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Container freight rate forecasting with improved accuracy by integrating soft facts from practitioners

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A R T I C L E I N F O

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A B S T R A C T

This study presents a novel approach to forecast freight rates in container shipping by integrating soft facts in the form of measures originating from surveys among practitioners asked about their sentiment, confidence or perception about present and future market development. As a base case, an autoregressive integrated moving average (ARIMA) model was used and compared the results with multivariate modelling frameworks that could integrate exogenous variables, that is, ARIMAX and Vector Autoregressive (VAR). We find that incorporating the Logistics Confidence Index (LCI) provided by Transport Intelligence into the ARIMAX model improves forecast performance greatly. Hence, a sampling of sentiments, perceptions and/or confidence from a panel of practitioners active in the maritime shipping market contributes to an improved predictive power, even when compared to models that integrate hard facts in the sense of factual data collected by official statistical sources. While investigating the Far East to Northern Europe trade route only, we believe that the proposed approach of integrating such judgements by practitioners can improve forecast performance for other trade routes and shipping markets, too, and probably allows detection of market changes and/or economic development notably earlier than factual data available at that time.

1. Introduction

In maritime shipping, freight rates as a price to be paid for movement of cargo tend to be very volatile as it is highly dependent on the interplay between supply of available transport capacity and demand for transport service (Stopford, 2008). Freight rates are at the core of the shipping business as success and failure of shipping companies largely depend of it. Depending on the ownership structure of ship fleet between cargo owner and ship owner, the fluctuations in freight rate characterizes shipping risk. With growing ship fleet of cargo owners, their risk increases, while growing hire from the spot market increases ship owners' risk (Stopford, 2008). The nature of this business makes it necessary to negotiate and fix transport contracts (often forward freight agreements) between shippers, carriers and/or other transport and logistics service providers involved therein well in advance to ensure a smooth cargo flow. In addition, momentary decisions in the shipping market such chartering a ship, often taken over the course of a week, are highly dependent on the freight rate prediction. Further, purchase, selling, newbuilding and scrapping decisions taken by shipowners are also highly dependent of freight rates (Jeon, Duru, & Yeo, 2020). Hence, a good prediction of future freight rate development is of utmost importance to ensure a well informed and profitable decision making for major players involved in the planning and execution of cargo movements.

Long time, the Baltic Dry Index (BDI) compiled every working day by the Baltic Exchange (2021) was regarded to be the dominant market indicator when it comes on freight rate developments in maritime shipping (Karamperidis, Jackson, & Mangan, 2013). But due to an ever-increasing degree of containerization in seaborne cargo, similar freight rate indexing dedicated to the container shipping industry became demanding. Therefore in 1998, the China Containerized Freight Index (CCFI) and later on the Shanghai Containerized Freight Index (SCFI) were established by the Shanghai Stock Exchange (SSE, 2021) to fill this gap (Xin, 2000). Although in the meantime other container freight indices were issued like the World Container Index (WCI) by Drewry (2021), or the Ningbo Containerized Freight Index (NCFI) by the Ningbo Shipping Exchange (Baltic Exchange, 2021), the Freightos Baltic Global Container Index (FBX) promoted by the Baltic Exchange (2021) and recently the Xeneta Shipping Index (XSI) by the freight benchmarking

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platform Xeneta (2021), only CCFI and SCFI got increased attention by academia so far (Chen, Rytter, Jiang, Nielsen, & Jensen, 2017; Hsiao, Chou, & Wu, 2014; Munim & Schramm, 2017; Nielsen, Jiang, Rytter, & Chen, 2014; Yifei, Dali, & Yanagita, 2018; Yin & Shi, 2018).

When it comes on forecasting container freight rates, autoregressive integrated moving average modelling (ARIMA) works well (Nielsen et al., 2014) and it can reflect Gross Rate Increase (GRI) patterns executed by carriers (Munim & Schramm, 2017), which was indeed a recurrent feature especially on the Far East – Europe trade lane between 2008 and 2013 (Chen et al., 2017). Nevertheless, in the end, ARIMA is a myopic sort of forecasting technique, as it does not take well-known external influencing factors to freight rate formation like supply of shipping capacity, demand for freight service or bunker price level into consideration. Meanwhile, Munim and Schramm (2017) found that ARIMA is appropriate for out-sample forecast of container freight rates, and Munim and Schramm (2020) concluded that it is even better than VAR with supply and demand as exogenous variables while performing out-sample forecasts. However, the purpose of this study is exploring further possibilities to include external influences into ARIMA models in case of CCFI and SCFI, which are at the same time useful for nowcasting purposes.

According to Lahiri and Monokrousos (2013), nowcasting is regarded as "[…] the task of predicting the present, the very recent past, and the very near future […]", which needs timely available data. However, this poses a real challenge in container shipping, as most market information can be only collected with significant time lag, which traditionally led consultancies to stick on quarterly data when it comes on observing market development (Drewry, 2021; MDS Transmodal, 2021). However, recent improvement in data collection methodology allows now gathering a wide range of certain factual data beside container freight rate indices in form of data on a monthly basis as follows:

- Alphaliner (2021) constantly monitors container fleet structure, vessel deployment, liner service development and terminal activities to report it on a weekly to monthly basis and offers a TOP 100 list of container shipping operators updated daily as a special feature.
- Clarkson (2021) observes container fleet structure, too, and further delivers transactional data covering the whole lifecycle of a vessel from its ordering at a shipyard over chartering, purchase to scrapping published on a regular basis in their weekly to quarterly container shipping market reports.
- CTS (2021) focus on aggregated container volumes and price index data per trade lane as reported by a panel of carriers and ports on monthly basis.
- SeaIntel (2021) constantly examines liner service development and provides aggregated figures concerning port-to-port schedule reliability of carriers on monthly basis.
- Container port throughput statistics are also available on monthly basis and these are used to make the RWI/ISL Container Throughput Index (ISL, 2021) with a coverage of 60% worldwide container trade activity.
- Navigation statistics from Suez Canal (SCA, 2021) or activity reports from Panama Canal (PCA, 2021) as the main bottlenecks in maritime shipping are compiled and published after the end of each month.
- Product prices for bunker fuel as a major cost component of running vessels are summarized in e.g. Monthly Oil Market Review (OPEC, 2021), with some other providers like Bunkerworld (2021) delivering daily spot market prices.

Alternatively, soft facts obtained by a rating, survey or poll collecting sentiments, perceptions and/or confidence (or shortly SPC) from a panel of practitioners active in the container shipping market on a regular basis can be employed. This includes a variety of leading indicators outlined in further detail in Section 2, which probably allows detection of market changes and/or economic development much earlier than the aforementioned hard facts being at best coincident if not just slightly lagging indicators, as they are all measures collected from present or past times (Karamperidis et al., 2013). Therefore, it was attempted to forecast container freight rates for the Far East to Northern Europe trade route, incorporating soft facts into time series forecasting to scrutinize whether it improves forecast performance.

