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Abstract *This paper describes the results of an effort to predict future freight volume in the truckload (TL) trucking industry. The approach involves the use of stepwise multiple linear regression models that relate freight volume to a variety of economic indicators. The models are built using a large set of actual freight data provided by J.B. Hunt Transport (JBHT), one of the world's largest TL carriers. The data was first analyzed using the overall set of national data, and then for specific industrial and regional segments. The overall results of these analyses should prove useful to a wide variety of transportation and logistics operations.*

Introduction

In order to survive, many truckload (TL) trucking companies have initiated dramatic changes in their operational philosophies. Companies that once sought to capture as much freight as possible, concluding that higher volumes yield higher revenues and profits, now search for "smart" loads to balance their overall freight density. Freight balance has now become a major component in many TL trucking companies' strategic planning activities because of its potential effect on overall profitability. To understand the importance of freight balance, suppose a TL company has 600 loads per week inbound to Chicago but only 400 outbound loads. That leaves 200 trucks per week in Chicago with no loads to move. Freight imbalance, simply put, costs TL companies money because it forces them either to reposition empty trucks (deadhead) or take outbound loads at reduced rates. When freight is in balance, companies can bid more aggressively for loads that help them achieve (or maintain) balance and, in turn, inflate bids for loads that do not.

Proper freight balance also allows for the creation of shorter, dedicated, non-random driving routes that eliminate empty and out-of-route miles, and more importantly, result in a higher quality of work life for the truck drivers, by increasing their ability to get home to their families. Many companies have found that driver turnover rates, as high as 85 percent to 110 percent per year for some companies, are primarily due to the inconsistency of work life and long periods away from home (Mele, 1989). These turnover rates result in enormous recruiting and training costs. By establishing truer freight balance, new patterns emerge

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that enable drivers to haul consistent routes, get home more frequently and still retain the high mileage needed for competitive compensation.

The quest for loads that create balanced, closed loop routes, minimize empty and circuitous miles, and generate quality revenue is a key goal in the pricing strategies of all major trucking firms. Concurrently, many large shippers are developing core carrier partnerships and are distributing their load volumes to fewer trucking companies. The carrier/shipper partnerships seek engineered freight solutions to reduce rates and improve customer service. The customers net higher reliability, reduced cycle times, and provisions for surges, promotions, and seasonality. Trucking companies realize bottom line benefits through the long-term, dedicated freight volume that results from these large contracts. This dedicated freight volume helps establish load consistency from which companies can better plan asset allocation, pricing, routing, and driver retention strategies. With several large accounts in place, trucking firms are then enabled to secure the proper random load mix to establish overall freight balance (Taylor *et al.*, 1997).

While it is apparent that freight balance plays a huge role in overall profitability, most carriers find it difficult to establish such balance because the TL market is volatile and future freight volumes are extremely difficult to accurately predict. Long-term forecasts are easy enough to find, e.g. DRI/McGraw-Hill forecasted a conservative 2.6 percent annual growth between 1996 and 2004, resulting in another billion tons of freight coming into the economy (McConville, 1996). However, the challenge lies in finding ways to predict volume accurately over the short term throughout each element of the transportation network.

In order to accomplish this feat, proper forecasting tools must be developed to help determine how changes in each industrial segment impact the overall freight demand. We propose that such forecasting tools should be based on measures related to national, regional and local economic conditions. In the following pages, we illustrate the use of stepwise multiple linear regression to develop a model that predicts TL volumes based on the state of a wide array of leading economic indicators. The models are built using a large set of data provided by J.B. Hunt Transport (JBHT), which operates over 10,000 tractors and 44,000 trailers and employs nearly 16,000 people. JBHT's annual revenues top $2 billion.

Forecasting freight volumes

Even a cursory review of literature reveals that there are a wide variety of forecasting techniques available. Here, we focus on the use of a forecasting method that incorporates a variety of economic, social and industrial indices. This method has been formally used to model business cycles since the 1930s. Mitchell and Burns (1938) originally designed a series of "leading indicators" to help evaluate economic data and to assist those responsible for business cycle dating in determining the direction of economic activity. Because the components of the indices are chosen to represent and monitor business activity from a variety of sectors, it is reasonable to assume that they serve as reliable predictors of national economic activity.

Many factors affect the national freight demand profile for TL trucking. Unfortunately, most of these are independent factors over which trucking companies have no direct control. For instance, rising interest rates increase the cost of building loans, which increases the cost of construction projects. These increased costs then lower demand for raw materials like lumber, which in turn, lowers the number of shipments from the Pacific Northwest.

