculty of Economics and Management of Sfax – Tunisia.
E-mail: nadhem.selmi@yahoo.fr

Article History
Received : 18 July 2023; Revised : 09 August 2023; Accepted : 18 August 2023;
Published : 16 October 2023

Abstract: Financial stress testing (FST) is an operational tool for detecting fragility and vulnerability in financial system. Looking at the FST process, we find that Financial Stress Index (FSI) is a particular case of FST. FSI is a measure of the banking sector's stress which gives a better picture of the bank's condition than a simple binary crisis indicator. It is argued that this type of a fragility index seems to be a highly useful measurement for monitoring the banking sector fragility. During this financial crisis phase, global interactions are important and fellow's shocks are the main driving forces of the economic sector. Our findings imply that policy responses to a pandemic, corona virus are unlikely to prevent the spread among countries, making fewer domestic risks internationally diversifiable when it is most desirable. In this paper we have also introduced a novel non parametric approach to measure stress for the analysis of financial data.

Keywords: Financial Stress Testing, MGARCH-A-DCC

1. INTRODUCTION

Recently, stressful events have been occurring with alarming regularity and with severe impact. In the last 15 years alone there have been about 13 stress events, some examples of which are the Gulf War, the Asian Crisis, the Russian Default, the September 11 attack and the Argentine Default. The most recent ones are the subprime crisis in 2007 in the USA followed by the financial crisis of the most important investment banks in September 2008 and currently the Covid-19 pandemic.

To cite this paper:
Nadhem Selmi (2023). Financial Stress Testing: Evidence of Asia, Euro Zone and the United State. *Asian Journal of Economics and Business*. 4(2), 293-304. *https://DOI:10.47509/AJEB.2023.v04i02.07*

Also, recent years have witnessed a worldwide rapid growth of financial markets accompanied by significant instabilities, resulting in numerous criticisms of existing risk management systems and motivated the search for more appropriate methodologies able to cope with rare events with heavy consequences. In response to increased financial instability in many countries, policy makers, researchers and practitioners became interested in a better understanding of the vulnerabilities of financial systems (Vila, 2000). One of the key techniques for quantifying vulnerabilities is Financial Stress Testing (FST) which is a general term encompassing one or various techniques for assessing resilience to MGARCH (Multivariate Generalised Auto-Regressive Conditional Heteroskedasticity) process. FST is used to determine the stability of a given system or entity (Hutchison & McDill, 1999). In order to observe the results, they involve testing beyond normal operational capacity often to a breaking point. In financial literature, FST has traditionally been referred to asset portfolios, but more recently is has been applied to whole banks, banking system and financial systems (Illing & Liu, 2003).

The problem is then how to monitor rare phenomena that lie outside the range of available observations. In such a situation we rely on a well-founded methodology, namely MGARCH-DCC (dynamic conditional correlation) in order to monitor Financial Stress Index (FSI). FSI is a particular case of FST.

The FSI utilised in this paper describes the banking sector's condition ranging from low levels of stress to high levels of stress, where the banking sector may face the risk of a crisis. Five variables collected from the balance sheet data were used to build the FSI. Stress is a continuous variable with a spectrum of values, where extreme values are identified as financial crisis that is why, MGARCH provides a firm theoretical foundation to build statistical process describing volatility events.

The aim of this paper is to develop a new approach for stress testing, based on FSI and MGARCH, in order to monitor and identify stress periods in the Asian banking system. After computing a stress index, a time series model was fitted and an MGARCH A-DCC was constructed.

The rest of this paper is organised as follows: Section 2 describes the Local Whittle method, and the ADCC multivariate GARCH models used to study the dependency effect on THE FSI. Section 3 is a discussion of the empirical results and Section 4 is a conclusion.

Bank of International Settlements (BIS) Committee on the Global Financial System (CGFS) (2000) defines FST as a generic term describing various techniques used by financial firms to gauge their potential vulnerability exceptional but plausible events. The two key-words used to define a stress event are exceptional and plausible.

FST assesses effects of only exceptional (that is low probability) events rather than of ordinary 'bad news'. While some authors view FST as a subgroup of risk modeling focusing on clustering events that can and should be included in a comprehensive risk model, authors describe the selection of scenarios for the system wide stress tests as an art rather than a science (e.g Kupiec, 2001). While recognising the difficulties involved in estimating an 'exact' risk model, especially for multi-factor scenarios for a system as a whole, the selection of stress test scenarios should be based on a measure of plausibility.