The remainder of the paper is as follows: Firstly, in Section 2, a selection of such SPC indices that may be relevant in our context of container shipping are reviewed. Section 3 outlines procedure of data sampling followed by a brief description of our forecast methodology. Results from subsequent empirical analysis including a comparison of forecast performance of ARIMA, ARIMAX and VAR models in this context are presented in Section 4 before concluding in Section 5.

2. Sentiment, perception or confidence indices

Before starting with a review of potentially useful survey based SPC indices it is worthwhile to have a brief look on the underlying terminologies. Table 1 shows exemplary definitions for the three terms in focus which imply a subtle ordering from simple 'feelings' over 'opinion' to 'belief' of someone having 'faith', 'trust' or being 'certain' what is held or expressed about something. Insofar, SPC indices typically rely on soft facts and measures gathered from individuals asked merely grand questions about their recent past, present or near future.

Employment of such SPC indices is common in finance (e.g. measurement of investor sentiment, c.f. Brown & Cliff, 2004; Baker & Wurgler, 2006, 2007; Schmeling, 2009; Baker, Wurgler, & Yuan, 2012; Huang et al., 2014, 2015; Sibley, Wang, Xing, & Zhang, 2016; Mascio & Fabozzi, 2019), real estate (e.g. the Architecture Billing Index (ABI), c.f. Machato & Nanda, 2016), manufacturing (e.g. the Purchasing Managers' Index (PMI), c.f. Lindsey & Pavur, 2005; Cho & Ogwang, 2006, 2008; Lahiri & Monokrousos, 2013) or service sector (e.g. the Non-Manufacturing Index (NMI), c.f. Cho & Ogwang, 2007; Lahiri & Monokrousos, 2013) as a whole. Common to all of them is that they try to capture tacit market knowledge from survey panel respondents, which may be incorporated in hard fact measures available later on. Regarding maritime shipping, at least some of these aforementioned rather general SPC indices like investor sentiment (Papapostolou et al., 2014, 2016), PMI (Heij and Knapp, 2014) or a composite climate index (Chen, Lu, Lu, & Luo, 2015) were already employed. But when it comes on prediction of container freight rate development, no such approach is known to the authors.

Given that a recent review of indices used in the maritime logistics sector by Karamperidis et al. (2013) based on a selection of peer-reviewed journals and trade press resulted in only two PMI indices

Table 1
Definitions of sentiment, perception and confidence.

Terminology	Derived from	Definition
Sentiment	Sentiment (fr.)	"A general feeling, attitude, or opinion about something" (Cambridge dictionary, 2021)
	Sentire (lat.) 'feel'	"A view or opinion that is held or expressed" (Oxford living dictionary, 2021).
Perception	Percipere (lat.) 'seize, understand'	"The ability to see, hear, or become aware of something through the senses" (Oxford living dictionary, 2021). "A belief or opinion, often held by many people and based on how things seem" (Cambridge dictionary, 2021)
Confidence	Confidere (lat.) 'have full trust'	"The feeling or belief that one can have faith in or rely on someone or something." (Oxford living dictionary, 2021) "The quality of being certain of your abilities or of having trust in people, plans, or the future" (Cambridge dictionary, 2021).

and the European Freight Forwarding Index (EFFI) by Danske Bank Markets, a simple internet research with Google employing keywords like "logistics", "maritime", "transport", "shipping" in connection with "sentiment", "confidence", "perception" and "index" was done to find viable candidates for further treatment. The logic behind this rather unstructured sampling approach was that such SPC indices are more acknowledged among practitioners and their main source of information is trade press media, which recently migrated more and more into the internet with a strong online presence due to their usual spatially dispersed readership. At the same time, such SPC indices are usually promoted online by their initiators via press releases and regular newsletters, which again can be found by simple internet research with Google. Whenever there was a hit, further inquiry was undergone to find out more details about the SPC index. Results of our efforts are summarized in Appendix A along the dimensions of official name (and abbreviation), initiator, data sampling approach, measures raised (and their scope), periodicity of publication and horizon.

Characterizing them according to the presence of practitioners active in container shipping markets included in their data sampling approach, three main groups can be identified: (1) maritime shipping sector, (2) transport and logistics service provider sector, and (3) shippers. Firstly, the Shanghai Shipping Prosperity Index (CSPI) and the Shipping Confidence Survey (SCS) clearly show a focus on certain actors originated in the maritime shipping sector – namely vessel owners, brokers, managers, charterers, operators and professional advisors. Secondly, the survey panels of the China Logistics Prosperity Index (CLPI), the European Freight Forwarding Index (EFFI) as well as the SCI Barometer (SCI) predominantly consists of transport and logistics service providers. Thirdly, the BVL Logistics Indicator (LI) as well as the Prognos/ZEW Transportmarkt Barometer (TMB) run sophisticated panels with transport and logistics service providers as well as shippers in order to provide insights from both sides of the market. Finally, the Logistics Manager's Index (LMI) as well as the Logistics Confidence Index (LCI) stick on an open online survey panel with the majority of respondents being transport, logistics and/or supply chain managers employed at shippers. Accordingly, their scope is different: CSPI and SCS try to catch trends in the maritime shipping sector, whereas the remainder want to offer a broader view of current transport and logistics market developments with EFFI, TMB, and LCI providing sub-indices dedicated to maritime shipping even for certain trade lanes. From a spatial point of view, (1) SCS, EFFI, and LCI regularly report a high amount of respondents from European countries, (2) the survey panels of LI, TMB and SCI are dedicated to Germany, CSPI and CLPI to China and LMI aims at USA/North America.

Regarding their usability in the context of our work, both CSPI and SCS take reference to measures that could be helpful to indicate freight rates development in tanker, dry bulk and container business, but their relevance for forecasting of freight rate development is rather limited especially due to their quarterly periodicity of release. Furthermore, LI, TMB, SCI as well as LMI can be ruled out as they turn out to be too much country-specific, so that in the end, CLPI, EFFI and LCI seem to be useful for our purpose: (1) the CLPI reflects current business volume of Chinese logistics companies as a main origin of containerized cargo nowadays, (2) EFFI refers to cargo volumes handled by European freight forwarding companies quite dominant in the sector (c.f. Transport Topics, 2020), and (3) LCI asks panelists for current and expected cargo volumes e.g. on the Asia to Europe trade lane. Following common market structure mechanics in maritime shipping (Stopford, 2008), one would expect that growing (diminishing) volumes of containerized cargo should come along with raising (falling) freight rates with some delay as all three SPC indices render transport activities usually organized by logistics service providers and/or freight forwarding companies. Unfortunately, fully access the EFFI data was not available and so the following analysis proceeds with CLPI and LCI concerning volume of cargo transported by sea.

