Research Article

Modeling and Prediction of the Volatility of the Freight Rate in the Roadway Freight Market of China

Wei Xiao,¹ Mi Gan ,^{1,2,3} Hongling Liu,¹ and Xiaobo Liu^{1,2,3}

¹School of Transportation and Logistics, Southwest Jiaotong University, No. 111 Erhuanlu Beiyiduan, 610031 Chengdu, China

²National United Engineering Laboratory of Integrated and Intelligent Transportation, Southwest Jiaotong University, Chengdu, Sichuan, China

³National Engineering Laboratory of Integrated Transportation Big Data Application Technology, Chengdu 611756, Sichuan, China

Correspondence should be addressed to Mi Gan; migan@swjtu.cn

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The trucking sector is an essential part of the logistic system in China, carrying more than 80% of its goods. The complexity of the trucking market leads to tremendous uncertainty in the market volatility. Hence, in this highly competitive and vital market, trend forecasting is extremely difficult owing to the volatility of the freight rate. Consequently, there is interest in accurately forecasting the freight volatility for truck transportation. In this study, to represent the degree of variation of a freight rate series in the trucking sector over time, we first introduce truck rate volatility (TRV). This investigation utilizes the generalized autoregressive conditional heteroskedasticity (GARCH) family of methods to estimate the dynamic time-varying TRV using the real trucking industry transaction data obtained from an online freight exchange (OFEX) platform. It explores the ability of forecasting with and without reestimation at each step of the conventional GARCH models, a neural network exponential GARCH (NN-EGARCH) model, and a traditional forecasting technique, the autoregressive integrated moving average (ARIMA) approach. The empirical results from the southwest China trucking data indicate that the asymmetric GARCH-type models capture the characteristics of the TRV better than those with Gaussian distributions and that the leverage effects are observed in the TRV. Furthermore, the NN-EGARCH performs better in in-sample forecasting than other methods, whereas ARIMA performs similarly in out-of-sample TRV forecasting with reestimation. However, the Diebold–Mariano test indicates the better forecasting ability of ARIMA than the NN-EGARCH in the out-of-sample periods. The findings of this study can benefit truckers and shippers to capture the tendency change of the market to conduct their business plan, increase their look-to-buy rate, and avoid market risk.

1. Introduction

Over the past five years, freight trucking in the Chinese industry has increased by 8.6%, generating a revenue of \$113 billion in 2018. Currently, although the freight transportation system of China is well developed, the majority of the transportation modes still comprise of long-haul trucks, which account for up to 80% of the cargo of the country. Despite the significant development of the trucking industry in recent years in terms of the scale, it is criticized for the intense price competition between forwarders. This competition is because most trucking companies in China are

owner-operators, and approximately 70% own only one truck [1, 2]. This status quo presents an immense challenge to the small owner-operators in the trucking business, because without sufficient information, the truckers frequently make low price bids [3]. Owing to this fragment characteristic, the freight rates in trucking are extremely volatile. Freight volatility represents the degree of change or dispersion of freight rates; theoretically, more considerable the volatility, more significant the fluctuation. The complexity of the trucking market introduces significant uncertainty in the market volatility. Hence, in this highly competitive and vital market, trend forecasting is extremely difficult, owing to the

volatility of the freight rate [4]. Typically, the price of road transportation follows a boom-bust pattern because of its bidding nature. Additionally, most shippers and truckers are on-the-spot oriented.

In view of the above factors, an understandable question is whether the freight volatility can be accurately forecasted. Accurately forecasting the daily movements of freight rates can reduce the price premium and consequently increase the efficiency of the market. Until now, only limited attempts have been presented in the literature for forecasting the freight volatility in trucking.

Considering that the freight trucking sector of China is continually growing and is still volatile and not well explained, it is important to explore methods to investigate its price fluctuation. The degree of variation in a freight rate series in trucking over time is defined as the truck rate volatility (TRV). Such an enthusiasm is driven by the availability of an unprecedented amount of data from online freight exchange (OFEX) platforms, such as the required type of truck, size of the vehicle, type of goods, deal truck rates, order posted time, and current location of the trucker.

We contribute to the TRV modeling and forecasting by testing the conventional generalized autoregressive conditional heteroskedasticity (GARCH) family models, autoregressive integrated moving average (ARIMA), and neural network exponential GARCH (NN-EGARCH) model. First, while the use of GARCH-type models is common in the modeling of financial returns, this is extremely limited in TRV modeling. Few studies have analyzed and compared symmetric and asymmetric GARCH-type models in multiple TRV time series. Second, we use multiple training and testing samples for analyzing the performance of forecasting and examine the presence of statistical differences between the competing methods. Third, the forecasting study presented here is based on the intraday trucking data related to one of the essential on-the-spot trucking markets in the roadway transportation of China. The trucking market of China is receiving increasing attention owing to its boom-bust nature. The market participants are searching for practical techniques to forecast the TRV. Therefore, TRV forecasting has become a specific focus for trucking decision makers.

2. Literature Review

The trucking sector plays as an essential role in the national economy of China. In recent years, there has been a growing interest in the time series modeling of trucking data, and the research that has been conducted mainly concerns on-the-spot full truckload pricing. Budak et al. [5] implemented an artificial neural network and a quantile regression to forecast the truckload spot rate based on the highway data of Turkey. The author applied the proposed model in route-based and general approaches to forecast spot marketing rates. Bai [6] developed a nonlinear regression model that incorporated predictor variables to forecast lane-level full-truckload freight rates. The author used an ARIMA model and a conventional nonlinear regression model. Miller [7] developed an ARIMA framework for advancing the forecasts

for three time series of monthly archival truckload trucking prices utilizing two public data sources. The framework also examined the evolution of price based on the temporal dynamics of the freight market. However, little research has been conducted on freight trucking volatility.

Thus far, freight volatility studies have concentrated on the time series modeling of shipping data over time. Autoregressive conditional heteroskedasticity (ARCH) [8] and GARCH [9] models are important parametric models for describing freight volatility. A GARCH model responds to the requirement for a foresight method that considers various properties of the probability distribution of a volatility series; it is used widely in academic studies. Owing to the above requirement, asymmetric GARCH models have expanded rapidly, e.g., the exponential GARCH (EGARCH) model [10], which can capture the fact that adverse shocks in a specific period may result in higher volatility than positive shocks. These models have been extensively used in shipping markets [11–14]. Kavussanos [15], Kavussanos [16] used a set of GARCH models to estimate the time-varying freight rate volatility in the tanker market and to demonstrate the instability of the prices of larger vessels compared to those of smaller ones. Chen and Wang [12] documented the asymmetric effects in the freight rate volatility corresponding to the negative changes in the freight rates compared to those associated to positive changes. Alizadeh and Nomikos [11] estimated GARCH family models, the relationship between the dynamics of the term structure, and the time-varying volatility in the shipping freight market using aggregate spot and time-charter data. Such studies demonstrate the capability of the GARCH family models in capturing the characteristics of a time-varying freight rate volatility in the shipping market. In addition, a GARCH model has recently been proved to perform well in capturing the traffic volume and occupancy volatility at coarse data resolutions in traffic areas [17].

