Limited Information-Processing Capacity and Asymmetric Stock Correlations

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Abstract

Through an orthogonalized impulse-response analysis, I studied the relationship between the variance risk premium, market variance and stock correlations in the French stock market from September 2002 through September 2006, using high frequency data-based measures. Variance risk premium is estimated using realized variances and index options-implied variances and used as a state vector to proxy investors' perceived uncertainty. I found that a shock to variance risk premium causes long lasting increases in the market variance pointing to the limitedness of investors' information-processing capacity. At the same time, the shock generates consecutive increases in realized correlations between individual stocks and the market portfolio. I propose then a possible explanation for the asymmetric/counter-cyclic behaviour of stock correlations.

Keywords: Limited Attention, Asymmetric Correlations, Variance Risk Premium, High-frequency Econometrics, Impulse-Response Analysis

1 Introduction

The analysis of comovement between stock returns is of crucial importance in financial risk management as it has important practical implications in asset allocation. A higher correlation among stocks implies lower gains from portfolio diversification. It has been acknowledged that correlations between stock returns do not remain constant over time, tending to decline in bull markets and to rise in bear markets (Lin et al. (1994), De Santis and Gerard (1997), Bollerslev et al. (1998), Ang and Bekaert (1999), Moskowitz (2003)). Using the extreme value theory, Longin and Solnik (2001) show that the correlation of large negative returns is much larger than the correlation of positive returns. Ang and Chen (2002) show that the correlation between the U.S. stocks and the aggregate market return is much higher in the market downturns than during the upside movements. Ledoit et al. (2003) show that the level of correlation changes depending on the phase of the business cycle.

In a recent paper Ang, Chen and Xing (2006) found the evidence that downside correlations are higher than the upside correlations, while such an asymmetry is not observed in conditional betas, suggesting that that conditional correlations may be better able to capture the asymmetric nature of risk than conditional betas. Increasing market volatility and decreasing idiosyncratic volatilities in down markets (Duffee (1995)) inhibit conditional betas from fully capturing this asymmetry[1].

The impact of uncertainty shocks or news is also considered in the literature to study time-varying cross-moments. Kroner and Ng (1998) show that the conditional covariance between large-firm returns and small-firm returns tends to be higher following bad news about large firms than good news. Peng (2005)

[1]See Braun, Nelson, and Sunier (1995), and Chou and Engle (2000) for some work on asymmetric betas.

and Peng and Xiong (2006) develop models where information-processing capacity constraints force investors to make attention allocation decisions. When investors with limited attention tend to ignore firm-specific information, return comovements increase more than that can be explained by the fundamentals. Building on these models, Peng et al. (2007) show that after a macroeconomic shock that affect market-wide uncertainty, investors focus their limited attention to processing market-level information. Only subsequently, after they reduce the market uncertainty to a reasonable level, they shift their attention back to processing firm-specific information.

Recently emerged literature on high-frequency data econometrics provides alternative ways of estimating daily realized covariance and correlation statistics in a non-parametric fashion (Andersen et al. (2001b, 2003) and Barndorff-Nielsen and Shepard (2004a, 2004b)). These new techniques ensure us to avoid using arbitrary and wide estimation windows to estimate such statistics. Importantly, it has been shown that the realized correlation statistics delivers approximate normality after a simple transformation. Andersen et al. (2001b) show that there is a "volatility effect in correlation": return correlations tend to rise on high-volatility days.

In this paper, the relationship between shocks to traders' perceived level of uncertainty and realized correlations is studied through an orthogonalized impulse-response analysis. Variance risk premium, defined as the difference in expected variances under risk-neutral and physical measures[2], is used to capture investors' attitudes towards uncertainty[3]. A standardized shock to variance risk premium is shown to cause a statistically significant and long-lasting increase in the market return variance pointing to limitedness of investors' information-processing capacity[4]. Realized correlations are derived from high-frequency data on 48 stocks in the French market following the method developed by Andersen et al. (2001b) and Barndorff-Nielsen and Shepard (2004a, 2004b). Except for six stocks, correlations of individual stocks with the market portfolio increase significantly in the day of the shock. Generally, these increases die out in three days following the shock. Similar increases in correlations are observed also between equiweighted sectoral portfolios and between portfolios of large and small stocks. These results suggest that the limitedness of investors' information-processing capacity may be an important factor behind the observed asymmetric correlations.