Many industrial and economic indices exist which *may* prove to be useful in the prediction of freight demand trends based on the fact that increased economic activity results in the increased flow of goods throughout the economy. Each month the US Department of Commerce publishes a series of economic indicators, including the Composite Indexes of Leading, Coincident, and Lagging Indicators. The Bureau of Economic Analysis has evaluated and continues to evaluate hundreds of economic time series. Only those series displaying good overall performance, available on a monthly basis, having a short lag time, and not subject to large revisions are considered as candidates for inclusion in the major composite indicators. Such series are widely used to evaluate the nation's economy (Ratti, 1985).

Analysis

After collecting nearly three years of historical freight data from JBHT, a preliminary summary was made by consolidating the total freight history into monthly data points. These monthly data summaries were then normalized to retain data confidentiality by dividing each monthly sum-total by the overall average. A graphical plot of the demand history seemingly indicates a gradual increase in the overall freight demand with possible seasonal trends occurring each year as shown in Figure 1.

We then collected data over the same period of time on 107 different economic and industrial indices listed in Table I. These were all judged to be related to economic activity and thus potentially useful as predictors of JBHT's freight volume.

We then propose the use of multiple linear regression analysis to model the cause and effect relationship between monthly values of the financial indicators and the monthly freight volume. The basic regression model is as follows:

$$y_i = \beta_0 + \sum_{j=1}^{n} \beta_j x_{ij} + \varepsilon_i \qquad (1)$$

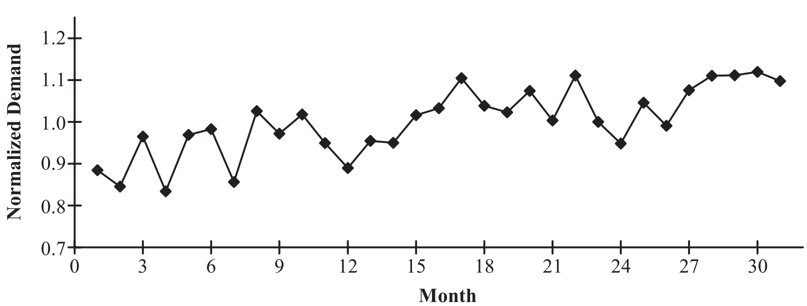

Figure 1. Normalized freight demand profile

American trucking associations' truck tonnage index
Purchasing managers' index
Dow Jones utilities index
S&P 500 stock index
Unemployment claims
Manufacturers' new orders of consumer goods and materials
Consumer expectation index
US exports
Total manufacturing production index
Iron and steel production index
Electric machinery production index
Aircraft and parts production index
Furniture and fixtures production index
Paper products production index
Canned and frozen foods production index
Foods production index
Consumer goods production index
Materials production index
Total manufacturing sales
Manufacturing sales of nondurable goods
Manufacturing finished goods inventories
Manufacturers' total unfilled orders
Manufacturers' unfilled orders of nondurable goods
Manufacturers' new orders of nondurable goods
Total retail store sales
Retail store sales of nondurable goods
Retail store sales of furniture stores
Retail store sales of apparel and accessory stores
Retail store sales of general merchandise stores
Retail inventories for durable goods stores
Retail inventories for apparel stores
Retail inventories for food stores
Retail inventories for general merchandise stores
Total wholesale inventories
Wholesale inventories of nondurable goods stores
Producer commodities price index of all food
Producer commodities price index of livestock
Producer commodities price index of fluid milk
Producer commodities price index of fresh and processed fish
Producer commodities price index of processed poultry
Producer commodities price index of metals and metal products
Producer commodities price index of nonferrous metals
Producer commodities price index of machinery and motive products
Producer commodities price index of construction materials and equipment
Producer commodities price index of construction materials
Producer commodities price index of prepared paint
Producer commodity price index of lumber
Producer commodity price index of household furniture
Producer commodity priceindex of floor coverings
Retail premium unleaded gasoline prices
Interest rates for conventional mortgages
Interest rates for prime six month commercial paper
Interest rates for three month treasury blls

(continued)