3. Data and methodology

3.1. Data sampling

Based on container trade volume, the Far East to Europe trade route ranks second worldwide with 15.5 million TEUs traded in 2017 (UNCTAD, 2017). Monthly container freight rate time series data (both CCFI and SCFI) for this route for September 2012 to June 2017 from one of most renowned shipping databases, Clarksons (2021), was taken. Moreover, two different SPC indices — CLPI (i.e. business confidence index) and LCI (i.e. current and expected volumes on Asia to Europe trade lane), were used as exogenous variables and their monthly time series data were collected from FBIC (2021) and TI (2021), respectively. Whereas the CLPI deals with current vs. past month business volume of Chinese logistics companies, LCI covers respondent's confidence about sea transport volumes on current and 6 months outlook period.

The lagged values of CLPI and LCI are used when forecasting future values of CCFI and SCFI. The values of CLPI and LCI for a particular time period are reported well in advance. For example, the LCI six-months outlook is published 6 months ahead of a particular month. Hence, future freight rates cannot influence the CLPI and LCI indices. One may argue that past freight rates might influence the CLPI and LCI. However, CLPI and LCI are based on perceptions of executives which are typically based on many factors including supply and demand development in the market. Thus, such indices can be used as exogenous variable when forecasting future freight rates.

The resulting monthly time series data is shown in Fig. 1. Descriptive statistics of the data are presented in Table 2 along with normality test according to Jarque and Bera (1980). As values of this J-B test of all variables are well above the 0.05 significance level, normality of the time series can be confirmed.

3.2. Stationarity check

Similar to any forecast modelling study, the dataset was divided into an in-sample (training) and an out-sample (testing) period. As a rule of thumb, about 90% of the sample was included in the training sample and 10% in the test sample. Table 3 presents the training and testing samples for each of the variables. To check stationarity of time series the PP test procedure by Phillips and Perron (1988) was used, both in natural log levels and in first difference log operator. While the CLPI is already stationary in log levels, all other variables are stationary in the first difference log operator. As stationarity of data is a perquisite for autoregressive forecast modelling, now we can proceed with the forecast models.

3.3. Granger causality tests

Granger causality test (Granger, 1969) has been used by researchers (Kavussanos & Nomikos, 2003; Alizadeh, 2013; Li et al., 2018) to examine casual relationships between maritime variables. Similar to

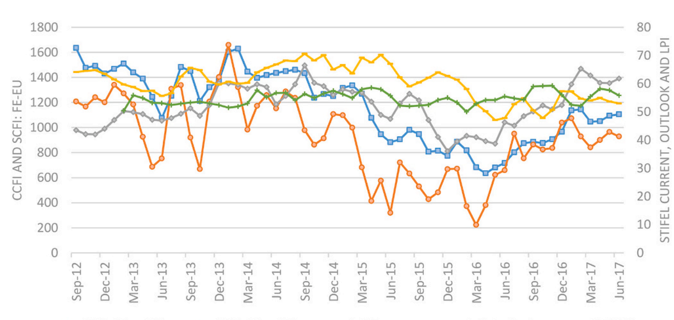

Fig. 1. Monthly time series data.

Table 2
Descriptive statistics.

Variables	N	Mean	Std. dev.	Min.	Max.	J-B test
CCFI: FE to EU	58	1166.57	279.86	635.02	1635.23	3.87 (0.14)
SCFI: FE to EU	58	916.41	316.03	223.50	1659.40	1.08 (0.58)
CLPI	53	0.55	0.02	0.50	0.59	1.80 (0.41)
LCI Current	58	51.80	7.44	36.10	66.50	2.03 (0.36)
LCI Outlook	58	60.31	6.16	47.10	70.60	2.32 (0.31)

For J-B test, *P*-values in parenthesis, $P > 0.05$ indicates normality of time series. All time series are monthly September 2012 to June 2017, except for CLPI, which started on February 2013.

Table 3
Sample definition and unit root test for stationarity.

Variables	In-sample			Out-sample
	Time series	PP-test (log level)	PP-test (1st diff. log)	Time series
CCFI: FE to EU	Sep 2012–Dec 2016	−8.47	−32.20***	Jan 2017–Jun 2017
SCFI: FE to EU	Sep 2012–Dec 2016	−16.49	−42.17***	Jan 2017–Jun 2017
CLPI	Feb 2013–Dec 2016	−21.54*	−44.80***	Jan 2017–Jun 2017
LCI Current	Sep 2012–Dec 2016	−7.28	−34.89***	Jan 2017–Jun 2017
LCI Outlook	Sep 2012–Dec 2016	−8.00	−32.15***	Jan 2017–Jun 2017

$^{+}P < 0.10$, $^{*}P < 0.05$, $^{**}P < 0.01$, $^{***}P < 0.001$; for PP-test, $P < 0.05$ indicates stationarity of time series.

Alizadeh (2013), the causal relationships between the freight indices and sentiment indices has been investigated through the VAR framework. The VAR model defined in Eq. (3) was used to test causal associations. The granger causality test results are presented in Table 4, with two significant results at 5% statistical significance level, namely CCFI granger causes CLPI and SCFI granger causes LCI current. This indicates some degree of associations among freight indices and sentiment indices.

Table 4
Granger causality test results.

Hypothesis	F-statistics (*P*-value), constant	F-statistics (*P*-value), trend	Remarks
CLPI granger causes CCFI	0.350 (0.705)	0.331 (0.719)	Not supported
CCFI granger causes CLPI	3.097 (0.050)	3.088 (0.050)	Supported
LCI Current granger causes CCFI	0.013 (0.987)	0.004 (0.996)	Not supported
CCFI granger causes LCI Current	1.952 (0.147)	1.873 (0.159)	Not supported
LCI Outlook granger causes CCFI	0.026 (0.975)	0.024 (0.977)	Not supported
CCFI granger causes LCI Outlook	0.649 (0.525)	0.691 (0.504)	Not supported
CLPI granger causes SCFI	0.780 (0.462)	0.772 (0.465)	Not supported
SCFI granger causes CLPI	0.993 (0.374)	1.006 (0.370)	Not supported
LCI Current granger causes SCFI	1.282 (0.282)	1.322 (0.272)	Not supported
SCFI granger causes LCI Current	4.224 (0.017)	4.107 (0.019)	Supported
LCI Outlook granger causes SCFI	1.161 (0.318)	1.137 (0.325)	Not supported
SCFI granger causes LCI Outlook	1.313 (0.274)	1.345 (0.265)	Not supported

Note that in the granger causality test, first differenced version of all variables was used for stationarity.

3.4. Forecast models

Based on the discussion in Section 2, three forecast models were chosen, namely ARIMA (Munim & Schramm, 2017), ARIMAX (Chen, Meersman, & van de Voorde, 2012) and VAR (Chen et al., 2012; Munim & Schramm, 2020) due to their proven usefulness in container shipping freight rate forecasting. While the ARIMA model solely relies on historical data of an endogenous variable, the ARIMAX is an ARIMA model of an endogenous variable incorporating additional explanatory exogenous variables. Similarly, VAR can incorporate multiple variables at a time for autoregressive modelling. All models are briefly described below.

