Modeling Price Volatility based on a Genetic Programming Approach

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ABSTRACT

Business profitability is highly dependent on risk management strategies to hedge future cash flow uncertainty. Commodity price shocks and fluctuations are key risks for companies with global supply chains. The purpose of this paper is to show how Artificial Intelligence (AI) techniques can be used to model the volatility of commodity prices. More specifically we introduce a new model – LIQ-GARCH - that uses Genetic Programming to forecast volatility. The newly generated model is then used to forecast the volatility of the following three indexes: the Commodity Research Bureau (CRB) index, the West Texas Intermediate (WTI) oil futures prices and the Baltic Dry Index (BDI). The empirical model performance tests show that the newly generated model in this paper is considerably more accurate than the traditional GARCH model. As a result, this model can help businesses to design optimal risk management strategies and to hedge themselves against price uncertainty.

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1. Introduction

Among the several functions of a company, risk management is quite an important one as it directly contributes to value creation (Allayannis and Weston, 2001; Lewellen, 2006), where volatility forecasting becomes exceedingly relevant (Christoffersen and Diebold, 2000). Financial hedging (or hedging henceforth) is the main strategy used by businesses to reduce the adverse impact of price fluctuations on profit margins (Gordon et al., 2009; Liebenberg and Hoyt, 2003). Meanwhile, successful hedging strategies rely on the capability of the company to forecast (with some degree of accuracy) the future volatility of commodity prices.

In spite of its importance, this is an area of risk management where Artificial Intelligence techniques have not been not widely used. In the current finance literature, GARCH models are widely used to model the volatility of financial time series (e.g. Kambouroudis et al., 2016; Prokopczuk and Simen, 2014). However, existing GARCH models suffer from three limitations: a) they assume that the volatility of the market and correlations among assets change slowly or not at all; b) they cannot control for extreme events and c) they cannot include all the information from the market. This point is particularly relevant when trying to control for the liquidity position in the market as incorporating liquidity into GARCH models is necessary so that forecasts can be updated regularly by using all the information extracted from traders' expectations on future supply and demand conditions.

Against this background, the purpose of this paper is to show how Artificial Intelligence (AI) techniques can be used to model the volatility of commodity prices; more specifically we propose a new estimator of the GARCH model that allows to incorporate existing information on the market liquidity in the estimation procedure. The proposed estimator – to be named LIQ-GARCH – uses a Genetic Programming approach to the model estimation that has been widely used to predict stock returns (Manahov et al., 2015) and energy consumption (Castelli et al., 2015). Our estimator is compared to the standard GARCH estimator for three time series, namely the Commodity Research Bureau (CRB) index, the West Texas Intermediate (WTI) oil futures prices and the Baltic Dry Index (BDI). These three time series have been chosen as they are extensively used by businesses around the world to hedge price risk along the supply chain. Our model exhibits overwhelmingly superior performance in forecasting the volatility of the three time series against the standard GARCH model.

Our paper adds to the existing literature in several ways. First, to the best of our knowledge, our LIQ-GARCH estimator is the first to extend the prevalent GARCH estimator by including market liquidity information. Second, our paper shows how Artificial Intelligence techniques can be used to improve forecasting models and support the development of risk management strategies when dealing with fluctuating commodity prices.

The remainder of the paper is organized as follows. Section 2 gives a short summary of the managerial implications of the model. Section 3 reviews the existing evidence on the relationship between volatility, liquidity and business performance. Section 4 introduces the LIQ-GARCH estimator while Section 5 illustrates the data and the variables used in the empirical analysis. Section 6 presents the results while discussing the possible uses of the new estimators to manage risk along the supply chain. Finally, Section 7 offers some concluding remarks.

2. Managerial Implications of LIQ-GARCH Model

Given that risk management constitutes an important aspect of company management, corporate hedging clearly plays a vital role in company management since it can help mitigate firms' risk bearing (Allayannis and Weston, 2001; Lewellen, 2006). In fact, it is well documented that corporate hedging can increase firm value and improve business performance (Bessembinder, 1991; Smith and Stulz, 1985). Existing studies have unveiled a positive relation between derivatives hedging and firm performance (see Bartram et al., 2011; Haushalter et al., 2007; Perez-Gonzalez and Yun, 2013). More recently, Chen et al. (2017) also provide robust evidence in support of the view that companies who use derivative hedging achieve higher returns than non-users.

Enhanced risk management can act as one possible assistance toward the management challenge of performance improvement in a highly volatile environment mentioned in Parnell et al. (2012). More importantly, accurate volatility forecasting can aid managers' proactive management against predicted risk (Jung et al., 2011). Recently, Big Data analytics has also proven to be a useful tool in enhancing risk and operations management (see. Cerchiello and Giudici, 2016; Choi et al., 2017; Choi et al., 2018).

Our LIQ-GARCH model is based on two key ingredients: Big Data and Artificial Intelligence technologies are capable of analyzing high frequency data and liquidity information which can capture supply and demand conditions of a good. The managerial implications of our model can be summarized in the following two aspects. On the one hand, our model can deliver a more accurate view of price volatility of a good at a higher predictive frequency than traditional models. Managers can make more robust, cost saving hedging decisions using our model. Since hedging can be costly when volatility is negligible, it is best not to take hedging positions when volatility is low and vice versa. Therefore, our model could support managers in making decisions, i.e. whether and when taking hedging positions is necessary, so as to save significant costs in risk and operations management. On the other hand, because our model delivers a more accurate view on supply and demand conditions of a good via liquidity information, managers can more effectively manage inventory of goods for both input and output channels to better suit prevailing market conditions. Therefore, our model can also help managers to improve the inventory management and avoid the disruption of critical supply chain networks.

