# Stability of Multi-Part Pricing in the U.S. Less-Than-Truckload Industry: Evidence From the Panel Stationarity Test With Structural Breaks

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*This paper aims to examine the stationarity of LTL carriers' multi-part pricing structures. We construct a spillover index of inter-firm linkages among base yield, fuel surcharge, and total yield (measured by fuel surcharge plus base yield), and use a heterogenous panel stationarity test developed by Hadri and Rao (2008) to allow for structural breaks. After accounting for cross-sectional dependence, results indicate that a structural break occurred in all three revenue dimensions but with quite different break patterns, since the inter-firm price structure gap has narrowed and converged toward the industry average. In short, competition has intensified in the LTL industry.*

*Keywords: freight, pricing, less-than-truckload, fuel surcharge, structural break, stationarity*

## INTRODUCTION

As a lifeblood of U.S. economy, trucking represents roughly 70 per cent of U.S. domestic freight by weight. In 2023, the nation's trucking freight bill totalled $987 billion in gross freight revenue and 8.5 million persons were employed in trucking-related activities. In 2022, trucks hauled 72.6 per cent of all freight transported in the U.S. (American Trucking Association, 2024). In particular after nearly more than a decade of thin profit margins, and except for the COVID-19 pandemic we have noted, the LTL sector has become highly prosperous, with booming e-commerce, shortened supply chains, and the smaller, lighter shipments accompanying them (Du and Buccola, 2020).

Trucking deregulation from the Motor Carrier Act of 1980 dramatically boosted the number of U.S trucking companies of all types. The aftermath of frequent mergers and acquisitions in the LTL industry is an industry structure consisting of a few large, full-service logistics companies and many small niche LTL providers. Another consequence of the 1980 deregulation has been the introduction of multi-part pricing schemes, permitting shipper-customers to observe how certain aspects of the carrier's costs are structured. Freight bills now, in particular, typically include three components: (1) the base charge for essential capital and labor inputs used to move freight from one point to another; (2) charges for any accessory services such as residential pickup and delivery and lift-gate attention; and (3) a fuel surcharge, which usually is billed either as a predetermined flat fee or as weight-based charge over the base rate, expressed per hundredweight. Separating the base from the fuel surcharge may help distinguish the LTL carrier's relatively permanent and predictable capital-labor complements from its more volatile fuel expenses, allowing customers to compare these components with other transportation options. For example as fuel sub-charges rise relative to base charges, customers generally will wish to substitute shorter- for longer-haul strategies. By the same token, charging fuel-related costs to non-fuel inputs like truck and warehouse capital would effectively subsidize shipping customers with a long-distance haul strategy and encourage one.

Despite, as detailed below, extensive literature on the trucking industry as a whole, the LTL sector in particular has received much less attention than it deserves. Analysis of LTL multi-pricing structure is even scarcer. The present study aims to examine the stability of leading U.S. LTL carriers' multi-part pricing structures. Examination of stability of LTL firms' multi-pricing structures can provide important implications of market power in the LTL industry in terms of base service and fuel services, respectively. Long-run convergence (or stationarity) of these series would indicate that although it is in fueling services that LTL carriers exercise market power (Du and Buccola 2020), this power has tended to dissolve as competitive forces have begun to assert themselves.

Besides presenting results of the traditional univariate stationarity tests, we conduct a heterogeneous panel stationarity test (Hadri and Rao, 2008) on a sample of quarterly firm-specific observations from 2015 Q1 to 2020 Q4 to determine whether individual firms' multi-part pricing rates – including fuel surcharge, base rate, and total rate – tend to converge to a long-run industry average. (Advantages of applying a panel stationarity test vs. traditional univariate test will be detailed in the next section.) As convergence may be affected by such disturbances as industry restructurings and aggregate economic activity fluctuations, we employ five different models for this purpose in the paper, varying in how disruption patterns are contrasted with the null hypothesis of stationarity. The recent nature of this data set permits a highly contemporaneous view of how multi-part pricing strategies are employed in the industry, of particular value given the frequency of mergers and acquisitions in the past few years.