The reminder of the paper is organized as follows. Section 2 introduces the methodology used to construct the measures of variance risk premium and realized correlations. Sources and statistical properties of the used data are given in Section 3. Section 4 describes the VAR methodology and presents estimation results. Section 5 concludes.

[2]See, among others, Demeterfi, Derman, Kamal, and Zou (1999), Britten-Jones and Neuberger (2000), Jiang and Tian (2005) and Carr and Wu (2008).

[3]Investors demand more compensation for risk when they perceive that the danger of big shocks to the state of economy is high (Bollerslev, Tauchen and Zhou (2009), Dreschler and Yaron (2009). Variance risk premium is shown to be procyclical, increasing in market downturns that are characterized by high volatility and high risk aversion (Bolllerslev et al. (2010), Bakshi and Madan (2006)). Thus, variance risk premium may constitute an appropriate state variable for the correlation analysis.

[4]See Kahnemann (1973) and Pashler (1998) for reviews of psychological research on this subject.

2 Variance Risk Premium and Realized Correlation Measures

The variance risk premium is the compensation for variance risk that stems from the randomness of return variances. It is defined as the difference between the conditional expectation of the future variance under physical and risk-neutral measures over the $[t, t+\Delta]$ time interval,

$$VRP_t = \mathrm{E}^{\mathbb{P}}(Var_{t,t+\Delta} \mid \mathcal{F}_t) - \mathrm{E}^{\mathbb{Q}}(Var_{t,t+\Delta} \mid \mathcal{F}_t) \tag{1}$$

where $\mathrm{E}^{\mathbb{P}}(\cdot)$ and $\mathrm{E}^{\mathbb{Q}}(\cdot)$ denote the time t expectation operator under the physical and risk-neutral measures respectively. These measures can not be directly observed in practice and have to be fairly approximated.

To start with, suppose that $(n+1)\Delta$ equidistant price observation are available over the Δ time interval and let $p_{i(\Delta/n)}$ denote the ith log-price observation. The realized variance, $\mathrm{RV}^n_{t,t+\Delta}$, is computed by summing the squared high-frequency returns over the $[t, t+\Delta]$ time-interval:

$$\mathrm{RV}^n_{t,t+\Delta} \equiv \sum_{i=1}^{n} \left[p_{t+i(\frac{\Delta}{n})} - p_{t+(i-1)(\frac{\Delta}{n})} \right]^2 \tag{2}$$

It follows then by the theory of quadratic variation, for increasingly finer sampling frequencies, or $n \to \infty$, the realized variance approximates arbitrarily the unobserved integrated variance, $\mathcal{V}_{t,t+\Delta}$.[5]

$$\lim_{n\to\infty} \mathcal{V}^n_{t,t+\Delta} \xrightarrow{a.s} \mathcal{V}_{t,t+\Delta} \equiv \int_t^{t+\Delta} V_s ds = \mathrm{Var}_{t,t+\Delta} \tag{3}$$

However, a host of microstructure effects (e.g. irregular trading, discreteness of prices, bid/ask bounce etc.)[6] prevents us from sampling the underlying returns too frequently. An intermediate sampling frequency, say five, ten, seventeen and a half or thirty minutes is employed in order to strike a reasonable balance between confounding market microstructure effects by sampling too frequently and misestimating the actual return variance when sampling too infrequently[7]. In this paper, I adopt five-minutes sampling frequency which is the most commonly used frequency in the literature.

The last term in equation 1, the risk-neutral expectation of the future variance can be computed using option prices. In the case that the underlying asset price is continuous, it can be expressed in a model-free fashion as a weighted average, or integral, of a continuum of a fixed d-maturity options[8].