3. Financial Hedging and Business Performance: A Review

Traditionally risk management has relied on a mixture of quantitative techniques and expert judgments where accounting and planning for liquidity shocks have been handled indirectly through scenario planning, risk budgeting and portfolio theory. However, risk management has recently started to benefit from Artificial Intelligence with the result that the traditional quantitative techniques used for risk management have started to be replaced by a variety of analytical techniques. These new techniques are particularly relevant to businesses with complex supply chains spanning several countries. While playing a vital role in fostering international trade and economic growth, global supply chains create new risks as well: indeed, in a world where markets are highly integrated, minor supply chain disruptions can have major impacts on the performance of the supply chain as markets react to negative shocks with increased speed and volatility (Tummala and Schoenherr, 2011).

Among the many risks that may affect the performance of supply chain, volatility of the commodity prices is a key one. Indeed volatile commodity prices cause fluctuations in the cost of raw materials that, if not properly managed, can adversely affect profit margins. It is well known that in some industries, the exposure to the commodity price risk exposure is quite substantial, such as gold price for mining companies (Tufano, 1998) and non-energy commodity price for automobile companies (Oxelheim and Wihlborg, 1995). The volatility of commodity prices can be detrimental to some companies. For instance, Ford Motor Co. has written off $1 billion value of its metal reserves in 2002 because of the unexpectedly sharp decrease of the metal price (White, 2002). In addition, extreme volatility might result into bankruptcy even for well-capitalized companies (Bessembinder and Lemmon, 2002).

Businesses usually manage their risk by taking hedge positions. In the automotive industry, the biggest risk is the volatility of metal price which is often hedged against commodity futures and options. Oil and airline companies have substantial risk exposures to oil price fluctuations (Jin and Jorion, 2006; Phan et al., 2014). Oil futures are often used by transport and power utility companies to hedge against the risk of oil price fluctuations. Carter et al. (2006) has quantified the "hedging premium" for airline companies and found that jet fuel hedging can reduce the underinvestment costs for airline companies. Furthermore, Mohanty et al. (2014) show that oil price volatility significantly influenced a number of other industries, including airlines, recreational services, restaurants and bars. As a result, accurate forecasting of oil price volatility is of great importance.

Shipping companies need to hedge against the freight rate volatility as well (Zhang and Shen, 2016; Zhang and Shen, 2017). Therefore, forecasts of shipping index plays a vital role in the management of shipping companies (Duru, 2010). Dry bulk freight futures contracts, which are traded on the International Maritime Exchange (Prokopczuk, 2011), are useful risk mitigation strategies for shipping companies. Samitas and Tsakalos (2010) provide supporting evidence that the use of derivatives hedging can minimize shipping firms' risk exposure and ensure their growth. However, the forecasting is still challenging due to the complexity of the bulk shipping market, especially for precise predictions (Goulielmos and Psifia, 2013).

When the expected volatility of prices is large, firms tend to increase their hedging positions to counterbalance the adverse effect of large future price swings. The increased hedging positions could help firms to limit their future losses and as a result, the risk attached to cash flow volatility risk can be reduced. This way, the firm can reduce the probability of financial distress and increase the financial flexibility (Gao et al., 2015). When expected volatility is negligible, the price will remain stable or follow historical trends. In this case, price swings are predictable. As a result, it would be costly for companies to hold option positions (Howard and D'Antonio, 1994). Companies then need not to buy options or take futures positions to hedge future price uncertainty and can thereby reduce costs from decreasing their hedging positions when the future volatility tends to be trivial.

The contribution of hedging to value creation and improved business performance is well established (Bessembinder, 1991; Smith and Stulz, 1985). Several studies have shown that there exists a positive relationship between derivatives hedging and firm performance (see Allayannis et al., 2012; Bartram et al., 2011; Haushalter et al., 2007; Perez-Gonzalez and Yun, 2013). More recently, Lau (2016) has shown that hedging can strengthen company's ROA and ROE while Chen et al. (2017) find that hedging companies announce higher returns than non–users. Typically hedging strategies are supported by a variety of econometric models aiming at forecasting the volatility of commodity prices. In spite of the fact that they are widely used for this purpose, they suffer from a variety of limitations. GARCH models are not designed to handle systemic changes caused by jumps in the availability of liquidity or changes in the market micro-structure[1]. For instance, information on the liquidity of the market are quite important to estimate volatility of prices over time accurately as the degree of liquidity in a market is very informative of the traders' expectations on future demand and supply on the market (Easley et al., 1996; Welker, 1995). The relationship between liquidity and volatility has been widely analyzed by several authors. Fleming and Remolona

1 Market micro structure is the process by which investors' demands and expectations can be ultimately translated into asset prices and trading volumes (Garman, 1976; Madhavan, 2000).

(1999) have investigated the relationship among liquidity, volatility and public information in the US Treasury market and have shown that that volatility and liquidity respond simultaneously to the release of new information. More recently, Collin-Dufresne and Fos (2016) have explored the relationship between liquidity and noise trading volatility and found that liquidity is an important driver of trading volatility. In addition, it has been found that the variation of the market liquidity (so called liquidity risk) is correlated with the informational content of the prices (Ng, 2011). Recent studies such as Zhang, Ding and Scheffel (2018) and Zhang and Ding (2018) have shown the significant liquidity effect on price volatility in commodity markets.

