

TIME-SERIES MODELS FORECASTING PERFORMANCE IN THE BALTIC STOCK MARKET

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Abstract. *Contradicting evidence on time-series and financial analysts' forecasting performance calls for further research in emerging markets. Motivation to use time-series models rather than analysts' forecasts stems from recent research that reports time-series predictions to be superior to analysts' forecasts in predicting earnings for longer periods and for small firms that are hardly followed by financial analysts, especially in emerging markets. The paper aims to explore time-series models performance in forecasting quarterly earnings for Baltic firms in 2000-2009. The paper uses simple and seasonal random walk models with and without drift, Foster's, Brown-Rozeff's and Griffin-Watts' models to forecast quarterly earnings. It also employs the firm-specific Box-Jenkins methodology to perform time-series analysis for individual firms. Forecasting performance of selected models is compared on the basis of goodness-of-fit statistics. The paper finds that naïve time-series models outperform premier ARIMA family models in terms of mean percentage errors and average ranks. The findings suggest that investors use naïve models to form their expectations.*

Key words: *time-series models, forecasting, forecast errors, average ranks, quarterly earnings.*

Introduction

The measurement of earnings expectations is important for studies of cost of capital, asset valuation and earnings-returns relationships. Early research focuses on time-series properties of quarterly accounting data and explores forecasting performance of time-series models. They examine their ability to forecast future values of quarterly earnings and to approximate the capital market's expectations model when exploring market responses to quarterly earnings announcements. Since the number of firms followed by financial analysts is increasing, analysts' forecasts receive high scholarly attention (Ramnath et al., 2008). A large body of research explores time-series and analysts' forecasting performance in terms of forecast errors. After Brown (1987) concludes the superiority of analysts' forecasts over time-series forecasts, the research on time-series properties of earnings experiences a deep decline. The further research uses analysts'

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forecasts to predict future earnings, as they exhibit better performance. However, analysts' forecasts are hardly available in emerging markets, especially for young and small firms. Furthermore, behavioral finance literature documents the tendency of financial analysts to overreact and/or under-react to earnings announcements. Analysts' forecasts may be biased due to incentives and the effect of behavioral biases and heuristics. Recent research re-examines time-series and analysts' forecasting performance and reports time-series forecasts to be superior to analysts' forecasts in predicting quarterly earnings for longer periods (Bradshaw et al., 2011; Bradshaw et al., 2013; Gerakos & Gramacy, 2013). The paper aims to explore time-series models performance in forecasting quarterly earnings for Baltic firms. The importance of time-series research in accounting and finance motivates the interest to examine time-series behavior of quarterly earnings in emerging markets such as the Baltic market, which is described as thinly traded market with limited liquidity. The paper estimates quarterly earnings of 40 Baltic firms over the period of 2000-2009 and uses the Box-Jenkins approach for predicting each firm's earnings separately. It also employs naïve time-series models as benchmark models used in prior research. Then the accuracy of each forecast is estimated using MAPE, average ranks and ANOVA two-way analysis, including Friedman's statistics. Although premier ARIMA family models work well in developed markets, they exhibit poor performance in the Baltic market compared to naïve time-series models. The findings suggest that investors use naïve models to form their expectations in the Baltic stock market.

The paper is structured as follows. The first section reviews accounting literature and discusses earnings forecasting issues. The next section describes the data and methodology. The third section discusses empirical findings and the last section concludes.

Literature review

Comprehensive literature review allows identifying some directions in prior research on quarterly accounting data. The early research¹ focuses on time-series properties of quarterly earnings announcements. They provide evidence that quarterly earnings approximate simple random walk process. The wide use of random walk is explained by the simplicity of use and the absence of restrictions for the sample size. Subsequent studies (Albrecht et al., 1977; Foster, 1977; Bathke & Lorek, 1984; Bernard & Thomas, 1990) compare simple random walk model with more complicated models such as random walk with drift, seasonal random walk with drift or Box-Jenkins, and prove them all to be reliable forecasting models.

