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Anticipating revisions in the Transportation Services Index

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Abstract. The Transportation Services Index (TSI) lags two months from its release date due to source data availability, and it is desirable to publish a preliminary TSI that is advanced two months ahead. We model and forecast TSI with a co-integrated Vector Autoregression, also considering two explanatory series that do not have publication delay. Thus we are able to produce forecasts and nowcasts of the index, and we demonstrate that – during normal economic conditions – out-of-sample performance is within the scope expected by the forecast confidence intervals. We also examine the performance of the models at the onset of the COVID-19 pandemic, and the large forecast errors at this regime change are beyond the bounds indicated by our model. The practical ramifications of this methodology is discussed.

Keywords: Co-integration, COVID-19, forecasting, nowcasting, vector autoregression

1. Introduction

The Transportation Services Index (TSI), produced by the U.S. Department of Transportation's Bureau of Transportation Statistics (BTS), measures the volume of freight and passenger transportation services provided monthly by the for-hire transportation sector in the United States. Monthly for-hire transportation data are available with a two-month lag for most transportation modes. As a result, the TSI lags two months from the release date. For example, the September release of the TSI contains data through July. We seek to temporally advance the TSI to provide a more timely picture of for-hire transportation activity, and render the series temporally comparable with other economic indicators, such as industrial production.

Specifically, this paper proposes a forecasting methodology to generate preliminary TSI that is advanced two months ahead. Such a preliminary publication would be revised the next month (with a one-step ahead forecast), and again revised the next month after that (when the actual data is obtained). It is important to quantify the uncertainty in such a forecast, so that BTS can indicate the degree to which such advance estimates to TSI might be revised. Due to features present in the components of TSI, we advocate a co-integrated Vector Autoregressive (VAR) model [11], demonstrating the model's out-of-sample performance across several time windows.

Section 2 discusses the construction of the TSI data, while Section 3 reviews the pertinent VAR methodology for generating forecasts. We also consider a situation where additional time series are known at some future time points, essentially allowing for nowcasting of the TSI data. Our empirical applications are in Section 4, where we examine performance across a rolling window, comparing to results obtained from a univariate approach. Because the COVID-19 pandemic has had a substantial impact on economic time series, we also examine forecast performance before and after the onset of this crisis. Finally, we describe a nowcasting application based upon using Industrial Production and Manufacturers' Value of Shipments as leading indicators. The ramifications of these results, as well as prac-

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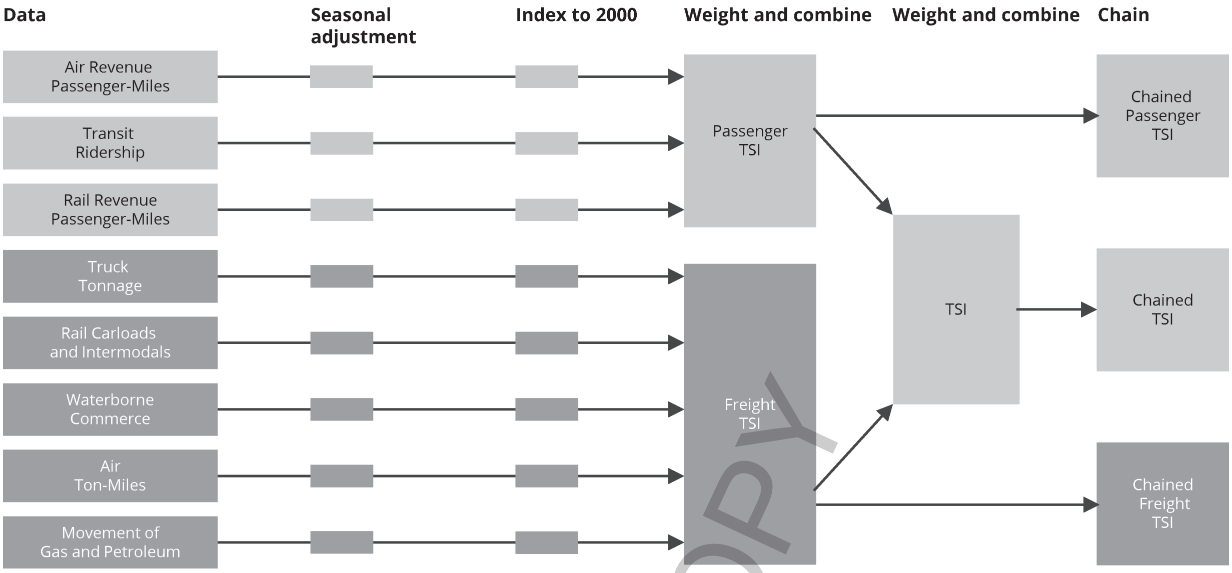

Fig. 1. Schematic overview of the construction of Transportation Services Index (TSI) components.

tical recommendations for production, are given in our concluding Section 5.

2. Data

Transportation activities have a strong relationship to the economy. The TSI is the broadest monthly measure of U.S. domestic transportation services and provides the best snapshot of the current state of these services. As an index, the TSI reflects real monthly changes in freight and passenger services provided by the for-hire transportation sector in the United States. For-hire transportation consists of the services provided by transportation firms to industries and the public on a fee basis. Airlines, railroads, transit agencies, common carrier trucking companies, and pipelines are examples of for-hire transportation.

The TSI consists of three indexes measuring the volume of for-hire transportation services provided monthly: a freight index, a passenger index, and a combined (or total) index. The indexes incorporate monthly data from multiple for-hire transportation modes. Figure 1 (Source: U.S. Department of Transportation, Bureau of Transportation Statistics, Transportation Services Index, available at www.transtats.bts.gov/OSEA/TSI) provides a synopsis of the process used to create each index. The freight index is a weighted average of data for trucking, freight rail, waterborne, pipeline, and air freight. The passenger index is a weighted average of data for passenger aviation, transit, and passenger rail. The combined index is a weighted average of all these modes.

Monthly data on each for-hire mode of transportation are seasonally adjusted, weighted, and then combined. The input data are highly seasonal, reflecting trends such as stores increasing inventory for the holiday season and households taking summer vacations. Seasonal patterns make it difficult to observe underlying long-term changes in the data, as well as monthly shifts and short-term trends, which are best viewed using seasonally adjusted data [1,2,6]. To control for seasonal influences, BTS seasonally adjusts the input data before indexing and weighting to create the indexes – this is indirect seasonal adjustment, discussed in Dagum [4]. The approach of using indirect adjustment has some disadvantages – the resulting aggregates can be seasonal, requiring further seasonal adjustment [14] – but nonetheless is quite widespread among statistical agencies (this method is used by the Bureau of Economic Analysis to produce U.S. Gross Domestic Product (GDP)[1] from two thousand component time series), because accounting relations that are deemed important to data users (such as economists and the media) are thereby preserved.