Although GARCH family models perform well in capturing the characteristics of volatility, they may not be outstanding for volatility forecasting problems. Donaldson and Kamstra [18] were one of the first to demonstrate that a neural network (NN) could capture the nonlinear characteristics of volatility, whereas the conventional GARCH models or derivatives could not be modeled. Following this work, there were several studies on hybrid NN-GARCH family models, e.g., Kristjanpoller and Minutolo [19] employed hybrid NN-GARCH models to predict the price volatility of bitcoins, and the computational results proved that the forecasting ability of the hybrid models was good. Tseng et al. [20] proposed a hybrid asymmetric volatility forecasting method with an NN to predict the financial derivatives in Taiwanese markets and concluded that the grey-GARCH model increased the forecasting power. The problem of forecasting volatility is well known; however, whether nonparameter methods can increase the forecasting accuracy of the freight trucking volatility is debatable. In comparison, some studies found evidence in favor of the excellent forecasting performances of hybrid models, whereas others claimed that simple ARIMA-based models presented relatively more accurate NN performances [21].

Our study provides insight on this debate. For validation and implementation, multiple training and testing samples are used to demonstrate the performance of the forecasting.

The remainder of this paper is organized as follows. In Section 4, the research methodology is presented. Section 4 describes the analysis results and related discussions. The summary of this study is presented in Section 5.

3. Methodology

3.1. GARCH Family Models

3.1.1. GARCH Model. In a GARCH model, modeling the volatility, requires two important properties: an autoregression part for the prediction of a future value by shaping the past values of volatility and a heteroskedasticity part to describe the probability distribution of the volatility. The GARCH (p, q) model is introduced as follows [9]:

$$\begin{aligned} r_t &= \mu + \varepsilon_t, \\ \varepsilon_t &= z_t \sigma_t, \quad z_t \sim i.i.d.N(0, 1), \\ \sigma_t^2 &= \omega + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^p \beta_j \sigma_{t-j}^2, \end{aligned} \quad (1)$$

where r_t is the return time series, μ is the expected return, ε_t is the error term that follows a normal distribution with mean zero and a time-varying variance, z_t is the standard Gaussian, σ_t^2 is the conditional variance, ω is a constant, α is the lagged squared error, and β is the lagged variance. The best (p, q) can be chosen by the Akaike information criterion (AIC) [22] or Schwarz information criterion (SIC) [23]. All the parameters ($\mu, \omega, \alpha, \beta$) are estimated by maximizing the log likelihood, and the rate volatility analysis is based on the estimated results of the parameters. The interpretations of the parameters are as follows. (1) α is the sensitivity of the volatility when external shocks occur. Describing the sensitivity of the market volatility when outside shocks occur, a larger α implies more rapid volatility responses to the market shocks. (2) β describes the memory of self-volatility. If $0 < \beta < 1$, a larger β implies a longer persistence and slower decrease in the volatility; if $\beta > 1$, the volatility will be enlarged owing its own fluctuant regularity in the earlier stage. (3) $\alpha + \beta$ is known as the GARCH process persistence parameter. If $\alpha + \beta < 1$, then it indicates the existence of mean-reversion in volatility; if $\alpha + \beta > 1$, the shocks have the tendency to increase. Although there are nonnegative restrictions on the parameters (i.e., $\omega, \alpha, \beta > 0$), $\omega = 0$ and $\alpha + \beta = 1$ are possible.

3.1.2. EGARCH Model. Conventional GARCH (CGARCH) models cannot identify the asymmetric effect from the market shocks because positive and negative impacts are considered to have the same magnitude of influence on the volatility. Generally, the leverage effect is employed to represent such asymmetric relations. Why does the leverage effect occur? Typically, when a price undergoes an unexpected drop, the volatility is higher than that when the price suddenly increases. In the presence of the asymmetric effect,

it is inappropriate to treat the conditional variance function as an asymmetric specification in a CGARCH model. To overcome this drawback of a GARCH model, an EGARCH model was proposed with the relaxation of the nonnegative constraints on the coefficients in a GARCH model. Therefore, EGARCH models draw significant attention in the analysis of stock, house, oil, and gas prices, even in the shipping market. The EGARCH (p, q) model is expressed in equation (2), and the parameters ($\mu, \omega, \alpha, \beta, \gamma$) are estimated by maximizing the log likelihood. The estimated parameters can aid in determining the presence of the asymmetric effect.

$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^q \{ \alpha_i (|z_{t-i}| - E[|z_{t-i}|]) + \gamma_i z_{t-i} \} + \sum_{j=1}^p \beta_j \ln(\sigma_{t-j}^2). \quad (2)$$

The economic definitions of α and β in equation (2) are consistent with those in a GARCH model, and parameter γ measures the asymmetry or the leverage effect. If $\gamma = 0$, then there is no asymmetric effect, i.e., the model is symmetric. If $\gamma > 0$ and statistically significant, then the asymmetric effect exists, and positive news generates more volatility than negative news; if $\gamma < 0$ and statistically significant, it implies that the volatility is asymmetric, and bad news (negative shocks) is more destabilizing than good news (positive innovation).

3.1.3. Maximum Likelihood Estimations with Different Densities. GARCH models are estimated by the maximum likelihood approach, whose concept is to interpret the density as a likelihood function, i.e., a function of the parameter set on the condition of a set of sample outcomes [24]. Previous studies have demonstrated the inability of a GARCH model estimated with a normal error distribution for excess kurtosis and illustrated that an appropriate distribution will reduce the excess kurtosis and skewness [10, 25]. Hence, three distributions were considered in this study: student- t , skewed student- t , and generalized error distributions, in which the student- t distribution includes a shape parameter and the skewed student- t distribution contains a shape parameter and an asymmetric parameter.

- (1) Student- t . The log-likelihood function for the student- t distribution is expressed as

$$\begin{aligned} L_T &= \ln \Gamma\left(\frac{v+1}{2}\right) - \ln \left[\Gamma\left(\frac{v}{2}\right) \right] - 0.5 \ln[\pi(v-2)] \\ &\quad - 0.5 \sum_{t=1}^T \left[\ln \sigma_t^2 + (1+v) \ln \left(1 + \frac{z_t^2}{v-2} \right) \right], \end{aligned} \quad (3)$$

where $\Gamma(\cdot)$ is the gamma function and v is the degree of freedom, which is also called the shape parameter, $2 < v < \infty$. A low v is associated with a fat tail.