The ARMA (p,q) model by Box and Jenkins (1970) has two parts: autoregressive (AR) and moving average (MA). When the endogenous variable is stationary at first difference, it can be modelled as first difference log operator, which is the integrated ($d = 1$) part. The AR part models the relationship between value of an endogenous variable at time t with its value at a previous date ($t - i$). The MA part models the relationship between value of a variable at time t with its error terms at a previous date ($t - i$). The ARIMA (p,1,q) model can be presented by the Eq. (1) as follows:

$$\Delta y_t = \sum_{i=1}^{p} \varnothing_i \Delta y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \tag{1}$$

Here, y_t is the container shipping freight rate at time t; thus, $\Delta y_t = y_t - y_{t-1}$. $\varnothing_i$ is the coefficient of Δy_{t-i}; θ_i is the coefficient of error terms at time $t - 1$, ε_{t-i}; and ε_t is the error term at time t.

The ARMAX model was first time tested by Bierens (1987) and Franses (1991) treated the ARMAX model as an extension of the ARMA model. An ARIMAX (p,1,q,x) model with first difference log operator can be presented by the Eq. (2) as follows:

$$\Delta y_t = \sum_{i=1}^{p} \varnothing_i \Delta y_{t-i} + \sum_{k=1}^{X} \beta_k x_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \tag{2}$$

Here, X is the number of explanatory exogenous variables; x_t is a X x 1 vector of exogenous variables at time t, and β_k is a 1 x X vector of parameters.

VAR models are stochastic in nature and useful to capture linear interdependencies among multiple variables. VAR is exclusive than ARIMAX in a sense that it allows more than one variable in the autoregressive process. Using VAR, the associations among values of a variable at time t, with its value and other exploratory variable's value at a previous time period ($t - i$) can be modelled. Eq. (3) represents a VAR model with a vector of m x m variables as follows:

$$\Delta y_t = \alpha + \sum_{i=1}^{p} \varphi_i \Delta y_{t-i} + \varepsilon_t \tag{3}$$

Here, Δy_t is a m x m vector of variables in first difference; α is a m x 1 vector of constants; φ_i is a time-invariant m x m matrix of the coefficients of Δy_{t-i}; and p refers to the number of autoregressive lags.

4. Empirical analysis

Following the stationarity test results, first difference log operator of CCFI and SCFI were taken before proceeding with forecast modelling using ARIMA and ARIMAX. Autocorrelation function (ACF) and partial autocorrelation function (PACF) of both series are reported in Appendix C. It might be noted that the static forecast approach was employed due to its practical relevance. Another issue to mention is that ARIMA model selection was based on lowest Akaike Information Criterion (AIC) and Phillip-Perron (PP) test results for stationarity. For ARIMAX, models were re-estimated incorporating soft facts (namely LCI and CLPI), but using the same ARIMA order identified in the ARIMA model estimations. Thus, forecasting results from ARIMA models and ARIMAX models with soft facts can directly compared. The employed forecasting approach is demonstrated in Fig. 2.

ARIMA and ARIMAX model estimation parameters for CCFI and SCFI are presented in Tables 5 and 6, respectively. In both tables, M1 is the ARIMA model as a base case, M2 is the ARIMAX model with LCI current data, M3 is the ARIMAX model with both LCI current and outlook data, and M4 is the ARIMAX model with CLPI. The LCI current and outlook have significant (at 5% level) influence on the CCFI index FE to EU container freight rate, but not on the SCFI index.

For estimated model diagnostic, normality of residuals are checked using the J-B test (Jarque & Bera, 1980), autocorrelation of residuals are checked using the L-B test (Ljung & Box, 1978), and ARCH effect is tested using the L-B test on the squared residuals. For the estimated ARIMA and ARIMAX models, as reported in Tables 5 and 6, the *P*-values of the reported tests are not statistically significant at 5% level. Hence, the diagnostic check requirements are met.

For VAR modelling, three models following the same logic as in ARIMAX were considered. In the first VAR model (M5), only LCI current is taken as exogenous variable, in the second one (M6) both LCI current and 6 months outlook as exogenous variable, and in the final one (M7) CLPI as exogenous variable. As stationarity of all variables have been confirmed earlier at first difference log operator, for the selection of appropriate VAR model, first existence of co-integration equation using Johansen co-integration test (Johansen, 1991) considering two lags suggested by the Hannan-Quinn (HQ) and Schwarz criterion (SC, Lütkepohl, 1985) was checked. However, at 5% statistical significance, no evidence was found for co-integrating equations among the variables. Thus, proceeding with VAR models (instead of vector error correction models) with two lags, VAR model parameters for both CCFI and SCFI data are presented in Tables 7 and 8, respectively.

Based on the estimated VAR results, CLPI and LCI does not influence the CCFI and SCFI. Similar to ARIMA group models, residuals are examined for normality, autocorrelation and ARCH effects. Except for M5 and M6 in Table 7, all VAR models reported in Tables 7 and 8 indicate normality of residuals, no autocorrelation and ARCH effect among residuals.

In addition to in-sample forecast, the out-sample forecast of container freight rate for the FE to EU trade route on both CCFI and SCFI indices were performed using the estimated parameters presented in Tables 5– 8. Three measures were adopted, namely root mean square error (RMSE), mean absolute percent error (MAPE) and mean absolute scaled error (MASE) to benchmark forecast accuracy of competing models. Equations to calculate these accuracy measures are outlined in Appendix B. All three measures for comparison were used, because RMSE and MAPE can be misleading depending on the out-sample forecast horizon. Thus, Hyndman and Koehler (2006) suggested using MASE when comparing different forecast models.

In-sample forecast performances of the final seven forecast models M1–M7 are presented in Table 9. Considering average values, M3 (i.e. ARIMAX with LCI current and outlook as exogenous variables) clearly outperforms all others. For CCFI container freight rate, the same forecast model M3 stands out. However, in the case of SCFI this obtained mixed results, as M3 is the best in terms of RMSE, M2 in MAPE and M4 in MASE.

Similarly, out-sample forecast performances of the five competing

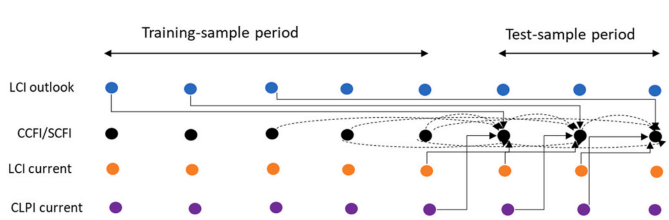

Fig. 2. Forecasting framework integrating soft facts as exogenous variables.