4. Using Genetic Programming (GP) to Forecast Volatility

In econometric and financial theories, volatility measures the variation degree of a price series $\{P_t, t=1, 2, 3\ldots\}$ over time, where the standard deviation is usually used as a proxy of volatility. We define return r_t as:

$$r_t = ln\left(\frac{P_t}{P_{t-1}}\right), t = 1,2, \ldots$$

Consider a conditional normal distributed residual model with time-varying volatility σ_t:

$$\mathrm{r}_t = \varphi + \varepsilon_t \tag{1}$$

$$\varepsilon_t | \mathrm{I}_{t-1} \sim \ \mathrm{N}(0, \sigma_t^2)$$

where I_{t-1} represents the information available at time t-1, and φ is the long run mean of the return series. The ARCH model specifies the conditional volatility σ_t that satisfies:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2,\ \alpha_0 > 0,\ 0 < \alpha_1 < 1.$$

A generalized ARCH model is denoted as GARCH (1,1), which can be described as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \sigma_{t-1}^2 \tag{2}$$

where $\alpha_0 > 0,\ \alpha_1 + \alpha_2 < 1$ for stationarity of the above process.

If the functional form of (2) is unknown, the estimator based on Genetic Programming can be used as it does not require assumptions on the functional form of the equation to be estimated. In Artificial Intelligence, genetic programming is a technique whereby programs are encoded as a set of genes that are then modified using an evolutionary algorithm – it is an application of genetic algorithms where the possible solutions consist of computer programs (Hirsh et al., 2000; Rasheed et al., 1997). The methods used to encode a computer program in an artificial chromosome and to evaluate its fitness with respect to the predefined task are central to the GP technique. In addition, it is well suited to work with high dimensional data (Viegas et al., 2018). Genetic programming can be viewed as an extension of the *genetic algorithm*, a model for testing and selecting the best choice among a set of results. Genetic programming makes the program or "function" the unit that is tested. Our GP estimator works as follows: it firstly generates a random population of functions, and then it evaluates the quality (fitness) of each individual function by evaluating the difference between the generated function and the targeted function. Next, one or two function(s) will be probabilistically selected based on their fitness in order to participate to the genetic operations. Normally there are two genetic operations, one is called crossover and another is called mutation. The crossover operation is used to create a new function (called offspring) by randomly choosing some subitems from two selected functions (called parents, which are usually polynomials) and recombining the subitems from the two functions together. The mutation operation is used to create a new offspring by choosing some random subitems from one selected function and altering them. After new individuals are created, their fitness will be calculated again, and genetic operations will also be performed again to evaluate the newly-generated functions. This whole process is repeated until an acceptable solution is found or another termination criterion is satisfied (usually up to some certain number of generations). The best individual function will be returned as the solution.

Our starting function is as follows:

$$f(L_{t-1}^2,\ \varepsilon_{t-1}^2,\ \sigma_{t-1}^2) = \ \sigma_t^2 \tag{3}$$

with the following objective function:

$$\min \sum_{t=0}^{T} [f(L_{t-1}^2,\ \varepsilon_{t-1}^2,\ \sigma_{t-1}^2) - \ \sigma_t^2]$$

and the objective function is subject to:

$$f(L_{t-1}^2,\ \varepsilon_{t-1}^2,\ \sigma_{t-1}^2) \geq 0$$

where L_t^2, ε_t^2, σ_t^2 are the squared liquidity, the squared residuals and the realized variance at time t respectively. By using the settings and the procedural of GP detailed in Appendix A1, we ran our GP system fifty times. Eventually, the GP procedure generates the following model:

$$\sigma_t^2 = \alpha_0 + \alpha_1\ \sigma_{t-1}^2 + \alpha_2\ X_{t-1} \tag{4}$$

where $X_t = (1 - L_t^2) * (L_t^2 - \ \sigma_t^2 - L_t^4)$ and L is the market liquidity. We name the new model as LIQ-GARCH (1, 1) i.e. liquidity-adjusted GARCH model.

5. Data, Variables and the Empirical Methodologies

5.1 Data and Variables

For our empirical analysis we use three time series: the Commodity Research Bureau (CRB) index, the WTI oil futures prices and the Baltic Dry Index (BDI). All the indexes are observed daily although over different periods of time. The sample period of CRB index runs from January 1, 1995 to November 30, 2017 while the sample period of the WTI index is from January 1, 2000 to November the 30th, 2017. Finally the sample period for BDI is from January 1, 1990 to November, the 30th 2017. The total number of observations is 17,606 and it is a large enough data set to illustrate our GP procedure.

Empirically, volatility measures are based on market returns and returns can be defined through the market price series, which is $r_t = ln\left(\frac{P_t}{P_{t-1}}\right)$.

Therefore, we estimated the volatility of the three time series via the sample return standard deviation (Christensen and Prabhala, 1998), which can be defined as:

$$\sigma_t = \sqrt{\frac{1}{T-1}\sum_{i=1}^{T}(r_{t-i} - \bar{r}_t)^2} \tag{5}$$

where $r_{t-i} = \ln(P_{t-i}/P_{t-i-1})$, with P_{t-i} representing the CRB index, WTI oil price and BDI, respectively at day t-i, and $\bar{r}_t = \frac{1}{T}\sum_{i=1}^{T} r_{t-i}$. We take T=21 as the monthly rolling average. The returns and volatilities of all three indexes are summarized in Table 1 while Fig. 1 plots the three indices; finally the realized volatility of the three series is presented in Fig 2.

