Analysis of Volatility transmission across South African Financial Markets

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Abstract

This paper analyses volatility transmission across four South African financial markets, using daily data for the period 2000-2009. These are the stock, bond, money and foreign exchange markets. The paper applies the TARCH procedure to the returns from the South African financial markets in order to estimate the cross-market volatility transmission. Results show that volatility transmission exists in South African financial markets on a weak form, with each market explaining its own volatility. The paper found transmission between stocks market and foreign exchange, and between foreign exchange and bond markets.

Key Words: GARCH; TARCH; EGARCH–in mean; Vector Autoregressive; Volatility transmission; financial markets.

JEL Classification: C5, C58, G1, G12

1. Introduction

Developments in financial markets have led to a growing interest in studying and analyzing volatility transmissions in financial markets, for example, Fleming *et al.* (1997), stated that portfolio managers transfer funds from stocks into bonds when they expect stock market volatility to increase. The risk reduction gained from funds transfer from one market to another, when market volatility is expected to increase, depends on the volatility linkages between the financial markets. Common market volatility arises from investor uncertainty induced from the initial shock event to the return of an asset.

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Volatility transmission is also important for derivatives dealers, because when a dealer's business cross more than one market, net volatility exposure depends on the cross-market correlations of volatility changes. Volatility linkages assist in setting regulatory policy, by influencing investment and risk management decisions. Fleming *et al*. (1997) gave examples of banking regulators, like risk managers, need to understand the nature of volatility linkages in order to appropriately assess capital adequacy.

Volatility transmission is important for determining monetary policy efficiency and in addressing financial stability issues. The extent to which volatility is transmitted across markets could result in a large shock in one market destabilizing another market. It also helps policy-makers to estimate the depth and duration of cross-market impact and common market shocks, which assists in the implementation of timely and effective monetary policy. And for financial stability interest, can be useful in determining different market price interrelationships, where the complexities signify a potential source of systemic financial instability (Hurditt, 2004).

A useful explanation on importance of volatility spillovers was indicated by Chinzara and Aziakpono (2008) through the statement that South African policy-makers have accepted linkages and volatility transmission in financial markets as an important factor behind macroeconomic policy implementation. The South African financial markets are of interest, because of their fast emerging and integration with the global financial international markets. South African financial markets resisted the 2008 global financial crisis impacts to an extent due to her regulations, liberalization system and process restriction difference, in relation to other foreign markets.

The intuition behind hedging as market linkages is basic; an example of volatility between markets is that of a trader operating in both the stock and bond markets, where information occurrence influencing expectations about stock returns directly affects stocks demand. This event may also affect his demand for bonds even if it does not alter his expectations about interest rates, because the trader considers the correlation between stock and bond returns when he rebalances his portfolio, with the same influence and process between the other markets. The trader therefore, takes a position in bonds to hedge his speculative position in stocks. Because the information event changes his demand for both stocks and bonds, an information spillover occurs, generating trading and volatility in both markets (Brooks, 2008:383).

Volatility plays an important role in finance, and several studies, including South African financial markets, have been done on how information flows across financial markets, including modelling and forecasting markets volatility. Studies on bond and stocks markets volatility and information flow have contributed to important findings, ideas achieved and changes occurring in the financial systems, with likely future occurrence. Volatility can be used for various means, for example, how a central bank adjusts interest rates and reduce exchange rate volatility, understand how an unexpected interest rate change could affect the conditional variance of the exchange rate (Brooks, 2008: 383). It can be applied to determine whether financial markets are efficient, and for determining returns and volatility in a market, or between different markets.

While most studies on volatility in South Africa and other foreign markets have mainly focused on returns linkages, information flow and volatility transmission of financial markets between countries for not more than three markets, this paper differs in that it considers four major markets in SA. Time series models provide an estimate of the variance of the relevant return series based on historical return data that are used to create volatility forecasts (Corredor and Santamaria, 2004). Like most other papers, high frequency daily data is used, with a period of 2000/01/03 to 2009/08/05 because, this period covers times when South Africa experienced series of interest rate cut and changes, surprises of political and news announcement such as the stepping down of the finance minister Trevor Manuel and most importantly, includes a time of global financial crisis and recession, having an implication on South Africa's integration in to the world economies. Specifically used daily data because of the assumption that the markets react quickly to news, accordingly, therefore low frequency would fail to capture such dynamics. The study focuses on the stock, bond, money and foreign exchange markets because they comprise and contribute largely to financial and development status of a country.

The objective of the paper is to analyse the volatility transmission between the stock market, foreign exchange market, money market and bond market within South Africa. Information transmission between financial markets has several ideas, innovation and implications for economic policy-makers. The South African bond, money, foreign exchange and stock markets volatilities are estimated and analyzed using GARCH, TARCH and EGARCH models because most authors in this field apply this econometric method and is assumed to be the best process for estimation, the best model among the three is then used to estimate the market volatility.

The remainder of the article is organized as follows. Section 2 provides the review of related theoretical and empirical literature. Section 3 describes the econometric methodology. Section 4 describes the data used, the model framework, namely GARCH, TARCH and EGARCH. The results are presented and discussed in Section 5 and concluded in Section 6.

2. Literature review

Various studies have indicated and concluded common occurrence of financial markets volatility transmission. Ebrahim (2004) indicated volatility spillovers from Eurocurrency to foreign exchange markets as small, showing volatility in the Euro Canada market to be more prone to exchange rate shocks than Euromark and Euroyen volatilities in relevant models, through satisfying evidence of price and volatility spillovers in the three models used. Ebrahim (2004) examined volatility transmission between the foreign exchange and money markets using trivariate generalized autoregressive conditional heteroscedasticity (GARCH) models for price and volatility spillovers between the markets. He estimated the models using data on U.S. dollar/ Canadian dollar (USD/CAD), U.S. dollar/Deutsche mark (USD/DEM), and U.S. dollar/Japanese yen (USD/JPY) daily exchange rate returns together with returns on 90-day Eurodollar, Euro Canada, Euromark, and Euroyen deposits between 4 January 1988 and 31 December 1998. Ebrahim (2004) studied the information transmission across the markets' different asset classes, instead of news flow between the markets in each asset class, and examined whether there are price and volatility spillovers between each exchange rate return and the two related Eurocurrency money market returns. Returns in the three markets were modelled without restricting constant correlations between markets and permitted time-varying.

Volatility spillovers is established as asymmetric, in that, bad news in one market raises the volatility in another market more than does good news, implying that the common factors between markets are small, with investors in one market processing information from other markets steadily, or that spillovers result from market impacts. The three models obtained suggested that shocks from Eurocurrency markets have small quantitative effects on foreign exchange markets. In relation to policy implementation Ebrahim (2004) adviced the Bank of Canada to take policy actions that follows a large exchange rate shock in order to moderate higher money market volatility.

Ebrahim (2004) used a trivariate GARCH model, where the conditional covariance matrix followed the positive-definite parameterization of Baba, Engle, Kraft, and Kroner (BEKK). The conditional covariance matrix dynamics was explained by a trivariate GARCH (1, 1) process using the positive-definite parameterization of Baba, Engle, Kraft, and Kroner (BEKK) of Engle and Kroner (1995). This allows past shocks from other markets to influence conditional variances and covariances, like asymmetries shocks impact and for seasonal and holiday effects.