BTS uses X-12-ARIMA [7] in SAS to seasonally adjust the data.[2] After de-seasonalizing the data, BTS indexes each series individually using the 12-month av-

[1]GDP is an economic measure of all goods and services produced and consumed in the country.

[2]BTS uses concurrent seasonal adjustment, de-seasonalizing the entire data series each month.

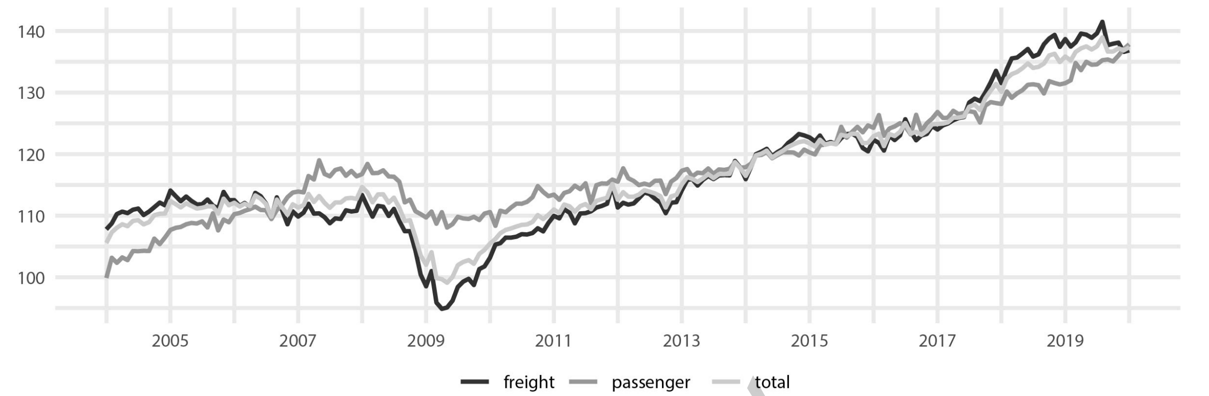

Fig. 2. The freight, passenger and combined indexes. The freight index is a weighted average of data for trucking, freight rail, waterborne, pipeline, and air freight. The passenger index is a weighted average of data for passenger aviation, transit, and passenger rail. The combined index is a weighted average of all these modes.

erage of data with 2000 as the reference year. BTS then weights each series by its contribution to the economy, as measured by GDP. Value-added is the contribution of an industry to GDP. The U.S. Bureau of Economic Analysis provides an annual measure of the value each for-hire transportation industry adds to GDP. The annual value-added estimates undergo several stages of conversion prior to being used as weights.

First, BTS splits the rail and air value-added into passenger and freight values using passenger and freight revenue data. Next, BTS divides the modal value-added GDP numbers by the indexed input series (annualized by taking an average of the monthly index values). BTS performs this calculation to avoid double counting changes in output in creating the TSI. Prior to adjustment, the value-added numbers capture changes in quantity and price of the transportation services produced in the economy. Finally, BTS uses linear interpolation to estimate monthly value-added numbers from the adjusted annual value-added numbers. BTS then uses the Fischer Ideal methodology [10] to combine the modal indexes, and chains them to generate period-to-period changes that are independent of the base year.

BTS releases the freight, passenger, and combined TSI indexes monthly. BTS research shows that changes in the TSI occur before changes in the economy, making the TSI a potentially useful leading economic indicator.[3] This relationship is particularly strong for freight traffic. The freight TSI usually peaks before an economic slowdown begins and hits a trough before an economic slowdown ends. An economic slowdown is a deceleration in the economy that occurs within periods of expansion and recession in the economy. In an economic expansion, the economy grows in real terms, as shown by increases in statistics like employment, industrial production, sales, and personal incomes. In a recession, the economy contracts, as shown by decreases in those statistics.

[3]For more information about this relationship, see Young et al. [24].

3. Forecasting with a co-integrated VAR model

The TSI data is plotted in Fig. 2, covering the time period January 2004 through January 2020. The persistent upward movements indicate a long-term trend is present in the data, rendering stationary time series models infeasible. There is no apparent seasonality, although cyclical swings may be present. Another feature is the evident co-movement of the three series, indicating that a co-integrated model may be appropriate. Given the central role of the VAR model [20] in time series econometrics, and the identified features of the TSI data, we posit a co-integrated VAR model for further analysis – see Christiano and Ljungqvist [3], Stock and Watson [21–23], and Friedman and Kuttner [8] for background.

In this section we present the formulas needed to forecast a co-integrated VAR model. We begin with the formulas of McElroy and McCracken [15], which pertain to a difference stationary process $\{y_t\}$ of dimension N. Such a process is assumed to be non-stationary, and such that after application of a degree p differencing polynomial $\Phi(B) = \sum_{j=0}^{p} \Phi_j B^j$ (where B is the backshift operator) we obtain a stationary process $\{\underline{y}_t\}$, viz.

$$\Phi(B) y_t = \underline{y}_t$$

$$\underline{y}_t = m + \Psi(B)\epsilon_t.$$

Here $\mu_t = \mathbb{E}[y_t]$ is the time-varying mean, $\{\underline{y}_t\}$ is stationary with mean vector m, and $\{\epsilon_t\}$ is a white noise process with covariance matrix Σ. By assumption, the matrix power series $\Psi(B)$ is invertible, and therefore equals $\Pi(B)^{-1}$ for a VAR (∞) matrix power series $\Pi(B)$. It follows that $\Phi(B)\mu_t = m$; if we wish to posit a more exotic mean function that is not reduced to a constant by differencing, then $\{\underline{y}_t\}$ will not be stationary.

In this formulation, $\Phi(B)$ can have mingled stationary and non-stationary effects, i.e., the roots of $\det \Phi(z)$ lie either on or outside the unit circle in the complex plane. For any matrix power series $\Theta(B)$, let $[\Theta(B)]_0^k = \sum_{j=0}^k \Theta_j B^j$, and let I_N denote the N-dimensional identity matrix. Then extending the results of McElroy and McCracken [15], when the process is Gaussian we obtain the forecast formula for forecast lead $h > 0$

$$\begin{aligned}&\mathbb{E}[y_{t+h}|y_{t:}] = [\Phi(1)^{-1}]_0^{h-1} m \\ &+ B^{-h}\{I_N - [\Phi(B)^{-1}]_0^{h-1}\Phi(B)\}y_t.\end{aligned} \tag{1}$$

Here $y_{t:}$ is shorthand for the infinite collection $\{y_s, s \leqslant t\}$. When the process is non-Gaussian but still linear (i.e., $\{\epsilon_t\}$ is i.i.d.), then the forecast is no longer a conditional expectation, but is still the minimum Mean Squared Error (MSE) linear estimator of y_{t+h} given $y_{t:}$.