## LITERATURE REVIEW

Earlier literature relevant to the freight industry, both TL and LTL, has focused mainly on three areas: determinants of shipper preferences (Danielis et al 2005; Danielis and Marcucci 2007, Fries *et al*, 2010, and Mesa-Arango and Ukkusuri, 2014); pricing (Figliozzi et al 2007, Topaloglu and Powell 2007, Toptal and Bingol 2011, and Shah and Brueckner 2012); or fuel efficiency (Vernon and Meier 2012, and Winebrake et al 2015a,b). There have been few new insights into pricing determinants and performance in the LTL sector. Kay and Warsing (2009) find LTL rates inversely proportional to weight, distance, and shipping density. Smith, Campbell, and Munday (2007) find the determinants of freight charges to be shipping volume, weight, distance, and the competitiveness of the local business environment. Özkaya *et al* (2010) offer a scorecard to quantify intangible factors in LTL pricing, finding the most significant to be negotiating power along with the freight class and economic value. Using data from Taiwan, Lin, Lin, and Young (2009) show that the frequent practice of dividing price into a separate distance and a weight-based factor tends to underestimate operating costs, corrected only by considering network capacity in pricing decisions. A recent study by Rinaldi and Bottani (2023) offers a comprehensive view of Covid's influences on various industries and over a range of countries. Based on their review, its effects did differ widely across such sectors as logistics & transport, food & beverages, textiles & fashion, automobiles and mechanical and depending upon the length of run considered – from the very short, to the short, to the intermediate term. For the trucking industry, most recent studies have focused on Covid's effects on driver stress, health, and safety (Lemke *et al*, 2020; Velasquez, B, 2021), on working conditions (Crizzle *et al*, 2021), on transport demand and freight capacity (Loske, 2020; Falchetta and Noussan, 2020; Richards and Rutledge, 2023; Li et al, 2023), on trucking rates and shortages (Du, 2021; Richards and Rutledge, 2023), and on employment (Phares, Miller, Burks, et al, 2023).

Going beyond these studies of the tangible and intangible drivers of LTL rates, Du and Buccola (2020) investigate an LTL price's uniquely multi-part character and find a clear though partial jointness between base transportation services (which involve relatively more capital and labor) and fueling services (which involve relatively more fuel). Rather than cover fuel expenses only, fuel surcharges include capital and labor costs, reflecting the joint character of LTL labor, capital, and fuel productivity. They find that base charges defray the more liquid inputs, where scale returns are constant, while fueling charges tend to cover the carrier's scarcer resources, where scale returns are decreasing. As a consequence, LTL market power is achieved primarily in the prices charged to fueling. In other words, the LTL industry appears to be competitive in its base-service dimension and monopolistically competitive in its fueling service dimension.

None of the above studies have subjected LTL multi-part pricing structures to time-series analysis. This analysis is notable because not only do the input compositions of LTL's fuel-related services differ substantially by firm but fuel surcharge list rates are normally updated each week due to the volatile fuel price, in contrast to the relatively more homogeneous and stable base transportation services. In our own effort in this direction, the advantages of the panel unit root test of Hadri and Rao (2008) specifically consider both serial correlation and cross-sectional (cross-firm) dependency, an important specification in a convergence study. Moreover, the method allows for structural breaks possibly arising from such random shocks as industry restructurings and macroeconomic disruptions. The test can also explicitly identify firm-differing, endogenously determined, and otherwise unknowable behavioral price-breaking points in the individual yield data series. The test is especially useful and powerful because monopolistically competitive carriers, as found in Du and Buccola (2020), probably respond differently to a similar external shock. Finally and perhaps most importantly, the presence and timing of any tendency of a carrier's multi-pricing rate to converge to a long-run industry average will provide significant insight into LTL market structure.

## DATA AND METHODOLOGY

The data set consists of quarterly yield (unit revenue) observations from 2015Q1 to 2020Q4 of eight major LTL firms in the US.[1] Three yield data series will be examined: fuel surcharge, base yield, and total yield (fuel surcharge plus base yield) from individual firms. The total sample size is 192 * 3 = 576 quarterly observations. Yield is measured per pound-mile. Fuel yield is calculated as fuel surcharge revenue divided by pounds and average length of haul (LOH) at an individual firm in a given quarter. Similarly, base yield is calculated as base service revenue (total revenue minus fuel surcharge revenue) divided by pounds and average LOH at the firm. Total yield is a firm's total revenue divided by pounds and average LOH. Data on revenue, poundage, and average LOH are available from firms' quarterly financial reports. For those who do not report fuel surcharge revenue separately, we employ their fuel surcharge list rates (averaged by weekly fuel surcharge list rates in a given quarter) multiplied by total revenue to do so. These firms included in the analysis are FedEx Freight, Yellow Roadway Corporation Worldwide (YRC Regional and National), Old Dominion Freight Lines, UPS Freight, XPO Logistics, Saia and ABF Freight – accounting for approximately 70% of total revenue in the industry as of 2020. Table I provides the summary statistics.