- (2) Skewed student- t . The skewed student density was proposed by Steel [26] and subsequently extended to a GARCH model [27]. Its log-likelihood function is

$$\begin{aligned}
L_T = & \ln \Gamma\left(\frac{v+1}{2}\right) - \ln \left[\Gamma\left(\frac{v}{2}\right) \right] - 0.5 \ln [\pi(v-2)] \\
& + \ln \left(\frac{2}{\xi + (1/\xi)} \right) + \ln(s) \\
& - 0.5 \sum_{t=1}^T \left[\ln \sigma_t^2 + (1+v) \ln \left(1 + \frac{sz_t + m}{v-2} \xi^{-I_t} \right) \right],
\end{aligned} \quad (4)$$

where $\Gamma(\cdot)$ is the gamma function, v is the degree of freedom (shape parameter), and ξ is the asymmetric parameter, and $I_t = \begin{cases} 1, & \text{if } z_t \geq -m/s, \\ -1, & \text{if } ez_t < m/s \end{cases}$, $m = (\Gamma((v+1)/2) \sqrt{v-2} / \sqrt{\pi} \Gamma(v/2)) (\xi - (1/\xi))$, and $s = \sqrt{(\xi^2 + (1/\xi^2) - 1) - m^2}$. The choice of the skewed student- t distribution has a remarkable impact on an EGARCH model.

$$E(|z_t|) = \frac{2\xi^2}{\xi + (1/\xi)} \frac{\Gamma((v+1)/2) 2\sqrt{v-2}}{\sqrt{\pi}(v-1)\Gamma(v/2)}. \quad (5)$$

Note that for student- t , $\xi = 1$.

- (3) Generalized error distribution (GED). If a GARCH model is assumed to follow a GED, the log-likelihood function of the GED is that given by Karlsson [28].

$$\begin{aligned}
L_T = & \sum_{t=1}^T \ln \left(\frac{v}{\lambda} \right) - 0.5 \left| \frac{z_t}{\lambda} \right|^v - \left(1 + \frac{1}{v} \right) \ln(2) \\
& - \ln \left[\Gamma\left(\frac{1}{v}\right) - 0.5 \ln(\sigma_t^2) \right],
\end{aligned} \quad (6)$$

where $\lambda = [(2^{-2/v} \Gamma(1/v)) / (\Gamma(3/v))]^{1/2}$.

3.2. Multilayer Perceptron (MLP). Neural networks have been widely used in financial quantitative applications. One of the most common architectures is called multilayer perceptron (MLP), which contains an input layer, a hidden layer, and an output layer. Each layer is represented by a vector, and $d = (x_1, x_2, \dots, x_d)'$, $m = (h_1, h_2, \dots, h_m)'$, and $c = (y_1, y_2, \dots, y_c)$ represent the input, hidden, and output layers, respectively. An MLP is defined as a weighted linear combination of the d input values

$$a_j = \sum_{i=0}^d w_{ji}^{(1)} x_i. \quad (7)$$

By implementing a logistic activation function, $g(\cdot)$, the activation of the hidden unit, j , is obtained as

$$z_j = g(a_j). \quad (8)$$

For each output k , the output layer is defined as follows:

$$a_j = \sum_{i=0}^m w_{kj}^{(2)} z_i. \quad (9)$$

Combining equations (7)–(9) and using a nonlinear activation function, $y_k = \tilde{g}(a_k)$, the MLP is defined as follows:

$$y_k = \tilde{g} \left(\sum_{j=1}^m w_{kj}^{(2)} g \left(\sum_{i=1}^d w_{ji}^{(1)} x_i \right) \right). \quad (10)$$

If the output function is linear, then $\tilde{g}(a) = a$, and the model will be reduced to

$$y_k = \sum_{j=1}^m w_{jk}^{(2)} g \left(\sum_{i=1}^d w_{ji}^{(1)} x_i \right). \quad (11)$$

In this study, a backpropagation neural network (BPNN) was used to train and learn the parameters [29]. Figure 1 displays the structure of a three-layer BPNN. In addition, “early stopping” was utilized to avoid overfitting in the NN training process, which was based on dividing the dataset into training, validation, and test sets. In this study, 80% of the dataset was for training, 10% for validation, and 10% for testing.

3.3. Hybrid GARCH Family Neural Network Models.

Donaldson and Kamstra [18] developed a hybrid forecasting model that integrated GARCH-type models and NNs. Based on the contribution of Donaldson, we introduce a hybrid model that combines a GARCH-type model with an MLP. This combination considers the output layer of the NN as a variable of the GARCH-type model. The NN-GARCH and NN-EGARCH are expressed as follows.

3.3.1. NN-GARCH (p, q, s). The NN-GARCH (p, q, s) model that integrates the GARCH (p, q) model with one single hidden layer of an NN with s hidden neurons is expressed as

$$\sigma_t^2 = \omega + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^p \beta_j \sigma_{t-j}^2 + \sum_{h=1}^s \xi_h \psi(z_t \lambda_h), \quad (12)$$

$$\psi(z_t \lambda_h) = \left[1 + \exp \left(\lambda_{h,d,w} + \sum_{d=1}^1 \left[\sum_{w=1}^m \lambda_{h,d,w} z_{t-d}^w \right] \right) \right]^{-1}, \quad (13)$$

$$z_{t-d} = \frac{[\varepsilon_{t-d} - E(\varepsilon)]}{\sqrt{E(\varepsilon^2)}}, \quad (14)$$

$$\frac{1}{2} \lambda_{h,d,w} \sim \text{uniform}[-1, +1], \quad (15)$$

where $\psi(z_t \lambda_h)$ is a logistic function of form $1/(1 + \exp(-x))$. The artificial NN (ANN) expression of equation (12) is analogous to equation (11) but with different notations, e.g., $\xi = w$, $\psi = g$, and $z_t \lambda_h = x_i$.

3.3.2. NN-EGARCH (p, q, s). The NN-EGARCH (p, q, s) is expressed as

FIGURE 1: A three-layer neural network with a BPNN.

$$\begin{aligned}
 \ln(\sigma_t^2) &= \omega + \sum_{i=1}^q \{ \alpha_i (|z_{t-i}| - E[|z_{t-i}|]) + \gamma_i z_{t-i} \} \\
 &\quad + \sum_{j=1}^p \beta_j \ln(\sigma_{t-j}^2) + \sum_{h=1}^s \xi_h \psi(z_t \lambda_h), \\
 \psi(z_t \lambda_h) &= \left[1 + \exp \left(\lambda_{h,d,w} + \sum_{d=1}^1 \left[\sum_{w=1}^m \lambda_{h,d,w} z_{t-d}^w \right] \right) \right]^{-1}, \\
 z_{t-d} &= \frac{[\varepsilon_{t-d} - E(\varepsilon)]}{\sqrt{E(\varepsilon^2)}}, \\
 \frac{1}{2} \lambda_{h,d,w} &\sim \text{uniform}[-1, +1],
 \end{aligned} \tag{16}$$

where $\xi = w$, $\psi = g$, $z_t \lambda_h = x_i$. $\psi(z_t \lambda_h)$ and z_{t-d} are defined in equations (7)–(9).

4. Case Study

In this section, we first describe the method with which we utilized micro-trucking data to estimate the TRV by embedding them in a framework. In the following, a practical framework is presented to illustrate the analysis procedures, i.e., database creation and data cleaning. Next, the statistical analysis of the TRV is described. Then, the implementation of the GARCH family models and the hybrid models to capture the characteristics of a volatility series and to conduct in-sample and out-of-sample forecasting is discussed. Finally, the detailed results and discussion are presented.

