

Research Article

Modeling of a Small Transportation Company's Start-Up with Limited Data during Economic Recession

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This paper presents a modeling method for analyzing a small transportation company's start-up and growth during a global economic crisis which had an impact on China which is designed to help the owners make better investment and operating decisions with limited data. Since there is limited data, simple regression model and binary regression model failed to generate satisfactory results, so an additive periodic time series model was built to forecast business orders and income. Since the transportation market is segmented by business type and transportation distance, a polynomial model and logistic curve model were constructed to forecast the growth trend of each segmented transportation market, and the seasonal influence function was fitted by seasonal ratio method. Although both of the models produced satisfactory results and showed very nearly the same of goodness-of-fit in the sample, the logistic model presented better forecasting performance out of the sample therefore closer to the reality. Additionally, by checking the development trajectory of the case company's business and the financial crisis in 2008, the modeling and analysis suggest that the sample company is affected by national macroeconomic factors such as GDP and import & export, and this effect comes with a time lag of one to two years.

1. Introduction

Transport infrastructure is critical to economic development of a country and can provide competitive advantage. Within China there is a diversity of transport companies which could be split between with large-scale transport enterprises (LTEs) and small- and medium-sized transportation enterprises (SMTEs). There are many distinct differences between the two types of enterprises. Generally, LTEs, more geographically spread, attract larger enterprises and resource management is not as critical. SMTEs especially in their start-up period need to be more agile in the use of their financial resources to ensure survival. This is particularly true during a period of economic change. This paper focuses on SMTEs since they are the main suppliers of road transportation services in China. They necessarily play the role of first-and/or-last kilometer carriers for door-to-door logistics services. Some 225 259 enterprises and 4 595 600 individually owned businesses were engaged in transportation, storage,

and postal services in 2008 [1]. The total value of the top 50 logistics enterprises, about 475.6 billion Yuan, is only 0.53% of the national added value of the logistics industry [2]. Compared with LTEs, SMTEs face much greater risk, especially during an economic downturn. The survival of a business entity depends heavily on its ability to anticipate and prepare for change rather than wait for it and then react to it [3].

Demand forecasting is so significant for SMTEs that it can help to improve equipment utilization and establish smarter operational and investment strategies. Realistically, business owners estimate the service demand from their past experiences which can be wrong or misleading. Almost all freight demand analysis usually accounts for a whole country, a region, or a corridor between cities by integration or by mode and is usually to do with public transportation planning [4–6]. Two previous research articles which examined SMTEs' demand forecasting tackled less than truckload (LTL) for both short-term and long-term forecasting. In [7],

TABLE 1: Business data by industry.

Industry	No. of customers		No. of orders		Money	
	Absolute value	Percentage %	Absolute value	Percentage %	Absolute value	Percentage %
Food	1	3.125	24	0.2221	91900	0.4495
Toy	1	3.125	154	1.4253	430492	2.1054
Chinaware	1	3.125	358	3.3133	949029	4.6414
Material	2	6.250	151	1.3975	363945	1.7799
Machine	3	9.375	4423	40.9348	4474611	21.8837
Craft	4	12.500	1001	9.2642	2867729	14.0250
Electronics	5	15.625	1999	18.5007	2541727	12.4307
Logistics	15	46.875	2695	24.9422	8727782	42.6845
Total	32	100	10805	100	20447215	100

it is believed that the combination of neural networks and traditional time series analysis is good for forecasting short-term logistic demand for an LTL carrier. A small-to-medium-sized road transport service which offered a limited collection and delivery service for small and large consignments in a number of geographical zones of equal area is reported in [8].

The objective of this study is to model the start-up and growth of a newly established truck transportation company during the economic recession whose main business is sea-port containers and bulk inland transportation. It ultimately aims to help SMTEs to look for ways of improving equipment utilization in the short to medium term by forecasting the orders and the trucks required, as well as the impact of financial crisis. The main feature of our work is its use of limited data to analyze and forecast a small transportation company's business as it starts up in a rapidly changing environment.

The context of the model has two distinct elements: enterprise start-up and the short time series. Obviously, most enterprises in their start-up period need to grow their business to an economic scale. If they fail to do so the long time survival of the enterprise may be under question. Hence, the model selected will have to accommodate such growth. The second element reflects the need for quick appraisal of likely demand, so that appropriate economic strategy can be developed by the enterprise. This differentiates start-up SMTEs from LTEs where there is possibly longer times series and higher correlation of performance with macroeconomic factors. The modeling proposed attempts to cope with these two elements.

2. Data

The data covers all the business orders of a small truck transportation company during a 40-month period (January 2008 to April 2011). Registered at the end of 2007, the small truck transportation company currently has a fleet of 30 trucks and 30 drivers. Some trucks are container trucks suitable for container transportation and others are bulk trucks designed for heavy long-distance bulk transportation services. This company mainly provides services for pier container transportation and inland bulk transportation. The container transportation service is mainly provided

for container customers who have exporting and importing businesses at three ports located in Shenzhen, namely, Yantian, Shekou, and Mawan. In order to make use of the empty containers at these ports, a small part of the bulk is transported for the container customers in container trucks at the same price as bulk transportation. Most of the rest is carried by bulk trucks for different customers.

All the business orders from this company are classified according to the categories of the customer industry (see Table 1). "Money" in this paper represents the gross income which equals the orders multiplying the unit price. The customers come from eight industries, and 15 logistics customers contribute 42.7% of the total money, three machine customers account for 40.9% of the orders and 21.9% of the gross income, and the remaining 14 customers from the food, toy, chinaware, material, craft, and electronics industries account for 34.123% of the orders and 35.432% of the total gross income.