As found in the pioneering work of Perron (1989) and Amsler and Lee (1995), traditional univariate unit-root tests, including the Augmented Dickey–Fuller (ADF) test (Dickey and Fuller, 1979) and the PP test (Phillips and Perron, 1988), are, in the presence of a structural break, biased toward accepting a false unit-root null hypothesis. Failure to consider the possible structural breaks into consideration into unit-root testing can lead to a significant loss of statistical power. It can also, due to the severe distortion size that a structural break can induce, bias estimates toward rejecting the null hypothesis of stationarity, a problem encountered in the KPSS test (Kwiatkowski et al., 1992) (Lee, Huang and Shin, 1997; Kurozumi, 2002; Lee and Strazicich, 2001; and Busetti and Harvey, 2001).

Due to these weaknesses of univariate unit root testing as mentioned above, we will now examine our hypothesis of multi-part pricing convergence (stationarity) through the heterogeneous panel stationarity test of Hadri and Rao (2008, HR). Compared to Hadri (2000) and Hadri and Larsson (2005), the HR method has several advantages over other models of panel stationarity with breaks. First, it incorporates cross-sectional (cross-firm) dependence, an important specification in any convergence analysis. Second, it solves several econometric problems such as serial correlation in errors, and any unobserved heterogeneity in the trend function used to compute the forms and dates of a potential structural break. Finally, it allows for a variety of unknown break dates in a given time series.

**TABLE 1**
**DATA SUMMARY STATISTICS**

**1.1 Fuel Surcharge Yield (in lb. mile) at Selected U.S. LTL Motor Carriers, By Carrier**

| | ABF | FXF | YRCR | YRCN | XPO | ODFL | SAIA |
|---|---|---|---|---|---|---|---|
| **Mean** | 0.0023 | 0.0020 | 0.0013 | 0.0008 | 0.0012 | 0.0010 | 0.0015 |
| **Std. Dev.** | 0.0002 | 0.0002 | 0.0002 | 0.0001 | 0.0001 | 0.0001 | 0.0001 |
| **Max** | 0.0028 | 0.0023 | 0.0016 | 0.0010 | 0.0015 | 0.0017 | 0.0017 |
| **Min** | 0.0018 | 0.0016 | 0.0010 | 0.0006 | 0.0009 | 0.0013 | 0.0013 |

**1.2 Base Yield (in lb. mile) at Selected U.S. LTL Motor Carriers, By Carrier**

| | ABF | FXF | YRCR | YRCN | XPO | ODFL | SAIA |
|---|---|---|---|---|---|---|---|
| **Mean** | 0.0102 | 0.0089 | 0.0108 | 0.0067 | 0.0087 | 0.0079 | 0.0067 |
| **Std. Dev.** | 0.0004 | 0.0005 | 0.0002 | 0.0002 | 0.0001 | 0.0004 | 0.0003 |
| **Max** | 0.0109 | 0.0099 | 0.0111 | 0.0071 | 0.0089 | 0.0086 | 0.0073 |
| **Min** | 0.0093 | 0.0083 | 0.0105 | 0.0063 | 0.0085 | 0.0072 | 0.0062 |

**1.3 Total Yield (in lb. mile) at Selected U.S. LTL Motor Carriers, By Carrier**

| | ABF | FXF | YRCR | YRCN | XPO | ODFL | SAIA |
|---|---|---|---|---|---|---|---|
| **Mean** | 0.0125 | 0.0109 | 0.0121 | 0.0076 | 0.0100 | 0.0089 | 0.0082 |
| **Std. Dev.** | 0.0006 | 0.0006 | 0.0003 | 0.0002 | 0.0002 | 0.0006 | 0.0003 |
| **Max** | 0.0136 | 0.0120 | 0.0126 | 0.0081 | 0.0104 | 0.0097 | 0.0086 |
| **Min** | 0.0115 | 0.0099 | 0.0117 | 0.0071 | 0.0096 | 0.0082 | 0.0076 |