4.1. Framework. To detect the potential trend of the TRV, as a first step, a study framework is proposed to illustrate the procedures for analyzing the volatility of truck rates.

The framework (Figure 2) consists of three major modules: database model, data cleaning, and application. These modules are integrated into an analysis framework, because they are sequential procedures in a data-driven study pipeline. As shown in Figure 2, first, the database model is used to create a data pool. Subsequently, the data cleaning is conducted for detecting and removing the errors or the corruption in the data pool. Finally, volatility exploration is performed by econometric methods. The three modules in the framework are discussed below.

4.1.1. Database Model. A database is derived from the OFEX platform, where the following information is provided: (I) trucker data including the trucker ID, types of truck, length of the vehicle, and registration location of the trucker; (II) shipper data including the shipper ID and registration location of the shipper; (III) order data containing the order ID, origin, and destination city; specified type and length of the vehicle; type of cargo; and creation order date; (IV) truck rates data including the order ID, trucker ID, shipper ID, and closed order date. The integration of the above data information helps to conduct a thorough investigation of the truck rates by best utilizing the microtrucking data.

4.1.2. Data Cleaning. When processing the data, we first remove the null values. Then, we observe that some trucking data have abnormal loads or rates or both, which mostly results from the mis-fill by the shippers. However, it is difficult to decide the precise boundaries to remove these abnormalities. In this study, the decision is made mainly based on empirical information. First, because the distribution of the truck rates is observed to be similar to a Gaussian distribution, a two-boundary outlier elimination is implemented to reject the abnormal rates with different standard deviation boundaries. Second, to ensure the reliability of the processed data, the operator of the OFEX platform verifies if the processed data are in line with the real truck rates provided by hundreds, and even thousands, of business calls with truckers and shippers. After several experiments with combinations of limits and standard deviations, standard deviations 1.65 and 1.96 of truck rates are selected as the first and second limits for the elimination boundaries, respectively, and the final dataset retains more than 90% of the records.

4.1.3. Application. The output of module (2) is utilized to format a volatility series, and the methods mentioned in Section 3 are employed to model and predict the volatility series.

4.2. Data Analysis. The truck rates from southwest China (Figure 3(a)) were sampled from the database module, from March 2018 to August 2018. As displayed in Figure 3(a), the study area contains three provinces (Sichuan, Yunnan, and Guizhou) and a centrally administered city (Chongqing). The colored routes represent the shortest routes between pairwise trips from Google Maps. In reality, given an origin-destination pair, these colored routes are the actual transport routes of the truckers by default. As seen from the provincial data volume, that in southwest China comprises a significant portion of the total data volume. Moreover, we find that the capitals are the main distribution centers. For example, Chengdu and Guiyang, the capitals of Sichuan and Guizhou, respectively, cover almost 50% of the provincial trucking data, and 85% for Kunming, the capital of Yunnan (Figure 3(c)). Besides, it can be easily seen that the high cage is the most prominent truck type from both province- and city-wide perspectives (Figures 3(d) and 3(e)) and even from

FIGURE 2: Truck rates volatility analysis framework.

FIGURE 3: Overview of the trucking market of southwest China: (a) map of southwest China; (b) nationwide truck components; (c) data volume by cities (top three marked only); (d) provincewide truck components; (e) city-wide truck components.

a nationwide standpoint (Figure 3(b)). Therefore, we focus on 12 route-specific rates between any two capitals (Chengdu, Sichuan, Yunnan, and Chongqing) at a high-cage-truck branch level. For brevity, a trip from city i to city j is defined as “iTj,” where $i, j \in \{\text{Chengdu (C), Chongqing (Q), Guiyang (G), and Kunming (K)}\}$, and $i \neq j$. For example, “CTG” denotes a trip from Chengdu to Guiyang.

To appropriately estimate the volatility of intraday rates series, the time series, as multiple truck rates per day, is transformed into an intraday mean-removal standard variance form (d_t), which is expressed as

$$d_t = \sqrt{\frac{\sum_{t=1}^{m_t} (P_t - \mu_t)^2}{\mu_t}}, \quad (17)$$

where m_t is the number of truck rates at day t ($t = 1, 2, \dots, T$), P_t is the truck rates at day t , and μ_t is the mean value of the intraday truck rates. The daily mean-removal standard variance series, d_t , represents the fluctuation in the trucking market. A larger d_t implies a larger bargaining gap between the truckers and the shippers.

As the market participants pay significant attention to the daily change ratio of rates, to analyze the short-term fluctuation tendency of each trip, the daily volatility is defined as

$$r_t = \frac{d_t}{d_{t-1}}, \quad (18)$$

where d_t and d_{t-1} are the standard variances of the truck rates at day t and $t-1$, and r_t is the volatility, which represents the daily variance returns or the change in the daily fluctuation in the market. Various route-specific volatility series (r_t) are plotted in Figure 4. Here, we use “R_#route name#”; to name each volatility series, e.g., “R_CTG” denotes a volatility series of the rates of a trip from C to G.

From the above figure, it is clear that for each volatility series, the volatilities display a pattern consisting of the fluctuation aggregation characteristic of the financial asset price changes. In the sequence of financial assets, high and low-volatility assets tend to cluster in a certain period, and they appear alternately. Particularly, the contrasts in the high and low volatilities of R_QTK and R_QTG are the most remarkable; high volatility before and after the emergence of the points is observed at the end of the month. This may be owing to the status quo of the trucking industry in China, which requires a monthly statement payment for both third-party logistics companies and long-term cooperated individual truckers. After careful observation and comparison of the volatility sequences, it can be seen that R_CTQ and R_KTG have the most frequent fluctuations, which indicates that their rates are likely to fluctuate more significantly than those of other routes. To further understand the route-specific volatility sequences, the following presents the analysis of the statistical characteristics of each volatility sequence. Basic statistical characteristics were examined and are listed in Table 1.

From the above statistics, the following can be concluded. (1) In terms of the skewness and kurtosis, the

skewness of all the wave sequences is greater than zero, and the kurtosis is greater than three. Therefore, all the volatility sequences are right-skewed and have the characteristics of a sharp peak and a thick tail. The volatility series do not follow a normal distribution because they reject the hypothesis of the Jarque–Bera (J–B) statistic at 5% significant level; therefore, in the following volatility modeling, nonnormal distributions (e.g., student- t , skewed student- t , and GED) were considered. Interestingly, the above characteristics are exactly similar to those of the stock indices and shipping indices, which offers some motivation for the approaches for the volatility analysis of the truck rates. (2) Based on the results of the Ljung–Box Q-statistics (Q (5) and Q (10)), all the volatility series are free of autocorrelation. (3) The volatility series are indicated to be stationary, based on the results of the augmented Dickey–Fuller (ADF) unit root test; specifically, the t -statistics values summarized in Table 1 are less than the value of the critics (−2.86). Because Xiaoxu Ding [33] had mentioned that a GARCH model was suitable for stationary time series, it is concluded that the above volatility series satisfy the prerequisite of GARCH models. The optimal lag length of the ADF is presented in square brackets, and it is determined by SIC. (4) To analyze the conditional volatility estimates (σ_t^2) of the trucking rate by a GARCH model, the conditional heteroscedasticity of the autocorrelation in the residual is tested by the ARCH Lagrangian multiplier (LM) test until the q^{th} order [34]. Only if the ARCH effect is detected, then can the GARCH model be employed. The results of the ARCH-LM test demonstrate the existence of the ARCH effects for all the volatility series.