Further analysis shows that there are two patterns as regards gaps in orders, regular and irregular. Regular orders are made either continuously on weekdays and broken at weekends and vacations (shown in Figure 1(a)) or discretely and regularly (shown in Figure 1(b)). Irregular orders are made randomly, as shown in Figures 2(a) and 2(b). The customers who make regular and irregular orders are listed in Table 2.

In order to find out whether the economic recession of 2008 had an effect on the company's business, further analysis of the orders and money per month was conducted for both regular and irregular businesses. It should be noted that the Chinese New Year usually falls in February when almost all businesses are at their lowest level of production. A three-year period is considered and the cycle starts from February of the first year to January of the last year. Therefore, "1" in Figure 3 represents February 2008 and "36" means January 2011.

The plots of the irregular orders and money per month shown in Figure 3 describe two factors. (1) The irregular business was affected by the economic recession which hit China between the third and fourth quarters of 2008. The downturn began in October 2008. (2) Orders declined rapidly from October 2008 and eventually disappeared.

Originating in the developed countries, the economic crisis soon spread to China, as shown by the decreasing number

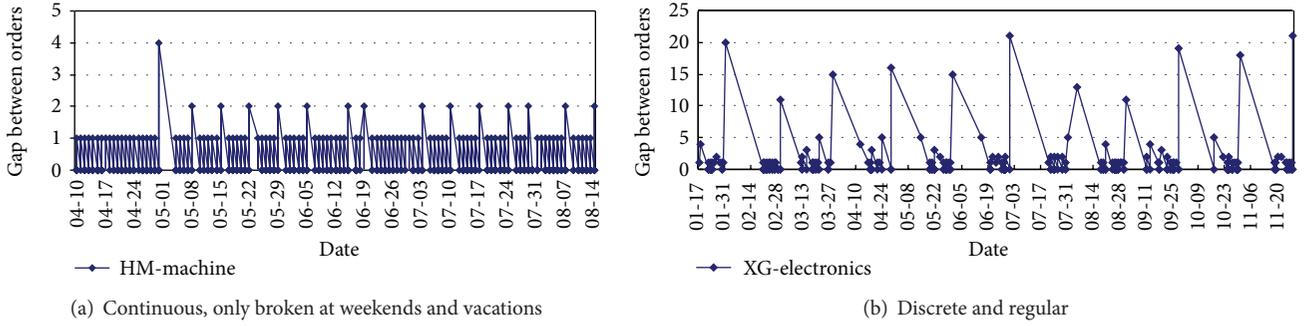


FIGURE 1: Gaps between regular orders in days.

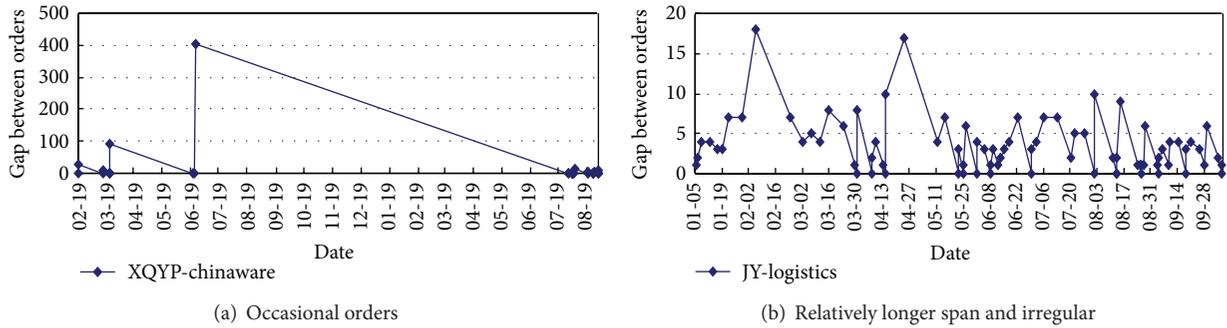


FIGURE 2: Gaps between irregular orders in days.

TABLE 2: Regular and irregular customers.

Regular: 12 customers, 9147 orders Name/industry		Irregular: 20 customers, 1658 orders Name/industry	
HYu/craft	YLM/toy	OWY/craft	QS/logistics
GL/craft	HM/machine	HS/craft	XQ/logistics
XG/electronics		HYa/electronics	YLX/logistics
GD/electronics		WLi/electronics	CH/logistics
WLin/electronics		ZH/food	GY/logistics
GH/logistics		LH/logistics	JFX/logistics
HF/logistics		LR/logistics	FY/logistics
KLD/logistics		QFT/logistics	XQ/chinaware
KZ/logistics		JY/logistics	SH/machine
HL/material		AD/material	HLD/machine

of orders. Those companies involved in overseas markets were affected first, in the third quarter of 2008. Pure OEM (original equipment manufacturing) and excessive reliance on overseas market were the two major factors which made these companies fail in the recession rapidly. Those companies relying on the home market were affected by a time lag, because of reduced business with the export-oriented companies and the declining purchasing power of workers laid off by those companies.

The regular orders and money per month in total are given in Figure 4, from which conclusions can be drawn as follows.

- (1) There is obvious periodicity by year both for orders and for income.
- (2) There is an increase in trend, but the slope is gradually decreasing.
- (3) Orders and money surprisingly increase after the arrival of the recession.

Some weak companies ceased trading almost immediately, but the robust ones survived. Businesses concentrated on those surviving companies.

Every coin has two sides. The recession had both negative and positive impacts on the company's business. Whereas the business trade was slowing down, the quality of the company's customers was better after the recession and a large number of irregular businesses disappeared. Graphs of the orders and income have similar shapes, so the regular group is the focus of the following work.