We express each firm's quarterly yield (in the form separately of fuel surcharge, base yield, and total yield) relative to the contemporaneous quarterly seven-firm mean yield, so that the series of interest for firm *i* at time *t* is:

$$y_{i,t} = ln\left(\frac{g_{i,t}}{\bar{g}_t}\right) \quad t = 1 \ldots\ldots T \tag{1}$$

where $y_{it}$ is relative yield, $g_{it}$ is yield at firm *i*, and $\bar{g}_t$ is average yield across all firms at time *t*. Under the null hypothesis of stationarity, the model yields:

$$y_{i,t} = r_{i,t} + Z_{i,t}\beta + \varepsilon_{i,t} \tag{2}$$

$$r_{i,t} = r_{i,t-1} + \mu_{i,t} \tag{3}$$

where $Z_{it}$ is the deterministic component, $\varepsilon_{it}$ are stationary errors, and $\mu_{it}$ are independent identically distributed errors with $E(\mu_{it}) = 0, var(\mu_{it}) = \sigma^2_{\mu,i} \geq 0$. $\{\varepsilon_{it}\}$ and $\{\mu_{it}\}$ are mutually independent across the two dimensions of the panel data. $r_{it}$ is a random walk process with initial values $r_{i0} = 0 \forall i$. $Z_{it}$ controls the dynamics of the above data-generating process (DGP). Setting $Z_{it} = [1]$ gives a level stationary process lacking any trend or breaks. To control for the unobserved heterogeneity across companies due to the approximative character of a firm's average length of haul,[2] we incorporate a fixed-effect estimator by including a company-specific dummy variable in equation (2) in the following form:

$$y_{i,t} = \alpha_i + r_{i,t} + Z_{i,t}\beta + \varepsilon_{i,t} \tag{4}$$

The company-specific effect, $\alpha_i$ , is unobservable and therefore cannot be controlled for directly. The standard method in fixed-effects models is to eliminate $\alpha_i$ by subtracting from each variable its respective company-specific means (de-meaning):

$$y_{i,t} - \overline{y}_i = (\alpha_i - \bar{\alpha}_i) + (r_{i,t} - \bar{r}_i) + (Z_{i,t} - \bar{Z}_i)\beta + (\varepsilon_{i,t} - \bar{\varepsilon}_i) \tag{5}$$

where $\overline{y}_i = \frac{1}{T}\sum_{t=1}^{T} y_{i,t}$, $\bar{r}_i = \frac{1}{T}\sum_{t=1}^{T} r_{i,t}$, $\bar{Z}_i = \frac{1}{T}\sum_{t=1}^{T} Z_{i,t}$ and $\bar{\varepsilon}_i = \frac{1}{T}\sum_{t=1}^{T} \varepsilon_{i,t}$ . Equation (5) can be rewritten as

$$\tilde{y}_{i,t} = \tilde{r}_{i,t} + \tilde{Z}_{i,t}\beta + \tilde{\varepsilon}_{i,t} \tag{6}$$

where all variables are in deviations from their company means. We estimate our model using equation (6).

Following Hadri and Rao (2008) and the notation in Ranjbar et al. (2015), five models are considered, varying according to the form of the $Z_{it}$ vector:

$$Model\ 0 : \tilde{Z}_{i,t} = [1, t]' \tag{7}$$

$$Model\ 1 : \tilde{Z}_{i,t} = [1, D_{i,t}]' \tag{8}$$

$$Model\ 2 : \tilde{Z}_{i,t} = [1, t, D_{i,t}]' \tag{9}$$

$$Model\ 3 : \tilde{Z}_{i,t} = [1, t, DT_{i,t}]' \tag{10}$$

$$Model\ 4 : \tilde{Z}_{i,t} = [1, t, D_{i,t}, DT_{i,t}]' \tag{11}$$

where dummy variables $D_{it}$ and $DT_{it}$ are respectively defined as:

$$D_{i,t} = \begin{cases} 1, if\ t > T_{B,i}, \\ 0, otherwise \end{cases} \tag{12}$$

$$DT_{i,t} = \begin{cases} t - T_{B,i}, if\ t > T_{B,i}, \\ 0,\ \ otherwise \end{cases} \tag{13}$$

$T_{B,i}$ in the relevant intercept and time-trend function determines the break date in firm $i$'s relative yield. Equations (4) – (8) specify the alternative effects a break may induce in the models' deterministic portions. In particular Model 0 is a trend-stationary process without breaks. Model 1 specifies a possible one-time break in level but not in trend. Models 2 through 4 are trend-stationary processes. Model 2 allowing for a break in level and none in time-trend slope, and Model 3 permitting a break in slope only but not in level. Model 4 admits a break in both level and slope.