Table 5
ARIMA and ARIMAX model parameters for CCFI data.

ARIMA(p,d,q) and ARIMAX(p,d,q,x) model parameters	M1: ARIMA (3,1,0)	M2: ARIMAX (3,1,0,x_1)	M3: ARIMAX (3,1,0,x_1,x_2)	M4: ARIMAX (3,1,0,x_3)
AR_1	0.209 (0.138)	0.131 (0.142)	0.0379 (0.146)	0.217 (0.144)
AR_2	−0.240 (0.135) $^+$	−0.232 (0.135)$^+$	−0.227 (0.130)$^+$	−0.230 (0.149)
AR_3	−0.232 (0.136) $^+$	−0.195 (0.138)	−0.294 (0.140)*	−0.230 (0.143)
LCI Current	–	0.513 (0.166)**	0.531 (0.158)***	–
LCI Outlook	–	–	0.634 (0.222)**	–
CLPI	–	–	–	−0.167 (0.342)
AIC	−105.62	−112.33	−117.9	−90.25
BIC	−97.89	–	–	–
Log likelihood	–	61.16	64.95	50.12
Residual diagnostics:				
L-B test (lag 10)	3.896	5.447	7.316	2.709
Res.^{2} L-B test (lag 10)	10.625	7.742	16.921	11.066
J-B test	1.041	1.811	2.563	1.088

$^+P < 0.10$, $^*P < 0.05$, $^{**}P < 0.01$, $^{***}P < 0.001$, standard error in parenthesis. M1 is the base ARIMA model, M2 is the ARIMAX model with LCI current data, M3 is the ARIMAX model with both LCI current and 6 months outlook data, M4 is the ARIMAX model with CLPI.

Table 6
ARIMA and ARIMAX model parameters for SCFI data.

ARIMA(p,d,q) and ARIMAX(p,d,q,x) model parameters	M1: ARIMA (3,1,0)	M2: ARIMAX (3,1,0,x_1)	M3: ARIMAX (3,1,0,x_1,x_2)	M4: ARIMAX (3,1,0,x_3)
AR_1	−0.146 (0.129)	−0.188 (0.128)	−0.191 (0.128)	−0.154 (0.135)
AR_2	−0.224 (0.124)$^+$	−0.244 (0.123)*	−0.255 (0.124)*	−0.241 (0.131)$^+$
AR_3	−0.369 (0.125)**	−0.394 (0.124)**	−0.399 (0.124)**	−0.381 (0.133)**
LCI Current	–	0.797 (0.547)	0.826 (0.548)	–
LCI Outlook	–	–	0.386 (0.773)	–
CLPI	–	–	–	−0.605 (1.164)
AIC	19.56	19.56	21.31	24.19
BIC	27.28	–	–	–
Log likelihood	–	−4.78	−4.66	−7.09
Residual diagnostics:				
L-B test (lag 10)	4.059	5.412	5.817	3.590
Res.^{2} L-B test (lag 10)	5.656	3.054	3.632	4.124
J-B test	3.375	2.346	2.112	2.328

$^+P < 0.10$, $^*P < 0.05$, $^{**}P < 0.01$, $^{***}P < 0.001$. M1 is the base ARIMA model, M2 is the ARIMAX model with LCI current data, M3 is the ARIMAX model with both LCI current and 6 months outlook data, M4 is the ARIMAX model with CLPI.

models are presented in Table 10. Considering the average values, in terms of RMSE and MAPE, M4 (i.e. ARIMAX with CLPI as an exogenous variable) outperform others. In terms of MASE, M2 (i.e. ARIMAX model with LCI current as an exogenous variable) is the best, while looking at average values. For CCFI, again the same model, M2, stands out. However, for SCFI, M4 is the best in terms of MAPE and MASE, but M1 in terms of RMSE. Finally, it has to be noted, that all three VAR models M5, M6 and M7 never outperformed the myopic ARIMA model approach of M1. At the same time, all exogenous variables were statistically non-significant to a 5% level as shown in Tables 7 and 8. This gives a

Table 7
VAR model parameters for CCFI data.

VAR(p) model parameters	M5: VAR(2)	M6: VAR(2)	M7: VAR(2)
Intercept	0.5657 (0.3860)	0.8739 (0.5428)	0.6883 (0.4263)
$CCFI_1$	1.1867 (0.1661)***	1.2378 (0.1774)***	1.179 (0.1547)***
$CCFI_2$	−0.2428 (0.1612)	−0.2484 (0.1742)	−0.2604 (0.1536)$^+$
$CLPI_1$	–	–	0.0383 (0.4300)
$CLPI_2$	–	–	0.1664 (0.4280)
LCI $Current_1$	−0.0608 (0.2206)	−0.1474 (0.2282)	–
LCI $Current_2$	0.0157 (0.2112)	0.1369 (0.2264)	–
LCI $Outlook_1$	–	−0.4098 (0.3193)	–
LCI $Outlook_2$	–	0.2236 (0.3054)	–
HQ (2)	−1.028838e+01	−1.624501e+01	−1.184674e+01
SC (2)	−9.973879e+00	−1.561601e+01	−1.150848e+01
AIC	−522.133	−835.496	−516.794
BIC	−503.013	−795.344	−498.728
Residual diagnostics:			
L-B test (lag 10)	18.708*	19.387*	13.403
Res.^{2} L-B test (lag 10)	17.052$^+$	14.370	9.963
J-B test	0.180	0.456	0.238
Result of Johansen co-integration test at 5% significance level	No co-integrating equation exists.	No co-integrating equation exists.	No co-integrating equation exists.

$^+P < 0.10$, $^*P < 0.05$, $^{**}P < 0.01$, $^{***}P < 0.001$. M5 is considering LCI current as exogenous variable, M6 with both LCI current and 6 months outlook as exogenous variable, and M7 with CLPI as exogenous variable.

Table 8
VAR model parameters for SCFI data.

VAR(p) model parameters	M5: VAR(2)	M6: VAR(2)	M7: VAR(2)
Intercept	1.6301 (1.2238)	2.5961 (1.8305)	2.2160 (1.0925)*
$SCFI_1$	0.8219 (0.1528)***	0.8292 (0.1528)***	0.7964 (0.1564)***
$SCFI_2$	−0.0718 (0.1582)	−0.0103 (0.1616)	−0.0941 (0.1544)
$CLPI_1$	–	–	1.6436 (1.4264)
$CLPI_2$	–	–	−1.2560 (1.4309)
LCI $Current_1$	−0.2776 (0.7114)	−0.5331 (0.7228)	–
LCI $Current_2$	0.2902 (0.6511)	0.7067 (0.6998)	–
LCI $Outlook_1$	–	−1.6232 (1.0507)	–
LCI $Outlook_2$	–	1.1206 (0.9986)	–
HQ (2)	−7.434	−1.352441e+01	−8.785
SC (2)	−7.120	−1.289541e+01	−8.447
AIC	−396.707	−707.247	−408.516
BIC	−377.587	−667.095	−390.449
Residual diagnostics:			
L-B test (lag 10)	8.550	8.721	7.831
Res.^{2} L-B test (lag 10)	8.609	7.214	6.692
J-B test	1.987	0.353	0.806
Result of Johansen co-integration test at 5% significance level	No co-integrating equation exists.	No co-integrating equation exists.	No co-integrating equation exists.