As the name suggests, multi factor stress-tests involve stressing several risk factors at a time. This may be appropriate at the desk level but single factor shocks by themselves, do not make for a comprehensive stress-testing program because seldom is one risk factor alone affected during actual stress events.

2. ECONOMETRIC METHODOLOGY

In many situations, the use of formal risk management models may add little in the way of the measurement rigour to the FST process. For example, the construction of a reasonably accurate estimate of the potential importance of an overall economic downturn and an increase in problem bank loans need not require the use of some complicated formal credit risk measurement process. Rather, historically informed judgmental estimates of the increase in Non-Performing Loans (NPL) and their corresponding provisions may, in many cases, give a more accurate picture of potential exposures.

Depending on the interpretation attached to the FST exposure estimate, it may be important to identify merely that the losses are likely to be significant rather than to attempt to identify the 'exact' magnitude of the losses

2.1. Detecting Structural Breakpoint

We first adopted the ICSS (Iterative Cumulative Sum of Squares) algorithm of Inclan and Tiao (1994) to detect the structural breakpoints on stock and currency market of the six countries during the study period. Next, a set of dummy variables were created in order to seize the normalised volatility of return.

Let the closing stock price at the end of the day be $\left(P_{i,t}\right)$ then the banks stock return $(r_{i,t})$ for market i at day t is

$$r_{i,t} = (\log P_{it} - \log P_{it-1}) \times 100 \tag{2.1}$$

We define

$$a_{i,t} = r_{i,t} - \mu_i \tag{2.2}$$

μ_i is with zero mean and unconditional variable σ^2_t, μ_i denotes the average return of market *i*.

Let $C_k = \sum_{t=1}^{k} a_t^2, k = 1, \ldots, T$ be the cumulative sums of squares of D_k series, then D_k statistic can be calculated as follows:

$$D_k = \left(\frac{C_k}{C_T}\right) - \frac{k}{T}, k = 1, \ldots., T and\ D_0 = D_T = 0 \tag{2.3}$$

The iterated cumulative sum of squares (ICSS) algorithm was based on the statistic D_k to detect for multiple breaks in the unconditional variance of $\{a_{i,t}\}$series. Thus, the ICSS algorithm based on the statistic D_k begins by testing for a structural break over the entire sample. If the ICSS detects a significant break, then the algorithm applies the new statistic to test for a break over each of the two sub-samples defined by the break. The algorithm proceeds in this manner until the statistic is insignificant for all of the sub-samples defined by any significant breaks; see Inclan and Tiao (1994) testing steps of the ICSS algorithm for more details.

2.2. Local Whittle Method

The classes of semi-parametric frequency domain estimators follow the local Whittle approach as suggested by Shimotsu (2006) and analysed by Shimotsu and Phillips (2010) (dubbing it as Gaussian semi-parametric estimator). The analysis applied process is as follows:

$$y_t = \mu + \sum_{j=0}^{t-1} \varphi_{j,d} x_{t-j}, t = 1 \ldots T \tag{2.4}$$

As for the Local Whittle estimator, it is defined as the maximisation of the local Whittle likelihood purpose, such as:

$$Q(g,d) = \log\left\{\frac{1}{m}\sum_{j=1}^{m} \lambda_j^{2d} I_y(\lambda_j)\right\} - \frac{2d}{m}\sum_{j=1}^{m}[\log(\lambda_j)] \tag{2.5}$$

Where: $m = m^{(T)}$ denotes a bandwidth number tending to infinity $T \to \infty$ except at a slower speed than T;

$I(\lambda) = \frac{1}{2\pi T}\left|\sum_{t=1}^{T} e^{it\lambda}\right|^2$, represents the periodogram of X_t, and $g_x(\lambda)$ the spectral density of X_t, $\lambda_j = \frac{2\pi j}{n}$, and j = 1,..., n.