4.3. Empirical Results

4.3.1. Characteristics of Volatilities. Based on the above statistical results, a GARCH model was implemented for estimating the volatility. After several experiments, GARCH (1, 1) with skewed student- t distribution (named as SST-GARCH (1, 1)) is preferred because it has the lowest AIC and SIC values (the comparison of GARCH model with different error distribution has pages, for reading easily, which are not put in the paper, but could be attached if required). The empirical results with SST-GARCH (1, 1) are reported in Table 2.

Interestingly, in our analysis, R_CTK possess the greatest α value. Compared with the other route-specific volatility sequences, the impact of the external shocks on route CTK is relatively large (0.101), followed by that on routes GTQ (0.068) and KTQ (0.014). In addition, the values of lag coefficient β are much more significant than the values of return coefficient α , which indicates that the trucking market in the southwestern part of China generally has a long memory and a weak sensitivity to the market fluctuations. Comparing the values of β , it can be seen that route CTQ has the strongest memory of market fluctuations (0.995), followed by route GTK (0.991), whereas route QTC has the weakest memory of market fluctuations (0.816). Based on the above analysis, we conclude that among the above 12 routes, CTK is the most sensitive to the entire

FIGURE 4: Route-specific volatility series: (a) R_CTG, (b) R_CTK, (c) R_CTQ, (d) R_GTC, (e) R_GTK, (f) R_GTQ, (g) R_KTC, (h) R_KTG, (i) R_KTQ, (j) R_QTC, (k) R_QTG, and (l) R_QTK.

market fluctuations, whereas CTQ is the least sensitive to them; however, its impact persists for a long time. This indicates that the QTK itself is relatively stable. Moreover, it can be seen that $\alpha + \beta < 1$ for all the volatility sequences, which implies that the volatility sequences themselves are mean-reverting processes. Furthermore, from the bottom of Table 2, it can be seen that the shape (ν) and skew (ξ) parameters are statistically significant and that the ARCH-LM test at different lags demonstrates the absence of the ARCH effects in all the volatility sequences after the SST-GARCH model.

4.3.2. Leverage Effects. A GARCH model assumes that the magnitude of the unexpected excess return is a prerequisite for determining the outcome; however, reliable results depend on the magnitude and the direction of the impact. Negative shocks have larger impact on the volatility compared to positive shocks. A further estimation of the volatility is expected as an EGARCH can counteract the limitations based on the CGARCH. After several experiments, EGARCH with skewed student- t distribution (named as SST-EGARCH (1, 1) and SST-EGARCH (2, 2)) is preferred, because it has the lowest AIC and SIC values. The

TABLE 1: Statistical description of the volatility.

	R_CTG	R_CTK	R_CTQ	R_GTC	R_GTK	R_GTQ	R_KTC	R_KTG	R_KTQ	R_QTC	R_QTG	R_QTK
Sample size	21254	20019	21094	26098	22213	21689	28087	27067	21683	27094	23090	21924
Mean	1.585	1.299	1.271	1.313	1.401	1.621	2.071	1.519	2.237	1.774	2.797	2.015
Median	0.972	1.016	0.936	1.047	0.88	1.071	0.96	0.915	0.925	1.215	0.987	0.941
Maximum	11.647	5.25	4.056	4.329	6.614	12.837	15.925	8.075	14.683	10.387	33.24	28.715
Minimum	0.123	0.134	0.178	0.196	0.127	0.098	0.048	0.086	0.089	0.049	0.056	0.123
SD	1.87	0.936	0.925	0.935	1.39	2.156	3.128	1.642	3.16	2.158	6.091	4.205
Skewness	3.434	1.873	1.334	1.65	2.274	3.495	3.045	2.434	2.539	2.516	3.956	5.373
Kurtosis	18.023	7.738	4.188	5.531	8.356	16.793	12.591	9.01	9.407	9.174	18.563	34.03
J-B	568.468 (0.000)	75.995 (0.000)	17.759 (0.000)	36.046 (0.000)	102.868 (0.000)	498.182 (0.000)	268.934 (0.000)	124.626 (0.000)	139.225 (0.000)	132.187 (0.000)	634.989 (0.000)	2246.588 (0.000)
ADF (lags)	-8.111 [0]	-9.925 [0]	-4.005 [0]	-5.997 [0]	-9.125 [0]	-8.010 [0]	-5.197 [0]	-5.550 [0]	-8.748 [0]	-8.949 [0]	-3.498 [0]	-7.751[0]
Q (5)	6.929 (0.226)	8.335 (0.139)	8.265 (0.142)	11.594 (0.053)	7.066 (0.216)	2.673 (0.750)	3.456 (0.630)	5.741 (0.332)	4.720 (0.451)	7.272 (0.201)	2.106 (0.834)	1.780 (0.879)
Q (10)	9.004 (0.532)	11.721 (0.304)	16.683 (0.182)	15.829 (0.105)	8.545 (0.576)	14.346 (0.158)	4.847 (0.901)	7.505 (0.677)	11.622 (0.311)	8.596 (0.571)	3.907 (0.951)	3.037 (0.981)
LM (lag = 1)	2.236 (0.036)	4.745 (0.000)	4.152 (0.001)	4.367 (0.000)	3.165 (0.005)	2.78 (0.011)	2.115 (0.027)	2.881 (0.009)	2.957 (0.010)	3.392 (0.041)	2.153 (0.041)	2.229 (0.037)

P-values are reported in parentheses. SD represents the standard deviation. J-B represents the Jarque-Bera test in which a goodness-of-fit test is performed for examining whether the time series follows a normal distribution [30]. Q (5) and Q (10) are the statistics of the Ljung-Box test [31] in which there is a serial autocorrelation for the series up to fifth and tenth orders. ADF represents the Augmented Dickey-Fuller (ADF) test with a null hypothesis of existence of autocorrelation in the sample series [32].

TABLE 2: SST-GARCH (1, 1) estimated parameters of the volatility series.