$^+P < 0.10$, $^*P < 0.05$, $^{**}P < 0.01$, $^{***}P < 0.001$. M5 is considering LCI current as exogenous variable, M6 with both LCI current and 6 months outlook data as exogenous variables, and M7 with CLPI as exogenous variable.

Table 9
In-sample forecast performance.

Forecast model	CCFI: FE-EU	SCFI: FE-EU	Average
M1	*ARIMA(3,1,0)*	*ARIMA(3,1,0)*	
RMSE	0.078	0.267	0.173
MAPE	0.911	2.849	1.880
MASE	0.919	0.808	0.864
M2	*ARIMAX(3,1,0,x_1)*	*ARIMAX(3,1,0,x_1)*	
RMSE	0.072	0.262	0.167
MAPE	0.845	**2.871**	1.858
MASE	0.852	0.814	0.833
M3	*ARIMAX(3,1,0,x_1,x_2)*	*ARIMAX(3,1,0,x_1,x_2)*	
RMSE	**0.067**	**0.261**	**0.164**
MAPE	**0.794**	2.876	**1.835**
MASE	**0.803**	0.816	**0.810**
M4	*ARIMAX(3,1,0,x_3)*	*ARIMAX(3,1,0,x_3)*	
RMSE	0.080	0.278	0.179
MAPE	0.936	3.069	2.003
MASE	0.902	**0.803**	0.853
M5	*VAR (2)*	*VAR (2)*	
RMSE	0.083	0.281	0.182
MAPE	0.949	3.328	2.139
MASE	0.958	0.945	0.952
M6	*VAR (2)*	*VAR (2)*	
RMSE	0.081	0.273	0.177
MAPE	0.947	3.350	2.149
MASE	0.957	0.957	0.957
M7	*VAR (2)*	*VAR (2)*	
RMSE	0.086	0.289	0.188
MAPE	0.972	3.439	2.206
MASE	0.940	0.903	0.922

M1 is the base case ARIMA model, M2 is the ARIMAX model with LCI current data, M3 is the ARIMAX model with both LCI current and 6 months outlook data, M4 is the ARIMAX model with CLPI; VAR models: M5 is considering LCI current as exogenous variable, M6 with both LCI current and 6 months outlook data as exogenous variables, and Model 7 with CLPI as exogenous variable.
Bold indicates best performance.

strong indication that neither CPLI nor LCI follow an autoregressive process, and so panelists of these SPC indices may not necessarily look on trends of past developments when they make their assessment about present or very near future market activity.

Furthermore, in Table 11, to benchmark our findings against factual data, two ARIMAX models using factual data as exogenous variables were estimated and compared their forecast performance with best models from Table 10. Among the ARIMAX models with factual data, one was estimated using total export volume in TEU from Far East (x_4) and another using transport volume in TEUs for the FE to EU route (x_5) published by CTS (2021) with 1 month lag. As can be seen in Table 11, overall, ARIMAX models with SPC indices outperforms models with factual data.

5. Conclusions

This study assess the performance of ARIMA, ARIMAX and VAR models integrating soft facts in form of measures about sentiments, perceptions and/or confidence about past, present and/or future market activity as exogenous variables to forecast CCFI and SCFI. CCFI and SCFI are well-established container freight rates indexes for the Far East to Northern Europe trade route. In extant literature, it is well established that ARIMA models perform well in forecasting container shipping freight rate (Munim & Schramm, 2017, 2020), despite it is a quite myopic sort of forecasting technique.

This study shows that adopting an ARIMAX approach to incorporate such soft facts like LCI into ARIMA models greatly improves forecast performance compared to a conventional ARIMA model as the base case and we believe that this approach should be useful to forecast container freight rates on other trade lanes, too. Given that all VAR models were outperformed even by the base case ARIMA model with LCI as well as CPLI being statistically non-significant in M5, M6 and M7, it seems to be

Table 10
Out-sample forecast performance.

Forecast model	CCFI: FE-EU	SCFI: FE-EU	Average
M1	*ARIMA(3,1,0)*	*ARIMA(3,1,0)*	
RMSE	0.071	**0.049**	0.060
MAPE	0.704	0.616	0.660
MASE	0.732	0.198	0.465
M2	*ARIMAX(3,1,0,x_1)*	*ARIMAX(3,1,0,x_1)*	
RMSE	**0.047**	0.078	0.063
MAPE	**0.553**	0.841	0.697
MASE	**0.574**	0.271	**0.423**
M3	*ARIMAX(3,1,0,x_1,x_2)*	*ARIMAX(3,1,0,x_1,x_2)*	
RMSE	0.051	0.082	0.067
MAPE	0.612	0.845	0.729
MASE	0.635	0.272	0.454
M4	*ARIMAX(3,1,0,x_3)*	*ARIMAX(3,1,0,x_3)*	
RMSE	0.068	0.051	**0.060**
MAPE	0.691	**0.559**	**0.625**
MASE	0.718	**0.179**	0.449
M5	*VAR (2)*	*VAR (2)*	
RMSE	0.072	0.057	0.065
MAPE	0.792	0.747	0.770
MASE	0.920	0.241	0.581
M6	*VAR (2)*	*VAR (2)*	
RMSE	0.083	0.120	0.102
MAPE	0.812	1.483	1.148
MASE	1.081	0.478	0.780
M7	*VAR (2)*	*VAR (2)*	
RMSE	0.065	0.069	0.067
MAPE	0.741	0.614	0.678
MASE	0.743	0.187	0.465

M1 is the base case ARIMA model, M2 is the ARIMAX model with LCI current data, M3 is the ARIMAX model with both LCI current and 6 months outlook data, M4 is the ARIMAX model with CLPI; VAR models: M5 is considering LCI current as exogenous variable, M6 with both LCI current and 6 months outlook data as exogenous variables, and M7 with CLPI as exogenous variable.
Bold indicates best performance.

Table 11
Selected out-sample forecast performance comparison.