[5]See, among others, Andersen and Bollerslev (1998), Comte and Renault (1998), Barndorff-Nielsen and Shephard (2002a, 2002b) and Andersen *et al.* (2001a, 2003).

[6]See, among others, Bai et al. (2001), Andreou and Ghysels (2002), Hansen and Lunde (2006) and Bandi and Russel(2005).

[7]See, for exemple, Barucci and Reno (2002), Ait-Sahalia et al. (2005), Andersen et al. (2003), Areal and Taylor (2002), Corsi et al. (2001), Bandi and Russell (2005), Bai et al. (2001), Andreou and Ghysels (2002), Bollen and Inder (2002) and Hansen and Lunde (2006).

[8]See, Demeterfi, Derman, Kamal, and Zou (1999) and Britten-Jones and Neuberger (2000). See also, Jiang and Tian (2005) and Carr and Wu (2007) for extensions to the case where the asset is a general jump-diffusion.

$$\mathrm{E}_t^{\mathbb{Q}}(Var_{t,t+\Delta}) = 2\int_0^{\infty} \frac{C(t+\Delta, K) - C(t,K)}{K^2} dK \tag{4}$$

where $C(t,K)$ denotes the price of a European call option maturing at time t with strike price K.

Methods used to construct a proxy for the physical expectation vary in practice. Carr and Wu (2008) use the ex-post forward realized variance defined in equation (2) to substitute for the expected return variance. Drechsler and Yaron (2008) use lagged implied and realized variances to forecast the expected variance. Todorov (2009) estimates the physical measure in a semi-parametric framework. Bollerslev et al. (2009) uses a multi-frequency auto-regression with multiple lags and Zhou (2010) uses a simple auto-regression with twelve lags to estimate the objective expectation of the return variance. Following Zhou (2010), I use twelve lags autoregressive estimate and, in order to construct a daily variance risk premium series, I applied this auto-regression for every day of a month.

Recently, Andersen et al. (2001b) and Barndorff-Nielsen and Shepard (2004a, 2004b) proposed new methods of estimating covariance and correlations between asset returns using intraday price observations. As mentioned earlier, these methods are fully non-parametric and model-free.

Consider a bivariate semimartingale log-price process (x^*, y^*). The quadratic covariation between x^* and y^* is defined as

$$[\mathrm{x}^*, \mathrm{y}^*](t) = p - \lim_{n\to\infty} \sum_{j=0}^{n} \{x^*(t_j) - x^*(t_{j-1})\}\{x^*(t_j) - x^*(t_{j-1})\} \tag{5}$$

for any sequence of partitions $t_0 < t_1 < \ldots < t_n$ with $\sup_j\{t_{j+1} - t_j\} \to 0$ for n $\to \infty$.

Under certain conditions defined in Barndorff-Nielsen and Shepard (2004b) the above expression gives the integrated covariance.

$$[\mathrm{x}^*, \mathrm{y}^*](t) = \int_0^t \Sigma_{x,y}(u)d(u) \tag{6}$$

where $\Sigma_{x,y}(u)d(u)$ denote the spot covariance between x and y. One can thus define the realized covariance estimator for day i as the sum of the cross-products of intraday returns, $x_{j,i}, y_{j,i}$, using five-minutes sampling frequency.

$$[\mathrm{x}^*, \mathrm{y}^*](i) \equiv \sum_{j=1}^{n} x_{j,i}y_{j,i} \tag{7}$$

Obviously, this covariance measure moves with the volatility of its components. It would be therefore trivial to analyse the behaviour of covariances in high volatility periods. Instead, one can use the correlation measure which is a standardized version of the covariance statistics.

$$\rho_{(xy),i} = \frac{\sum_{j=1}^{n} x_{j,i} y_{j,i}}{\sqrt{\sum_{j=1}^{n} x_{j,i}^2 y_{j,i}^2}} \tag{8}$$

3 Data and Summary Statistics

As mentioned above, the variance risk premium series that I employ as a proxy for the investors' perceived uncertainty is based on the risk-neutral and objective measures of future index variance. The variance risk premium estimated for the estimation period that spans from September 2002 through September 2006.