A paper by Yang and Doong, (2004) adopted a bivariate EGARCH framework and investigated the dynamic price and volatility spillovers between stock prices and exchange rates for the G-7 countries. The framework can help not only to understand the short-run movements but also to investigate the volatility transmission mechanism between the two markets the dynamic price and volatility spillovers between stock prices and exchange rates for the G-7 countries.
The data set consists of weekly (Friday) closing exchange rates and stock market indices for the G-7 countries. The sample period runs from 01/05/1979 to 01/01/1999, yielding 1045 observations.

Since the returns of the two markets exhibit very strong ARCH effects, the authors modelled the conditional variances of and volatility spillovers between the two markets through a multivariate version of Exponential GARCH (EGARCH) model. The results from the multivariate EGARCH Model were such that, for the first moment interdependencies, there were significant price spillovers from foreign exchange to the stock market for Canada and Japan. Currency depreciation (appreciation) often drags down (up) stock prices for Canada and Japan. In the long run for an economy with a significant import (export) sector, the unfavourable effects of currency depreciation (appreciation) on imports (exports) may induce a bearish stock market. However, in the short run, currency depreciation may have a negative effect on the stock market because the domestic counterpart of currency depreciation is inflation, which may exert a dampening effect on the stock market. Turning to the second moment interdependencies, the paper concluded that there exists volatility spillover from the stock to foreign exchange markets for France, Italy, Japan, and the US. And no volatility spillover was found from the foreign exchange to the stock markets at all.

To model the short-run dynamic relationships between stock prices and exchange rates, authors adapted the following Vector Autoregressive (VAR) model, where, $\beta_{i,0}$, $\beta_{ij,t-1}$, and $\beta_{ij,t-2}$ are parameters to be estimated and ε*i*,*t* is the residual.

$$R_{i,t} = \beta_{i,0} + \sum_{j=1}^{2} \beta_{ij,t-1} R_{j,t-1} + \sum_{j=1}^{2} \beta_{ij,t-2} R_{j,t-2} + \varepsilon_{i,t} \quad \text{for } i, j = 1, 2.$$

Volatility is also important for a variety of investment and management decisions. Fleming, *et al* (1997) estimated a stochastic volatility of the trading model with GMM and their results showed that specification explained most of the data's properties, producing strong volatility linkages between the three markets. Examined the volatility linkages in the stock, bond, and money markets, and extended the speculative trading model to predict strong volatility linkages in the markets, through common information obtained and expected impacts across markets, and information spillover caused by cross-market hedging.

Fleming *et al.* (1997) anticipated common information and information spillover to play an important role. The trading model examines the degree of information spillover in that, information spillover is complete in frictionless markets, making volatility changes across markets perfectly correlated, which deteriorates when transactions costs, institutional constraints, and other practical considerations are accounted for, reducing cross-market hedging impact. Fleming *et al.* (1997) extended the stochastic volatility model, in relation to other authors' work, and assumed that log volatility follows an AR(1) process, generated restrictions on the unconditional moments of daily returns, and used Hansen's (1982) generalized method of moments (GMM) to apply restrictions and directly estimate the contemporaneous correlation between log information flows in different markets. Analyzed using daily data returns on the S&P 500 stock index futures, T-bond futures, and T-bill futures for the period January 1983 to August 1995. They estimated univariate specifications of the empirical model for each three contracts to illustrate model accuracy of the markets' time-series returns behavior. The models' bivariate specifications were estimated as to measure the correlations between the log information flows.

The correlation estimated 69% for the stock and bond markets, 67% for the stock and money markets, and 64% for the bond and money markets, which showed strong linkages between these markets, but rejected the hypothesis that correlations are perfect, and implying that the markets do not share the same information flow. Fleming *et al.* (1997) concluded that information spillover resulting from cross-market hedging is incomplete, and that strong volatility linkages are important characteristics of the stock, bond, and money markets. Determined the daily returns for each market as the log of price relatives, using closing prices for the nearest-to-maturity contract. They generated a continuous series of returns by switching to a new contract when nearby contract approaches maturity. Computed a series of specification tests similar to GARCH models, to show that AR (1) model of volatility method describes much of the skewness, excess kurtosis, and inter temporal dependence apparent in the raw returns.

Hurditt (2004) studied volatility transmission across Jamaican financial markets. The paper followed Fleming *et al.* (1996)'s work on asset returns volatilities and method. Hurditt (2004) applied multivariate GARCH method to returns obtained from Jamaican bond, foreign exchange and stock markets. The empirical model was used to estimate coefficients showing common market impact and cross-market volatility spillovers. The market liquidity changes, in terms of bond maturities were considered when computing volatility spillovers. The paper applied GARCH-BEKK procedure, to measure the impact of Jamaica Dollar liquidity on the asset returns volatility linkages. Used modeled variance series as inputs in a simple vector autoregressive (VAR) model to produce ten-day volatility impulse responses, to indicate a market asset return variance level and its impact on lagged variances from returns in the same market and the other two markets.

Hurditt (2004) assumed an economy with various active speculators, trading with each other due to difference in anticipated future outcomes, and risks transfer through market transactions. At the start of a trading round, all the financial markets are in equilibrium. Trivariate representation of the BEKK model was applied to examine volatilities and pair-wise volatility linkages between the Jamaican markets, using daily data frequency of the main Jamaica Stock Exchange (JSE) Index, the 30-day private repurchase agreement rates and the weighted average selling exchange rate to compute the continuously compounded market returns. Specifically, used 30-day private interest rate on bonds traded in Jamaica's money market. Money market covering a broad cross-section of public and private securities of various maturities, selected on the basis of continuity in the series and its consistency in reflecting the rates on public money and bond market securities, bank lending rates and other private rates. He used equivalent yield transformation to determine interest rates, which were then converted to a daily series.

In order to avoid the unrealistic assumptions on the variance-covariance matrix and to avoid non-positive variance-covariance matrix certainty, applied Engle and Kroner (1995)'s proposed BEKK model -named after Baba, Engle, Kraft, and Kroner (1991) and concluded that there is presence of high levels of common market returns volatility relative to cross-market spillovers, within the Jamaican financial system. Foreign exchange market displayed the most distinct common market volatility spillovers, followed by the stock market, and having strong common market spillover, relative to the bond market indicates uncertainty force, as a usual feature of risky markets. He also concluded that cross-market spillover effects, due to changes in the liquidity conditions have smaller influence on spillovers to the bond market than for the foreign exchange and the stock markets. Changes in liquidity have no significant impact on volatility spillover durations, implying that monetary policy is successful in controlling volatility impulse impact within and between liquid markets.

A study by Gonzalez *et al*. (2003) examined whether, given domestic turbulence and international shocks, the Mexican stock market becomes more volatile in the 1990s. The study also examines the extent to which volatility change can be associated with underlying processes as opposed to irregular events and the nature of the relation between market liberalization and volatility.The data consist of the weekly equity returns of the Mexican Stock Exchange for the period from 15 November 1991 through 28 July 2000. A total of 455 observations were obtained. Considering the methodology of the paper Mexican equity returns are examined to determine if market volatility changed during the decade of the 1990s.