	R_CTG	R_CTK	R_CTQ	R_GTC	R_GTK	R_GTQ	R_KTC	R_KTG	R_KTQ	R_QTC	R_QTG	R_QTK
ω	0.154**	0.760**	0.000**	0.021**	0.837**	0.254**	0.167**	0.003**	0.117**	0.841*	3.228**	0.395**
Prob.	(0.000)	(0.010)	(0.000)	(0.000)	(0.016)	(0.000)	(0.000)	(0.043)	(0.000)	(0.074)	(0.000)	(0.000)
α	0.005**	0.101**	0.003**	0.007**	0.004**	0.068**	0.012**	0.011**	0.014**	0.004**	0.005**	0.010**
Prob.	(0.000)	(0.000)	(0.001)	(0.039)	(0.021)	(0.000)	(0.000)	(0.032)	(0.012)	(0.047)	(0.000)	(0.000)
β	0.946**	0.889**	0.995**	0.950**	0.991**	0.922**	0.963**	0.982**	0.978**	0.816**	0.915**	0.946**
Prob.	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\alpha + \beta$	0.951	0.990	0.998	0.957	0.995	0.990	0.975	0.993	0.992	0.820	0.920	0.956
ξ (Skew)	29.000**	2.191**	5.657**	2.940**	2.446**	4.421**	6.278**	4.836**	30.000**	5.225**	30.000**	9.079**
Prob.	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)
ν (Shape)	2.901**	3.375**	10.016**	6.020**	3.228**	2.497*	2.479**	3.095**	2.718**	2.504**	2.062**	2.188**
Prob.	(0.000)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ARCH-LM (3)	0.079	0.016	0.255	0.6584	0.065	0.112	0.024	0.477	0.382	0.299	0.073	0.046
ARCH-LM (5)	0.348	0.213	5.795	1.1083	0.204	0.306	0.100	0.763	0.522	0.729	0.162	0.124
ARCH-LM (7)	0.530	0.778	7.940	2.0307	0.339	2.863	0.229	1.550	0.935	1.079	0.378	0.185

**Significance at (5%); *significance at (10%).

empirical results with the SST-EGARCH are reported in Table 3.

In general, as each γ_i is significant and not equal to zero, the leverage effects exist in all the route-specific trucking submarkets, which indicates that the same extent of the positive and negative shocks will generate different impacts on the volatilities. Coefficient β , which measures the persistence of self-volatility, is also statistically significant for all the series. The more the value of β is close to one, the greater are the persistence shocks on the volatility. From the left part of Table 3, it can be seen that the volatility duration of R_KTC will be longer when compared to those of R_GTQ, R_QTG, and R_QTC; specifically, the fluctuations brought by the external shocks will continue to affect the rate over a relatively longer period. R_QTG having minimal β (0.281)

suggests that for particular (positive/negative) external shocks, the rate of route QTG could be rapidly returning to normal after the external shocks, i.e., the influence of the shocks has less impact on the future rate. Coefficient γ represents the leverage component, past standardized innovations. The γ values of R_KTC, R_QTG, R_GTQ, and R_QTC are -0.081 , -1.677 , -0.706 , and -0.694 , respectively, which are all less than zero, indicating that negative external shocks could cause higher volatility than positive ones. From the right part of Table 3, we can also conclude that for the other eight route-specific trucking markets, negative external shocks can induce higher volatility than positive external shocks. To identify a model that is highly suitable for the TRV, Table 4 presents the comparison results of the SST-GARCH and SST-EGARCH models. Three criteria are

TABLE 3: SST-EGARCH estimates of the volatility series.

	SST-EGARCH (1, 1)						SST-EGARCH (2, 2)					
	R_GTQ	R_QTG	R_QTC	R_KTC	R_KTG	R GTK	R_GTC	R_CTK	R_KTQ	R_CTQ	R_CTK	R_QTK
ω_0	1.990**	3.784**	0.478**	0.247**	0.837**	0.441**	**	1.318**	3.443**	-0.111**	-0.249**	3.260**
Prob.	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.027)	(0.000)	(0.000)	(0.000)	(0.000)	(0.050)	(0.000)
α_1	-1.540**	1.623**	0.606**	0.051**	-0.141**	0.369**	0.136**	0.027**	0.381**	-0.578**	0.299**	0.670**
Prob.	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.019)	(0.000)	(0.000)	(0.000)	(0.000)	(0.011)	(0.000)
α_2	—	—	—	—	-0.540**	0.748**	0.388**	-0.271**	0.397**	-0.518**	0.254**	-0.130**
Prob.	—	—	—	—	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_1	0.533**	0.281**	0.640**	0.859**	-0.613**	0.522**	-0.226**	0.121**	-0.056**	-0.170**	-0.088**	-0.215**
Prob.	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.014)	(0.000)	(0.000)	(0.000)	(0.000)	(0.040)	(0.000)
β_2	—	—	—	—	0.023**	-0.271**	0.622**	0.323**	-0.144**	0.756**	-0.838**	0.381**
Prob.	—	—	—	—	(0.000)	(0.033)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ_1	-0.706**	-1.677**	-0.694**	-0.081**	0.253**	-0.507**	0.301**	-0.122**	-0.350**	-0.870**	-0.157**	-1.026**
Prob.	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.013)	(0.000)	(0.000)	(0.000)	(0.000)	(0.033)	(0.000)
γ_2	—	—	—	—	-0.631**	-0.633**	-0.666**	-0.198**	-0.613**	0.633**	-0.474**	0.042**
Prob.	—	—	—	—	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ξ	30.000**	4.047**	6.866**	30.000**	30.000**	2.543**	1.842**	30.000**	30.000**	30.000**	3.227**	10.097**
Prob.	(0.031)	(0.000)	(0.010)	(0.035)	(0.026)	(0.000)	(0.000)	(0.000)	(0.015)	(0.000)	(0.000)	(0.000)
ν	2.023**	2.084**	2.485**	2.400**	3.043**	2.650**	3.029**	2.191**	2.195**	6.550**	3.503**	2.027**
Prob.	(0.031)	(0.000)	(0.010)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ARCH-LM (3)	0.104	0.091	0.179	0.010	0.510	0.029	0.291	0.141	3.60E-04	0.676	0.482	0.052
ARCH-LM (5)	0.324	0.195	0.484	0.085	1.619	0.301	0.789	0.415	0.522	13.804	1.337	0.133
ARCH-LM (7)	1.826	0.293	0.723	0.194	2.114	0.624	1.053	0.570	0.780	14.906	2.400	0.180

P-values are reported in the parentheses; **significance at (5%); *significance at (10%).

considered to evaluate the performances of the two models: log-likelihood values [35], AIC, and SIC, which indicate that SST-EGARCH is better than the SST-GARCH model.

From the above analysis, we are interested in the results of the leverage effect. Conventionally, the relation between demand (the number of orders) and supply (the number of truckers) is discussed when referring to pricing issues [36]. However, this may not be the essential factor for the pricing fluctuation in this study, because the trucking market of China has been oversupplied (the number of truckers is larger than the number of orders) for a long time [4]. Thus, any regular change in the difference between the supply and the demand results in little pricing fluctuation. Therefore, we considered investigating another critical factor, the type of cargo. The rate is easily influenced by the price of the freight itself; concurrently, the attributes of the shipment will decide the costs of transportation. If the transported cargo is a dangerous product, then it requires a particular truck, and also the trucker will undertake more risks, and hence, the rate is likely to be higher. Based on this, we plot the type of transported cargo of each route and display it in Figure 5.