The null hypothesis of stationarity of HR test is given by

$$H_0: \sigma^2_{\mu,1} = \sigma^2_{\mu,2} = \ldots = \sigma^2_{\mu,N} = 0, \tag{14}$$

against the alternative

$$H_1: \sigma^2_{\mu,i} > 0, i = 1, 2, \ldots, N_1;\ \sigma^2_{\mu,i} = 0, i = N_1 + 1, \ldots, N. \tag{15}$$

The alternative hypothesis allows for $\sigma^2_{\mu,i}$ to be heterogeneous across firms and includes the homogeneous alternative, i.e. $\sigma^2_{\mu,i} = \sigma^2_{\mu}$ for all $i$.

Based on the Hadri and Rao (2008)'s estimation strategy, models 1 to 4 can be estimated by the following 3-step procedure:

1) Break-point estimation: The appropriate break points are selected by minimizing the sum of squared residuals (SSR) of form:

$$\left(\hat{T}_{B,i}\right) = \underset{\hat{T}_{B,i}}{\arg\min}\, SSR\left(T_{B,i}\right) \tag{16}$$

2) Model selection: The appropriate model is selected by minimizing the Schwarz Bayesian Information Criterion (BIC):

$$BIC_{ik} = \ln\left(\frac{SSR_{ik}}{T}\right) + q_{i,k}\frac{lnT}{T} \tag{17}$$

where $SSR_{ik}$ is the sum of squared residuals of the $i$'th firm and $k$'th model; $q_{i,k}$ is the number of regressors; and T is sample size.

3) Computation of test statistics with unknown break: The univariate test statistic is calculated as:

$$LM(\lambda_i, k, T) = \widehat{\omega}_{\mathrm{i}} T^{-2} \sum_{t=1}^{T} \hat{S}^2_{i,t} \tag{18}$$

where $\hat{S}_{i,t} = \sum_{j=1}^{t} \widehat{\varepsilon}_{ij}$ is the partial sum of the estimated errors obtained from equation (2) and $\lambda_i$ is the company $i's$ break date, estimated by minimizing the sum of squared residuals (SSR) from the relevant regression under the null hypothesis (see Bai 1994, 1997 for details). Finally, the heteroskedasticity- and autocorrelation-consistent estimates of the long-run variance of $\varepsilon_{i,t}$ are represented by $\widehat{\omega}_{\mathrm{i}}$. The finite-sample critical values of the individual univariate test statistic are calcuated by a Monte Carlo simulation based on 20,000 replications.

4) In the presence of heterogeneity across individuals, the statistic of interest is the average of individual univariate stationarity tests allowing for structural breaks. The panel statistic is thus given by

$$\hat{LM}_{T,N,k}(\varpi) = \frac{1}{N}\sum_{i=1}^{N} LM(\lambda_i, k, T) \tag{19}$$

We computed the empirical distribution of the panel test statistics with the Bootstrap technique in Maddala and Wu (1999) using 20,000 Monte Carlo replications.

## EMPIRICAL RESULTS AND DISCUSSIONS

To compare our results from the Hadri and Rao (2008) stationarity procedure, we also employ three conventional univariate unit-root tests on each LTL carrier's relative rate: the ADF test, the PP test, and the

KPSS test (Kwiatkowski et al., 1992). Regression results in Table II show that under both the ADF and PP tests, the null hypothesis of a unit root cannot at any firm. Still, ABF Freight be rejected at the 5% significance level – while in contrast under the KPSS test, the null hypothesis of trend stationarity (or stationarity around a deterministic trend) is rejected at 5% in every other firm. That is, all three univariate unit root or stationarity tests imply, when taking serial correlation into account only, that no firm's fuel surcharge, base yield, or total yield converges to the industry average during the sample period, the only exception being that ABF Freight's relative fuel surcharge yield was stationary.