The following GARCH (1, 1) model was estimated for peso denominated weekly returns for the Mexican equity market:

$$R_t = \mu + e_t$$

$$e_t \sim N(0, h_t)$$

$$h_t = \alpha + \beta\varepsilon_{t-1}^2 + \theta h_{t-1}$$

Where Rt is the equity return for week t, *M is* the expected return, e_t is the error for period t, and N is the conditional normal density with mean zero and a variance of ht. A statistically significant β coefficient indicates significant heteroscedasticity among the errors. If the β is positive, volatility among the returns is increasing over time. A negative β coefficient indicates decreasing volatility.A preliminary review of the data concludes that there has been increased volatility in this market as the Mexican economy has become more integrated into the world economy.

3. Methodology and data analysis (theoretical model, empirical model)

The following indices were used for the selected stock, money, bond and foreign exchange markets: FTSE/JSE All Share index, SA (South African) t-bill 91 days (tender rates), SA govt average, Bond yield of 10+ yrs, MSCI ZAR to 1 USD. The choice of these indices is motivated by the fact that they are the best representative indices for the selected markets. All the indices were obtained from the Thompson DataStream. Daily returns are computed from each market index by forming log differences of the data.

$$r_t = 100\% \times \ln\left(\frac{p_t}{p_{t-1}}\right)$$

Where: r_t denotes the continuously compounded return at time t, P_t is the asset price at the current time t, P_{t-1} is asset price at the previous day time t and ln denotes the natural logarithm. In order to understand the returns and volatility co-movement, it is important to analyze the market dynamics and transmission mechanisms driving these markets. A model that clearly shows how returns and volatility are transmitted from one market to another in a recognized fashion, as well as ensuring that multilateral interactions are simultaneously analyzed.

Using a combination of graphical and trend analysis as well as more formal estimation techniques, the study examined volatility in the stock, money, bond and foreign exchange markets. To obtain estimates of market volatility, the study experimented with various volatility models that include the GARCH, TARCH and EGARCH. An analysis of volatility interactions and the transmission of volatility shocks across the market are crucial to understanding financial instability. The long term trend of volatility is also examined. Volatility linkages are then analyzed using the VAR, block exogeneity, impulse response and variance decomposition.

3.1 *Determining the appropriate GARCH model*

The mean equation was estimated and tested for autocorrelation for each of the stock market. No evidence of significant autocorrelation was found in the mean equation. Consequently, we estimated the GARCH models based on these mean equations. The univariate GARCH (1, 1), EGARCH (1, 1, 1) and TARCH (1, 1, 1) models were estimated and in the interest of space we only reported results for the model which was found to be the most appropriate (TARCH model) and The results are reported in Table 1 below:

Table 1

	GARCH(1,1)				**EGARCH**				**TARCH**			
PARAMETER	**TBR**	**GBY**	**EXR**	**JSE**	**TBR**	**GBY**	**EXR**	**JSE**	**TBR**	**GBY**	**EXR**	**JSE**
δ	N/A	N/A	-0.118^{b}	N/A	N/A	N/A	122^{b}	N/A	N/A	N/A	0.105^{c}	N/A
ω	0.154	0.000^{c}	0.008^{a}	0.029^{a}	-1.460^{b}	-0.131^{a}	0.106^{a}	0.058^{a}	0.113^{a}	0.000	0.008^{a}	0.029^{a}
α	-0.002	0.357^{a}	0.068^{a}	0.096^{a}	-0.170	0.232^{a}	0.140^{a}	0.132^{a}	-0.004^{a}	0.071^{a}	0.078^{a}	0.022^{b}
β	0.017	0.795^{a}	0.929^{a}	0.889^{a}	0.562^{a}	1.003^{a}	0.987^{a}	0.983^{a}	0.828^{a}	0.842^{a}	0.831^{a}	0.902^{a}
α+β	0.015	1.152	0.997	0.985	0.391	1.235	1.128	1.115	0.824	0.913	0.909	0.924
γ	N/A	N/A	N/A	N/A	0.085	0.228^{a}	0.029^{a}	-0.085^{a}	-0.005^{a}	0.027	0.025^{c}	0.115^{a}
F-LM	0.002	0.000	3.527^{c}	0.999	2.604	0.000	3.960^{b}	0.179	0.033	0.000	2.310	0.680
SIC	-1.386	1.427	2.795	3.170	-3.339	1.728	2.795	3.157	2.262	1.543	2.797	3.156
AIC	-1.400	1.410	2.778	3.156	3.356	1.709	2.776	3.137	2.248	1.524	2.775	3.136

Note: $^{a, b, c}$ *implies the coefficient is significant at 1%, 5% and 10% respectively.*
δ - *GARCH-in-mean coefficient.*
ω - *The constant term for the various GARCH models.*
α – *The coefficient of the squared residual term.*
β – *Variance squared coefficient*
α+β - *Condition for stationarity of the GARCH model*
γ – *Leverage/asymmetric coefficient*

For the exchange rate market in all models, the *arch–in mean* coefficient (δ) was statistically significant implying that for all the stock markets, there is significant risk premium in returns. This is in contrast with the behavioural finance suggestion that riskier foreign exchange markets are more rewarding than less risky ones.

In selecting our appropriate model to model volatility, we test for arch effect. Although the presence of arch effect in the data does not indicate standard interference, ignoring it may result in loss of efficiency (Eviews 6, 2008). When testing for arch effect we look at whether it eliminates the excess volatility. If F-stats and observed R-squared are significant it shows that there is no arch effect (excess volatility has been eliminated). Considering the table of results above the TARCH model eliminates the arch effect for all markets unlike the GARCH model were the arch effect is not eliminated in the exchange rate market, and for EGARCH where the arch effect is not eliminated in the exchange rate market also. So as a result TARCH will be the best model because it eliminates excess volatility in the markets.

In selecting the best model, we also considered the stationarily condition (i.e. $\alpha + \beta < 1$), the ability of a model to best capture ARCH effect. For the GARCH model the condition is satisfied for three markets but ($\alpha + \beta > 1$) which makes the model not good enough. Considering the EGARCH model ($\alpha + \beta > 1$), for the other 3 markets and only satisfy the condition for the money market which again makes it good enough to estimate volatility transmission. The TARCH model tends to be the best ($\alpha + \beta < 1$) as required. Taking a look at the information criteria (SIC and AIC), the TARCH model also is the best since the values are smaller as compared to the values of other models.

Using the above mentioned criteria TARCH model was considered to be the best and as a result was used in the study for the estimation of the volatility transmission across South African financial markets.