As can be noted from Figure 5, the proportion of the transported goods in the different routes is quite different. In the above eight classifications of goods, the class “saplings/vegetables/fruit” is most evidently seasonal. For route CTG, the class “saplings/vegetables/fruit” accounts is approximately 50%, which indicates that when the fruit/vegetable

harvest or market economy is dull, the price fluctuation in the fruits and vegetables are more likely to affect the volatility of CTG. The main types of goods transported by GTK and GTQ are heavy cargo: 63.24% and 55.91%, respectively. For CTK, CTK, KTC, KTG, KTQ, QTC, QTG, and QTK, the main types of products are comprised of building materials, general cargo, and shipping commodities. Because these types do not have distinct seasonality, and if there is a significant fluctuation, then this fluctuation is highly possible from industry changes. In particular, route GTC is different from the others, because its main transported cargo is scrap iron (64.44%), whereas the other routes have few such goods. In China, the transportation charge of scrap iron is generally stable and fixed, because most of the steel or iron enterprises are under long-term co-operation with either third-party logistic companies or individual drivers, with a monthly statement. Under the execution of the monthly report, the truckers and shippers are more concerned about the negative external influences, because bad news is likely to aggravate further premium. In addition, for those who have long-term co-operation, bad news may influence the settlement date. It is expected to delay the settlement date, and hence, the truckers do not receive the money on time. The individual truckers who are only activated in the spot market receive money after each transportation, bad news may make the trucking market worse. Thus, individual truckers might be more challenging to earn money. Therefore, bad

TABLE 4: Comparison results of the SST-GARCH and SST-EGARCH models.

Route-specific TRV	SST-GARCH			SST-EGARCH		
	Log likelihood	AIC	BIC	Log likelihood	AIC	BIC
R_CTG	-194.814	2.625	2.744	-188.893	2.600	2.798
R_CTK	-150.786	2.050	2.168	-135.304	1.852	2.050
R_CTQ	-169.209	2.290	2.409	-150.653	2.100	2.298
R_GTC	-146.639	1.995	2.114	-137.083	1.918	2.121
R_GTK	-188.153	2.538	2.657	-172.112	2.433	2.631
R_GTQ	-174.673	2.362	2.481	-163.380	2.252	2.391
R_KTC	-214.237	2.879	2.999	-207.813	2.835	2.973
R_KTG	-198.087	2.668	2.787	-181.178	2.499	2.697
R_KTQ	-246.540	3.301	3.42	-239.179	3.257	3.453
R_QTC	-201.419	2.711	2.832	-188.135	2.551	2.689
R_QTG	-213.183	2.865	2.984	-175.283	2.383	2.521
R_QTK	-190.879	2.574	2.692	-177.581	2.452	2.650

FIGURE 5: Types of goods transported in the trips.

news may result in more tensivity for the market participants than good news, which reflects the impact of negative shocks on the volatility.

4.3.3. Volatility Forecasting. The NN-GARCH model is compared to several benchmark methods, including asymmetric GARCH models and the ARIMA model. The appropriate ARIMA model is determined based on the low AIC, and the stationarity of volatility series has been checked in Table 1. According to the criterion, ARIMA (2, 1, 2) is selected for R_CTG, R_CTK, R_CTQ, and R_QTC, and ARIMA (1, 1, 0) is selected for the remaining TRV series. Concurrently, the NN-EGARCH model and asymmetric EGARCH models are in consistent with the results presented Sections 4.3.1 and 4.3.2. We implemented a static forecast approach (Figure 6) to conduct a next-day TRV forecast without reestimation of the model for the next step, that is, using the actual value of the predictor variable in the previous period for making a prediction in the out-of-sample.

FIGURE 6: Illustration of the static forecast approach.

To assess the forecast accuracy, we considered two performance measures: mean absolute percentage error (MAPE) and mean absolute scaled error (MASE). MASE was proposed by Hyndman and Koehler [37] which is independent of the scale of data. They were calculated based on the following equations:

TABLE 5: In-sample forecast performance.

Route-specific TRV	Forecasting models					
	SST-EGARCH		ARIMA		NN-EGARCH	
	MAPE	MASE	MAPE	MASE	MAPE	MASE
R_CTG	0.781	0.985	0.898	1.109	0.775	1.006
R_CTK	1.205	0.918	1.125	0.886	1.015	0.837
R_CTQ	0.886	0.985	0.891	0.984	0.881	1.018
R_GTC	1.325	0.912	1.514	0.976	1.299	0.991
R_GTK	0.915	0.954	0.851	0.943	0.801	0.890
R_GTQ	0.531	0.899	0.622	1.016	0.512	0.895
R_KTC	0.489	0.936	0.458	0.895	0.451	0.884
R_KTG	0.587	0.998	0.612	1.036	0.553	0.968
R_KTQ	0.425	0.943	0.501	1.042	0.413	0.922
R_QTC	0.554	0.901	0.585	0.944	0.499	0.834
R_QTG	0.774	0.933	0.785	0.938	0.752	0.939
R_QTK	0.667	0.976	0.590	0.874	0.584	0.870

Bold values indicate best performance.

$$\text{MAPE} = 100 \times \frac{1}{N} \sum_{t=1}^N \frac{|\hat{y}_t - y_t|}{y_t}, \quad (19)$$

$$\text{MASE} = \text{mean} \left| \frac{|e_t|}{(1/(N-1)) \sum_{i=2}^N |\hat{y}_t - \hat{y}_{t-1}|} \right|,$$

where N is the number of observations, y_t and $\hat{y}_t$ represent the actual and the predicted price values at time t , respectively, e_t is the forecast error calculated as $(y_t - \hat{y}_t)$, and $(\hat{y}_t - \hat{y}_{t-1})$ is the forecast error of the naïve forecast.

We divided the dataset into training (in-sample) and test (out-of-sample) samples. The in-samples were from March 1, 2018 to August 11, 2018, and the out-of-samples were from August 12, 2018 to August 31, 2018. For the out-of-sample, we examined forecasting the next-day TRV with and without reestimating the forecast model at each step for each employed model. The computational results were obtained with the R software. Results of the in-sample and out-of-sample forecast performances of the employed models are presented in Tables 5 and 6, respectively. Based on Table 5, the NN-EGARCH models perform better than ARIMA and SST-EGARCH in the in-sample forecast. As per Table 6, the ARIMA and NN-EGARCH models outperform SST-EGARCH in the out-of-sample forecast for any case. Concurrently, the forecasting performances of SST-EGARCH and NN-EGARCH have been improved remarkably after reestimation at each step. In contrast, the predictive improvement of ARIMA models has a slight difference after reestimation of model at each step.