Finally, we estimate the liquidity of the three markets. We adopt a widely used proxy for liquidity: the bid-ask spread (BAS) which is positively correlated with price volatility in financial markets (Bollerslev & Melvin, 1994; Wang & Yau, 2000). In our paper, we use the effective spread estimator developed by Roll (1984) and used in a number of financial papers such as Goyenko et al. (2009) and Corwin and Schultz (2012). The proxy utilizes the autocovariance of the daily price changes as an effective measure of the bid-ask spread. Roll's starting point is that the traded assets have fundamental value (Lux and Marchesi, 1999) - denoted as V_t – as:

$$V_t = V_{t-1} + \eta_t, \tag{6}$$

where η_t reflects new information arrival which is assumed to be independent of the previous period information under the efficient market hypothesis. Next, Roll (1984) denotes S_t as the last observed trade price on day t and assumes that S_t follows the following process:

$$S_t = V_t + \frac{1}{2}EQ_t, \tag{7}$$

where E is the effective spread and Q_t is a buy/sell indicator for the last trade that equals +1 for a buy and -1 for a sell. He further assumes that Q_t is equally likely to be +1 or -1 and Q_t is also serially uncorrelated, and independent of η_t. Then he takes the first difference of (7) and plugs in the result from equation (6), which yields:

$$\Delta S_t = \frac{1}{2} E \Delta Q_t + \eta_t, \tag{8}$$

where ΔQ_t measures the change of the order type from two consecutive days, and Δ is the change operator, namely, $\Delta Q_t = Q_t - Q_{t-1}$ (Goyenko et al., 2009).

As a result,

$$Cov(\Delta S_t, \Delta S_{t-1}) = -\frac{1}{4} E^2, \quad \text{or equivalently,} \quad spread = 2\sqrt{-\text{cov}(\Delta S_t, \Delta S_{t-1})}.$$

However as the autocovariance is positive, the formula is undefined. We therefore use a modified version of the Roll estimator (Goyenko et al., 2009):

$$l = spread = \begin{cases} 2\sqrt{-\text{cov}(\Delta S_t, \Delta S_{t-1})}, \text{cov}(\Delta S_t, \Delta S_{t-1}) \le 0 \\ 0, \text{cov}(\Delta S_t, \Delta S_{t-1}) > 0 \end{cases}. \tag{9}$$

For one particular day's liquidity, it is effectively the average of the previous month's (the past 21 days) liquidity measures. If L_t be the rolling average of liquidities from the past 21 trading days, this is then equal to:

$$L_t = \frac{1}{21} \sum_{i=1}^{21} l_{t-i},$$

where l_{t-i} is the liquidity measure at day t-i.

The full sample regression results of the LIQ-GRACH model in equation (4) has been reported in Tables 2-1 to 2-3 for CRB, oil and BDI series respectively. From those three tables, it is observable that the LIQ-GRACH model is occupied with outstanding data fitness ability since all independent variables coefficients are statistically significant at 10% level with huge F-value for all three series.

5.2 Empirical Methodologies

To test the performance of our proposed LIQ-GARCH (1, 1) model against the standard GARCH (1, 1) model we use three different empirical methodologies. First, we use the full sample data to estimate the model parameters and compute the model's fitting errors for each index. Under the second methodology, we estimate parameters for each year included in our sample. Then, we forecast the one-day ahead volatility for the same year based on the estimated parameters for both models on a yearly basis. For example, we use data from the year 2000 to estimate the parameters of the model predicting daily volatilities during the year 2000. Then we use data from the year 2001 to estimate the parameters of the model predicting daily volatility during the year 2001. Under the third methodology, we compute the parameters of the model for each year during the period 2008-2016. We then forecast the one-day ahead volatility for the next year (i.e. for the period 2009-2017) based on the estimated parameters on a yearly rolling basis. For example, we use data from the year 2008 to estimate parameters of the model which predicts daily volatilities during the year 2009. Then we use data from the year 2009 to estimate parameters of the model which predicts daily volatilities during the year 2010. Finally we compute the forecasting errors based on the three methods for both models.

To evaluate the model performance, we use the Mean Squared Error (MSE) since our daily data can be quite noisy (Bollerslev et al., 2016; Pong et al., 2004). The MSE can be defined as:

$$\text{MSE} = \frac{1}{T}\sum_{t=1}^{T}(Observed_t - Predicted_t)^2$$

where T represents the number of observations embedded in the forecasting period, $Observed_t$ presents the observed variance from the market and $Predicted_t$ presents the variance predicted from the models. Under the first methodology, MSE is calculated as the average during the full sample period while under the second and third methodologies, MSE is calculated as the average during the specific year. We denote GARCH (MSE), LIQ-GARCH (MSE) as the MSEs for GARCH (1, 1) and LIQ-GARCH (1, 1) respectively. We also define the improvement rate for the LIQ-GARCH model compared with the GARCH model as:

$$Improvement\ \ rate = \frac{GARCH(MSE) - LIQ-GARCH(MSE)}{GARCH(MSE)}.$$

6. Empirical Results

Tables 3 to 5 show the values of the three MSEs indicators for the three time series. More specifically, Table 3 refers to the CBR index while Table 4 and 5 report the results for the WTI oil futures prices and for the BDI series, respectively. In general, our model outperforms the GARCH model in all cases. In the case of the CRB index, the improvement rate is around 46% and it is statistically significant when the full sample is used for the estimation. Moreover, the improvement rate is around 32% on average when the sub-sample (2000-2008) is used. In the case of the out-of-sample forecasts (i.e. 2009-2017), our model dominates the GARCH model with a 97% improvement rate.