3. Modeling and Forecasting

Most modeling and forecasting approaches with limited data are about rapidly changing industries like motion pictures, telecommunications, or new products with a short history [9–13]. They suggest that combining ARIMA and diffusion models can improve one-year-ahead predictions, especially in the high technology market. The drawback, however,

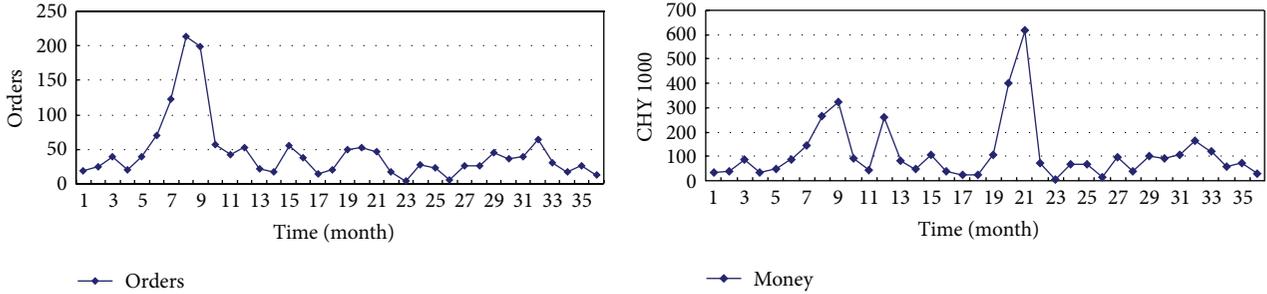


FIGURE 3: Irregular orders and money per month in total.

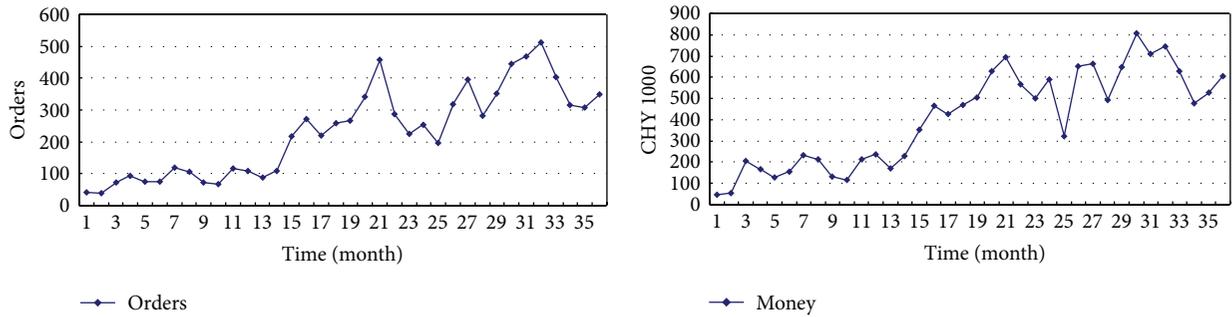


FIGURE 4: Regular orders and money per month in total.

is the need for enough historical data points to create a time series. The necessity of judgment in forecasting with insufficient data for statistical methodology was discussed in [14]. The key is to impose a structure with methods such as surveys of intentions or expectations, judgmental bootstrapping, structured analogies, and simulated interaction. A case study about fashion products, generally characterized by high demand uncertainty, high stock out costs, and a high risk of obsolescence, proposes that preorder data and judgments can be used to overcome the lack of data in demand forecasting. Advance order data can be obtained by allowing a selected group of customers to preorder at a discount from a preview catalogue. Judgments can be obtained from purchase managers or other company experts [15].

A significant improvement in nonlinear time series analysis (NTSA) has been seen since the 1990s [16]. Tong listed the following as the five most promising directions: the interface between NTSA and chaos, the nonparametric/semiparametric approach, nonlinear state space modeling, financial time series (in both discrete time and continuous time), and nonlinear modeling of panels (e.g., spatially distributed) in time series. A polynomial spline approximation was employed to estimate the functional coefficient regression models for nonlinear time series [17]. A time-varying coefficient time series model with a time trend function and serially correlated errors to characterize the nonlinearity, nonstationarity, and trending phenomena was discussed in [18]. A time series can be decomposed into trend, cycle, and seasonal and random components [19]. That is, moving averages, isolating seasonal factors and seasonal

adjustments are common methodology for treating seasonal adjustment of time series.

No single model or combination model has been proved to outperform the rest. In order to model and forecast the small truck transportation company's start-up and growth after the economic recession from the limited data described in Section 2, relative variable analysis and time series analysis were used to predict the orders and turnover. Meanwhile, correlation analysis, and polynomial and logistic curve models were also employed to find the trend by combining seasonality adjustment to predict order number and turnover.

Simple linear regression and binary linear regression are two basic versions of the generalized linear model (GLM) proposed by [20] as a way of unifying various other statistical models, including linear regression, logistic regression, and Poisson regression.

Linear regression was employed to search for the relation between orders and import & export in months or orders and import & export and GDP in quarters for GDP only available in quarters. The general form of a linear regression model is

$$y = a + b_i x_i + e \quad i = 1, 2, \dots, n, \quad (1)$$

where y is the dependent variable, denoting the orders. x_i ($i = 1, 2, \dots, n$) is the predictor variable with a subscript i , and n is the number of variables. e is noise.

In statistics, signal processing, econometrics, and mathematical finance, a time series is a sequence of data points, measured typically at successive times at uniform time intervals. Time series forecasting is the use of a model to predict future values based on previously observed values. Methods

for time series analyses may be divided into two classes: frequency-domain methods and time-domain methods. The former include spectral analysis and, recently, wavelet analysis; the latter include autocorrelation and cross-correlation analysis.