A notable disadvantage as compared to log-periodogram estimation is that a statistical optimisation is highly needed. Still, this estimator underlying assumptions are weaker than those pertaining to the log-periodogram regression (LPR) estimator. In this regard, Nelson (1991) had shown that while $d \in \left(-\frac{1}{2}, \frac{1}{2}\right)$;

$$\sqrt{m}\left(\hat{d}_{LW} - d\right) \xrightarrow{d} N\left(0, 1/4\right) \tag{2.6}$$

Hence, the asymptotic distribution turns about to be extremely simple, which facilitates easy asymptotic inference. More particularly, this estimator is discovered to be more efficient than the LPR one. The reliability and asymptotic normality ranges concerning the Local Whittle estimator have explicitly been demonstrated by Velasco (1999) to equate those associated with the LPR estimator.

This Exact LW procedure as frequency labelled, implies replacing $I_{\Delta^{d_y}}\left(\lambda_j\right)$ in (2.1) by $I_{\Delta^{d_y}}\left(\lambda_j\right)$, and is only valid if μ = 0 in (2.2). Since the relevant means are different from zero, White and Pagano (2008) suggested demeaning $\{y_t\}$ with an appropriate estimator $\hat{\mu}$, and computing the exact LW estimator starting from the demeaned data. So, the objective function to be minimised turns out to be:

$$R_E(m,d) = \log\left\{\frac{1}{m}\sum_{j=1}^{m} I_{\Delta^d(y-\hat{\mu})}(\lambda_j)\right\} - \frac{2d}{m}\sum_{j=1}^{m}\log(\lambda_j) \tag{2.7}$$

Where: $I_{\Delta^d(y-\hat{\mu})}(\lambda_j)$ is the periodogram of $\Delta^d(y-\hat{\mu})$. For fractional differences, to be determined, it is assumed that $\{y_t\}$ is given by a process similar to equation (2.1). It turns out that the first sample observation y_1 is a reliable mean estimator in the case of large values of d, while the usual arithmetic mean $\bar{y}$ helps ensure a significant task for small coefficient values of d. In this way, Shimotsu and Phillips (2010) suggested putting forward the subsequent weighted estimator, such as:

$$\hat{\mu}(d) = v(d)\bar{y} + (1 - v(d))y_1 \tag{2.8}$$

$$v(d) = \begin{cases} 1, & d \leq 0.5 \\ \frac{1+\cos(4\pi d)}{2}, & 0.5 < d < 0.75 \\ 0 & d \geq 0.75 \end{cases} \tag{2.9}$$

For the purpose of attaining, a feasible procedure, he considers two necessary steps, the first of which serves to determine an estimator of $\hat{d}$ independent from μ in order to get an estimator of the constant: $\hat{\mu} = \hat{\mu}(\hat{d})$. As for the second step, the slope and Hessian of $R_E(m,d)$ are used to compute the feasible estimator as follows:

$$\hat{d}_{2ELW} = \hat{d} - \frac{R'_E(m,\hat{d})}{R''_E(m,\hat{d})} \tag{2.10}$$

Besides, Shimotsu and Phillips (2010) demonstrated that the two-step ELW estimator (2ELW) proved to be consistent registering the same limiting distribution as the LW and ELW estimators under $-0.5 < d < 2$. Similarly, as shown by Bollerslev and Wright (2000), if an unknown mean (initial value) appears to undergo certain change by its sample average, simulations suggest that the ELW estimator is inconsistent for $d > 1$. It is actually for this reason that we undertake to apply the 2ELW. In addition, Andersen et al. (2002) resorted to modify the ELW.

2.2. Asymmetric DCC Model (A-DCC)

Apart from the DCC model, we also consider A-DCC useful to appeal to the specifications of Cappiello and Engle (2006). The A-DCC model is often applied to introduce asymmetries which revolve in the correlation dynamics. Such a choice is often made because the DCC pertaining correlations usually follow a scalar Baba, Engle, Kraft and Kroner (BEKK)-like process which makes it too restrictive to apply the model on the entire series at once. In addition to the DCC, the A-DCC model is also a subject of application. The A-DCC (1,1,1) model is expressed as:

$$\sigma_t^{\delta} = w + \alpha_1 |\varepsilon_{t-1}|^{\delta} + \gamma_1 |\varepsilon_{t-1}|^{\delta} I_{[\varepsilon_{t-1}<0]} + \beta_1 \sigma_{t-1}^{\delta} \tag{2.11}$$

$$Q_t = (1-\theta_1-\varphi_1)\bar{Q} - r_1\bar{N} + \theta_1(u_{t-1}u'_{t-1}) + \tau_1(n_{t-1}n'_{t-1}) + \varphi_1 Q_{t-1} \tag{2.12}$$