For the risk-neutral measure I used the the squared VCAC index that is directly available from the NYSE Euronext since January 2000. The VCAC index is based on the CAC40 index options covering the out-of-the-money strike prices for the near and next term maturities and constructed following the widely used VIX methodology of the Chicago Board of Options Exchange[9]. This model-free implied volatility is proved to be a better approximation to the risk-neutral expectation of the integrated volatility than the Black-Scholes implied volatility. This new measure has also a practical advantage: since the VCAC index is constructed for replicating the risk-neutral volatility of a fixed 30 days maturity, with monthly data there are no issues with telescoping option maturities.

The realized variance series on which the objective measure of future index variance is based are calculated summing the five-minute squared returns on the CAC40 index within one-month interval. Trading on the CAC40 starts at 9:00am and continues till 5:30pm. A typical month with 22 trading days has thus $22 \times 102 = 2246$ five-minute subintervals. The high frequency data for the CAC40 index is provided by the Euronext until the end of 2004. For the rest, NYSE Euronext provides only the tick-by-tick transaction prices for all securities. I employed a slightly modified version of the tick method of Dacorogna *et al.* (2001) to pick out the security prices at each intraday interval. These prices are then used to construct the CAC40 index values.[10]

In order to have a daily-standardized estimate of the variance risk premium, the monthly estimates of expected variances under risk-neutral and objective measures are divided by 22.

NYSE Euronext provides also the intraday transaction prices of individual assets with different capitalizations. Among 250 stocks, I have collected data concerning 48 stocks, 36 of which are classified as large

[9] This method is developed by Demeterfi *et al.* (1999).

[10] Begining from December 1st, 2003, index is calculated on the basis of the of the free-float capitalization instead of the market capitalization. The details for this new calculation method can be found on www.euronext.com. The list of the CAC40 index components as well as their number of shares and their free float and the capping factor which is taken into account in the calculation are periodically updated and published on the website.

stocks/blue chips and 12 are as mid and small caps[11]. These assets are also grouped in sectors following the first level ICB categorisation given in NYSE Euronext site. In the data set, there are 14 stocks in Consumer Services sector, 7 in Technology, 12 in Industrials and 15 in Consumer Goods sector. Table 1 reports selected stocks' names and symbols with their sectoral and capitalisation-based groupings. I constructed also an equiweighted portfolio of these 48 stocks and defined it as the market portfolio. Then, using equation (8) above, I calculated correlations between individual stocks and the market portfolio along with the correlations between the capitalisation-based portfolios and between the sectoral portfolios.

4 Estimation Strategy and Results

The empirical analysis focuses on the responses of both the market portfolio variance and the realized correlations to artificially generated shocks to investors' percieved uncertainty. To asses these responses, I first estimate a series of bivariate VAR's formulated as follows:

$$Y_t = C + \sum_{p=1}^{P} \Phi_p Y_{t-p} + \epsilon_t \tag{9}$$

where $\Phi_1, \Phi_2, \ldots, \Phi_p$ are matrices (2x2) containing the VAR parameters to be estimated, C is a (2x1) vector of model constants and ϵ_t is a vector of innovations. In this model, the variance-covariance matrix of the innovations, $\Omega = E(\epsilon_t \epsilon_t')$, can be a non-diagonal matrix reflecting the fact that the innovations be contemporaneously correlated. $Y_t, Y_{t-1}, \ldots Y_{t-p}$ are (2x1) vectors containing the variables used in estimations. For all of the estimations, the state variable, the variance risk premium constitutes the first element of these vectors. For each estimation, the VAR order, p, is determined depending on the Akaike Information Criterion. To ensure approximate normality for the VAR model I take the logarithm of variance risk premium and the market portfolio variance. For the realized correlations I take the following the Fisher-z transformation that transforms correlations to approximate normality.