Our time series analysis began by regrouping the data, splitting the distance into five sections and business into two kinds. The first model was the polynomial, as in the following:

$$O_{ds} = \mu + \beta_1 t_y + \beta_2 t_y^2 + \beta_3 t_y^3 + s_i. \quad (2)$$

Then for an alternative of the logistic curve regression

$$O_{ds} = \alpha_{ds} \cdot \left(\frac{e^{\beta_{ds} t_m}}{1 + e^{\beta_{ds} t_m}} \right). \quad (3)$$

Therefore, the turnover forecast is as the following for both trend forecast models:

$$\text{money} = \sum_{d=1}^5 \sum_{s=1}^2 V_{ds} \cdot O_{ds}, \quad (4)$$

where V_{ds} is average price or value of distant d and type s , O_{ds} the orders of distant d and type s , S_i the noise, t_y is the time by year, and 1 = the starting year, 2008 in this case. α_{ds} and β_{ds} are coefficients of the logistic model in subgroups of a distance d ($=1, 2, 3, 4, 5$) and a type s ($=1, 2$). t_m ($=1, 2, \dots, 36$) represents the time by month.

Any time series is made up of systematic components, such as a trend, cycle, and seasonal and random elements, which are by definition unpredictable. Therefore, a set of time series data can be decomposed into trend, cycle, and seasonal and random components. The four elements can be combined in either an additive or a multiplicative model [19]:

$$X_{t_m} = T + C + S + R \quad (5)$$

$$X_{t_m} = T \times C \times S \times R, \quad (6)$$

where X_{t_m} represents the dependent variable of orders, T the trend component, C the seasonal factor, and R the random element.

Moving averages are often used to isolate the trend. We propose, however, to extract the trend directly from the original data with both the polynomial and logistic curve models and then to decompose the combination of the cycle and seasonality by the additive model in (5). Considering the close relationship between transportation and economics, we can ignore the cyclical component by taking the seasonality as a cycle of 12 months. The cycle was previously defined as running from February to January of the next year, as the lowest demand usually falls in February.

We take the additive model, (5), and rewrite it as

$$X_{t_m} - T = S + R. \quad (7)$$

Let SR ($= S + R$) be the combination of the seasonal and random components and then divide SR by the trend T to get the seasonal ratio S_c (including the random). Hence, the seasonal factor can be obtained by averaging the three ratio

TABLE 3: Segmentation of the distance.

d	1	2	3	4	5
distance	<90 km	90–179 km	180–350 km	351–800 km	>801 km

components (February 2008 to January 2009, February 2009 to January 2010, and February 2010 to January 2011) for each month \bar{S}_c , $c = 1, 2, \dots, 12$. For example, for February, the average seasonal ratio \bar{S}_c is as follows:

$$\bar{S}_1 = \frac{1}{3} \left(\frac{X_{t_m} - T}{T} \Big|_{t_m=1} + \frac{X_{t_m} - T}{T} \Big|_{t_m=13} + \frac{X_{t_m} - T}{T} \Big|_{t_m=25} \right), \quad (8)$$

where t_m ($=1, 2, \dots, 36$) represents months from the beginning in the series. Now the forecasting value of X_{t_m} can be obtained by

$$\hat{X}_{t_m} = T + S + R = T(1 + \bar{S}_c) \quad (9)$$

$$t_m = 1, 2, \dots, 36; \quad c = 1, 2, \dots, 12.$$

Then the total orders in (10) and (4) should be changed to

$$\text{orders} = \sum_{d=1}^5 \sum_{s=1}^2 O_{ds}^{tr} (1 + \bar{S}_c) \quad (10)$$

$$\text{money} = \sum_{d=1}^5 \sum_{s=1}^2 V_{ds} \cdot O_{ds}^{tr} (1 + \bar{S}_c). \quad (11)$$

O_{ds}^{tr} is the trends forecast by the polynomial or logistic model.

4. Application

First, simple linear regression analysis is taken to model the relationship between the national export & import and the orders. The result is given in Figure 5.

The predicted regular orders per month = $-148.296 + 0.330 * \text{national import \& export}$.

Then the binary linear regression of the orders and imports & exports and GDP per quarter is presented in Figure 6.

The predicted regular orders per quarter = $-560.432 + 1.076 * \text{GDP} + 0.158 * \text{import \& export}$.

As the relative analysis cannot give satisfactory results even intuitively, we turn to the time series analysis. The whole regular business is separated by distance and truck type when the time series analysis is chosen. Distance is separated into five categories according to the rates and transport time, and container and bulk are the two types of services. Variable d represents the different segmentation of the distance shown in Table 3. Type variable $s = 1$ represents container and $s = 2$ the bulk.

The result shows that almost all the container transport orders are included in distance groups 1, 2, and 3, with just one out of 7755 regular container orders from February 2008 to January 2011 in container group 4. Most bulk transport orders are included in distance groups 1, 3, and 5. As the data of bulk

TABLE 4: The seasonal ratios in the polynomial model.

Group	Cycle											
	1	2	3	4	5	6	7	8	9	10	11	12
11	-0.4104	-0.3695	-0.1292	-0.0093	-0.1897	-0.1207	0.2280	0.3509	0.5158	0.0453	0.0209	-0.1597
21	-0.4775	-0.3617	-0.2347	0.1407	0.2389	0.3525	0.3019	0.2410	0.0508	-0.1913	0.0472	0.2199
31	-0.4325	-0.1774	0.5607	-0.1737	-0.1317	0.3161	0.2004	0.3484	-0.1109	-0.5404	-0.2736	0.3707
12	0.5909	-0.8788	0.1113	-0.0745	0.4005	0.3488	-0.3943	-0.1522	-0.0579	-0.1450	0.2265	0.2134
22	-0.6800	0.6150	0.3167	-0.1666	-0.4749	-0.0283	-0.4198	-0.3530	-0.1552	-0.0745	-0.4022	-0.2205

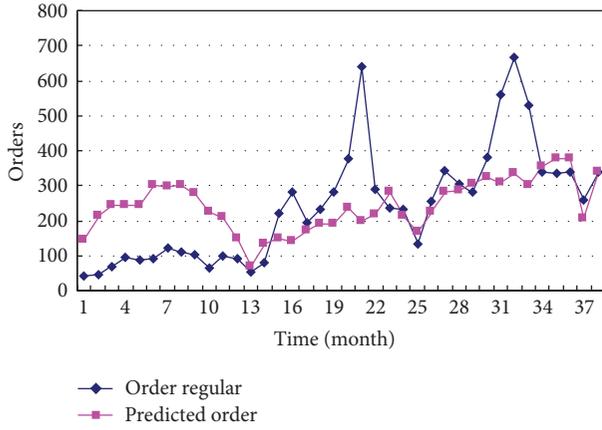


FIGURE 5: Simple linear regression of the regular orders and national import & export.