4. The data

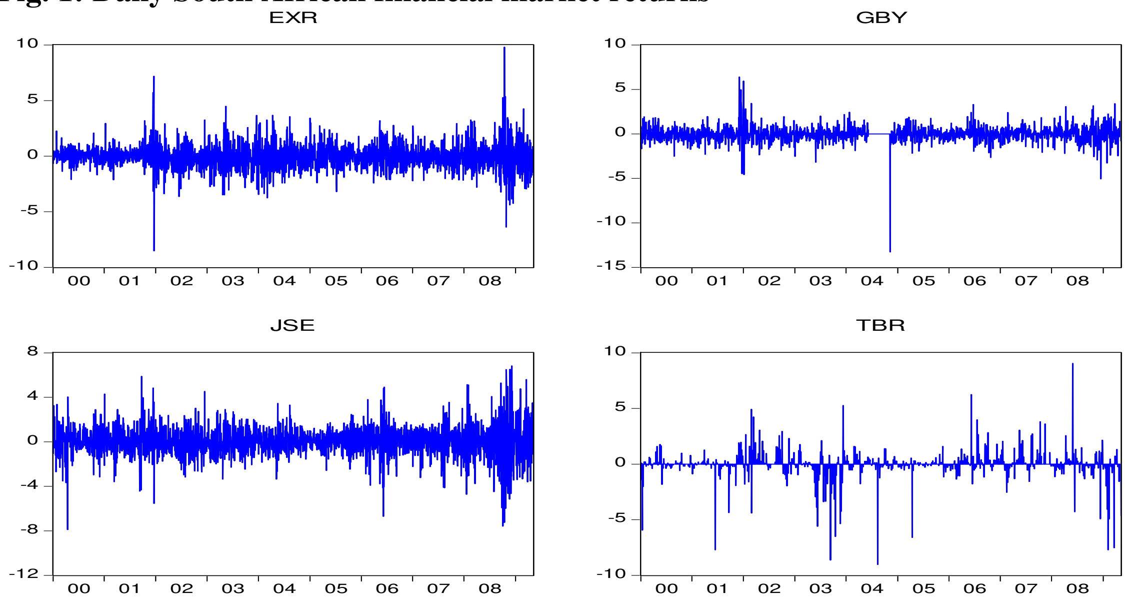
As proxies for the stock, bond, foreign exchange and money markets, we used the FTSE/JSE all share, SA govt. average. Bond yield: 10+ yrs, MSCI ZAR to 1 USD and the SA T-bill 91 days (tender rates). Our data consists of daily closing prices for each contract, obtained from Thompson DataStream, for the period 3 January 2000 to 7 May 2009. Daily data is preferred to low frequency data as it captures the dynamic interactions that occur within a day, a property that cannot be captured by low frequency data. Financial markets in general, and the stock market in particular, react promptly as soon as new information becomes available that is reaction can even be within hours, minutes or seconds. Thus, lower frequency data distorts such reactions. To maintain a uniform measurement interval across markets, we exclude days when any of the four markets are closed meaning that weekends were not included in this study and also a holiday in the associated money markets results in that day being excluded from the creation of the series. We compute the daily returns for each market as the log of price relatives. This procedure yields 2439 return observations for each market. Daily returns are computed from stock, bond, foreign exchange and money market price series by forming log difference of the data. In the case of stock market series, for example the daily return, r_t, is given by :

$$r_t = 100\% \times \ln\left(\frac{p_t}{p_{t-1}}\right)$$

Where P_t and P_{t-1} and represent previous and current prices respectively.

Figure 1 shows the graphs showing the trends of the spread of the four stock markets over a period of 10 years. The same data used to compute the graphs was used to estimate the volatility transmission across financial markets in South Africa.

Fig. 1: Daily South African financial market returns



5. Analysis of empirical results

To investigate the volatility transmission between financial markets we used a VAR model. Before estimating a VAR model we determined the lag length and we did this by using (Eviews 6 manual, 2008) to autocorrelation using the autocorrelation LM test. We started the estimation with a VAR lag length of 2 and the LM stat was found to be insignificant meaning that we fail to reject the null hypothesis (No serial correlation) and conclude that there was no autocorrelation and as a result we estimated the VAR model using 2 lags. Below are the results from the autocorrelation LM test which showed insignificance at lag 2:

Table 2: Autocorrelation LM test

Lags	LM-Stat	Prob
1	16.25785	0.4351
2	16.76656	0.4009

Probs from chi-square with 16 df.

Considering 2 as the lag order the volatility transmission VAR model run and below are the observed results:

Table 3: Vector autocorrelation test

Vector autocorrelation estimates

	VOL_EXR	VOL_GBY	VOL_JSE	VOL_TBR
VOL_EXR(-1)	1.133647	0.140727	0.026386	-0.004432
	(0.02046)	(0.08329)	(0.03817)	(0.00262)
	[55.4171]	[1.68957]	[0.69131]	[-1.69026]
VOL_EXR(-2)	-0.164148	-0.054444	-0.021705	0.003957
	(0.02032)	(0.08275)	(0.03792)	(0.00261)
	[-8.07705]	[-0.65796]	[-0.57242]	[1.51887]
VOL_GBY(-1)	-0.002619	0.907013	0.000526	-0.000190
	(0.00499)	(0.02031)	(0.00931)	(0.00064)
	[-0.52517]	[44.6658]	[0.05657]	[-0.29644]
VOL_GBY(-2)	0.006124	-0.038740	-0.001703	0.000321
	(0.00498)	(0.02030)	(0.00930)	(0.00064)
	[1.22849]	[-1.90879]	[-0.18307]	[0.50254]
VOL_JSE(-1)	0.057607	0.044205	0.900693	-0.001938
	(0.01114)	(0.04536)	(0.02078)	(0.00143)
	[5.17127]	[0.97460]	[43.3340]	[-1.35690]
VOL_JSE(-2)	-0.043138	-0.063994	0.073925	0.001965
	(0.01120)	(0.04559)	(0.02089)	(0.00144)
	[-3.85224]	[-1.40355]	[3.53816]	[1.36859]
VOL_TBR(-1)	0.044121	0.022677	0.211028	0.820923
	(0.15820)	(0.64415)	(0.29518)	(0.02028)
	[0.27888]	[0.03521]	[0.71491]	[40.4799]
VOL_TBR(-2)	-0.056452	-0.029542	-0.101708	0.013784
	(0.15680)	(0.63843)	(0.29256)	(0.02010)
	[-0.36003]	[-0.04627]	[-0.34765]	[0.68577]
C	0.018584	0.055420	-0.028306	0.105829
	(0.05763)	(0.23465)	(0.10753)	(0.00739)
	[0.32247]	[0.23618]	[-0.26324]	[14.3255]
R-squared	0.973578	0.796090	0.950645	0.703315
Adj. R-squared	0.973491	0.795418	0.950482	0.702337

Vector autocorrelations allows the value of a variable to depend on more than just its own lags or combination of white noise terms (Brooks, 2008). In this case vector autocorrelation is estimated in order to examine whether there are lead-lag relationships between the financial markets. Given that the t-stats are in [ ] and the standard errors in ( ), it is observed that the volatility of exchange rate of the previous day is significant at 5% meaning that the exchange rate volatility of the previous day has an effect on the exchange rate volatility. The exchange rate volatility 2 days before has an effect also since it's significant at 5%. GBY volatility is said to have no effect on exchange rate volatility since the t-stats are insignificant for both lags. JSE volatility on the other hand is significant at 5% for both lags meaning that it affects the EXR volatility. VOL_TBR has no effect because it is insignificant at 5% and 10% for both lags.