Table I.
Potential freight demand indicators

Composite long term government securities
American trucking associations' truck tonnage index three month CMA
Dow Jones transportation index
Dow Jones composite index
Composite index of leading indicators
Contracts/orders plant equipment
Housing starts
Gross domestic products
US imports
Metal mining production index
Nonelectric machinery production index
Motor vehicle and parts production index
Lumber and lumber products production index
Textile mill products production index
Rubber and plastic products production index
Tobacco products production index
Final products production index
Equipment production index
Manufacturing and trade inventories
Manufacturing sales of durable goods
Manufacturing materials/supplies inventories
Manufacturing work in processinventories
Manufacturers' unfilled orders of durable goods
Manufacturers' new orders of durable goods
Wage and salary disbursements
Retail store sales of durable goods
Retail store sales of building supply stores
Retail store sales of automobile dealers
Retail store sales of food stores
Retail inventories for all retail stores
Retail inventories for building supply stores
Retail inventories for nondurable goods stores
Retail inventories for furniture and appliance stores
Automotive retail inventories
Wholesale inventories of durable goods stores
Producer price index of all commodities
Producer commodities price index of grains
Producer commodities price index of eggs
Producer commodities price index of meat
Producer commodities price index of dairy products
Producer commodities price index of sugar and confectionery
Producer commodities price index of iron and steel
Purchasing power of the 1982 US dollar
Producer commodities price index of agricultural machinery
Producer commodities price index of electric machinery and equipment
Producer commodities price index of concrete ingredients
Producer commodity price index of flat glass
Producer commodity price index of plywood
Producer commodity price index of commercial furniture
Retail unleaded gasoline prices
Gasoline production
Interest rates for three month CD
Interest rates for prime 90 days
Interest rates for six month treasury bills

Table I.

where:

- y_i Freight demand for period i.
- β_j Regression parameter j (change in y_i per unit change in the predictor variable).
- ε_i Forecasting error or the random variation of the freight demand in period i.
- X_{ij} Predictor variable j (i.e. economic index value) in period i.

Our analysis then proceeded through several phases. First, a preliminary screening was done to identify indices providing the highest correlation to demand trends and to identify reasonable lead times (acknowledging the fact that changes in trucking volume would most likely lag behind changes in one or more indices). The correlation levels and lead times were recorded and used to identify the best potential regressor variables for a multivariable model. These screening analyses were performed initially on the overall national demand profile, then further by various industrial and regional segments.

Next, stepwise regression was used to identify indices contributing useful information to the overall model. Using *SAS 6.12 for Windows* statistical analysis software package, we were able to analyze sets of potential freight volume indicators at the overall national level, and then on specific industrial and regional segments. To check for model adequacy, standard residual analyses for each set of indices were then conducted.

Experimental results and model validation

Based on the 31-month data set of actual loads supplied by JBHT, the experiments were able to identify the most suitable set of predictor variables from the various economic and industrial indices to predict TL trucking freight demand trends. Analyses were conducted first on all of the data (National TL results) then on subsets of the data that represented specific industrial and regional sectors.

National TL results

The preliminary screen to identify the highest correlations between each of the 107 various economic and industrial indices reveals the seven top indicators as shown in Table II.

The index most highly correlated to freight volume was found to be the producer commodities price index of construction materials and equipment (PCPI-CM&E) with a three-month lead at the 57.86 percent level. The six remaining indicators range in correlation from 56.51 percent to 50.89 percent.

Using the total data set at the national level, the stepwise regression procedure produces a model with only one predictor variable, the PCPI-CM&E. No other indices meet the 10 percent significance level required to gain entry to the model. Thus the best predictive model for normalized freight demand $\hat{y}_i$ (the "hat" indicating a prediction), in period i is:

Results of preliminary screen		Correlation	Lead (months)
Producer commodities price index of construction materials and equipment		0.5786	3
Retail store sales of automotive dealers		0.5651	3
Standard and poor's 500 stock index		0.5348	3
Producer commodities price index for household furniture		0.5330	3
US exports		0.5320	3
Dow Jones industrial stock index		0.5281	3
Producer commodities price index for commercial furniture		0.5089	3
Stepwise regression procedure			
Indices entered:	Producer commodities price index construction materials and equipment		
Indices removed:	None		
Indices remaining:	Producer commodities price index construction materials and equipment		
Overall model R^2:	0.5786		
Observed F:	35.6949		
Associated p-value:	0.0001		
Model results	Estimate	Observed t-value	Associated p-value
β_0 parameter:	–2.828957	–4.401	0.0002
β_1 parameter:	3.849040	5.975	0.0001
Prediction accuracy of fitted model			
Average forecasting error and standard deviation for 31-month model		6.86%	4.47%
Average forecasting error and standard deviation for 24-month model		2.30%	5.16%