The forecast error, which can be used to determine covariances of multi-step ahead forecast errors, is

$$y_{t+h} - \mathbb{E}[y_{t+h}|y_{t:}] = [\Phi(B)^{-1}]_0^{h-1}\epsilon_{t+h}. \tag{2}$$

Computing the variance matrix of the forecast errors yields the h-step ahead forecast error MSE matrix:

$$\text{Var}(y_{t+h} - \mathbb{E}[y_{t+h}|y_{t:}]) = \sum_{j=0}^{h-1} \Omega_j \Sigma \Omega_j', \tag{3}$$

where Ω_j is the jth coefficient of $\Phi(z)^{-1}$. To develop a $1-\alpha$ symmetric confidence interval for an h-step ahead forecast, we would then center the interval at the point forecast and determine the width as corresponding to the square root of the appropriate diagonal entry of the MSE matrix, multiplied by the $1 - \alpha/2$ quantile (e.g., using a Gaussian distribution).

Next, we consider an extended scenario where some of the variables are observed into the future y_{t+h}; this is a type of nowcasting problem, where some of the variables are not present at current times, and other variables that are available can be used to assist with forecasting. Partition y_t into core variables x_t (which are of chief interest for forecasting) and ancillary variables z_t (which are not of interest per se, but are available at future time points). A conditional forecast takes the form $\mathbb{E}[x_{t+h}|x_{t:}, z_{t+h:}]$, which says that we condition on future values of $\{z_t\}$ if $h > 0$. The information set can be rewritten as $\{x_{t:}, z_{t+h:}\} = \{y_{t:}, z_{t+1:t+h}\}$. Then the usual projection results yield

$$\begin{aligned}&\mathbb{E}[x_{t+h}|x_{t:}, z_{t+h:}] = \mathbb{E}[x_{t+h}|y_{t:}] \\ &+ \text{Cov}(x_{t+h} - \mathbb{E}[x_{t+h}|y_{t:}], z_{t+1:t+h} \\ &- \mathbb{E}[z_{t+1:t+h}|y_{t:}]) \cdot \text{Var}[z_{t+1:t+h}|y_{t:}]^{-1} \\ &(z_{t+1:t+h} - \mathbb{E}[z_{t+1:t+h}|y_{t:}]).\end{aligned} \tag{4}$$

The quantity $z_{t+1:t+h}$ consists of h vectors, being composed of the random vectors $z_{t+1}, \ldots, z_{t+h}$. Equation (4) is a general formula, which we specialize to the case of a co-integrated VAR. Suppose x has dimension M, so that z has dimension $N - M$. Then $x_t = [I_M, 0]y_t$ and $z_t = [0, I_{N-M}]y_t$. Then it follows from Eq. (2) that

$$\begin{aligned}x_{t+h} - \mathbb{E}[x_{t+h}|y_{t:}] &= [I_M, 0][\Phi(B)^{-1}]_0^{h-1}\epsilon_{t+h} \\ &= [I_M, 0]\sum_{j=0}^{h-1}\Omega_j\epsilon_{t+h-j}\end{aligned}$$

and for $1 \leqslant k \leqslant h$,

$$\begin{aligned}&z_{t+k} - \mathbb{E}[z_{t+k}|y_{t:}] \\ &= [0, I_{N-M}][\Phi(B)^{-1}]_0^{k-1}\epsilon_{t+k} \\ &= [0, I_{N-M}]\sum_{j=0}^{k-1}\Omega_j\epsilon_{t+k-j}.\end{aligned}$$

As a result,

$$\begin{aligned}&\text{Cov}(x_{t+h} - \mathbb{E}[x_{t+h}|y_{t:}], z_{t+k} - \mathbb{E}[z_{t+k}|y_{t:}]) \\ &= \text{Cov}\left([I_M, 0]\sum_{j=0}^{h-1}\Omega_j\epsilon_{t+h-j},\right. \\ &\left.[0, I_{N-M}]\sum_{j=0}^{k-1}\Omega_j, \epsilon_{t+k-j}\right) \\ &= [I_M, 0]\sum_{j=1}^{k}\Omega_{h-j}\Sigma\Omega_{k-j}'[0, I_{N-M}]'.\end{aligned}$$

Similarly, for $k \leqslant \ell$ we have

$$\begin{aligned}&\text{Cov}(z_{t+k} - \mathbb{E}[z_{t+k}|y_{t:}], z_{t+\ell} - \mathbb{E}[z_{t+\ell}|y_{t:}]) \\ &= [0, I_{N-M}]\sum_{j=1}^{k}\Omega_{k-j}\Sigma\Omega_{\ell-j}'[0, I_{N-M}]'.\end{aligned}$$

Hence setting $V = \text{Var}[z_{t+1:t+h}|y_{t:}]$, we have

$$V_{k,\ell} = [0, I_{N-M}] \sum_{j=1}^{k \wedge \ell} \Omega_{k-j} \Sigma \Omega_{\ell-j}' [0, I_{N-M}]'.$$

Putting things together, we can insert these calculations into Eq. (4), obtaining

$$\begin{aligned} &\mathbb{E}[x_{t+h}|x_{t:}, z_{t+h:}] = [I_M, 0]\mathbb{E}[y_{t+h}|y_{t:}] \\ &+ [I_M, 0] \left[\Omega_{h-1}\Sigma\Omega_0', \ldots, \sum_{j=1}^{h} \Omega_{h-j}\Sigma\Omega_{h-j}' \right] \\ &[0, I_{N-M}]' V^{-1} \cdot (z_{t+1:t+h} - \mathbb{E}[z_{t+1:t+h}|y_{t:}]), \end{aligned}$$

where $\mathbb{E}[y_{t+h}|y_{t:}]$ is computed from Eq. (1) and $\mathbb{E}[z_{t+k}|y_{t:}] = [0, I_{N-M}]\mathbb{E}[y_{t+k}|y_{t:}]$ for $1 \leqslant k \leqslant h$. The MSE is given by the upper left block of the quantity Eq. (3) minus the following:

$$\begin{aligned} &[I_M, 0] \left[\Omega_{h-1}\Sigma\Omega_0', \ldots, \sum_{j=1}^{h} \Omega_{h-j}\Sigma\Omega_{h-j}' \right] \\ &[0, I_{N-M}]' V^{-1} \cdot [0, I_{N-M}] \\ &\left[\Omega_{h-1}\Sigma\Omega_0', \ldots, \sum_{j=1}^{h} \Omega_{h-j}\Sigma\Omega_{h-j}' \right]' [I_M, 0]'. \end{aligned}$$

4. Empirical application

We examined the trivariate series of freight, passenger and combined index using a co-integrated VAR model. (The series are ordered this way in our analysis.) We first discuss the fit of this model on a span of data that excludes impacts from the COVID-19 pandemic, and examine forecast performance on both pre- and post- pandemic time periods. We also investigate an augmentation of the basic model using more currently available explanatory series, and assess the benefits of this nowcasting framework.