In the case of the WTI oil futures prices, our model outperforms the GARCH model and the (statistically significant) improvement rate is around 97%. Besides, the improvement rate is around 93% on average in the case of the in-sample test during the period from 2000 to 2008. In the case of the out-of-sample forecast, our model outperforms the GARCH model with a 92% improvement rate.

Finally, in the case of the BDI series, our model outperforms the GARCH model: the improvement rate is around 60% and the result is statistically significant. Besides, the improvement rate is around 88% on average for the in-sample test during the period from 2000 to 2008. In the case of the out-of-sample forecasts, our model has a 94% improvement rate. Each year, our model outperforms the GARCH model.

The accuracy of the new LIQ-GARCH model compared to the standard GARCH model can be explained as follows. First GP is a flexible analytical technique that can search for the best general functional form with best fitting to the data. Second, the LIQ-GARCH model uses the liquidity variable to predict the volatility. These results point out that liquidity plays a significant role in forecasting volatility as liquidity captures the supply and demand dynamics in the market, which are the driving price volatility.

7. Conclusions

Among the many risks that may affect the performance of the supply chain, volatility of the commodity prices is a key one. Indeed the cost of raw materials can fluctuate as a result of the volatile commodity prices. While hedging is the main mitigation strategy used by businesses to reduce the adverse impact of volatile commodity prices, successful hedging strategies rely on the capability of the business to forecast the future volatility of commodity prices in such a way that all the information provided by the market is used.

This paper has proposed a new GARCH model that uses Artificial Intelligence techniques to model the volatility of commodity prices and incorporate existing information on the market liquidity in the estimation procedure. The proposed estimator is compared to the standard GARCH estimator for three time series, namely the Commodity Research Bureau (CRB) index, the West Texas Intermediate (WTI) oil futures prices and the Baltic Dry Index (BDI). Our model exhibits overwhelmingly superior performance in forecasting the volatility of the three time series against the standard GARCH model.

Our paper adds to the existing literature in several ways. First, to the best of our knowledge, our LIQ-GARCH estimator is the first to extend the prevalent GARCH estimator by including market liquidity information. Second, our paper shows how Artificial Intelligence techniques can be used to improve forecasting models and support the development of risk management strategies when dealing with fluctuating commodity prices.

Our model exhibits overwhelmingly superior forecasting performance, with the improvement rate round 90% for both in-sample and out-of-sample tests compared with GARCH model. This model can be used to develop optimal hedging strategies. Indeed, firms can increase their hedging positions to stabilize future cash flows if expected volatility is predicted to be large. Conversely, firms may reduce their hedging positions to save hedging costs if future volatility is expected to be negligible.

A1. Appendix

The parameters of our GP system are as follows:

Terminal Set: L_{t-1}^2, ε_{t-1}^2, σ_{t-1}^2.

Function Set: +,-, x.

Fitness Measure: the difference between the value of the individual function and the corresponding desired output σ_t^2.

GP Parameters: population = 10000, the maximum length of the program = 1000 (i.e. up to 1000 subitems within one polynomial function), probability of crossover operation = 0.8 (i.e. 80% of population functions will be mixed with other functions to generate new functions) and probability of mutation operation = 0.1 (i.e. 10% of population functions will be mutated to generate new functions).

Termination Criterion: when the fitness measure reaches 0 or the system runs up to 100 generations, the system will terminate.

The detailed procedural for GP is provided as follows:

Algorithm 1: GP system for volatility forecasting

```
Initialisation: Initialise the population of the first generation ;
while not find the "good enough" forecasted volatility function or not reach the
  maximum number of generations;
do
    for each individual volatility function in the generation do
        Evaluation: Evaluate each volatility function's fitness ;
    Select Parents: Select the individual volatility functions from the population
    of the current generation to bread ;
    Crossover: Pair the selected parents up to produce offspring volatility
    functions;
    Mutation: Randomly alter the volatility function with a given probability ;
    Elitism: Select the best volatility function from the population of the current
    generation and insert it into the next new generation;
    Update Population: Update the population of the current generation;
```

Tables

Variable	Obs	Mean	Std. Dev.	Min	Max
r_{CRB}	5,976	0.0001462	0.0101206	-0.068769	0.0575027
r_{Oil}	4,673	0.0001728	0.0236473	-0.165445	0.1640972
r_{BDI}	6,957	-1.27E-06	0.0165009	-0.120718	0.1365755

Variable	Obs	Mean	Std. Dev.	Min	Max
σ_{CRB}	5,976	.0093653	.0038294	.0030272	.0325791

σ_{Oil}	4,673	.0215703	.0099035	.0062546	.0775113
σ_{BDI}	6,957	.0111866	.0085346	.0010856	.0536088

Table 1: Statistical summary of three time series returns (r) and volatilities (σ) for the full sample period, which are from Jan. 1, 1995 to Nov. 30, 2017 for CRB index, from Jan. 1, 2000 to Nov. 30, 2017 for WTI oil futures and from Jan. 1, 1990 to Nov. 30, 2017 for BDI.