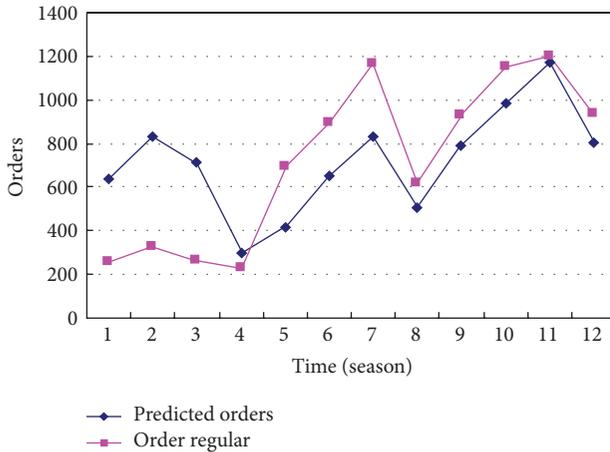


FIGURE 6: Binary linear regression: regular orders and import & export and GDP.

groups 2 and 3 are insufficient for modeling, we merge bulk groups 1, 2, and 3 into a new bulk group 1 and bulk groups 4 and 5 into a new bulk group 2.

Thus, $O_{41} = O_{51} = O_{32} = O_{42} = O_{52} = 0$, and only the remaining five subgroups need to be estimated. The results of the polynomial trend models and seasonal ratios in Table 4

are listed in the following calculations and shown in Figures 7 and 8:

$$O_{11} = (-55.7778 + 91.58333t_y) \cdot (1 + \bar{S}_c^{11})$$

$$O_{21} = (10 + 27.45833t_y) \cdot (1 + \bar{R}_c^{21})$$

$$O_{31} = (4.9444 + 9.08333t_y) \cdot (1 + \bar{R}_c^{31})$$

$$O_{12} = (-1.98967 + 2.961088t_y^2 - 0.38809t_y^3) \cdot (1 + \bar{R}_c^{12}) \quad (12)$$

$$\cdot (1 + \bar{R}_c^{12})$$

$$O_{22} = (-43.6667 + 58.0833t_y - 13.5833t_y^2) \cdot (1 + \bar{R}_c^{22})$$

$$\cdot (1 + \bar{R}_c^{22}).$$

Forecast orders of all groups are presented in Figures 7 and 8.

Putting (12) into (11) we can calculate the money (turnover). The results show that (1) the container and the bulk have linear and quadratic trends, respectively and (2) the results are acceptable until March 2011, but the linear trend just increases and the quadratic trend abruptly decreases after April 2011, which is not in line with the actual situation.

Therefore, an alternative logistic model is needed. Equation (3) is the assumed trend function of orders. Let (10) and (11) be the total orders and money prediction formulation.

The order-prediction models are given in (13), with the second bulk group showing a polynomial trend:

$$O_{11} = 10.638 \times \frac{e^{0.95+0.104i}}{1 + 0.0519e^{0.95+0.104i}} \cdot (1 + \bar{R}_c^{11})$$

$$O_{21} = 1.51 \times \frac{e^{0.95+0.104i}}{1 + 0.0169e^{0.95+0.104i}} \cdot (1 + \bar{R}_c^{21})$$

$$O_{31} = 3.96 \times \frac{e^{0.95+0.104i}}{1 + 0.145e^{0.95+0.104i}} \cdot (1 + \bar{R}_c^{31}) \quad (13)$$

$$O_{12} = 12.823 \times \frac{e^{-1.605+0.1643i}}{1 + 0.164e^{0.95+0.104i}} \cdot (1 + \bar{R}_c^{12})$$