4.1. Co-integrated VAR modeling

To investigate co-integrating relations among the series, we initially used the data from January 2004 through December 2019. This restricted data span was utilized due to the obvious outliers arising from the COVID-19 pandemic, which exerted an influence on economic time series in early 2020. From univariate modeling of each series, we found that an ARIMA (1, 1, 0) models each series well, indicating that differencing reduces the series to a causal AR (1) process. Thus, it seems natural to use a second order VAR model, or VAR (2), with possible unit roots. Indeed, after fitting and residual analysis, the VAR (2) model was the best candidate (according to AIC comparisons) among contending VAR (p) (for $p \leqslant 5$) models.

To decide on the number of unit roots, and hence the co-integrating rank of the series, we performed Johansen's test [9] using the CA.JO function in the *URCA* package [17] in R [18]. The test statistic values for the Johansen's max-eigen test and Johansen's trace test are {25.14, 5.90, 2.70} and {33.74, 8.60, 2.70}, respectively. The first set of test values provide evidence for testing that the co-integrating rank is

$$H_0 : r = r^* \quad \text{versus} \quad H_1 : r = r^* + 1$$

for $r^* = 0, 1, 2$, whereas the second set of values are associated with testing that the co-integrating rank is

$$H_0 : r = r^* \quad \text{versus} \quad H_1 : r^* < r \leqslant 3$$

for $r^* = 0, 1, 2$. The critical values for the tests for a nominal 5% level are {22.00, 15.67, 9.24} for the max-eigen tests and {34.91, 19.96, 9.24} for the trace test. There are no results in the literature about uniform superiority of one test over the other. When the two tests do not agree in terms of the estimate of the co-integration rank, then some authors argue that the max-eigen test value is preferred [5,16], whereas others point toward higher power of the trace test at the cost of bigger size distortion [12]. Based on the observed test results and the nature of the plots, we chose the co-integrating rank to be one, i.e., the process is modeled with the restriction that the VAR polynomial has two unit roots.

For estimation of the model, we considered Maximum Likelihood Estimation (MLE) with a constant term in the model; more details on the estimation methods are given in Roy and McElroy [19]. The MLE method imposes the constraint that the co-integration rank is one, and hence results in two roots being exactly equal to one with the remaining roots being less than one in magnitude. The MLE for the constant term in the model was $\mu_{MLE} = (0.343, 0.168, 0.223)'$. (All estimates were rounded to three decimal places.) The coefficients of the estimated VAR (2) polynomial, as well as the error variance matrix, are given below:

$$\widehat{\Phi}_{1,MLE} = \begin{bmatrix} 0.006 & -0.813 & 1.392 \\ -0.678 & -0.450 & 1.991 \\ -0.729 & -1.124 & 2.622 \end{bmatrix},$$

$$\widehat{\Phi}_{2,MLE} = \begin{bmatrix} 1.204 & 1.296 & -2.086 \\ 0.963 & 2.105 & -2.933 \\ 1.003 & 1.754 & -2.526 \end{bmatrix},$$

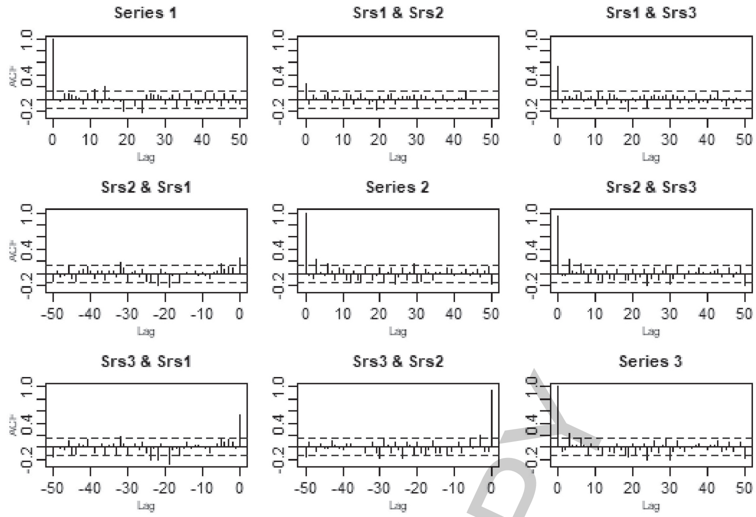

Fig. 3. Autocorrelation and cross-correlation plot for the estimated residual series.

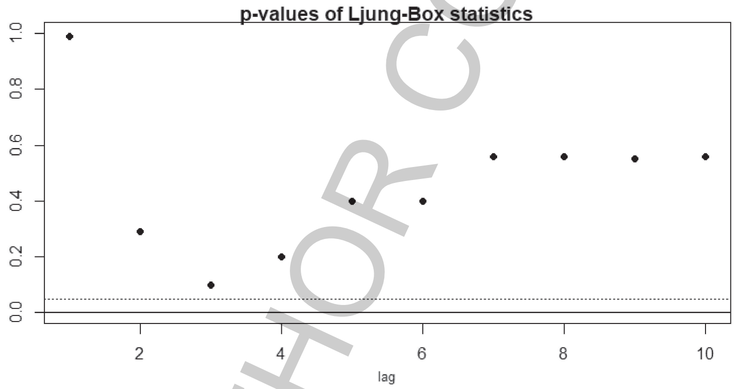

Fig. 4. Ljung-Box p-values for the estimated residual series.

$$\widehat{\Sigma} = \begin{bmatrix} 1.146 & 0.369 & 0.628 \\ 0.369 & 1.860 & 1.376 \\ 0.628 & 1.376 & 1.138 \end{bmatrix}.$$

The absolute value of roots for the VAR polynomial are

$$\lambda_{MLE} = (1.000, 1.000, 0.972, 0.514, 0.154, 0.154).$$

Other than the two unit roots, the MLE method estimates one root with magnitude close to one. Thus, the estimated co-integrated process is expected to be nearly nonstationary.

The diagnostic checks based on residual analysis for the MLE fit reveal that the residuals are well-behaved, and they mimic the properties of standard multivariate white noise residuals. Figure 3 shows the autocorrelation plot for the residuals: observe that at non-zero lags most of the correlations are not significantly different from zero. At lag zero there is significant cross-correlation, which is another point in favor of multivariate modeling. Also, Fig. 4 shows the p-values at different lags for a multivariate Ljung-Box test based on the residuals; all these results are consistent with a white noise hypothesis.