3. EMPIRICAL RESULTS

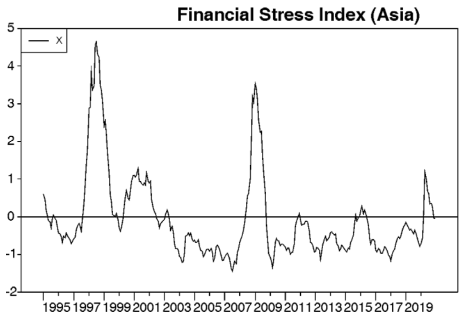
In this section, we describe the data and our empirical findings. Data consists of 6019 monthly observations of the financial stress index in Asia, Euro Zone and the United States. It covers a 26 years period, from January1995 to December 2020.

Table 1: The structural breaks and their emergence dates

n_i	*Asia*	*Euro-zone*	*United-States*
1	07-96	09-96	12-96
2	10-97	01-98	11-97
3	12-02	11-02	09-02
4	02-03	05-03	07-03
5	03-07	08-07	07-07
6	03-11	05-11	01-12
7	01-14	03-14	02-19
8	11-19	12-19	02-20

Sanso et al. (2004) could detect multiple break points for each series. The series generally having distinct date breaks do not prevent the existence of joint periods corresponding to the major events showing some structural breaks. These dates coincide with Mexico crisis in 1995, Russian federation default and Brazil crisis in 1998, Severe Acute Respiratory Syndrome, (SARS) in 2002, the Argentina debt crisis and Turkey stock market crash in 2003, the global financial crisis in 2007, the Euro crisis in 2011, the Taper Tantrum in 2014, People's Republic of China (PRC) led market distress in September 2016, Brexit vote in 2017, PRC-US trade tension onset in November 2019 and Covid-19 increase in December 2020.

In our case, and if we followed this interpretation, we found that the index identified eight periods where the stress was above average. The highest degree of stress was observed in subprime crisis 2008.



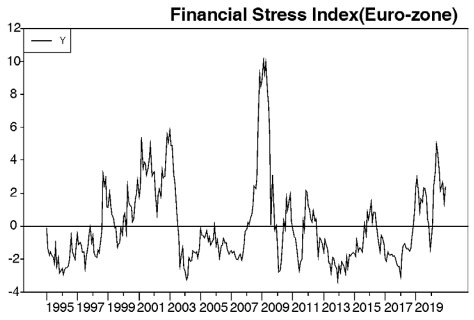


Figure 1: Financial Stress Index

The Figure 1 shows high volatility at specific dates: November 1997, October 2008 and December 2020 respectively for Asian crisis, Subprime crisis and Covid-19. In addition, most of these dates coincide with the crises in different markets where returns on indices were negative. Everything confirmed the asymmetric behaviour of the volatility shocks. Furthermore, this observation of high volatility suggested a change in the trend of the variance in these particular periods and the existence of break points (ICSS algorithm).

Table 2: The descriptive statistics of the FSI

	Asia	*Euro-zone*	*United States*
T	312	312	312
Mean	-0.0648	0.0516	-0.022
Standard Deviation	1.144	2.47	1.493
Skewness	2.013	1.538	1.195
Kurtosis	4.109	2.815	0.802
J.B	430.37	226.17	82.692
ARCH	6.98 (0.01)	5.86 (0.02)	8.27 (0.00)

Table 1 gives the descriptive statistics of the FSI. As shown, for risk-neutral investors, the FSI-United States seems to outperform Euro-zone and Asia in the sense that it provides a higher average return with a lower standard deviation. It is also evident that the United States stock market is significantly more volatile than the other FSI studied. This result indicates that FSI-United States is the riskiest among these three markets. Furthermore, the summary statistics show that the three markets display a wide level of standard deviation ranging from 1.144 (United States) to 2.47 (Euro-zone). The wide range of standard deviation indicates that a better efficient frontier can be reached if investors include the three markets in their asset allocation strategy. The coefficients of skewness indicate that the series, typically, have asymmetric distribution skewed to the right. This implies that there is a higher probability for investors to get positive rather than negative generated returns as in the case of the three markets studied. Thus, the global investors are optimistic to get positive returns by including the American and European markets in their portfolio. The excess of kurtosis statistics ranges in value from 0.802 of the US-FSI to 4.109 for Asia. This means that the probability of outliers of returns in both signs is higher than the normal in these markets.