$$Zcorr_{(xy)} = ln \frac{1 + \rho_{(xy)}}{1 - \rho_{(xy)}} \tag{10}$$

Once the stability condition is satisfied, the VAR model in equation (9) can be transformed in an infinite order moving average vector model.

$$Y_t = C + \sum_{j=0}^{\infty} \Psi_j \epsilon_{t-j} \tag{11}$$

[11]In order to ensure a reasonable degree of liquidity I selected assets with more than 3000 transaction observations by month.

where the (2x2) moving average coefficient matrices, Ψ_j obey the recursion $\Psi_j = \Phi_1 \Psi_{j-1} + \Phi_2 \Psi_{j-2} \ldots + \Phi_p \Psi_{j-p}$ with Ψ_0 an identity matrix.

When Ω is not diagonal, the fact that the innovations in the second elements of VAR's tend to move with the innovation generated in the variance risk premium series prevents us from isolating the effect of the latter. Given that Ω is positive definite, there exists a unique diagonal matrix D with positive values along the diagonal and a unique lower triangular matrix A such that $\Omega = ADA'$. One can then define a standardized shock process, $u_t = A^{-1}\epsilon_t$, which is diagonal resulting in the following alternate moving average representation:

$$Y_t = C + \sum_{j=0}^{\infty} \Psi_j A \epsilon_{t-j} \tag{12}$$

Depending on this representation, an orthogonalized impulse-response function is defined as the effect of ith component of a standardized shock process, $u_{i,t}$, on the process $Y_{j,t}$ at lag n.

$$\frac{\partial Y_{j,t+n}}{\partial u_{i,t}} = \{\Psi_j A\}_{ji} \tag{13}$$

where, the lower triangular matrix, A, which must be used to estimate the orthogonalized impulse-responses are calculated using Cholesky decomposition.

The estimation results are given in Table 2. The first row of the table reports responses of the logarithm of the market portfolio's return variance (LMPV) to a standardized shock to perceived market-wide uncertainty as proxied by the logarithm of the variance risk premium (LVRP). The response of LMPV on the day of the shock is 0.054 and is statistically significant. This can be considered as a trivial result when we refer to well documented effect of uncertainty resolution on price fluctuations[12]. Since the magnitude of uncertainty resolution determines the degree of asset fluctuations, a positive shock to perceived uncertainty will increase the market volatility.

Under efficient market hypothesis, a market-wide shock should cause immediate adjustment of the asset prices. That is, as the investors can resolve uncertainty instantaneously, the full impact of a shock to LVRP should be reflected in LMPV immediately after the shock is observed. In other words, under this hypothesis there should be no significant responses of LMPV after the day of the shock. Related results are at odds with this efficiency hypothesis: responses of LMPV are all positive and statistically significant in all the five days following the shock tending to decline in the last two days. This impulse-response trajectory is consistent with the hypothesis that investors have limited information-processing capacity. Investors can only resolve a

[12]See, for example, Epstein and Turnbull (1980), Veronesi (1999), Brennan and Xia (2001) that link uncertainty resolution process and price fluctuations via Bayesian updating of investors' prior beliefs upon new information

finite amount of uncertainty per day.

The other rows of the Table 2 show how this limit on information-processing capacity affects correlation structure in the market. Except for six stocks among forty-eight, a shock to LVRP increases the realized correlations between the individual stocks and the market portfolio in the day of the shock. Generally, this increase in realized correlations can be observed up to three subsequent days with very few statistically significant decreases thereafter up to five days. After a market-wide shock that increases the perceived uncertainty, investors allocate their attention to resolve the market-wide uncertainty which carries more weight in investors' portfolios (Peng (2005), Peng and Xiong (2006), Peng et al. (2007)) and the weight of the market-level uncertainty in the total variance of individual stocks increases. Moreover, since they can not resolve this uncertainty instantaneously because of their limited information-processing capacity, realized correlations between the individual stocks and the market portfolio remain high in the subsequent days. As a consequence, individual stocks tend to move more with the market portfolio, limiting the gains from diversification when investors are most in need of these gains i.e., during high volatility periods.