	σ_t^2
σ_{t-1}^2	0.97^{***} (445.61)
X_{t-1}	$6.77e\text{-}10^{***}$ (6.23)
F-value	99999.99^{***}

Table 2-1: Regression results for the CRB series for the whole sample period (Jan. 1, 1995 to Nov. 30, 2017), the result confirms the marvelous fitness of LIQ-GARCH model via statistically significant coefficients of both independent variables as well as tremendous F-value. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

	σ_t^2
σ_{t-1}^2	0.98^{***} (419.42)
X_{t-1}	$3.31e\text{-}10^{**}$ (2.41)
F-value	90988.86^{***}

Table 2-2: Regression results for the oil series for the whole sample period (Jan. 1, 2000 to Nov. 30, 2017), the result confirms the marvelous fitness of LIQ-GARCH model via statistically significant coefficients of both independent variables as well as tremendous F-value. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

	σ_t^2
σ_{t-1}^2	0.99^{***} (131.57)
X_{t-1}	$-8.05e\text{-}13^{*}$ (-1.62)
F-value	17311.68^{***}

Table 2-3: Regression results for the BDI series for the whole sample period (Jan. 1, 1990 to Nov. 30, 2017), the result confirms the marvelous fitness of LIQ-GARCH model via statistically significant coefficients of both independent variables as well as tremendous F-value. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

	GARCH(MSE)	LIQ-GARCH(MSE)	Improvement Rate	P-value
Full-sample (1995-2017)	4.08E-08	2.17E-08	46.72%	0
Year				
Yearly sub-sample in-sample fitting				

2000	3.34E-08	1.91E-08	42.67%	0.06
2001	2.90E-08	1.93E-08	33.38%	0.04
2002	1.93E-08	1.92E-08	0.23%	0.45
2003	3.16E-08	1.92E-08	39.21%	0.05
2004	2.76E-08	1.91E-08	30.66%	0.09
2005	2.29E-08	1.63E-08	28.59%	0.06
2006	2.37E-08	1.92E-08	18.79%	0.07
2007	2.69E-08	1.96E-08	27.06%	0.01
2008	2.38E-07	7.19E-08	69.83%	0
Average	5.03E-08	2.48E-08	32.27%	
Out-of-sample: Prediction based on previous year fitting				
2009	8.39E-08	1.07E-09	98.73%	0
2010	1.24E-08	1.59E-10	98.72%	0
2011	1.77E-08	1.01E-09	94.28%	0
2012	3.94E-09	1.44E-10	96.35%	0
2013	1.00E-09	3.96E-11	96.04%	0
2014	2.31E-09	7.97E-11	96.55%	0
2015	1.80E-08	2.36E-10	98.69%	0
2016	1.00E-08	1.60E-10	98.40%	0
2017	1.54E-09	2.85E-11	98.14%	0
Average	1.68E-08	3.25E-10	97.32%	

Table 3: Model comparison in forecasting volatility for the time series of CRB index. This table presents the volatility prediction results comparison for GARCH model and LIQ-GARCH model regarding the CRB index. MSE stands for the mean squared error and the improvement rate is defined as $\frac{MSE_{GARCH}-MSE_{LGARCH}}{MSE_{GARCH}}$. P-values are the paired test results between MSE of GARCH model and MSE of LIQ-GARCH model. The full sample period is from January 1, 1995 to November 30, 2017 with in-sample test method employed. The in-sample test period is 2000-2008 and the tested year is the same as the sample year within the period. The out-of-sample

test period is 2009-2017 and the sample year is one year ahead of the tested year within the period. For all sample volatility forecasting, we use one-day ahead perdition approach. The yearly t-statistics is achieved by comparing the daily data of two series, namely, the GARCH and LIQ-GARCH estimated volatility.

	GARCH(MSE)	LIQ-GARCH(MSE)	Improvement Rate	P-value
Full-sample (1995-2017)	1.75E-06	3.82E-08	97.81%	0
Year				
Yearly sub-sample in-sample fitting				

2000	2.16E-06	1.20E-08	99.44%	
2001	3.44E-07	2.20E-08	93.60%	0
2002	2.65E-07	5.41E-09	97.96%	0
2003	2.95E-07	1.86E-08	93.69%	0
2004	2.70E-07	1.50E-08	94.44%	0
2005	3.20E-07	2.95E-08	90.78%	0
2006	2.90E-07	2.76E-08	90.48%	0
2007	3.21E-07	7.82E-09	97.56%	0
2008	2.12E-06	4.32E-07	79.62%	0.02
Average	7.09E-07	6.33E-08	93.07%	
Out-of-sample: Prediction based on previous year fitting				
2009	2.50E-06	4.20E-07	83.20%	0.01
2010	3.70E-07	9.70E-08	73.78%	0
2011	1.05E-06	6.42E-08	93.89%	0
2012	4.20E-07	2.07E-08	95.07%	0
2013	4.22E-08	4.41E-09	89.55%	0
2014	6.60E-07	2.38E-08	96.39%	0
2015	2.22E-06	2.44E-08	98.90%	0
2016	2.53E-06	1.12E-08	99.56%	0
2017	9.41E-08	9.88E-10	98.95%	0
Average	1.10E-06	7.41E-08	92.14%	

Table 4: Model comparison in forecasting volatility for the time series of WTI oil price.