Forecast model	CCFI: FE-EU	SCFI: FE-EU	Average
Best model from Table 10	*ARIMA(3,1,0, x_1)*	*ARIMA(3,1,0, x_3)*	
RMSE	**0.047**	**0.051**	**0.049**
MAPE	**0.553**	**0.559**	**0.556**
MASE	**0.574**	**0.179**	**0.376**
ARIMAX with far east export volume	*ARIMA(3,1,0, x_4)*	*ARIMA(3,1,0, x_4)*	
RMSE	0.071	0.060	0.066
MAPE	0.747	0.644	0.696
MASE	0.777	0.207	0.492
ARIMAX with FE-EU transp. volume	*ARIMA(3,1,0, x_5)*	*ARIMA(3,1,0, x_5)*	
RMSE	0.078	**0.047**	0.063
MAPE	0.805	0.621	0.713
MASE	0.838	0.199	0.519

Bold indicates best performance.

that panelists do not necessarily look on the past when they assess market activity in the future. Moreover, M1 including the two LCI indexes from Transport Intelligence assessing current volume development and outlook 6 months ahead on trade lane level delivered superior forecast performance.

The findings of this study have significant implications for the shipping business literature. It provides evidence on the relevance of soft facts as forms of sentiments, perceptions and/or confidence. Using soft facts improve overall forecasting performance of freight rates in comparison to univariate modelling. Hence, such indices should be continued as a standard practice. As the study mainly estimated next-month freight rate forecasts in a recursive horizon, shipowners and cargo owners can implement the best performing models when forecasting freight rates for decision making within a month horizon. CCFI and SCFI indexes are often utilized in forward freight agreements and the party with improved forecast are likely to have minimal risk.

Unfortunately, no data is available after August 2017 and probably a simple reason for this is that the data sampling procedure was not in line with the General Data Protection Regulation (EU) 2016/679. However, given the ongoing trend of digitization and digitalization of the maritime shipping industry, it cannot denied that future research employing real-time data originating from container booking platforms or terminal operation systems as well as a constant tracking of container vessels via their automatic identification system (AIS) transceivers or container shipment movements via their container identification system according to ISO 6346:1995 may help to improve further predictability of container shipping freight rates. In addition, due to growing implication of container freight indices in hedging shipping risks, future studies should analyze not only return but also volatility of container freight rates.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Hans-Joachim Schramm: Conceptualization, Data curation, Writing - original draft. **Ziaul Haque Munim:** Methodology, Formal analysis, Writing - original draft, Writing - review & editing.

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Appendix A. Indices of sentiment, perception and confidence

Name/abbreviation	Initiator	Data sampling approach	Measures raised	Scope of measures	Periodicity	Horizon	Link
BVL Logistics Indicator (LI)	German Logistics Association (BVL), ifo Institute	Panel of 4000 companies in the transport, logistics and forwarding, manufacturing, wholesale or retail business	Business sentiment	Service providers vs shippers in Germany	Monthly since 2005	Current and next 6 months	BVL (2021)

(*continued on next page*)

(*continued*)

Name/abbreviation	Initiator	Data sampling approach	Measures raised	Scope of measures	Periodicity	Horizon	Link
China Logistics Prosperity Index (CLPI)	Fung Business Intelligence (FBIC)	Survey among a representative panel of logistics companies	Business volume but further KPIs reported	Logistics sector in China	Monthly since 2013	Previous and current month	FBIC (2021)
European Freight Forwarding Index (EFFI)	Danske Bank Markets	Survey among a sample of European freight forwarding companies	Volumes present in comparison to 2 months before/after	Sea/air/road mode of transport, several European countries	Monthly since 2009	Current and next 2 months	n.a.
Logistics Manager's Index (LMI)	ASU, Rudgers, PSU, UNR, CSU in conjunction with CSCMP	Open survey among North American logistics executives	Inventory, warehousing, transportation	Shippers from USA/North America	Bimonthly since 2016, monthly since 2018	Next 12 months	ASU (2021)
Prognos/ZEW Transportmarkt Barometer (TMB)	Centre for European Economic Research (ZEW), Prognos	Panel of 200–300 experts of shippers and transport industry from Germany	Development of transport volume and prices	Road/rail/sea/air mode of transport at Germany	Quarterly Q2/2005–Q2/2016	Next 6 months	ZEW (2021)
SCI Barometer (SCI)	SCI Consulting	Panel survey of about 200 representative companies from logistics sector	Business climate, (perceived) price development, and other questions	Logistics sector in Germany	Monthly since 06/2003	Last, current and next 3 months	SCI (2021)
Shanghai Shipping Prosperity Index (CSPI)	Shanghai International Shipping Institute (SISI)	Panel of executives from the maritime shipping industry in China	Judgement of current production and operation of their companies and prediction of forthcoming development	Tanker/bulk/container as well as ports sector	Quarterly since Q4/2009 (but data collection on monthly basis)	Current and next month	SISI (2021)
Stifel/TI Logistics Confidence Index (LCI)	Stifel, now Transport Intelligence (TI)	Open accessible survey	Volume development on trade lanes from/to Europe to/from Asia and North America	Air/Sea transport on certain trade lanes	Monthly 02/2012–08/2017	Current and in 6 months	TI (2021)
Shipping Confidence Survey (SCS)	Moore Stephens (now BDO), backed by UK Chamber of Shipping	Panel of managers from the maritime industry with worldwide coverage, but respondents mostly from UK/Europe	Perception about business KPI, major investments, and development of freight rates	Tanker/bulk/container sector	Quarterly since 05/2008	Next 12 months	BDO (2021)

Appendix B. Forecast accuracy measures

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(d_t - y_t)^2} \tag{4}$$

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{(d_t - y_t)}{d_t}\right| \tag{5}$$

$$MASE = mean\left|\frac{e_t}{\frac{1}{n-1}\sum_{t=2}^{n}\left|y_t - y_{t-1}\right|}\right| \tag{6}$$

Here, e_t is the forecast error calculated as$(d_t - y_t)$, d_t is the actual container freight rate at time t, y_t is the forecasted freight rate at time t, n is the total number of observations and $y_t - y_{t-1}$ is the forecast error of the naïve forecast.