Considering VOL_GBY only VOL_GBY and VOL_JSE are significant meaning they have an effect on GBY volatility. For VOL_JSE the volatilities for all other markets besides the JSE are insignificant, that is they do not have an effect on JSE volatility. Lastly for VOL_TBR all the other markets besides VOL_TBR are insignificant at 5% level meaning the volatility of other markets does not affect the TBR volatility. Overall, from the above observations it can be concluded that there is no volatility transmission between financial markets. It can also be concluded that volatility transmission is high within the same market, for example, the effect of VOL_JSE on VOL_JSE.

Using the same lag order of 2, block exogeneity, impulse response and variance decomposition were estimated to examine the volatility transmission between SA financial markets. The results for the block exogeneity, impulse responses and variance decomposition are reported in Table 4, Figure 3 in appendix and Table 5 respectively. The block exogeneity test attempts to separate the set of variables that have significant impacts on each of the dependent variables from those that do not. The block exogeneity test follows an F-distribution (Brooks, 2002:339), and is analogous to testing for Granger causality.

Table 4: Block exogeneity test

VAR Granger Causality/Block Exogeneity Tests

	dependent variables			
excluded variables	**VOL_EXR**	**VOL_GBY**	**VOL_JSE**	**VOL_TBR**
VOL_EXR		22.029[0.00]	0.679[0.71]	3.178[0.20]
VOL_GBY	2.771 [0.25]		0.078[0.96]	0.338[0.84]
VOL_JSE	42.042[0.00]	3.692[0.16]		1.898[0.39]
VOL_TBR	0.131 [0.94]	0.002[0.10]	0.727[0.70]	

As shown in the table, except for the volatility of the JSE, the other markets insignificantly influence exchange rate volatility at 1% level. In other words, only the JSE volatility has an effect to EXR as compared to other markets. Considering VOL_GBY only exchange rate volatility is significant meaning that the other markets have no effect to the volatility of GBY. For the volatility of the JSE all the 3 markets are insignificant at 1% meaning that they do not have an effect at all to the volatility of the stock exchange. Furthermore, looking at the volatility of TBR as the dependant variable it is observed that all the markets are insignificant at 1% level meaning they also don't have an effect to the volatility of TBR. On the other hand, VOL_GBY and VOL_TBR are the most endogenous variables since they do not significantly influence any of the financial markets volatilities.

The impulse response function was estimated using the Cholesky approach and the results are reported in Figure 2. This traces out the responsiveness of a dependent variable to shocks to each of the other variables in the VAR framework. Variance decompositions show the proportion of the movements in the explained stock market that are due to its 'own' innovations, against those from other markets. In this case we only reported the variance decomposition results for 1, 5, 10 steps ahead. The main focus is to examine which of the market volatilities mostly influence SA financial markets volatilities.

Table 5: Variance decomposition for volatility

variance decomposition of VOL_EXR				
period	VOL_EXR	VOL_GBY	VOL_JSE	VOL_TBR
1	100.0000	0.0000	0.0000	0.0000
5	98.6061	0.0265	1.3660	0.0013
10	96.8092	0.1781	3.0119	0.0008

variance decomposition of VOL_GBY				
period	VOL_EXR	VOL_GBY	VOL_JSE	VOL_TBR
1	0.2563	99.7437	0.0000	0.0000
5	1.3880	98.5961	0.0159	0.0000
10	3.1027	96.8733	0.0239	0.0001

variance decomposition of VOL_JSE				
period	VOL_EXR	VOL_GBY	VOL_JSE	VOL_TBR
1	5.6139	0.0002	94.3859	0.0000
5	6.3010	0.0009	93.6592	0.0389
10	6.5857	0.0045	93.3300	0.0799

variance decomposition of VOL_TBR				
period	VOL_EXR	VOL_GBY	VOL_JSE	VOL_TBR
1	0.0176	0.0134	0.0021	99.9670
5	0.1531	0.0164	0.0550	99.7755
10	0.2180	0.0204	0.0634	99.6982

As evident from Table 5, the volatility of exchange rate tends to explain most of the variation in the VOL_EXR (approximately 100%) considering one period, 98.6% for period 5 and 96.8 for period 10. This shows that a greater % of the variation in exchange rate volatility is explained by itself compared to that explained by the other 3 markets. Analysing the volatility for GBY it is also observed that approximately 99.7%, 98.6% and 96.9% for periods 1, 5 and 10 respectively of the variation in VOL_GBY is explained by itself compared to that explained by the other markets. The same for JSE, above 90% of variation is explained by itself at periods 1, 5 and 10 to that explained by other financial markets. Lastly, considering VOL_TBR approximately 99% of the variation in volatility is explained by itself compared to that explained by the other 3 markets.

The impulse response function was estimated using the Cholesky approach and the results are reported in Figure 2 which shows that the response of markets volatility to own is generally high and positive than to other financial markets. The response of VOL_EXR to own is high and positive as shown in the graph. The volatility of GBY to own is high and positive but tends to decrease slowly with time. Considering JSE, the response of VOL_JSE to own is high and always positive but decreases slowly after 2 days. Furthermore, the response of VOL_TBR to own is high and decreases getting closer to zero in ten days. The response of VOL_TBR to VOL_EXR and VOL_TBR to VOL_JSE tend to be very low and negative after 2days which approaches zero on the third day. Overall the VOL_EXR, VOL_TBR, VOL_JSE, VOL_GBY tend to respond insignificantly to the volatility of other markets as shown on the graphs. This gives evidence that there is volatility transmission within the same market, for example, VOL_EXR to VOL_EXR and there is no volatility transmission between volatilities of different financial markets.

Basing on results for the block exogeneity, impulse responses and variance decomposition reported above there is strong evidence that there is volatility transmission across South African financial markets. According to block exogeneity test (table 4) and variance decomposition (table 5), there is volatility transmission between foreign exchange (EXR) and stocks markets (JSE), between foreign exchange (EXR) and bond markets (TBR). The money markets showed no sign of volatility transmission.

6. Conclusion

This paper used the VAR and univariate GARCH models to investigate volatility transmission between the money, bond, stocks and foreign exchange markets. Three models are estimated for FTSE/JSE all share, SA govt. average. Bond yield: 10+ yrs, MSCI ZAR to 1 USD and the SA T-bill 91 days (tender rates) market returns in order to determine whether volatility transmission exist between the markets. The long term trend of volatility is also examined. Volatility linkages are then analyzed using the VAR, block exogeneity, impulse response and variance decomposition. The results show that there is weak volatility transmission across South African financial markets.

According to block exogeneity test and variance decomposition, there is volatility transmission between foreign exchange (EXR) and stocks markets (JSE), between foreign exchange (EXR) and bond markets (TBR). The money markets showed no sign of volatility transmission.