The differencing operator that reduces the process to stationarity is $(I_3 - UB)$, where

$$U = \begin{bmatrix} 0.942 & -0.134 & 0.192 \\ -0.134 & 0.693 & 0.442 \\ 0.192 & 0.442 & 0.366 \end{bmatrix}$$

$$\widehat{\Pi}_{MLE} = \begin{bmatrix} 0.210 & 0.483 & -0.694 \\ 0.285 & 0.655 & -0.941 \\ 0.274 & 0.629 & -0.904 \end{bmatrix},$$

and $\widehat{\Pi}_{MLE}$ is the estimated long-run equilibrium matrix.

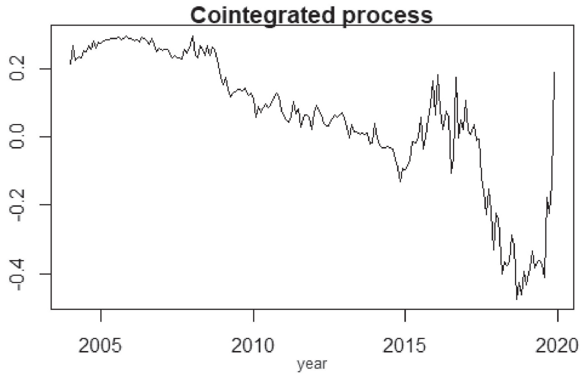

Fig. 5. Demeaned co-integrated process $\widehat{\beta}' y_t$

Based on $\widehat{\Pi}_{MLE}$, the estimated co-integrating vector is $\widehat{\beta} = (-0.241, -0.554, 0.796)'$. A plot of the co-integrated process $\widehat{\beta}' y_t$ is shown in Fig. 5. The process clearly exhibits nearly nonstationary behavior, which is due to the third root of λ_{MLE}, which is close to one. When an AR (1) is fit to this co-integrated process, a coefficient of 0.959 is obtained, which explains the observed nonstationary features.

4.2. Forecasting of TSI series

4.2.1. Pre-COVID-19 forecasts

To further investigate the fit of the model and its utility, we analyze forecasts with a moving-window approach. This procedure mimics the way this model would be used in production to produce forecasts. As with the co-integration fit in Section 4, we used data starting January 2004 for this analysis. We produced rolling window forecasts for the period January 2016 through October 2020, and refitted the models posited in Section 3 for every window of observations.

The first window of observations was January 2004 through December 2016, to which the model of Section 4 is fitted. Of course, this results in slightly different parameter estimates than those presented above for the entire sample. The fitted model was then used to forecast one and two steps ahead, i.e., January and February 2017. Continuing in this way, the window is shifted by one month and the model refitted. The new fit was used to generate one- and two step-ahead forecasts for February and March 2017. This exercise was repeated until we reached the end of the available data; the result is a different model for each window of data for the months January 2017 through December 2019, as well as their respective forecasts. These forecasts were then compared to the true values, and the relative percent error is reported in Table 1.

Table 1
Relative forecast error comparing forecasts of VAR (2) to true observed values over the last three years of observations

	Freight	Passenger	Combined
1 step-ahead forecast error	0.9563%	0.4813%	0.7375%
2 step-ahead forecast error	1.1824%	0.5824%	0.9353%

Table 2
Relative forecast error comparing forecasts of univariate ARIMA (1, 1, 0) models to true observed values over the last three years of observations

	Freight	Passenger	Combined
1 step-ahead forecast error	0.8541%	0.6893%	0.6461%
2 step-ahead forecast error	1.0688%	0.7786%	0.7839%

It is desirable to have parameter stability as the window moves through the data. We investigated stability by observing the trajectories of estimates of each parameter as the window shifted over time. No large fluctuations were observed in the trajectories, indicating that the fitted models were very similar over the different time windows.

We can graphically summarize the accuracy of one-step and two-step ahead forecasts for the pre-COVID-19 period from January 2016 through February 2020. The passenger series was forecasted most accurately, with every true observation falling within a 95% confidence interval as calculated with a normal quantile and standard error via (3). Figures 6 and 7 plot one- and two-step-ahead forecasts along with 95% confidence bounds. Superimposed are the true observed series for the values being forecasted; the fact that the various confidence intervals tend to contain the true values indicates that the model and forecasting mechanism are operating as desired.

4.2.2. Comparison with univariate models

The forecast performance of the multivariate co-integrated model for the freight, passenger and the combined series could be contrasted with that of base univariate models. For univariate models, ARIMA (1, 1, 0) models seem to be adequate for each of the series. Table 2 provides the rolling window forecast errors for the three series for the same period as utilized in Section 4.2.1, viz. January 2017 through December 2019.

For the freight, the univariate model provides about 12% reduction in the forecast error over the VAR (2) model forecasts. However, for the passenger series the VAR (2) forecasts have about 30% smaller forecast error when aggregated over the forecasting window. The combined series is essentially like the freight, with the components of freight getting larger weight in the combination. We did not produce indirect forecasts for