Table II. Regression model results for the national freight demand profile

$$\hat{y}_i = -2.8290 + 3.8490\ (\mathrm{PCPI-CM\&E})_{i-3} \tag{2}$$

where $(\mathrm{PCPI\text{-}CM\&E})_{i\text{-}3}$ represents the producer commodities price index of construction materials and equipment in period i-3. The model is found to be highly significant with an observed F-value at 35.695 and the associated p-value near zero at 0.0001. A check of residuals versus the PCPI-CM&E as well as checks for unequal variances prove promising, as plots of the residuals versus the predicted values, $\hat{y}_i$, show no distinct patterns. Overall, the assumptions of the regression model are satisfied. Even though the correlation of the predictor variable seems intuitively low (at approximately 58 percent), the model produces good results. A plot of the actual versus predicted values is shown in Figure 2. The average prediction error in this model is under 3 percent with a relatively low standard error.

Regional and industry group TL results

After developing the national model, the data were then subdivided by industry type and region and similar experiments were performed, again using freight density data provided by JBHT. Many of the industrial and regional models produce good results. A summary of all model results is located in Table III.

As a whole, we find the overall forecasting errors to be adequate. However, specific forecasts for the distribution, glass/plastics, and grocery segments yield disappointing results. This may be due to the proportionally small allotment of the total freight demand profile (roughly 6 percent) to these segments. Developing an accurate forecasting measure for such small segments may not be possible as small fluctuations in their demand greatly impact the potential for outliers.

Some intuitive results are found in Table III, including the retail inventories for all retail stores indicator as the best predictor of freight volume, which appears to be reasonable. Similarly, the PCPIs for processed poultry and meats seem to be reasonable predictors for food manufacturing. For regional analysis, the US import levels index seems to be a reasonable and intuitive predictor for the West marketing region.

Notice for example that the volume of freight in the area labeled "General Merchandise", which accounts for over 13 percent of total volume, is well modeled using the Manufacturers' New Orders of Durable Goods and the Aircraft and Parts Production Index, with an R^2 value of nearly 85 percent.

Also of note are the results obtained from the overall national and miscellaneous freight models. These two models exhibit very low model correlations, yet produce small forecast errors. The freight volume represented by these segments is large enough to negate minor monthly fluctuations. These variations reduce overall model correlations, but do not appear to impact the overall forecasting ability of the models.

Results from the regional analyses produce similar results. The West region yields the smallest forecast error. However, results from the other regional tests suggest that the national economic and industrial indicators used for the experiments may not provide good model parameters for other regional demand patterns.

Some of the model parameters developed for specific industrial or regional groups produce acceptable freight density estimation errors. However, the

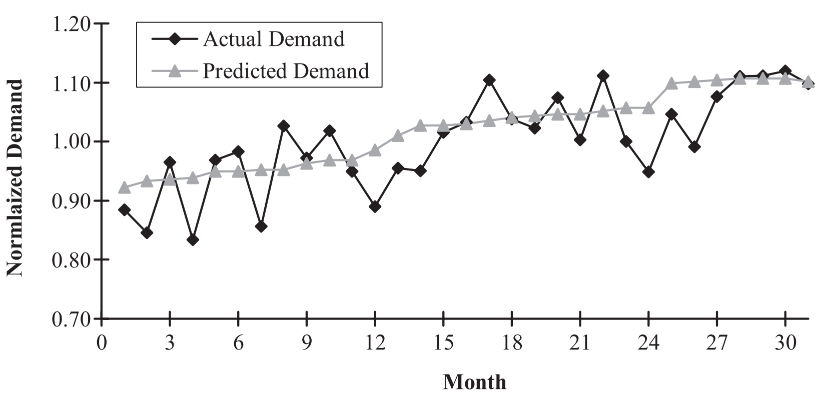

Figure 2.
Actual national demand vs. predicted demand three month lead of PCPI-CM&E