Note:

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APPENDIX

Figure 2: Impulse response

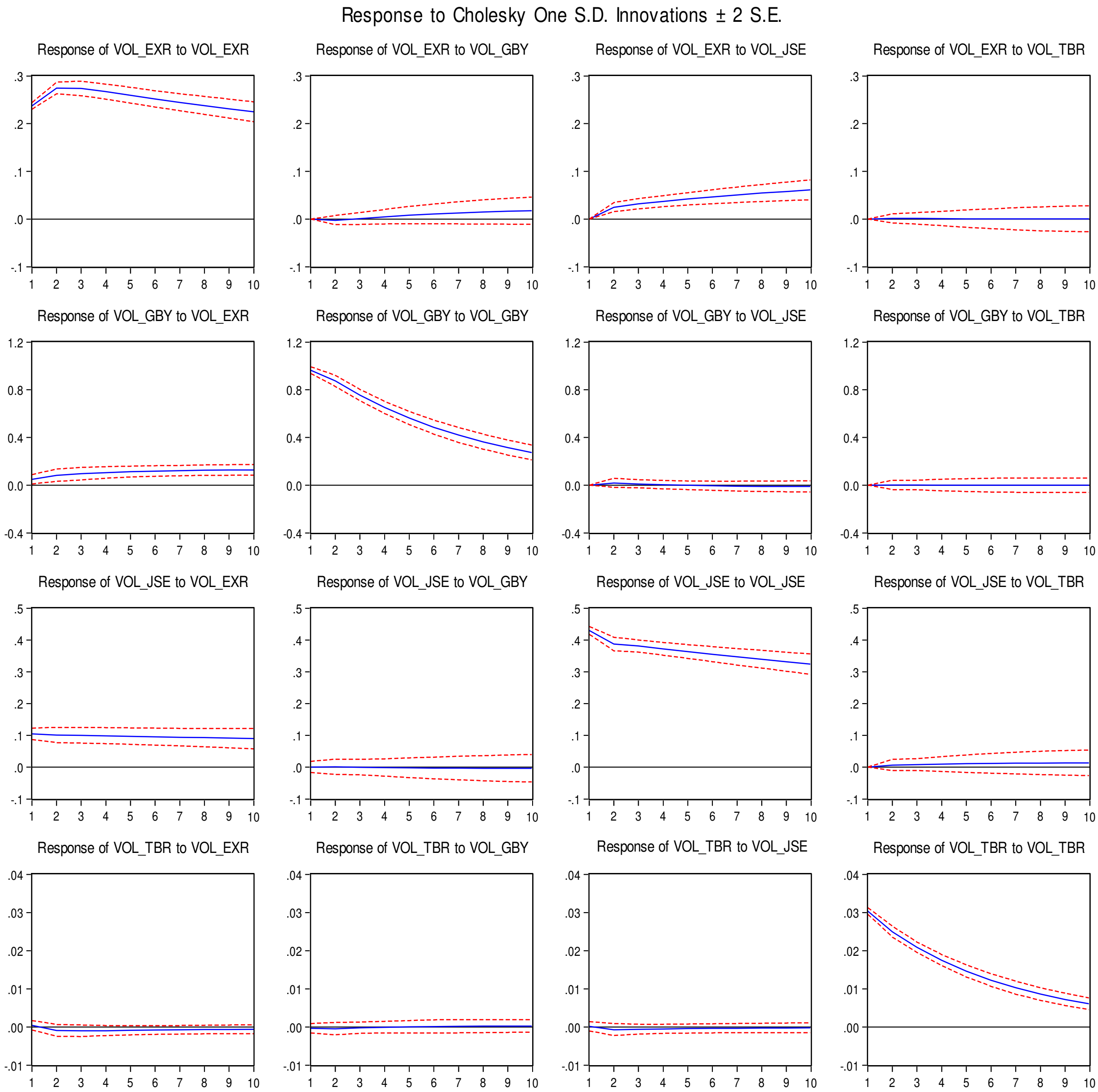

Figure 3: volatility graphs

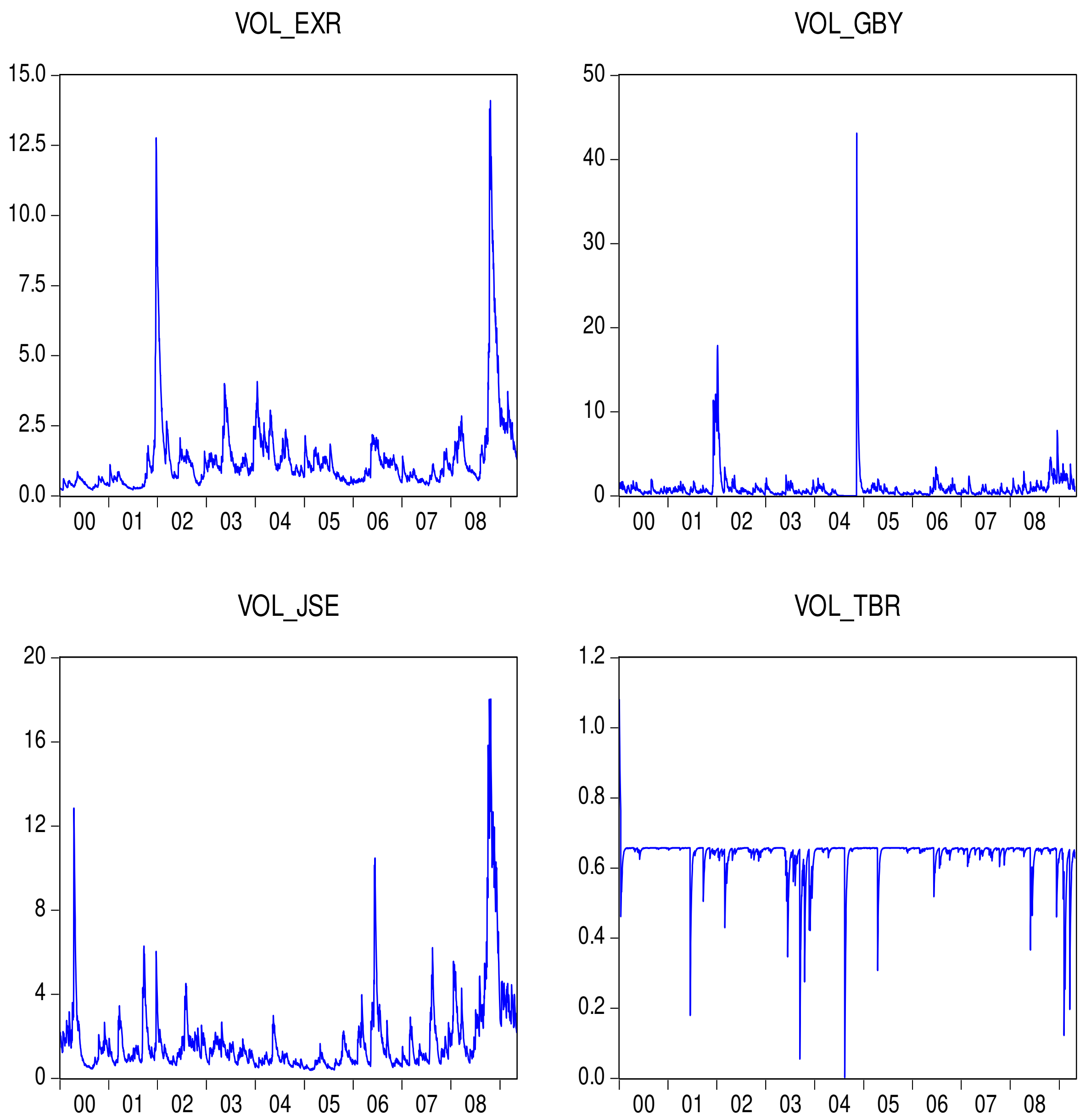

Table A1: EGARCH JSE

Dependent Variable: JSE
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 05/17/09 Time: 19:17
Sample (adjusted): 1/04/2000 5/07/2009
Included observations: 2438 after adjustments
Convergence achieved after 18 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)
*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.057517	0.021949	2.620474	0.0088
AR(1)	0.064233	0.021227	3.026058	0.0025
	Variance Equation			
C(3)	-0.098620	0.013646	-7.227137	0.0000
C(4)	0.132230	0.017537	7.539987	0.0000
C(5)	-0.084603	0.011019	-7.678090	0.0000
C(6)	0.982544	0.004384	224.1170	0.0000
T-DIST. DOF	12.44427	2.675360	4.651440	0.0000