$$O_{22} = (-43.6667 + 58.0833t_y - 13.5833t_y^2) \cdot (1 + \bar{R}_c^{22}).$$

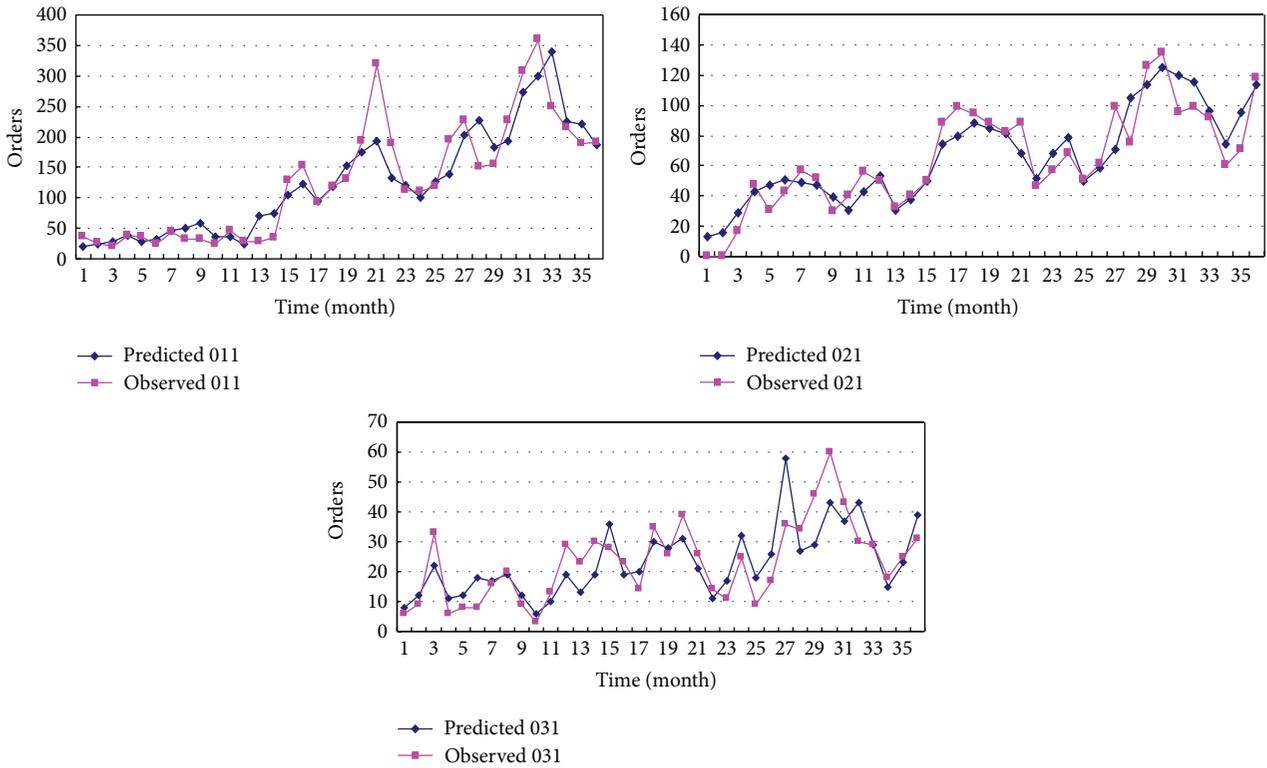


FIGURE 7: The orders of container transportation predicted by the polynomial model.

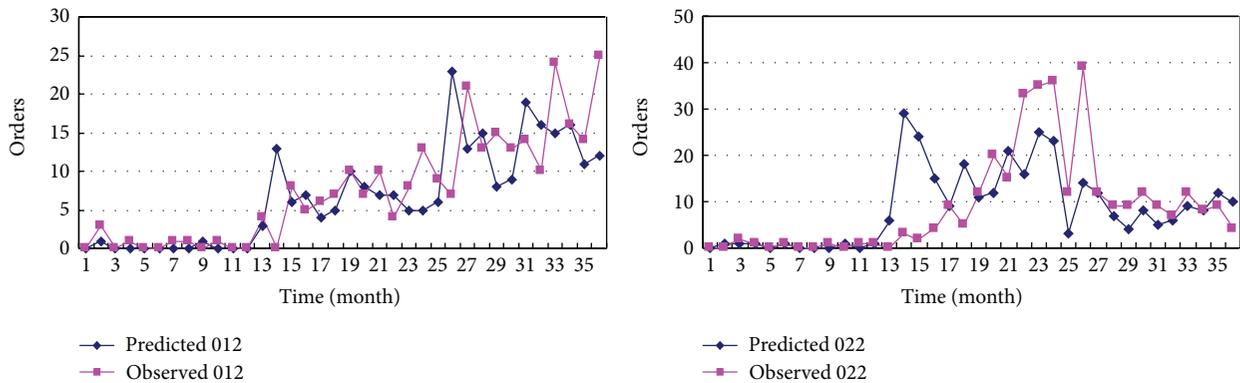


FIGURE 8: The orders of bulk transportation predicted by the polynomial model.

Results of calculation of seasonal ratios are presented in Table 5.

The results of the logistic model are shown in Figures 9 and 10. Only the group O_{22} could not be fitted by the logistic model.

The results of the polynomial and logistic models are compared in Figure 11. The predictions given by the two models are not very different at present but the logistic trend will be more significant in the future.

In conclusion, the initial modeling of the orders cannot immediately account for the demand in terms of exports & imports or GDP. The polynomial trend does not give a sound prediction in the sample, and the logistic modeling of

the orders seems appropriate. The forecasted total money is presented in Figure 12.

Model selection depends primarily on two aspects. One is the forecast in the sample. The second is the prediction out of the sample. The forecasts of the polynomial model decrease abruptly out of the sample and the logistic has a better performance in this aspect. Therefore the logistic model outperforms the polynomial model out of the sample.

Now let us turn to the analysis in the sample. There are some specific criteria, such as the coefficient of determination R^2 and F -test, which measure the goodness-of-fit to discriminate which model is better than the others with regard to linear regression models. This is not the case with nonlinear