**TABLE 2**
**CONVENTIONAL STATIONARITY TEST W/O STRUCTURAL BREAK**

**2.1 Conventional Stationarity Test on Relative Fuel Surcharge Yield, By Carrier**

| Univariate Unit Root Test/Stationarity Test | | | |
|---|---|---|---|
| **LTL Carriers** | **ADF** | **PP** | **KPSS** |
| **ABF** | -3.6524** | -3.6707** | 0.1481 |
| **FXF** | -1.5178 | -1.6130 | 0.1436* |
| **YRCR** | -2.5689 | -2.6097 | 0.1204* |
| **YRCN** | -2.0221 | -2.1316 | 0.1200* |
| **XPO** | -2.1585 | -2.2133 | 0.1248* |
| **ODFL** | -0.6138 | -0.8693 | 0.1274* |
| **SAIA** | -2.0552 | -2.1576 | 0.1357* |

Notes: To compare HR (Hadri and Rao, 2008) stationarity test results, we performed three univariate unit root tests: the Augmented Dickey–Fuller test (Dickey and Fuller, 1979), the PP test (Phillips and Perron, 1988) and the KPSS test (Kwiatkowski et al., 1992). *, ** and *** denotes the significance levels at 10%, 5% and 1%, respectively.

**2.2 Conventional Stationarity Test on Relative Base Yield, By Carrier**

| Univariate Unit Root Test/Stationarity Test | | | |
|---|---|---|---|
| **LTL Carriers** | **ADF** | **PP** | **KPSS** |
| **ABF** | -2.0238 | -2.0992 | 0.1432* |
| **FXF** | -2.2403 | -2.2750 | 0.1557** |
| **YRCR** | -2.5932 | -2.6910 | 0.1479** |
| **YRCN** | -1.4786 | -1.6063 | 0.1380* |
| **XPO** | -2.2597 | -2.3892 | 0.1460** |
| **ODFL** | -2.9916 | -3.0167 | 0.0357** |
| **SAIA** | -1.8036 | -1.8105 | 0.1281* |

Notes: To compare HR (Hadri and Rao, 2008) stationarity test results, we performed three univariate unit root tests: the Augmented Dickey–Fuller test (Dickey and Fuller, 1979), the PP test (Phillips and Perron, 1988) and the KPSS test (Kwiatkowski et al., 1992). *, ** and *** denotes the significance levels at 10%, 5% and 1%, respectively.

**2.3 Conventional Stationarity Test on Relative Total Yield, By Carrier**

| Univariate Unit Root Test/Stationarity Test | | | |
|---|---|---|---|
| **LTL Carriers** | **ADF** | **PP** | **KPSS** |
| **ABF** | -1.9708 | -2.0534 | 0.1411* |
| **FXF** | -2.0473 | -2.0849 | 0.1542** |
| **YRCR** | -2.6610 | -2.8197 | 0.1456** |
| **YRCN** | -1.4899 | -1.6755 | 0.1352* |
| **XPO** | -2.3681 | -2.5033 | 0.1530** |
| **ODFL** | -2.2969 | -2.3405 | 0.1434* |
| **SAIA** | -1.8901 | -1.9099 | 0.1269* |

Notes: To compare HR (Hadri and Rao, 2008) stationarity test results, we performed three univariate unit root tests: the Augmented Dickey–Fuller test (Dickey and Fuller, 1979), the PP test (Phillips and Perron, 1988) and the KPSS test (Kwiatkowski et al., 1992). *, ** and *** denotes the significance levels at 10%, 5% and 1%, respectively.

Hadri and Rao's (2008) panel test for stationarity however shows something fundamentally different. Here, and allowing only for serial correlation, the *total* yields at some carriers were found in individual tests to be stationary while in the conventional tests they had not been. Yet after accounting for both structural breaks and cross-sectional dependence, the panel statistics indicate the null hypothesis of stationarity *following a break cannot* be rejected at 5% significance level in any relative yield series at any firm. Both individual ( $LM(\lambda_i, k, T)$ and panel test statistics ($\hat{LM}_{T,N,k}(\varpi)$) are presented in Table III 3.1 to 3.3. Regression results show that both break patterns and break dates tend – especially in relative fuel yields – to differ greatly across firms, indicating they respond quite differently from one another based on unique technologies, route structures, and marketing strategies once breaks are accounted for.