R-squared	0.003937	Mean dependent var	0.039500
Adjusted R-squared	0.001479	S.D. dependent var	1.354484
S.E. of regression	1.353482	Akaike info criterion	3.136939
Sum squared resid	4453.384	Schwarz criterion	3.153589
Log likelihood	-3816.928	Hannan-Quinn criter.	3.142991
F-statistic	1.601629	Durbin-Watson stat	2.001422
Prob(F-statistic)	0.142600		
Inverted AR Roots	.06		

Table A2: GARCH JSE

Dependent Variable: JSE
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 05/17/09 Time: 19:17
Sample (adjusted): 1/04/2000 5/07/2009
Included observations: 2438 after adjustments
Convergence achieved after 7 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.086997	0.022391	3.885319	0.0001
AR(1)	0.068207	0.021908	3.113322	0.0018
		Variance Equation		
C	0.028574	0.009145	3.124429	0.0018
RESID(-1)^2	0.096302	0.013202	7.294240	0.0000
GARCH(-1)	0.888771	0.015019	59.17816	0.0000
T-DIST. DOF	10.43526	2.089028	4.995269	0.0000

R-squared	0.003008	Mean dependent var	0.039500
Adjusted R-squared	0.000958	S.D. dependent var	1.354484
S.E. of regression	1.353835	Akaike info criterion	3.155624
Sum squared resid	4457.540	Schwarz criterion	3.169896
Log likelihood	-3840.706	Hannan-Quinn criter.	3.160812
F-statistic	1.467502	Durbin-Watson stat	2.007635
Prob(F-statistic)	0.197166		
Inverted AR Roots	.07		

Table A3: TARCH JSE

Dependent Variable: JSE
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 05/17/09 Time: 19:17
Sample (adjusted): 1/04/2000 5/07/2009
Included observations: 2438 after adjustments
Convergence achieved after 11 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-1)^2*(RESID(-1)<0) + C(6)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.056432	0.022432	2.515728	0.0119
AR(1)	0.064780	0.021697	2.985743	0.0028
Variance Equation				
C	0.028896	0.007626	3.789288	0.0002
RESID(-1)^2	0.021905	0.009507	2.303985	0.0212
RESID(-1)^2*(RESID(-1)<0)	0.115011	0.018001	6.389258	0.0000
GARCH(-1)	0.902369	0.012980	69.51779	0.0000
T-DIST. DOF	12.42470	2.809788	4.421937	0.0000

R-squared	0.003955	Mean dependent var	0.039500
Adjusted R-squared	0.001497	S.D. dependent var	1.354484
S.E. of regression	1.353470	Akaike info criterion	3.139280
Sum squared resid	4453.305	Schwarz criterion	3.155929
Log likelihood	-3819.782	Hannan-Quinn criter.	3.145332
F-statistic	1.608834	Durbin-Watson stat	2.002567
Prob(F-statistic)	0.140569		

Inverted AR Roots	.06

Table A4: EGARCH GBY

Dependent Variable: GBY
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 05/17/09 Time: 19:18
Sample (adjusted): 1/05/2000 5/07/2009
Included observations: 2437 after adjustments
Convergence achieved after 24 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.002023	0.000529	-3.823403	0.0001
AR(1)	0.256391	0.014574	17.59180	0.0000
AR(2)	0.007906	0.015200	0.520161	0.6030
	Variance Equation			
C(4)	-0.130850	0.007453	-17.55715	0.0000
C(5)	0.231954	0.018941	12.24634	0.0000
C(6)	0.227623	0.018786	12.11672	0.0000
C(7)	1.002586	0.002325	431.1594	0.0000
T-DIST. DOF	2.623750	0.119248	22.00240	0.0000

R-squared	0.058149	Mean dependent var	-0.019506
Adjusted R-squared	0.055434	S.D. dependent var	0.801089
S.E. of regression	0.778568	Akaike info criterion	1.708851
Sum squared resid	1472.384	Schwarz criterion	1.727886
Log likelihood	-2074.235	Hannan-Quinn criter.	1.715770
F-statistic	21.42328	Durbin-Watson stat	2.004592
Prob(F-statistic)	0.000000		

Inverted AR Roots	.28	-.03

Table A5: GARCH GBY

Dependent Variable: GBY
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 05/17/09 Time: 19:18
Sample (adjusted): 1/05/2000 5/07/2009
Included observations: 2437 after adjustments
Convergence achieved after 60 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	4.46E-09	0.004824	9.24E-07	1.0000
AR(1)	0.213282	0.021499	9.920453	0.0000
AR(2)	-0.037644	0.019598	-1.920817	0.0548
		Variance Equation		
C	1.23E-11	3.41E-11	0.361720	0.7176
RESID(-1)^2	0.357086	0.045471	7.853060	0.0000
GARCH(-1)	0.794543	0.003102	256.1179	0.0000
T-DIST. DOF	2.894410	0.196792	14.70796	0.0000

R-squared	0.058789	Mean dependent var	-0.019506
Adjusted R-squared	0.056465	S.D. dependent var	0.801089
S.E. of regression	0.778143	Akaike info criterion	1.410408
Sum squared resid	1471.382	Schwarz criterion	1.427063

Table A6: GARCH GBY

Dependent Variable: GBY
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 05/17/09 Time: 19:18
Sample (adjusted): 1/05/2000 5/07/2009
Included observations: 2437 after adjustments
Convergence achieved after 39 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*RESID(-1)^2*(RESID(-1)<0) + C(7)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	-8.16E-07	0.000589	-0.001385	0.9989
AR(1)	0.220422	0.019370	11.37951	0.0000
AR(2)	-0.035870	0.018802	-1.907720	0.0564
Variance Equation				
C	-2.60E-10	5.25E-10	-0.494285	0.6211
RESID(-1)^2	0.271275	0.045902	5.909860	0.0000
RESID(-1)^2*(RESID(-1)<0)	-0.026577	0.042801	-0.620961	0.5346
GARCH(-1)	0.841533	0.002941	286.1168	0.0000
T-DIST. DOF	2.881471	0.220956	13.04093	0.0000