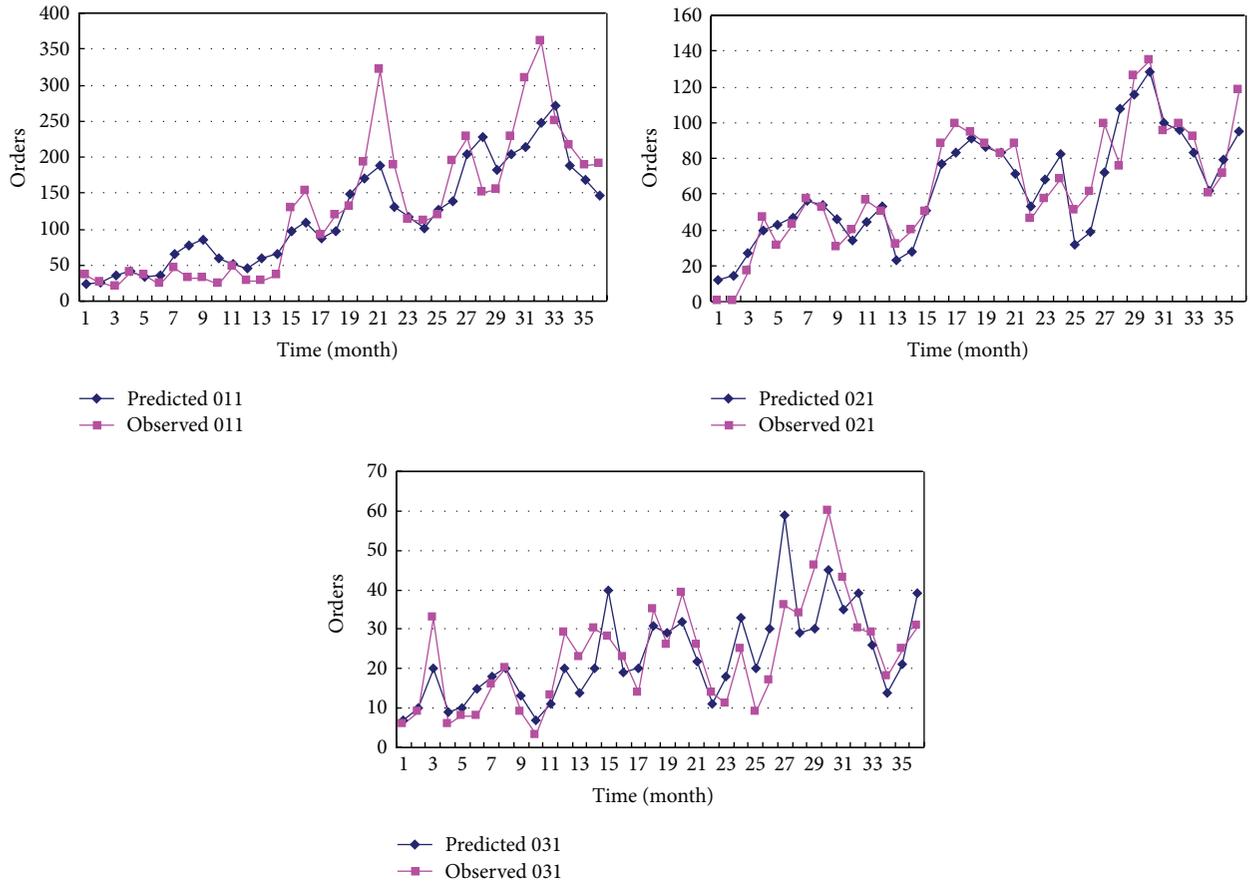


FIGURE 9: The container orders predicted by the logistic model.

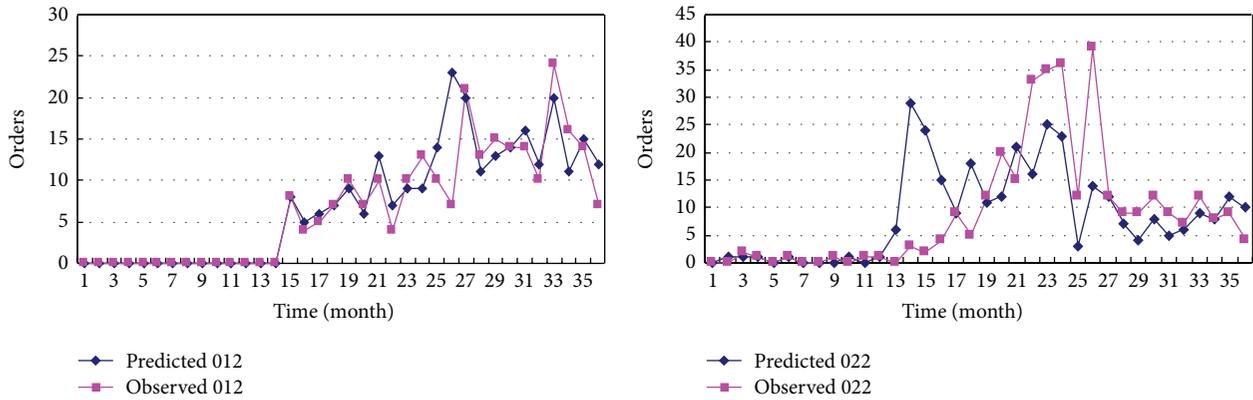


FIGURE 10: The bulk orders predicted by the logistic model.

TABLE 5: Calculation of seasonal ratios by the logistic model.

Group	Cycle											
	1	2	3	4	5	6	7	8	9	10	11	12
11	-0.1069	-0.0242	0.4384	0.6197	0.2914	0.4368	0.4109	0.6343	0.7970	0.2457	0.1089	-0.0297
21	-0.5951	-0.5055	-0.0923	0.3730	0.4713	0.6163	0.2290	0.1802	0.0183	-0.2400	-0.0248	0.1769
31	-0.1282	0.2625	1.5265	0.2267	0.2936	0.9351	0.4475	0.5893	0.0670	-0.4422	-0.1267	0.6150
12	0.3373	1.1651	0.6528	-0.0700	0.1107	0.0369	0.2534	-0.1151	0.4275	-0.1993	0.0686	-0.1443
22	-0.6800	0.6150	0.3167	-0.1666	-0.4749	-0.0283	-0.4198	-0.3530	-0.1552	-0.0745	-0.4022	-0.2205

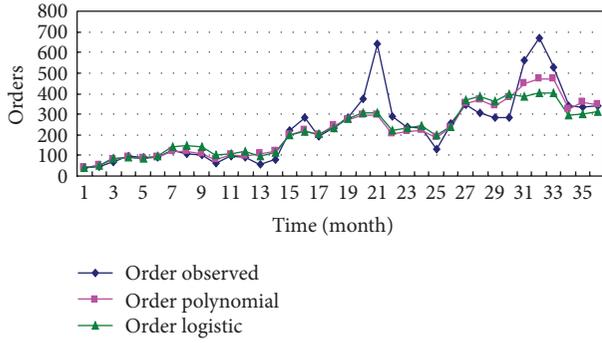


FIGURE 11: Comparison of the results of the two forecasting models: orders.