Table 3: Estimation of the long memory parameters

	Asia	*Euro-zone*	*United States*
LW	0.428	0.327	0.322
2LW	0.627	0.523	0.698
2ELWd	0.529	0.328	0.739

Note: LW, 2ELW and 2ELWd indicate Local Whittle, 2 Stage Exact Local Whittle and Exact Local Whittle with detrending, respectively.

Table 3 indicates that the long memory property in the Asia period appears to be slightly higher than that in the Euro-zone and the U.S. This may be due to the more asymmetric number of FSI volatility in the outbreak's periods. It can be seen that the volatility is highly persistent in all countries during the epidemic corona virus.

Based on table 3, the LW do actually prove that $0 \leq \hat{d} \leq 0.5$. Indeed, this consists of a long-memory process case through still stationary, with a slow or smooth decay in the catching-up process.

In reality, this coincides with the "stochastic divergence" case liable to comparison with the initial deterministic divergence case. Regarding the 2ELW estimator, it has been demonstrated that $0.5 \leq \hat{d} \leq 1$, corresponding to a long memory process case, which is non-stationary though still reverting. In such a case, the process is featured with high persistence, whereby any distant past output difference would still have a long-lasting present inference.

We find that the dependence between the United States-index and Asia (0.628) is less than the dependence between the United States index and Euro-zone (0.728). This result can be explained by the contagion stress index fact that Asian countries are based in index on China. Regarding the A-DCC model, it has been shown that τ_1 tends to be zero for two country pairs, the United

Table 4: Parameter Estimates for DCC and A-DC Models

		Asia- Euro zone	*Asia- United States*	*Euro zone – United States*
DCC	α_c	0.07	0.12	0.23
	θ_1	0.78	0.55	0.58
A-DCC	θ_1	0.238 (0.00)	0.628 (0.00)	0.728 (0.00)
	τ_1	0.823 (0.00)	0.528 (0.23)	0.238 (0.87)
	τ_1	0.986 (0.00)	$-1.023.10^{-6}$ (0.99)	$0.98.10^{-4}$ (0.82)
	BIC	2718.29	3218.81	4214.89

States-Asia and the United States-Euro-zone, in total panel boxes. Concerning the reimaging case, it has been proved that conditional correlation is significant and positive, highlighting shock asymmetry through dynamic conditional correlations.

We find β_c being bigger than α_c, under restriction that coefficients and $\alpha_c + \beta_c <1$. The evidence from these results suggests that the big shock led to small corrections in the oncoming mutual fluctuations (or covariance) between markets. The DCC model for each country shows significant coefficients for covariance matrix of μ_t.

The analysis and discussion of FST results can be facilitated and enhanced by a clear presentation of the output generated from stress tests. For bottom-up approaches, descriptive statistics (e.g mean, median, standard-deviation, skwness, kurtosis) and peer-group analysis can be niteded to convey how the impact at the aggregate level is distributed across individual institutions.

The decomposition shows that the stress in identified periods is reflected in most of the variables. The most stressed variable is currency liabilities, reaching its peak in 2007, followed by a variation of capital with a remarkable decrease in 2000; total deposits witnessed an important drop in 2014, and loans to private sector saw a significant increase in 2020.

CONCLUSION

In this paper we introduced a novel non parametric approach to measure stress for the analysis of financial data arising from balance sheets. We compared the results achieved from our approach with classical methods based on long memory via MGARCH. The empirical evidence achieved on a real data set show that our approach performed better in terms of error rate. Following this, we proposed a methodology for FSI inequality decomposition based on A-DCC process in order to detect stressful sectors according to our database.. Furthermore, the results from a DCC process with contemporaneous restrictions indicate that although a domestic financial shock Furthermore, the results from a MGARCH process with A-DCC process indicate that although a domestic financial shock still accounts for most of the variations in domestic FSI, regional shocks play an important role in emerging Asia and Euro-zonestill accounts for most of the variations in domestic FSI, regional shocks play an important role in emerging Asia.

The information provided by FSI can also help to identify weaknesses in data collection, reporting systems, and risk management. The entire process itself can help to increase expertise in risk assessment by supervisors as well as promote a broader understanding of risks by different regulatory institutions.

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