Results concerning the realized correlations between four sectoral portfolios and between two capitalization-based portfolios are given in the last seven rows of the Table 2. Realized correlations increase contemporaneously with the shock to LVRP and in the three or four subsequent days. The effect of the limit on information processing capacity gives rise to an increase in the realized correlations between assets irrespective of their sectoral or capitalization-based characteristics.

5 Conclusion

In this paper, I have analysed the effect of a shock to investors' perceived uncertainty, as proxied by the variance risk premium, on stock comovements in the French stock market. Variance risk premium measure is derived from CAC40 intraday index levels and index options prices. Daily variance, covariance and correlation measures are also computed basing on high-frequency trade data concerning 48 individual stocks of different sectors and capitalization levels. Then an equiweighted portfolio of these 48 stocks is constructed to define the market portfolio.

Orthogonalized impulse-responses show that a shock to variance risk premium causes long lasting increases in the market variance pointing to the limitedness of investors' information-processing capacity. As investors can not resolve the market-wide uncertainty instantaneously, the increases in market portfolio variance persist for several days following the shock. When the market-wide uncertainty increases, investors concentrate more heavily on resolving the uncertainty about the market factor at the expense of asset specific factors, as the market factor tends to carry more weight in investors' portfolios. In consequence, individual stocks tend to be more correlated with the market portfolio as shown in the paper.

The results allow us to propose the limitedness of investors' information-processing capacity as a possible cause of the increases in stock correlations during market downturns. This phenomenon of asymmetric correlations plays an important role during financial crisis limiting diversification opportunities when investors are most in need of the gains stemming from diversification.

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Table 1: List of Selected Stocks

Stock Name	Symbol	Sector	Compartment
TF1	TFI	Consumer Services	Blue Chips
CARREFOUR	CA	Consumer Services	Large Caps
VIVENDI	VIV	Consumer Services	Large Caps
AIR FRANCE-KLM	AF	Consumer Services	Large Caps
PUBLICIS GROUPE S.A.	PUB	Consumer Services	Large Caps
LAGARDERE S.C.A.	MMB	Consumer Services	Large Caps
CASINO GUICHARD	CO	Consumer Services	Large Caps
SODEXO	SW	Consumer Services	Large Caps
ACCOR	AC	Consumer Services	Large Caps
PPR	PP	Consumer Services	Large Caps
CLUB MEDITARENEE	CU	Consumer Services	Mid-Caps
CANAL +	AN	Consumer Services	Mid-Caps
HAVAS	HAV	Consumer Services	Mid-Caps
THOMSON	TMS	Consumer Services	Mid-Caps
ALCATEL-LUCENT	ALU	Technology	Large Caps
ATOS ORIGIN	ATO	Technology	Large Caps
CAP GEMINI	CAP	Technology	Large Caps
DASSAULT SYSTEMES	DSY	Technology	Large Caps
NEOPOST	NEO	Technology	Large Caps
STMICROELECTRONICS	STM	Technology	Large Caps
ALTEN	ATE	Technology	Mid-Caps
GFI INFORMATIQUE	GFI	Technology	Small Caps
SAFRAN	SAF	Industrials	Blue Chips
THALES	HO	Industrials	Blue Chips
ZODIAC AEROSPACE	ZC	Industrials	Blue Chips
BOUYGUES	EN	Industrials	Large Caps
LAFARGE	LG	Industrials	Large Caps
SAINT GOBAIN	SGO	Industrials	Large Caps
SCHNEIDER ELECTRIC	SU	Industrials	Large Caps
VALLOUREC	VK	Industrials	Large Caps
ALTRAN TECHN.	ALT	Industrials	Mid-Caps
CARBONNE LORRAINE	CRL	Industrials	Mid-Caps
INGENICO	ING	Industrials	Mid-Caps
HAULOTTE GROUPE	PIG	Industrials	Mid-Caps
UBISOFT ENTERTAIN	UBI	Consumer Goods	Blue Chips
REMY COINTREAU	RCO	Consumer Goods	Blue Chips
S.E.B	SK	Consumer Goods	Blue Chips
BIC	BB	Consumer Goods	Blue Chips
HERMES INTL	RMS	Consumer Goods	Large Caps
L'OREAL	OR	Consumer Goods	Large Caps
LVMH	MC	Consumer Goods	Large Caps
MICHELIN	ML	Consumer Goods	Large Caps
PERNOD RICARD	RI	Consumer Goods	Large Caps
PEUGEOT	UG	Consumer Goods	Large Caps
RENAULT	RNO	Consumer Goods	Large Caps
BENETEAU	BEN	Consumer Goods	Mid-Caps
FAURECIA	EO	Consumer Goods	Mid-Caps
VALEO	FR	Consumer Goods	Mid-Caps