Industrial or regional market segment	Indices remaining in model resulting from stepwise selection process	Indices' R^2	Model R^2	Model F-value	Model p-value	Percent of total volume	Average forecasting error (%)
Nation	PCPI-CM&E	0.5786	0.5786	35.6949	0.0001	100.00	6.86
Alcohol	Dow Jones utilities index	0.6845	0.6845	49.8910	0.0001	2.11	11.98
Beverage	PCPI – Iron and steel	0.6564	0.7062	26.4380	0.0001	1.09	13.97
	MNO – Durable goods	0.5720					
Consumer goods	Electrical machinery production index	0.7525	0.7525	75.0520	0.0001	9.97	11.66
Distribution	Dow Jones transport index	0.7761	0.7761	93.5710	0.0001	1.73	53.80
Food manufacturing	PCPI – processed poultry	0.6063	0.6712	23.4780	0.0001	7.58	13.90
	PCPI – meats	0.5677					
General merchandise	MNO – nondurable goods	0.7973	0.8436	59.3130	0.0001	13.23	22.13
	Aircraft and parts Production index	0.7127					
Glass and plastics	Aircraft and parts Production index	0.8125	0.8356	58.4400	0.0001	3.39	52.31
	PCPI – construction materials	0.6438					
Grocery	Composite index of leading indicators	0.6787	0.6787	48.5817	0.0001	0.92	54.82
Healthcare	US import	0.6625	0.7924	31.8080	0.0001	1.03	9.00
	Manufacturing and trade inventories	0.6489					
	Foods production index	0.6257					
Logistics	Retail inventories – all retail stores	0.8313	0.8313	113.7520	0.0001	1.49	12.82
Manufacturing	PCPI-CM&E	0.8094	0.8752	84.1490	0.0001	5.30	11.56
	PCPI – concrete ingredients	0.8079					
Paper	Retail unleaded gasoline prices	0.8159	0.8159	101.9630	0.0001	11.96	5.54
Retail	PCPI – prepared paint	0.6964	0.6964	61.9370	0.0001	13.62	13.99
Miscellaneous	ATA – truck tonnage index CMA	0.2905	0.4293	8.2740	0.0001	25.19	6.82
	Retail premium unleaded gasoline prices	0.1655					
North	Retail sales: automotive dealers	0.6299	0.6299	44.2450	0.0001	32.56	32.82
Northeast	PCPI – machinery and motive products	0.5253	0.5253	25.4470	0.0001	16.05	22.44
South	Long term government securities	0.3279	0.3279	12.6930	0.0001	22.36	11.56
Southeast	Retail inventories: all retail stores	0.7414	0.7414	65.934	0.0001	12.37	39.20
West	US imports	0.5482	0.5482	32.756	0.0001	15.85	3.88

Table III. Detailed summary of all model results

summation of each industry's monthly projection (a hypothetical measure of national demand) produces significantly worse results than those produced by the national model. A similar summation attempt of the regional segments also produces amplified error results. A summary of the national estimation model compared to the summation of the industrial and regional models is shown in Table IV.

Table IV. Summary of overall forecast results

Forecast period	Actual volume (normalized)	National model forecast	Sum of industry forecasts	Sum of regional forecasts
Month 32:	1.1432	1.1086	1.0784	0.8932
Month 33:	1.1848	1.1086	1.0824	0.8954
Month 34:	1.2950	1.1031	1.0883	0.8973
Month 35:	1.1482	1.1031	N/A	0.9122
Month 36:	1.1653	1.1059	N/A	0.9091
Average	1.1873	1.1059	1.0830	0.9014
Average residual		0.0814	0.1246	0.2932
Average error (%)		6.86	10.50	24.70

Conclusions

The volatility in the demand for transportation services raises many perplexing questions for carriers. In order to protect themselves against future market volatility as well as prepare for increased or decreased demand shifts throughout various sectors, trucking companies need to have tools in place to facilitate capacity planning, pricing strategies and marketing efforts. Such tools would also assist these firms in surmounting the problems of driver turnover (especially in the TL industry), the challenges to current operational structures, and the changing logistical strategies from shippers.

Large bodies of research exist on the usefulness, reliability, and timeliness of various social and economic indicators. However no research body addressing the modeling of freight volumes based upon independent economic and industrial factors is available. Therefore, research in this area is critical to national freight carriers. The problem is developing a broad enough model to deliver an accurate picture of the future while capping the difficulty of formulating and using the model.

The results from the series of prescreening analyses and stepwise regression experiments presented herein suggests that TL trucking freight volume can be modeled with reasonable prediction errors and with relative simplicity. The forecasting accuracy of these models varies depending on the number of variables in the model, the magnitude of freight involved, and the affect of backdating the economic time series.

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