**TABLE 3**
**HADRI AND RAO (HR, 2008) STATIONARITY TEST W/T STRUCTURAL BREAK**

**3.1 HR Stationarity Test Results on Relative Fuel Surcharge Yield, By Carrier**

| ***Individual LM Test Statistics for Model Allowing for Serial Correlation*** | | | | | | |
|---|---|---|---|---|---|---|
| **Firm** | **Test Statistics** | **Critical Value (5%)** | **Optimum Lag(s) based on BIC** | **Selected Model** | **Break Date** | **Stationary (Yes/No)** |
| **ABF** | 0.143** | 0.142 | 2 | 3 | 2015 Q2 | N |
| **FXF** | 0.747** | 0.094 | 4 | 3 | 2018 Q4 | N |
| **YRCR** | 0.081 | 0.118 | 1 | 3 | 2016 Q1 | Y |
| **YRCN** | 0.087** | 0.080 | 2 | 4 | 2016 Q4 | N |
| **XPO** | 0.166** | 0.118 | 4 | 3 | 2016 Q1 | N |
| **ODFL** | 0.302** | 0.111 | 4 | 3 | 2019 Q3 | N |
| **SAIA** | 0.068 | 0.079 | 4 | 4 | 2016 Q4 | Y |

| ***Panel Test Statistics Allowing for Heterogeneity and Cross-sectional Dependence*** | | |
|---|---|---|
| **HR Test Statistics** | **Critical Value (5%)** | **Panel Stationary (Yes/No)** |
| **0.228** | **5.436** | **Yes.** |

Notes: Model 1 examines a shift in the level but no trend process and Model 2 examines a trend function with a shift in the level-only process. Model 3 specifies a trend function with a shift in the slope-only process while Model 4 specifies a trend function with a break in both slope and level, respectively. We use the Schwarz Bayesian Information Criterion (BIC) to find the appropriate break-type model for the series. The optimum lag(s) are used in the Sul et al. (2005) procedure to estimate the consistent long-run variance. We computed the empirical distribution of panel test statistics using Bootstrap techniques found in Maddala and Wu (1999) and using 20,000 replications.

**3.2 HR Stationarity Test Results on Relative Base Yield, By Carrier**

*Individual Test Statistics for Model Allowing for Serial Correlation*

| Firm | Test Statistics | Critical Value (5%) | Optimum Lag(s) based on BIC | Selected Model | Break Date | Stationary (Yes/No) |
|---|---|---|---|---|---|---|
| **ABF** | 0.175** | 0.089 | 2 | 3 | 2018 Q3 | N |
| **FXF** | 0.113** | 0.095 | 2 | 4 | 2019 Q2 | N |
| **YRCR** | 1.462** | 0.280 | 4 | 1 | 2019 Q2 | N |
| **YRCN** | 0.126** | 0.103 | 2 | 2 | 2019 Q2 | N |
| **XPO** | 0.218** | 0.212 | 4 | 1 | 2018 Q3 | N |
| **ODFL** | 0.238** | 0.079 | 4 | 4 | 2016 Q4 | N |
| **SAIA** | 0.084 | 0.231 | 1 | 1 | 2016 Q4 | Y |

*Panel Test Statistics Allowing for Heterogeneity and Cross-sectional Dependence*

| HR Test Statistics | Critical Value (5%) | Panel Stationary (Yes/No) |
|---|---|---|
| **0.345** | **7.05** | **Yes.** |

Notes: Please see notes about model selection under Table 3.1.

**Fuel Surcharges**

In fuel surcharge yield, every LTL firm experienced a structural break. Model 3 (slope-only break with trend stationary) is found valid at ABF Freight, FedEx Freight (FXF), Yellow Roadway Regional (YRCR), XPO Logistics and Old Dominion Freight Liners (ODFL), while Model 4 (both-slope-and-level break with stationary trend) is valid at Yellow Roadway National (YRCN) and Saia. Five of the seven firms experienced breaks in 2015 and 2016 while FedEx Freight did in 2018 Q4 and Old Dominion did in 2019 Q3. Individual LM test shows YRC Regional and Saia's relative fuel yields are the only two stationary processes.