Table 2: Orthogonalized Impulse Responses to Shocks in LVRP

Responding variables are given in the first column. LMPV in the first row indicates the logarithm of the market portfolio variance. Fisher-z transformed correlations of individual stocks with the market portfolio are indicated by the symbol of the relevant stock. The last seven rows concern the responses of Fisher-z transformed correlations between sectoral and capitalization-based portfolios. G, S, T and I represent Consumer Goods, Consumer Services, Technology and Industrial Sectors respectively. BL-MS is used to indicate the correlation between the portfolio of Blue Chips and Large Caps and the portfolio of Mid-Caps and Small Caps. Significance at the 10%, 5% and 1% levels is indicated by *, ** and *** respectively.

Variable	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5
LMPV	0.0544 ***	0.0478 ***	0.0538 ***	0.0518 ***	0.0365 ***	0.0229***
TFI	0.0147 ***	0.0055	0.0107	0.0156 *	-0.0096	-0.0029
CA	0.0490 ***	0.0202 **	0.0186 **	0.0187 **	0.0142	0.0093
VIV	0.0503 ***	0.0008	0.0277 ***	0.0262 ***	0.0061	-0.0092
AF	0.0260 ***	0.0069 ***	0.0059 **	0.0056 **	0.0054 **	0.0051 **
PUB	0.0213 ***	0.0113	0.0178 **	0.0158 *	-0.0080	0.0057
MMB	0.0179 ***	0.0131	0.0195 **	0.0165 *	0.0105	0.0160 *
CO	0.0175 ***	0.0189 **	0.0066	0.0180 **	0.0027	0.0026
SW	0.0066 ***	0.0106	0.0198 **	0.0099	0.0094	-0.0018
AC	0.0114 ***	0.0145	0.0083	0.0233 **	0.0099	0.0015
PP	0.0269 ***	0.0099	0.0231 **	0.0283 ***	0.0046	0.0047
CU	0.0072 ***	-0.0015	-0.0019	-0.0018	-0.0017	-0.0017
AN	-0.0090***	-0.0013	-0.0076	-0.0107	-0.0041	-0.0074
HAV	0.0160 ***	0.0013	0.0131 *	0.0052	-0.0158 **	-0.0044
TMS	0.0358 ***	0.0050	0.0233 **	0.0176 *	0.0137	-0.0031
ALU	0.0413 ***	0.0189 **	0.0302 ***	0.0256 ***	0.0242 **	-0.0032
ATO	0.0225 ***	0.0119 ***	0.0114 ***	0.0109 ***	0.0105 ***	0.0100 ***
CAP	0.0299 ***	0.0176 *	0.0120	0.0123	0.0158 *	-0.0116
DSY	0.0220 ***	-0.0111	0.0057	0.0156 *	0.0070 **	0.0048 **
NEO	0.0085 ***	-0.0006	-0.0009	-0.0009	-0.0008	-0.0008
STM	0.0426 ***	0.0284 ***	0.0524 ***	0.0320 ***	0.0133	-0.0207 **
ATE	0.0045 ***	0.0057 **	0.0056 **	0.0054 **	0.0051	0.0049 **
GFI	0.0065 ***	0.0107	0.0057	0.0153 *	0.0053 *	0.0053 *

