Volatility is one of the most important instruments in economics and finance. Prices of commodities have shown large fluctuations. High volatility of one commodity today may impact the volatility of another commodity tomorrow. In this paper, I apply the Ljung-Box Q tests using the GARCH (1,1) model estimated by Quasi-Maximum Likelihood (QML) to find volatility spillover among auto and steel industry, coal and oil industry, food and agriculture industry, toys and gold industry, as well as agriculture and gold industry from a large dataset containing 49 different industries based on the daily returns and price index from 2010 to 2019.

The knowledge about the spillover of financial information from one market to another gained considerable attention over the last few decades (Jebbar, 2014). It is hypothesized that the changes in market volatility are related to the volatilities of macroeconomic variables. In present value models such as those of Shiller (1981), changes in the volatility of either future cash flows or discount rates cause changes in the volatility of stock returns. This macroeconomic hypothesis can be confirmed by exploring volatility spillover and its properties.

My research contributes to the current literature by applying existing models into new datasets with daily returns for the auto and steel industry, coal and oil industry, food and agriculture industry, toys and gold industry, as well as agriculture and gold industry. I analyze the empirical volatility-based correlations between each pair and investigate how much volatility in one sector affects the volatility in another sector. What I find is that there is a high correlation between the residuals of coal and oil, steel and auto industry. The high correlation occurs when lag = 1, 5, and 10. Volatility spillover effects exist between coal and oil, auto and steel, agriculture and food in the whole sample 2010-2019.

The empirical model is:

\[(1) \ Y_t = a + b_1 Y_{t-1} + b_2 Y_{t-2} + \ldots + b_p Y_{t-p} + \gamma'X_t + \sigma_i i_t \]

\(Y_t, X_t, \text{returns for an industry, value of the variable } Y \text{ at time } t, \text{for } t = 1, 2, \ldots, n \)

\(Y_t, \text{returns for an industry, value of the variable } Y \text{ at time } t, \text{for } t = 1, 2, \ldots, n \)

\(X_t, \text{other control variables: federal funds' effective rate and 5-year breakeven inflation rate with time lags} \)

\(\sigma_i, \text{conditional volatility, modeled as GARCH (1,1)} \)

\(\epsilon_i, \text{error term, iid (0, 1)} \)

Based on (1), the null is:

\(H_0 = \text{corr}(\varepsilon_i^{(1)} - 1, \varepsilon_i^{(2)} - 1) = 0 \text{ for } h = 1, 2, \ldots, H \)

for industry “1” and “2”

\(\sigma_i, \text{variance of } \epsilon_i = 1 \)

Write compactly:

\(2) \ Y_i^{(1)} = a + b_1 Y_{i-1} + b_2 Y_{i-2} + \ldots + b_p Y_{i-p} + \gamma'X_i + \sigma_i i_t \)

\(Y_i^{(1)}, \epsilon_i^{(1)}, a, b_1, b_2, \ldots, b_p, \gamma, \sigma_i \)

\(i_t, \epsilon_i^{(1)}, \text{time lag} \)

The way I choose the time lag is that I pick the smallest \(p\) such that \(i_t\) appears to be uncorrelated.

The strength of the data source is that there are few other data sources online providing daily observations and reliable daily returns for different industries. Additionally, the data source provides more recent and more observations than other data sources available online. Moreover, the data source was collected and calculated in a more reliable manner than other data sources. Three different indexes like NYSE, AMEX, and NASDAQ stock were applied to an industry portfolio to make the dataset. This is beneficial when I apply time series in the GARCH (1,1) the empirical model with time lags. One of the key variables is the returns for the same industry at different periods with different time lags. Other independent variables are federal funds' effective rate with time lags and the 5-year breakeven inflation rate with time lags.

Key summary of findings for the whole sample 2010-2019:

- There is volatility spillover from agric to food, food to agric as expected.
- There is volatility spillover from coal to oil, oil to coal as expected.
- There is volatility spillover from steel to auto, auto to steel as expected.
- There is no volatility spillover from toys to gold, gold to toys as expected.
- There is no volatility spillover from agric to gold but there is volatility spillover from gold to agric (not as expected).

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