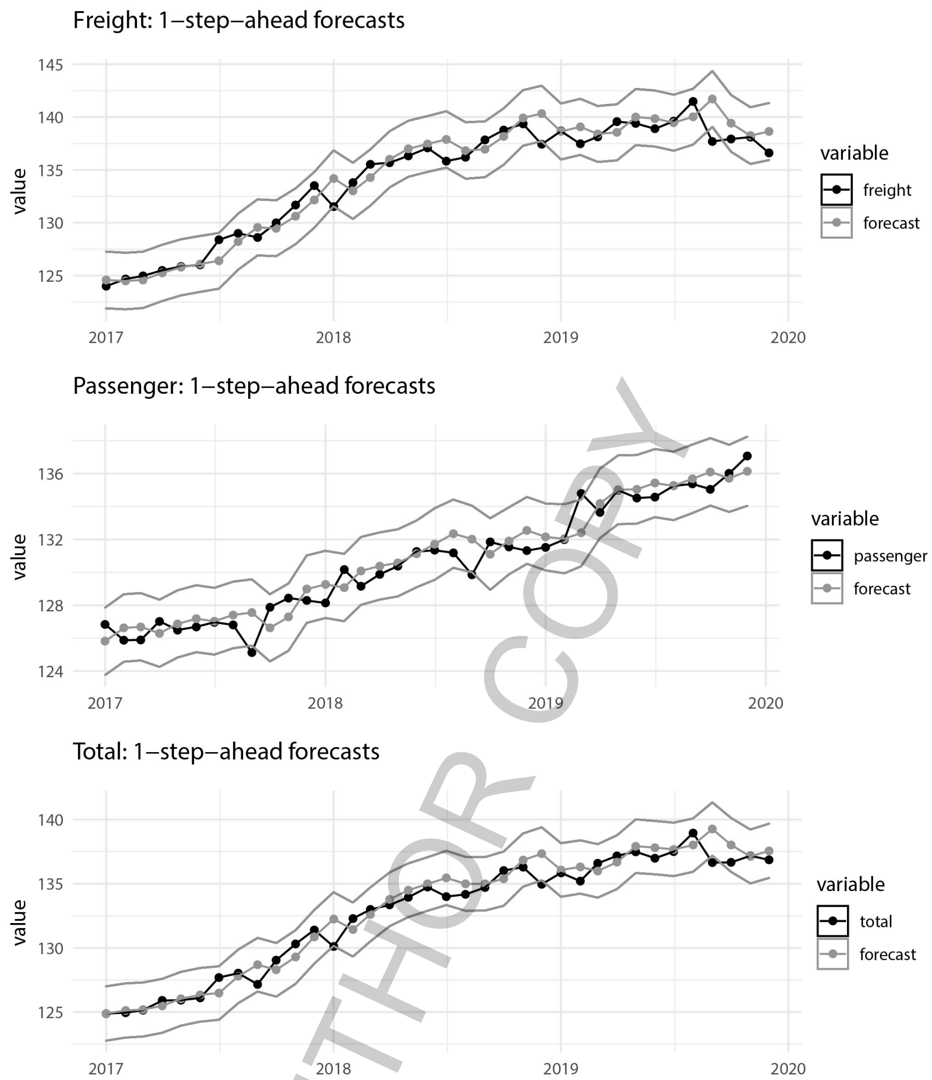

Fig. 6. One-step-ahead forecasts for each TSI series type. Shaded region represents a 95% confidence interval for the point forecast series.

the combined series using forecasts from the freight and the passenger series, since the combined series is a weighted average of the sub-components of the freight and the passenger series. The forecast performance for the combined series (based on direct forecasts) is similar to that for the freight series. While no model was uniformly better than the other in terms of aggregate forecast error, the confidence bands based on the VAR (2) model are wider, and are likely to provide better coverage of the forecast uncertainty.

4.2.3. Post-COVID-19 forecasts

Next, we examine the performance of the forecasting model when the time series is subject to rapid changes, such as those observed after the onset of the COVID-19 pandemic. The one-step-ahead forecasts over the extended time period for the three TSI series are shown in Fig. 8; similarly, two-step-ahead forecasts can be found in Fig. 9. The methodology for obtaining these forecasts remained the same as in Section 4.2.1, updating the model for each new window of data as would be done in a production setting. Several interesting features are remarkable. First, there is a large forecast error during the rapid downturn of the series; such a structural change in the series typically warrants additional terms in the model, such as outlier dummies and or level shift indicators. Therefore, the current model would need to be modified to include such regression factors if one is interested in forecasting in the post-COVID-19 era.

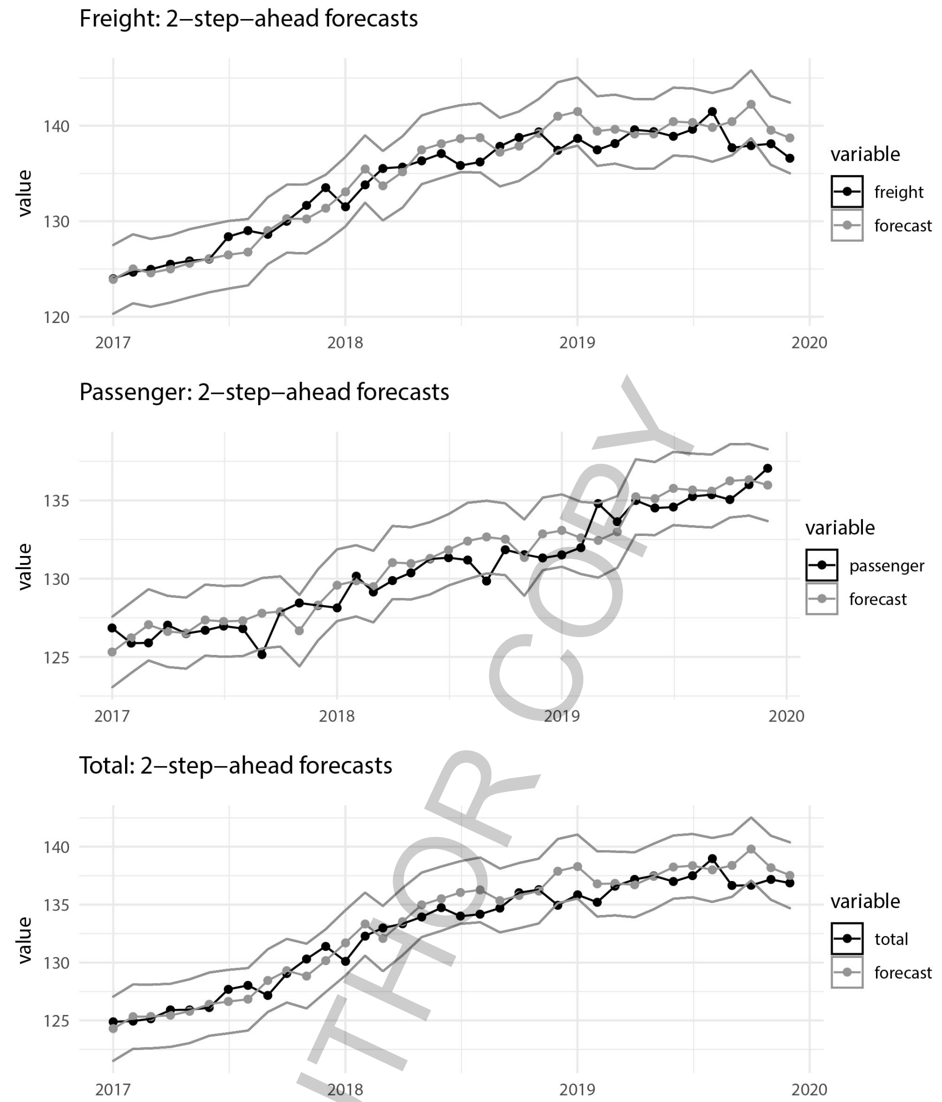

Fig. 7. Two-step-ahead forecasts for each TSI series type. Shaded region represents a 95% confidence interval for the point forecast series.

Another observation is that the passenger and combined indexes both experienced large dips in March 2020 due to the COVID-19 pandemic. However, the freight series did not experience a large drop until April 2020, the following month. Since the series were modeled jointly, the large drop in the freight series was actually forecasted remarkably well. The freight April 2020 value falls inside the 95% confidence interval, even though it fell in one month to its lowest value since April 2017. This demonstrates the utility of multivariate modeling, as a purely univariate model – that did not borrow information from passenger and combined, which are leading freight – would not capture this phenomenon. Furthermore, because passenger and combined only lead by one month (in terms of indicating the onset of the pandemic effect), this predictive benefit to freight does not carry over to two-step-ahead forecasts, as Fig. 9 confirms. In particular, the two-step ahead forecast of April 2020 for freight fails to decrease appropriately, because these forecasts are based on information up to February 2020, when both passenger and combined were still at normal levels.