Appendix C. ACF and PACF diagrams

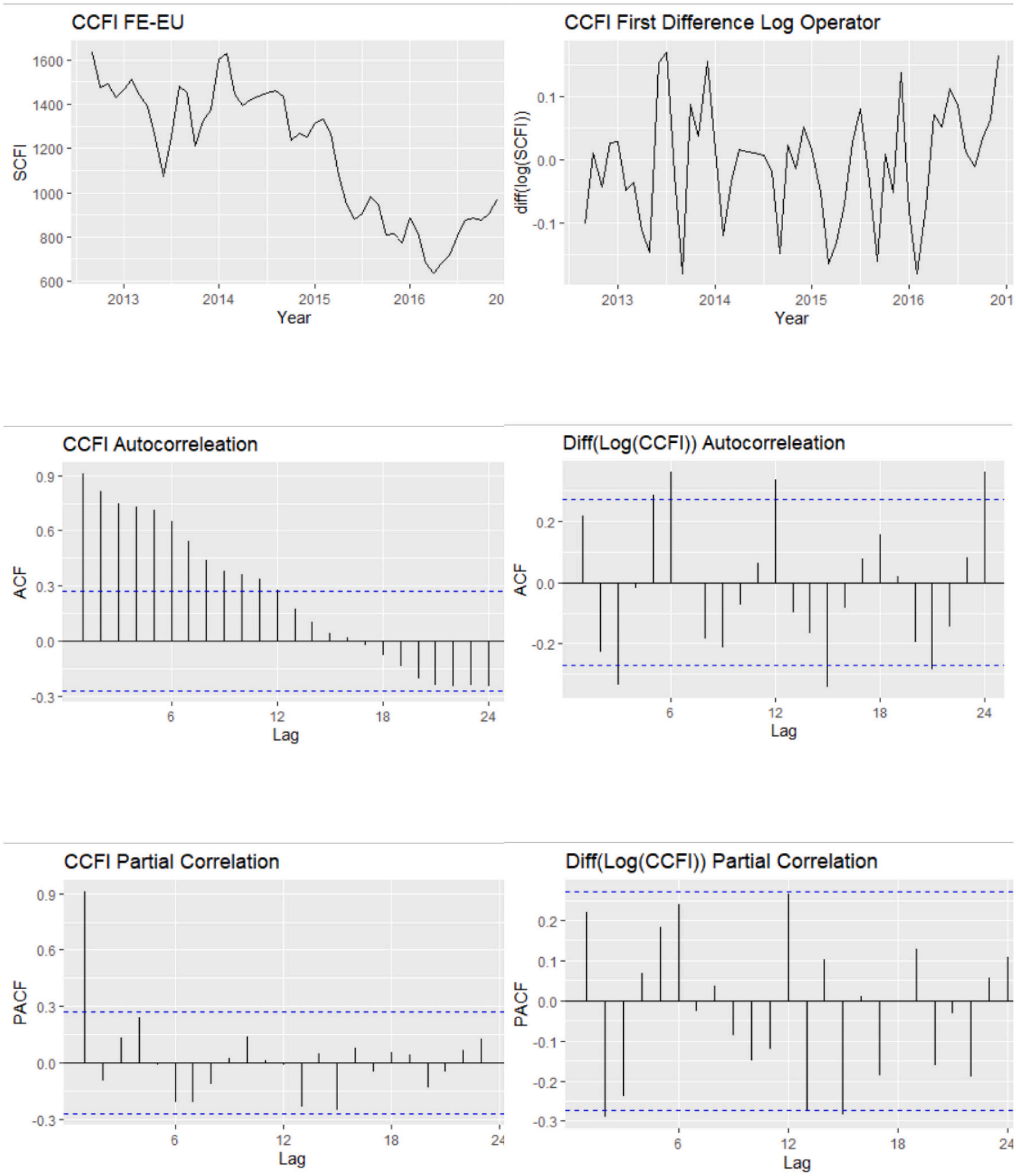

Fig. B1. CCFI autocorrelation analysis.

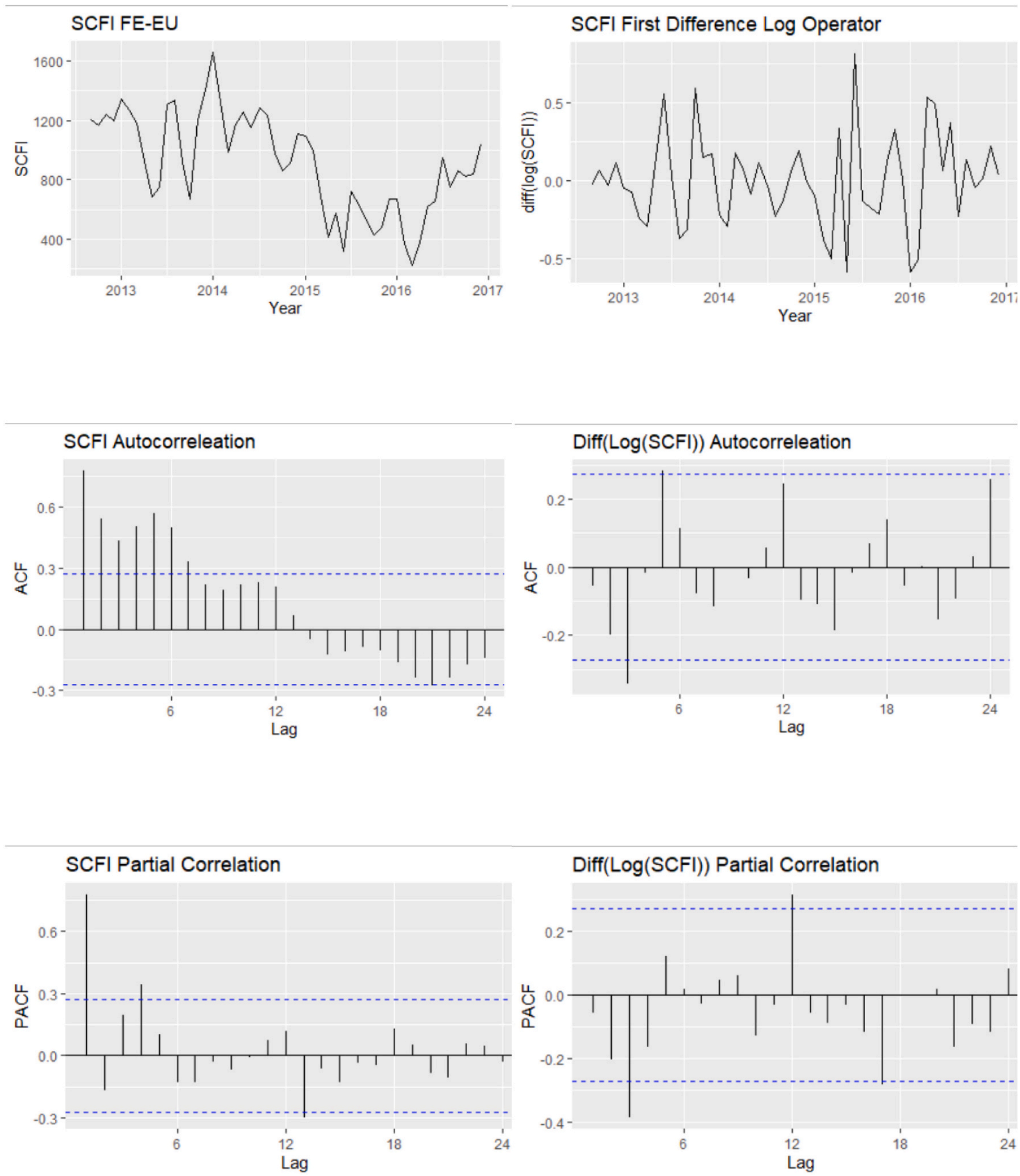

Fig. B2. SCFI autocorrelation analysis.

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