This table presents the volatility prediction results comparison for GARCH model and LIQ-GARCH model regarding the WTI oil futures. MSE stands for the mean squared error and the improvement rate is defined as $\frac{MSE_{GARCH}-MSE_{LGARCH}}{MSE_{GARCH}}$. P-values are the paired test results between MSE of GARCH model and MSE of LIQ-GARCH model. The full sample period is from January 1, 2000 to November 30, 2017 with in-sample test method employed. The in-sample test period is 2000-

2008 and the tested year is the same as the sample year within the period. The out-of-sample test period is 2009-2017 and the sample year is one year ahead of the tested year within the period. For all sample volatility forecasting, we use one-day ahead perdition approach. The yearly t-statistics is achieved by comparing the daily data of two series, namely, the GARCH and LIQ-GARCH estimated volatility.

	GARCH(MSE)	LIQ-GARCH(MSE)	Improvement Rate	P-value
Full-sample (1995-2017)	1.39E-07	5.61E-08	59.66%	0
Year				
Yearly sub-sample in-sample fitting				
2000	8.72E-09	1.13E-10	98.70%	0
2001	7.53E-09	1.14E-10	98.49%	0
2002	7.42E-09	1.10E-10	98.52%	0
2003	8.93E-09	2.78E-10	96.88%	0
2004	2.15E-08	4.59E-10	97.86%	0.04
2005	2.99E-08	1.10E-09	96.33%	0
2006	6.74E-08	6.44E-08	4.51%	0.08
2007	5.48E-08	7.02E-10	98.72%	0
2008	3.03E-07	7.48E-09	97.53%	0.06
Average	5.66E-08	8.31E-09	87.50%	
Out-of-sample: Prediction based on previous year fitting				
2009	3.93E-06	1.44E-07	96.34%	0
2010	4.49E-07	2.71E-08	93.95%	0
2011	1.46E-07	1.12E-08	92.32%	0

2012	4.02E-07	1.91E-08	95.26%	0
2013	5.48E-07	2.52E-08	95.40%	0
2014	8.20E-07	1.09E-07	86.73%	0
2015	7.99E-07	5.06E-08	93.66%	0
2016	8.56E-07	2.75E-08	96.79%	0
2017	5.81E-08	1.84E-09	96.83%	0
Average	8.89E-07	4.61E-08	94.14%	

Table 5: Model comparison in forecasting volatility for the time series of Baltic Dry Index.

This table presents the volatility prediction results comparison for GARCH model and LIQ-GARCH model regarding the BDI. MSE stands for the mean squared error and the improvement rate is defined as $\frac{MSE_{GARCH}-MSE_{LGARCH}}{MSE_{GARCH}}$. P-values are the paired test results between MSE of GARCH model and MSE of LIQ-GARCH model. The full sample period is from January 1, 1990 to November 30, 2017 with in-sample test method employed. The in-sample test period is 2000-2008 and the tested year is the same as the sample year within the period. The out-of-sample test period is 2009-2017 and the sample year is one year ahead of the tested year within the period. For all sample volatility forecasting, we use one-day ahead perdition approach. The yearly t-statistics is achieved by comparing the daily data of two series, namely, the GARCH and LIQ-GARCH estimated volatility.