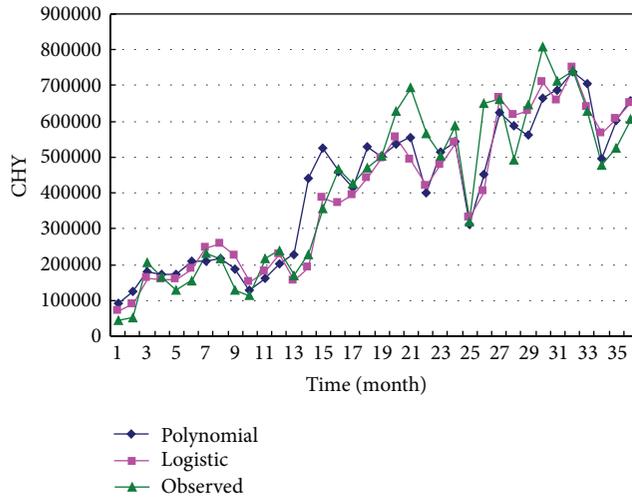


FIGURE 12: Comparison of the results of the two forecasting models: income.

regression models (NLRMs), however. According to [20], we cannot use the t -test (to test the significance of an individual coefficient) or the F -test (to test the overall significance of the estimated regression) because we cannot obtain an unbiased estimate of the error variance σ^2 from the estimated residuals. Furthermore, the residuals (the difference between the actual y values and the estimated y values from the NLRM) do not necessarily sum to zero, ESS and RSS do not necessarily add up to the TSS, and therefore $R^2 = \text{ESS}/\text{TSS}$ may not be a meaningful descriptive statistic for such models. An alternative of pseudo R square to \bar{R}^2 is proposed by [21] as follows:

$$\bar{R}^2 = 1 - \frac{\sum_{i=1}^n \hat{u}_i^2}{\sum_{i=1}^n (y_i - \bar{y})^2}, \quad (14)$$

where n is the observation number, y = regress, and $\hat{u}_i = y_i - \hat{y}_i$, where \hat{y}_i are the estimated y values from the (fitted) NLRM. Results are shown in Table 6.

From Table 6, the values of \bar{R}^2 of orders prediction by the two models are nearly the same. When it comes to the income prediction, the value of \bar{R}^2 of the logistic model has

TABLE 6: Measure of goodness-of-fit of polynomial and logistic trend models.

Model	Difference	Polynomial trend seasonal adjustment	Logistic trend seasonal adjustment
\bar{R}^2 /orders prediction	0.0066	0.7826	0.7760
\bar{R}^2 /money prediction	-0.0453	0.8569	0.9022

a slight advantage over the polynomial model. As previously described, the logistic model is better than the polynomial one in predicting performance out of the sample. The comparison in the sample shows, however, that performances of the two models are very similar. On balance, however, the logistic model is better than the polynomial.

5. Conclusions and Discussion

This paper introduces a small truck transportation company's start-up whose main business is pier containers and whose minority business is long-distance bulk transportation. We have attempted to elucidate how our analysis led to useful information for SMTE owners. Modeling the forecasting of order numbers of both kinds of businesses and the total turnover contributes to establishing the company's strategy for investment and operations.

Initial modeling of orders by simple regression and binary regression models cannot immediately account for demand in terms of exports or GDP. The results show that the company's business is certainly affected by the national macroeconomic factors such as GDP and import & export, and this effect comes with a time lag of one to two years since transportation service demand is derived demand. The seasonal fluctuation of orders, however, is much more dramatic than that of the national GDP and total import & export. It may be the main reason why the regression models did not perform well in forecasting. Competitive environment factors such as customers and competitors affect performance directly for SMTEs.

There are insufficient data about customers and competitors to support the simple regression model. Therefore, the time series analysis is the inevitable choice. We segmented the data by business and transportation distance to get a set of time series data. The polynomial and the logistic trend models combined with additional seasonal components were employed to fit the data of different segments. Both fitted the sample data very well, but the polynomial trend does not give sound forecasting for the fast decreasing trend out of the sample. From the perspective of goodness-of-fit, the polynomial trend model is still acceptable.

We have to say that forecasting in future is obviously at variance with reality. On the one hand, small transportation companies are not necessarily bound to continue to grow into large ones because of indifferent marketing and the lack of economies of scale. On the other hand, most small transportation companies can survive for a relatively long period thanks to their flexible operation mode. Usually a polynomial trend model does not work well for unlimited increasing or

decreasing trends while higher-order coefficients are positive or negative, respectively. One of the reasons why the logistic modeling of the orders seems appropriate is that it has given the upper limit of business. Acceptable goodness-of-fit and forecasting performance can only be provided by the logistic model, even though the performance of the two models in the sample is nearly the same to solve the question in this paper.

Unexpectedly, the analysis presented the process of the financial crisis's effect on SMTEs. First, irregular business disappears immediately the crisis emerges; at the same time, the regular business increases rather than decreases and then slows down with a time lag of one to two years, which is established by the logistic model. Within the effective distance of the truck transportation, the total transportation demand is relatively stable and the market is competitive or contestable. The growth rate of most small and medium transportation enterprises will become slower after their quick growth period and have an upper limit scale of business.

Our approach can cope with the different impetus of SMTEs' growth and a period of financial stress. One would expect that in less periods of financial stress then growth might be more rapid for SMTEs but not that they necessarily will continue to grow rapidly. With further data one could explore how later SMTEs might develop in more benign economic contexts. We believe, however, that the proposed model would still achieve a reasonable fit.

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