4.3. Nowcasting of TSI series

While the TSI co-integrated model is able to produce useful one- and two-step ahead forecasts, the performance will deteriorate as the forecast horizon increases.

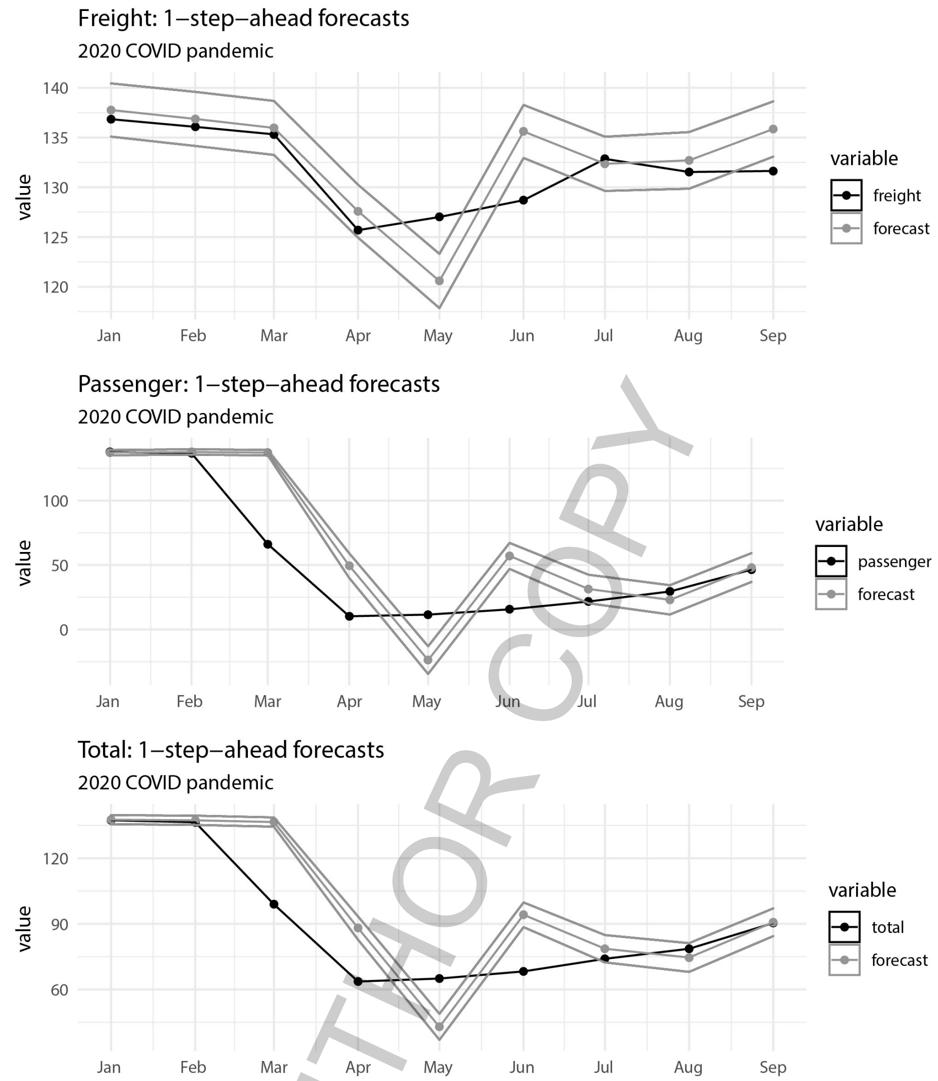

Fig. 8. One-step-ahead forecasts during the 2020 COVID-19 pandemic. Shaded region represents a 95% confidence interval for the point forecast series.

Since there may be a temporal lag in releasing the value of the series, it is worthwhile to examine nowcasting for the TSI series using other related time series for which current values are available. Two such possible series are Industrial Production and Manufacturers' Value of Shipment. The Manufacturers' Value of Shipment series comes from the U.S. Census Bureau's Manufacturers Shipments, Inventories, and Orders (M3) survey. Data published from the M3 survey are based on a panel of approximately 5,000 reporting units that represent approximately 3,100 companies, and provide an indication of month-to-month change for the manufacturing sector. The Value of Shipment series represents the dollar value of products sold by manufacturing establishments.[4] Industrial Production measures the real output for manufacturing, mining, and electric and gas utilities. It measures movement in production output, and highlights structural developments in the economy.[5] The three TSI series are plotted along with Industrial Production and Manufacturers' Value of Shipment in Fig. 10.

We use the TSI series along with the Industrial Production and the Manufacturers' Value of Shipment series to build a five-dimensional VAR system, and then use the nowcasting formula derived in Section 3 to now-

[4] https://www.census.gov/manufacturing/m3/index.html.
[5] https://fred.stlouisfed.org/series/INDPRO.