R-squared	0.059327	Mean dependent var	-0.019506
Adjusted R-squared	0.056616	S.D. dependent var	0.801089
S.E. of regression	0.778081	Akaike info criterion	1.524345
Sum squared resid	1470.542	Schwarz criterion	1.543380
Log likelihood	-1849.414	Hannan-Quinn criter.	1.531264
F-statistic	21.88491	Durbin-Watson stat	1.933752
Prob(F-statistic)	0.000000		

Inverted AR Roots	.11+.15i	.11-.15i

Table A7: EGARCH EXR

Dependent Variable: EXR
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 05/17/09 Time: 19:24
Sample (adjusted): 1/04/2000 5/07/2009
Included observations: 2438 after adjustments
Convergence achieved after 14 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

	Coefficient	Std. Error	z-Statistic	Prob.
@SQRT(GARCH)	-0.122117	0.060061	-2.033204	0.0420
C	0.112528	0.053347	2.109351	0.0349
AR(1)	0.036373	0.020338	1.788433	0.0737
		Variance Equation		
C(4)	-0.106176	0.014445	-7.350570	0.0000
C(5)	0.140023	0.018940	7.393066	0.0000
C(6)	0.029405	0.010795	2.723966	0.0065
C(7)	0.987493	0.003949	250.0518	0.0000
T-DIST. DOF	7.108549	1.129908	6.291263	0.0000

R-squared	-0.001108	Mean dependent var	0.012998
Adjusted R-squared	-0.003992	S.D. dependent var	1.120955
S.E. of regression	1.123190	Akaike info criterion	2.776208
Sum squared resid	3065.582	Schwarz criterion	2.795237
Log likelihood	-3376.198	Hannan-Quinn criter.	2.783126
Durbin-Watson stat	1.997421		
Inverted AR Roots	.04		

Table A8: GARCH EXR

Dependent Variable: EXR
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 05/15/09 Time: 14:48
Sample (adjusted): 1/04/2000 5/07/2009
Included observations: 2438 after adjustments
Convergence achieved after 14 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
@SQRT(GARCH)	-0.118016	0.060068	-1.964719	0.0494
C	0.103292	0.052705	1.959799	0.0500
AR(1)	0.031519	0.020718	1.521320	0.1282
	Variance Equation			
C	0.007678	0.002921	2.628666	0.0086
RESID(-1)^2	0.067962	0.009173	7.408755	0.0000
GARCH(-1)	0.929080	0.009077	102.3549	0.0000
T-DIST. DOF	7.134585	1.144043	6.236292	0.0000

Table A9: TARCH EXR

Dependent Variable: EXR
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 05/17/09 Time: 21:34
Sample (adjusted): 1/04/2000 5/07/2009
Included observations: 2438 after adjustments
Convergence achieved after 31 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*RESID(-1)^2*(RESID(-1)<0) + C(7)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
@SQRT(GARCH)	-0.105496	0.060809	-1.734878	0.0828
C	0.097752	0.053264	1.835220	0.0665
AR(1)	0.034444	0.020715	1.662773	0.0964
		Variance Equation		
C	0.008002	0.002950	2.712210	0.0067
RESID(-1)^2	0.078054	0.010688	7.302747	0.0000
RESID(-1)^2*(RESID(-1)<0)	-0.025438	0.014122	-1.801258	0.0717
GARCH(-1)	0.930518	0.009263	100.4546	0.0000
T-DIST. DOF	7.197647	1.167662	6.164154	0.0000

R-squared	-0.000732	Mean dependent var	0.012998
Adjusted R-squared	-0.003615	S.D. dependent var	1.120955
S.E. of regression	1.122979	Akaike info criterion	2.777679
Sum squared resid	3064.429	Schwarz criterion	2.796708
Log likelihood	-3377.991	Hannan-Quinn criter.	2.784596
Durbin-Watson stat	1.995517		
Inverted AR Roots	.03		

Table A10: EGARCH TBR

Dependent Variable: TBR
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 05/17/09 Time: 19:21
Sample (adjusted): 1/04/2000 5/07/2009
Included observations: 2438 after adjustments
Convergence achieved after 24 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)
*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.000122	3.15E-05	-3.874031	0.0001
AR(1)	-2.24E-05	5.57E-06	-4.020193	0.0001
	Variance Equation			
C(3)	-1.459931	0.743201	-1.964383	0.0495
C(4)	-0.170276	0.140890	-1.208571	0.2268
C(5)	0.085007	0.069790	1.218041	0.2232
C(6)	0.561548	0.015377	36.51766	0.0000
T-DIST. DOF	2.009296	0.015756	127.5295	0.0000

R-squared	-0.000325	Mean dependent var	-0.013428
Adjusted R-squared	-0.002794	S.D. dependent var	0.737434
S.E. of regression	0.738463	Akaike info criterion	-3.355716
Sum squared resid	1325.693	Schwarz criterion	-3.339066
Log likelihood	4097.618	Hannan-Quinn criter.	-3.349664
Durbin-Watson stat	2.019278		

Inverted AR Roots	-.00

Table A11: TARCH TBR

Dependent Variable: TBR
Method: ML - ARCH
Date: 05/17/09 Time: 19:22
Sample (adjusted): 1/04/2000 5/07/2009
Included observations: 2438 after adjustments
Convergence achieved after 25 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-1)^2*(RESID(-1)<0) +
C(6)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.021987	0.019109	-1.150637	0.2499
AR(1)	-0.007765	0.012871	-0.603304	0.5463
		Variance Equation		
C	0.113154	0.013136	8.614015	0.0000
RESID(-1)^2	-0.003530	0.001380	-2.558183	0.0105
RESID(-1)^2*(RESID(-1)<0)	-0.004549	0.001259	-3.612507	0.0003
GARCH(-1)	0.827902	0.020147	41.09218	0.0000

R-squared	0.000086	Mean dependent var	-0.013428
Adjusted R-squared	-0.001970	S.D. dependent var	0.737434
S.E. of regression	0.738160	Akaike info criterion	2.248166
Sum squared resid	1325.148	Schwarz criterion	2.262437
Log likelihood	-2734.514	Hannan-Quinn criter.	2.253354
F-statistic	0.041908	Durbin-Watson stat	2.004452
Prob(F-statistic)	0.999006		
Inverted AR Roots	-.01		

Table A11: GARCH TBR

Dependent Variable: TBR
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 05/17/09 Time: 19:22
Sample (adjusted): 1/04/2000 5/07/2009
Included observations: 2438 after adjustments
Failure to improve Likelihood after 34 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.001060	0.005381	0.197041	0.8438
AR(1)	0.000281	0.000948	0.295992	0.7672
	Variance Equation			
C	0.154366	0.111722	1.381704	0.1671
RESID(-1)^2	-0.001915	0.001264	-1.515710	0.1296
GARCH(-1)	0.017353	0.306091	0.056692	0.9548
T-DIST. DOF	2.059178	0.041713	49.36569	0.0000

R-squared	-0.000396	Mean dependent var	-0.013428
Adjusted R-squared	-0.002453	S.D. dependent var	0.737434
S.E. of regression	0.738338	Akaike info criterion	-1.400075
Sum squared resid	1325.788	Schwarz criterion	-1.385804
Log likelihood	1712.691	Hannan-Quinn criter.	-1.394887
Durbin-Watson stat	2.019751		
Inverted AR Roots	.00		