Table : Table 2 (Continued) : Orthogonalized Impulse Responses to Shocks in LVRP

Variable	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5
SAF	0.0073 ***	-0.0012	0.0001	0.0094	0.0076 ***	0.0075 ***
HO	0.0142 ***	0.0087	0.0153 *	0.0208 **	-0.0058	-0.0029
ZC	0.0072 ***	0.0019	0.0028	0.0085	0.0051	0.0095
EN	0.0289 ***	-0.0020	0.0257***	0.0171 *	0.0120	-0.0085
LG	0.0290 ***	0.0191 **	0.0237 **	0.0167 *	0.0154	0.0059
SGO	0.0222 ***	0.0004	0.0184 *	0.0196 **	-0.0020	0.0062
SU	0.0285 ***	0.0167 *	0.0235 ***	0.0159 *	0.0042	-0.0112
VK	0.0206 ***	0.0144 *	0.0146 *	0.0145 *	0.0144	0.0143
ALT	0.0219 ***	0.0264 ***	0.0334 ***	0.0231 **	0.0234 **	-0.0046
CRL	-0.0067 ***	-0.0008	-0.0004	-0.0003	-0.0003	-0.0003
ING	0.00346 **	-0.0027	-0.0032	-0.0031	-0.0030	-0.0028
PIG	0.0033 **	0.0035	0.0034	0.0032	0.0031	0.0029
UBI	0.0096 ***	0.0016	0.0008	0.0007	0.0007	0.0006
RCO	-0.0023	0.0115	-0.0029	-0.0054	-0.0097	-0.0202 ***
SK	-0.0042 ***	-0.0002	-0.0001	-0.0001	-0.0001	-0.0001
BB	-0.0076 ***	-0.0061	-0.0115	-0.0136 *	-0.0004	-0.0025
RMS	0.0044 ***	0.0026	0.0024	0.0022	0.0021	0.0021
OR	0.0122 ***	0.0203 **	0.0338 ***	0.0392 ***	0.0020	0.0034
MC	0.0219 ***	0.0170 *	0.0350 ***	0.0285 ***	0.0102	-0.0023
ML	0.0199 ***	-0.0016	0.0209 **	0.0267 ***	-0.0006	-0.0021
RI	0.0147 ***	-0.0052	-0.0010	0.0075 ***	0.0052 *	0.0062 **
UG	0.0272 ***	0.0046	0.0370 ***	0.0267 ***	-0.0026	-0.0118
RNO	0.0246 ***	0.0104	0.0321 ***	0.0269 ***	0.0082	-0.0085
BEN	0.0135 ***	0.0125 *	0.0115	0.0027	0.0017	0.0009
EO	-0.0125 ***	-0.0020	-0.0010	-0.0009	-0.0008	-0.0008
FR	0.0174 ***	-0.0041	0.0155 ***	0.0013	0.0018	0.0022
G-S	0.0417 ***	0.0236 **	0.0303 ***	0.0313 ***	0.0030	0.0030
G-T	0.0400 ***	0.0009	0.0313 ***	0.0332 ***	0.0265 ***	-0.0121
G-I	0.0366 ***	0.0071	0.0236 **	0.0274 ***	0.0031	-0.0083
S-T	0.0509 ***	0.0238 **	0.0323 ***	0.0379 ***	0.0203 **	-0.0032 *
S-I	0.0399 ***	0.0224 **	0.0421 ***	0.0297 ***	0.0196 *	-0.0016
T-I	0.0320 ***	0.0214 **	0.0204 **	0.0328 ***	0.0141	-0.0000
BL-MS	0.0411 ***	0.0162 *	0.0337 ***	0.0313 ***	-0.0018	0.0070