**Base Yield**

In the base yield, every firm experienced a structural break as well. Model 1 (one-time break in the level but no trend) is found valid for Roadway Regional, XPO Logistics, and Saia. Model 2 (level-only break with trend stationary) is only valid for Yellow Roadway National. Model 3 (slope-only break with trend stationary) is valid at ABF Freight and Model 4 (both-slope-and-level break with trend stationary) valid at FedEx Freight and Old Dominion. In contrast to various break dates in fuel surcharge yield, base yield breaks, occurred mostly in 2018 and 2019, with Old Dominion and Saia exhibiting a break in late 2016. Except for Saia's relative base yield, individual LM test shows all other firms' base yields are nonstationary processes.

**Total Charges**

Now consider total LTL net revenue. Every firm experienced a structural break in total yield. Model 1 (one-time break in level but no trend) is found valid for FedEx Freight only, while Model 2 (level-only break with trend stationary) is valid at Yellow Roadway National, XPO Logistics, Old Dominion and Saia. Model 3 (slope-only break with trend stationary) is descriptive of ABF Freight and Model 4 (both slope-and-level break with trend stationary) only of Yellow Roadway Regional. Except for ABF Freight's and Saia's break early in 2015 Q2, every other firm exhibits a total net revenue break quite late (in 2018 and 2019) and at Old Dominion even in 2020 Q1. Estimated break dates in the respective models are shown in the sixth column of Table 3.1 to 3.3.

Most importantly, after hitting its break point, the cross-firm gap in fuel, base, and total yield has been narrowing and converging toward the sectoral average, again using the seven-firm average as benchmark. Results at the 5% significance level and optimal lags under the BIC criterion are presented in the third and fourth columns of Table 3.1 to 3.3. Unlike the conventional univariate unit root tests, a null hypothesis of panel stationarity after taking structural breaks and cross-sectional dependence into account cannot be rejected here in any yield data at a 5% significant level. In other words it must be accepted at every firm as a whole, suggesting that pricing strategies at all seven firms are converging toward the long-run industry average. These results, that is, provide strong evidence that conventional univariate unit root tests are seriously biased when ignoring structural breaks and especially cross-sectional dependence.

### Implications

The HR test has revealed a sharp contrast between the non-stationarity of most individual firm yields and a panel stationarity across firm yields. The reason for this contrast is interesting. Non-stationarity in the majority of individual yields is consistent with the merger and acquisition activity in the industry at this time: the three largest acquisitions in LTL history were taking place in 2015. FedEx acquired TNT express at $4.8 billion, becoming the largest LTL carrier in the US. UPS Freight purchased Coyote Logistics at $1.8 billion. XPO Logistics bought Norbert Dentressangle at $3.8 billion and Con-Way at $3 billion. In January 2021, UPS agreed to sell its freight business to its rival TFI International for $800 million. (Data are from various news reports.) The industry was in a continuous process of restructuring resources and facilities to improve efficiency, and in which firm marketing and positioning strategies continued to change. On the other side however, panel stationarity results show strongly that even with this individual-firm variation, industry structure had been stable as a whole, a few large, full-service logistics companies operating at the center, as it were, among many small niche providers in the decades after deregulation.

This stationarity and convergence to the industry average following a variety of individual-firm structural breaks has important implications. Long-run convergence of fuel yields suggests that despite the industry appearing to be essentially competitive in base services and monopolistically competitive in fueling services as in Du and Buccola (2020), fueling market power tended to dissolve as competitive forces began to assert themselves.

## CONCLUSIONS

We have examined the stability of Less-Than-Truckload multi-part pricing structures in recent years. We show that after accounting for structural breaks and cross-sectional dependance – in contrast to the conventional stationarity test accounting for serial correlation only – the industry has evinced relative fuel, base, and total pricing stability over the long run. Following its earlier structural breaks, the LTL industry has grown into a comparatively lean, competitive environment.


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## ENDNOTES

1. As Yellow Roadway Worldwide has two subsidiaries, Yellow Roadway Regional and National, and both have reported their own specific yield data separately, we regard them as two separate identities. In total then, our sample includes seven firms in the paper.
2. In our sample only ABF, Saia, XPO, and ODFL report average length of haul (LOH) by quarter in their financial reports. YRC Worldwide only reports an approximation of its regional and national average LOH information in financial reports. We obtained only annual LOH information at FedEx Freight. To account for

the unobserved heterogeneity across firms on account of the presence of mean-only LOH approximations in some cases, we include firm-level dummies in equation (2).

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