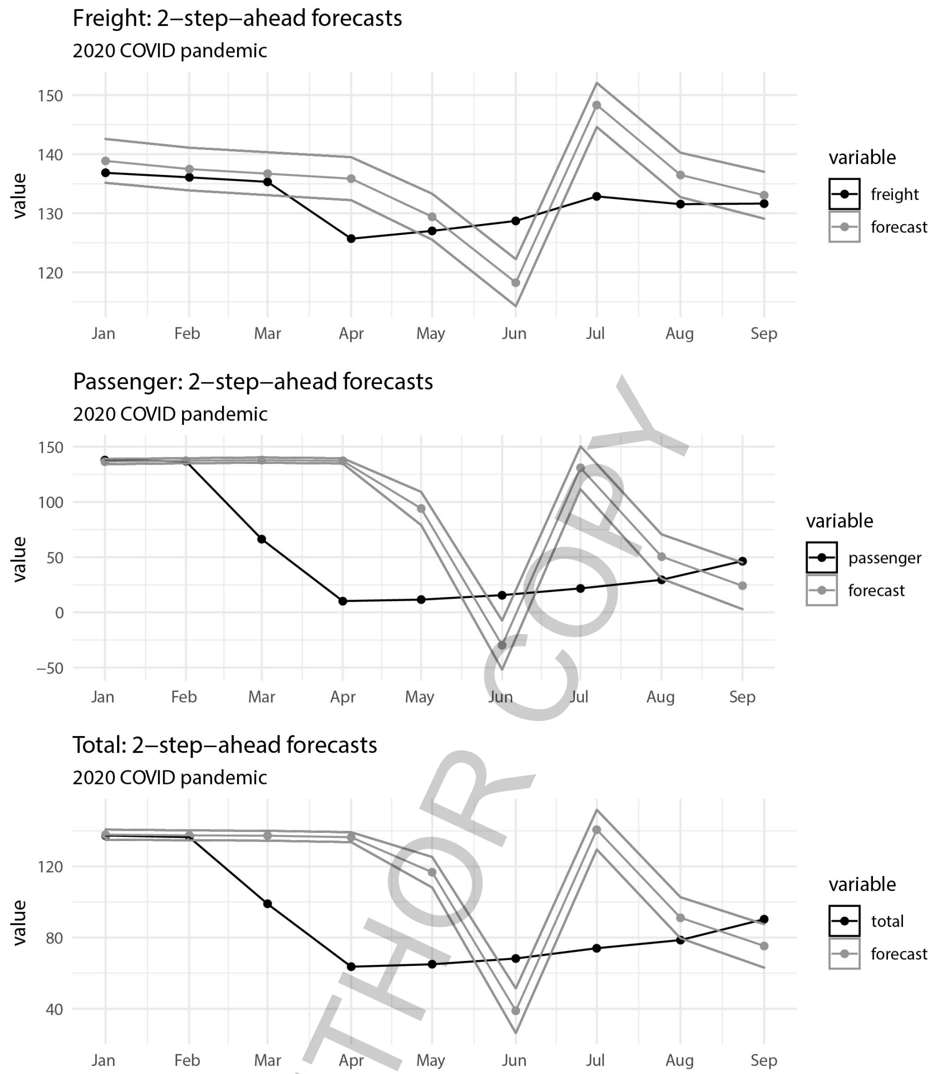

Fig. 9. Two-step-ahead forecasts during the 2020 COVID-19 pandemic. Shaded region represents a 95% confidence interval for the point forecast series.

cast the TSI series. The rank of the co-integrated system is one. The VAR order is two, which leaves the total number of parameters around sixty.

We start making forecasts in January 2017, ensuring we have enough data to estimate parameters in the five dimensional VAR (2) model. We window the data in the same way as discussed in Section 4.2, viz. we consider data up through December 2019 to avoid COVID-19 pandemic effects. Table 3 gives the relative forecast error of the nowcasts.

Comparing the nowcast values to the results of Section 4.2, where only the three components of TSI were included, we see that the nowcast error is slightly higher than the forecast error based on the three-dimensional co-integrated system. This could be because over the forecast period the TSI series is well modeled by the co-integrated VAR (2); hence the forecasts outperform the nowcasts since the latter depends on two additional series, which add noise to the system (as well as many additional parameters that need to be estimated). While the nowcasting errors were slightly larger than the one-step forecast errors from the three-dimensional TSI model, in absolute term they were still quite small. Moreover,

Table 3
Relative forecast error comparing nowcasts of VAR (2) to true observed values from January 2017 through December 2019

	Freight	Passenger	Combined
1 step-ahead forecast error	1.8111%	1.5078%	1.3375%
2 step-ahead forecast error	2.1901%	1.6444%	1.5975%

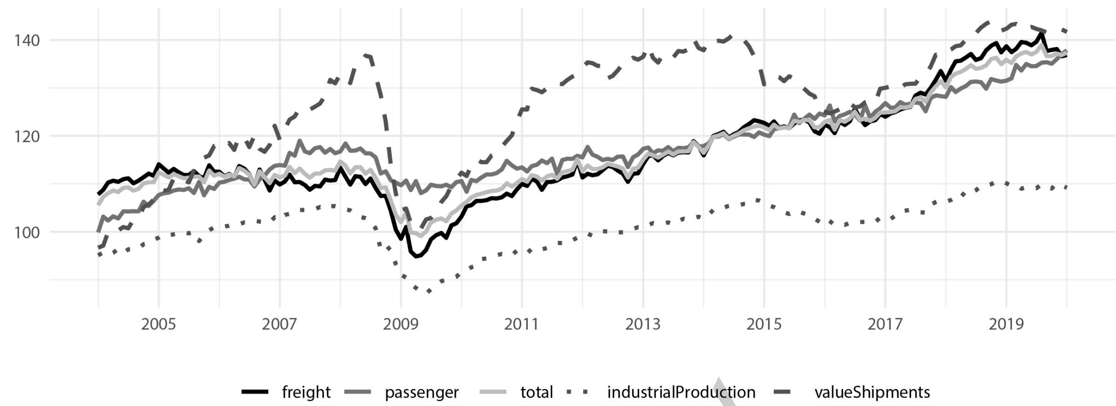

Fig. 10. The freight, passenger and combined indexes along with Industrial Production and Value of Shipment. The Industrial Production and Manufacturers' Value of Shipment series are more timely, and are used for nowcasting the other three series.

if there is a considerable lag in the TSI series, nowcasts may be preferred over longer horizon forecasts.

5. Discussion

Preliminary TSI can now be published using the 2-step ahead forecasts (with confidence intervals) from the fitted co-integrated VAR model, and this seems to be an improvement over using a univariate ARIMA (1, 1, 0) model. The analysis of out-of-sample forecasts indicates the forecast error is tolerable (Table 1) and within a range expected by the model (Figs 6 and 7).

For future usage, we recommend that the fitted model be updated each month as data is added, and all diagnostics be checked a(s discussed in Section 4.1). In particular, each month the time series data is extended by one time point, and the same VAR model can be fitted using the procedure described above to get the parameter MLEs. Then residuals can be computed, and examined for model adequacy. On the basis of these results, the new forecasts can be generated for leads 1 and 2 (for lead 1, this is really an update of the 2-step ahead forecast that was generated the previous month).

The analyst must be aware of the impact of extreme events – such as a pandemic or crisis – upon the model, and take appropriate action by including level shift or temporary change regressors; Lytras and Bell [13] discuss how crises (e.g., the Great Recession) can be modeled with outlier regressors, and the same strategy may be effective with COVID-19. Sustained divergences of the model's forecasts from reality can be assessed ex post by examining out-of-sample forecast errors (i.e., revisions) against the forecast error intervals (Figs 6 and 7); large deviations indicate that a new model specification may be desirable. We recommend that an annual review be conducted by an internal panel, in order to determine if the VAR model specification needs updating.

Other improvements to our basic approach can be envisioned. The use of external regressors can be entertained, as these are easily inserted into the model. External series, such as Industrial Production and the Manufacturing Value of Shipments, could be used as external regressors or can be directly incorporated into the TSI VAR model. In order to be practicable these external regressors must have the same publication standards – in terms of quality and longevity – as the TSI data.

Disclaimer

This report is released to inform interested parties of research and to encourage discussion. The views expressed on statistical issues are those of the authors and not those of the U.S. Census Bureau. All time series analyzed in this paper are from public data sources.

Acknowledgments

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