When utilizing MAPE, MAPEs in the out-of-sample for NN-EGARCH are lower than those for ARIMA for R_CTK, R_CTQ, R_GTC, R_GTK, and R_KTG, whereas for the remainder route-specific TRV series, ARIMA performs better. To obtain the measurement of the forecast accuracy for the group of route-specific TRV series, we adopt the mean of the average MAPE values. The average MAPEs for ARIMA and NN-EGARCH are 0.322 and 0.328, respectively, which indicates that NN-EGARCH and ARIMA perform similarly when next-day TRV forecasting with reestimation.

Further, the Diebold–Mariano (DM) test [38] is implemented to compare the out-of-sample prediction results obtained from ARIMA and NN-EGARCH model. The DM test is widely used in determining whether the difference of time series predicting accuracy by different models is substantially crucial from a statistical perspective [39]. Table 7 summarizes the results of the DW test for the comparisons of ARIMA and NN-EGARCH for the reestimation forecasting of the group of TRV series. The prominent feature is that it is possible to reject the null hypothesis that ARIMA and NN-EGARCH models have the equal predictive capacity at the traditional levels of significance. Thus, it seems that even though NN-EGARCH model performs better than ARIMA in R_CTK, R_CTQ, R_GTC, R_GTK, and R_KTG, the predictive improvement offered by NN-EGARCH is not statistically significant. This feature indicates that the underlying process that generates TRV data is substantially linear, as well as the weak possibility of existence of nonlinear dynamics in the data. Consequently, the NN-EGARCH does not display statistically better forecasts than ARIMA model.

5. Conclusions

The trucking sector plays an essential role in the national economy, whose research has strongly attracted the interest of numerous shippers, truckers, and market managers in the past years. Participants and decision makers are continuously demanding accurate modeling and forecasting of a future TRV. A predictive improvement, even a simple one, is large for these participants, particularly for the individual truckers because it would allow them to better understand the market change and avoid lower bid or premium.

This study model forecasts the time-varying TRV by proposing a practical framework to estimate the TRV and demonstrate the applicability of the econometric volatility and nonlinear and linear models in the trucking sector. Particularly, an SST-GARCH model is employed to determine the effects of market shocks on the volatility of the TRV, and an SST-EGARCH model is utilized for capturing the asymmetric impact. In addition, we compare the

TABLE 6: Out-of-sample predictive performance in a static forecast approach.

Route-specific TRV	Forecast with/without Reestimation at each step	Forecast Models					
		SST-EGARCH		ARIMA		NN-EGARCH	
		MAPE	MASE	MAPE	MASE	MAPE	MASE
R_CTG	Without reestimation	0.610	2.082	0.317	1.089	0.418	1.521
	With reestimation	0.494	1.717	0.316	1.087	0.333	1.215
R_CTK	Without reestimation	0.943	3.121	0.289	0.985	0.659	2.312
	With reestimation	0.644	2.192	0.289	0.985	0.270	0.981
R_CTQ	Without reestimation	0.611	2.115	0.324	1.102	0.477	1.584
	With reestimation	0.360	1.211	0.323	1.098	0.302	1.014
R_GTC	Without reestimation	1.003	3.215	0.304	1.032	0.525	1.785
	With reestimation	0.953	3.165	0.291	0.987	0.290	1.032
R_GTK	Without reestimation	0.791	2.887	0.379	1.215	0.568	2.021
	With reestimation	0.593	2.272	0.378	1.212	0.338	1.235
R_GTQ	Without reestimation	0.629	2.215	0.355	1.265	0.590	1.898
	With reestimation	0.405	1.473	0.350	1.241	0.363	1.201
R_KTC	Without reestimation	0.647	1.954	0.238	0.875	0.434	1.442
	With reestimation	0.565	1.608	0.238	0.875	0.303	1.016
R_KTG	Without reestimation	0.641	2.332	0.342	1.182	0.553	2.012
	With reestimation	0.643	2.271	0.340	1.178	0.333	1.188
R_KTQ	Without reestimation	0.804	3.254	0.328	1.210	0.837	2.895
	With reestimation	0.635	2.702	0.328	1.210	0.331	1.128
R_QTC	Without reestimation	0.729	2.112	0.323	1.118	0.469	1.612
	With reestimation	0.652	1.785	0.321	1.115	0.368	1.285
R_QTG	Without reestimation	0.705	2.546	0.361	1.231	0.597	1.854
	With reestimation	0.588	2.252	0.345	1.175	0.357	1.199
R_QTK	Without reestimation	1.047	3.661	0.345	1.145	0.629	2.125
	With reestimation	0.801	2.751	0.343	1.141	0.352	1.214

Bold values indicate best performances.

TABLE 7: DM test of the out-of-sample forecast performance with reestimation.

Route-specific TRV	Comparison between models: NN-EGARCH. vs. ARIMA	
	DM test	P-value
R_CTG	-1.732	0.231
R_CTK	-1.297	0.577
R_CTQ	-0.855	0.877
R_GTC	-0.619	0.924
R_GTK	-1.007	0.745
R_GTQ	-1.382	0.460
R_KTC	-1.417	0.392
R_KTG	-1.109	0.624
R_KTQ	-0.912	0.828
R_QTC	-1.398	0.445
R_QTG	-1.448	0.387
R_QTK	-1.245	0.581

forecasting abilities of the conventional GARCH-type models, NN-EGARCH, and ARIMA by a complete forecasting analysis. The empirical results in this manuscript offer practical information for shipper, truckers, and decision makers, as well as significant contributions to the existing trucking literature.

First, basic statistical analysis is conducted as a fundamental analysis to obtain the time-variation feature of the TRV, which is followed by stationary and ARCH effect tests. It is unexpected to observe that the statistical characteristics of the TRV have similarities with those of the shipping rates

and the financial series; specifically, they are stationary but nonnormal, with a fat tail and a sharp peak. In addition, a strong ARCH effect is characterized. Concurrently, 12 TRV series in southwest China indicate mean-reverting processes. Besides, we document that the asymmetric impact between the past innovations and the current volatility is significant. The asymmetric volatility caused by the adverse shocks is higher than that by the positive shocks, which can be explained by the more significant worries for a bad market news.

Second, the forecast of the TRV with/without reestimation at each step by the different methods considered in our study is precise. The employed models allow reaching the test-sample MAPEs of less than 10% in forecasting with reestimation. Meanwhile, we interestingly find that reestimation at each step improves forecast performance for the hybrid models but forecasts of ARIMA, with or without reestimation in each step, are not much different. Similar to this study, Munim et al. [21] also found that for neural networks reestimation improves forecast performance but not much for ARIMA. Furthermore, NN-EGARCH and ARIMA perform similarly in predicting with reestimation for the next-day TRV forecasting in terms of the average MAPEs for the group of the TRV time series. However, results of the DW test reveal that the improvement in prediction offered by nonlinear method (e.g., NN-EGARCH) is not significant in any case.

Finally, with the growing market share of the trucking sector and extreme volatility of the freight rates in trucking,

further research is required for verifying the enhancement provided by the temporal and between-route correlations for the forecasting accuracy.

Data Availability

The data used in this study were obtained from the National Engineering Laboratory of Big Data Application in Integrated Transportation, Chengdu, Sichuan, China.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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