Figures

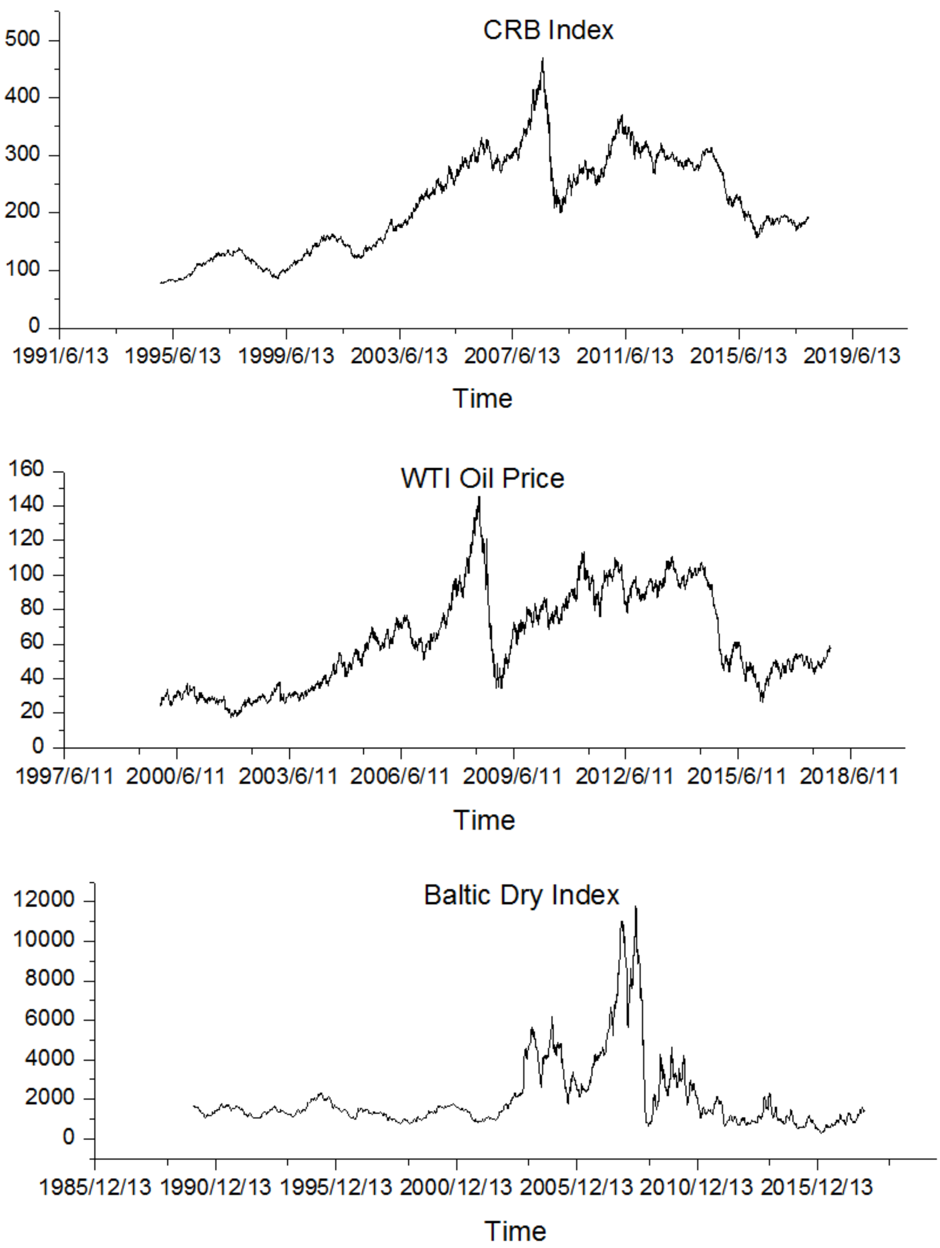

Figure 1: Three time series representation, which are CRB index, oil price and BDI, respectively.

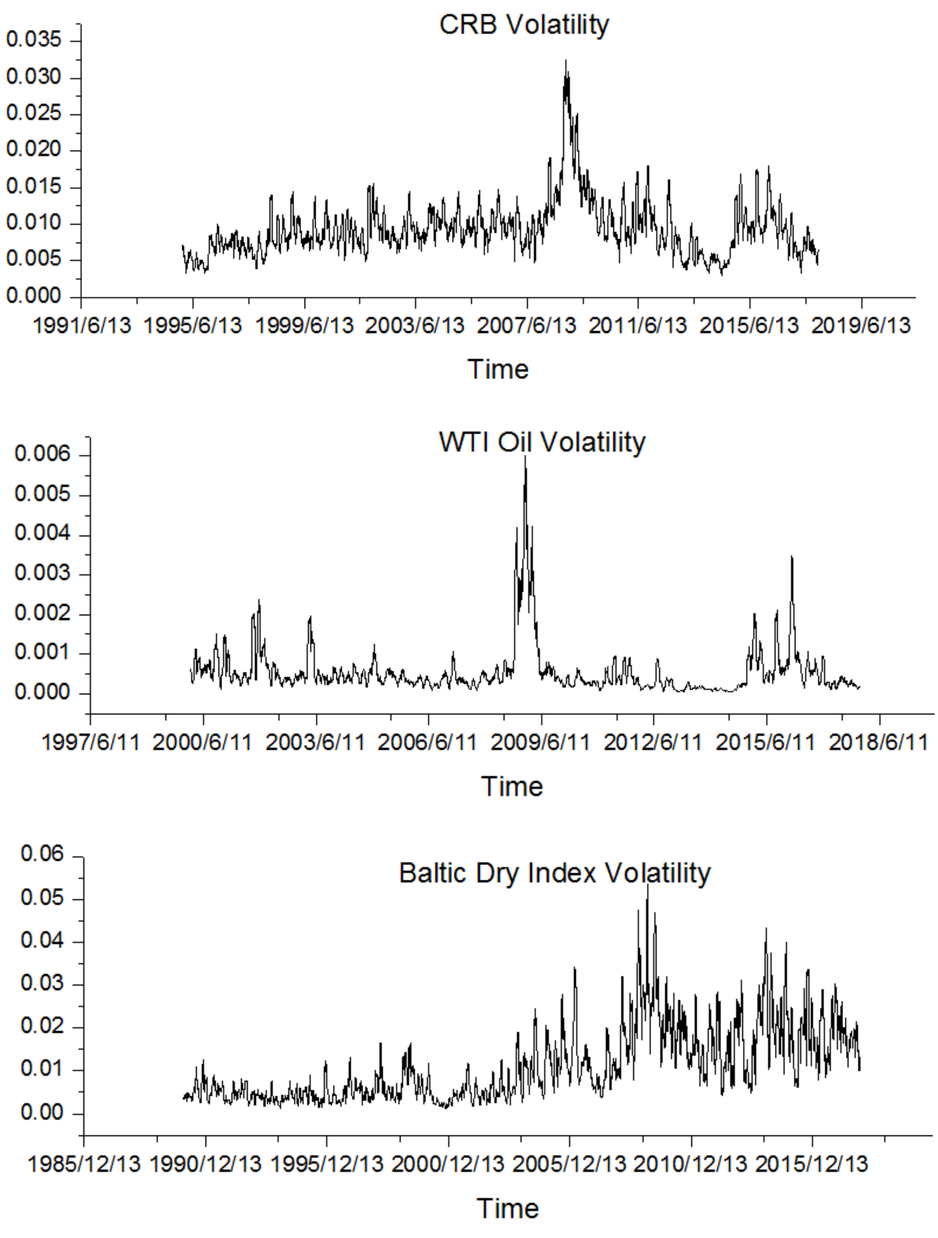

Figure 2: Volatilities of three time series representation, which are volatilities of CRB index, oil price and BDI, respectively.

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