Brown and Kennelly (1972) use seasonal martingale and sub-martingale models to forecast quarterly earnings. The earnings forecast literature describes these models as

¹ See in Beaver (1970); Ball & Watts (1972); Brown & Kennelly(1972); Watts (1975); Brooks & Buckmaster(1976); Griffin (1977); Foster (1977); Albrecht et al.(1977); McKeown & Lorek (1978); Brown & Rozeff (1979); Lorek (1979); Bathke & Lorek (1984); Bernard & Thomas (1990), etc.

standards of comparison that are available for forecast producers and users at minimal cost. They also perform Box-Jenkins modeling, which enables to select the most appropriate time-series model consistent with the process generating each firm's time-series of quarterly earnings data. They report better performance of individually fitted Box-Jenkins forecast models over a particular class of time-series models applied for all firms' time-series data. However, subsequent research (Watts, 1975; Griffin, 1977; Foster, 1977; Brown & Rozeff, 1979; Lorek, 1979; Collins & Hopwood, 1980; Bathke & Lorek, 1984; Lorek & Willinger, 2006) suggests premier models for individual firm quarterly earnings, which may generate forecasts that are equal or superior to those generated by the Box-Jenkins model. Prior research identifies the following models:

- *Foster's model*, defined as a seasonally differenced first-order autoregressive model with a constant drift term. In terms of customary $(pdq) \times (PDQ)$ Box-Jenkins terminology, where: p, P represent autoregressive and seasonal autoregressive parameters; d, D represent consecutive and seasonal differencing; q, Q represent moving average and seasonal moving average parameters, this model is identified as $(1, 0, 0) \times (0, 1, 0)$.
- *Griffin-Watts' model*, defined as a consecutively and seasonally differenced first-order moving average and seasonal moving average model. This model is identified as $(0, 1, 1) \times (0, 1, 1)$.
- *Brown-Rozeff's model*, defined as a seasonally differenced first-order autoregressive and seasonal moving average model. In terms of Box-Jenkins terminology, this model is identified as $(1, 0, 0) \times (0, 1, 1)$.

These premier models are based on the diagnostic tests incorporated in Box-Jenkins procedures. The models are supported with obtained predictive evidence. Foster (1977) conducted cross-sectional autocorrelation function (ACF) and partial autocorrelation function (PACF) analyses to derive the model. In terms of absolute percentage errors it performed better than firm-specific Box-Jenkins ARIMA models in one-quarter ahead quarterly earnings predictions using the sample of sixty-nine firms. However, Brown and Rozeff (1978), Griffin (1977), and Foster (1977) himself note that *Foster's model* does not fit the data, as it fails to incorporate a systematic seasonal lag (a seasonal moving average component). The main defect of the model is the assumption that first-order autoregressive process describes time-series behavior of the fourth differences in quarterly data of all firms. Watts (1975) and Griffin (1977) report that cross-sectional autocorrelation function (ACF) and partial autocorrelation function (PACF) could be modeled by the $(0, 1, 1) \times (0, 1, 1)$ model, which is a multiplicative first-order moving average process in first differences of seasonal differences. Brown and Rozeff (1979) extend the model by supplementing an autoregressive process with a seasonal moving-average parameter, which accounts for seasonality. They compare it with the *Box-Jenkins, Foster and Griffin-Watts models* and conclude that their model as well as *Griffin-Watts' model* outperforms *Foster's model* based on goodness-of-fit statistics. Brown and Rozeff

(1978) obtain *MAPE* for one-, five-, and nine-quarter-ahead forecasts for each model and conclude that their model outperforms *Foster's model* at all time horizons and also outperforms the *Griffin-Watts* and *Box-Jenkins models* at longer horizons.

Lorek (1979) examines the predictive ability of firm-specific *Box-Jenkins models*, *Foster*, *Griffin-Watts* and *Brown-Rozeff models*. After firm-specific models are identified, a comparison can be made of the (pdq) x (PDQ) forms of the models versus the quarter-to-quarter and quarter-by-quarter findings of prior research. Since prior research reports one-step-ahead quarterly earnings predictions, Lorek (1979) was the first to compare the predictive ability of *Foster* and other parsimonious models, relative to firm-specific models over longer time horizons. *Griffin-Watts' model* appears to be the best-performing model.

Lorek's (1979) findings are inconsistent with Brown and Rozeff (1979), Foster (1977), Griffin (1975), and Watts (1977). Lorek (1979) argues that it may be premature to single out a particular parsimonious time-series model for quarterly earnings. The diversity in results may be determined by the underlying firm-specific time-series. Collins and Hopwood (1980) discuss the value of multivariate techniques relative to univariate ones. They explore whether a univariate model should be identified individually for each firm or whether a generally identified model would provide forecasts that are equal to or superior to those generated by individually identified models. Prior research provides controversial or inconclusive results, and this motivates the further research in the area. Lorek and Willinger (2006) prove *random walk with drift model* to be superior over *ARIMA-based models* in the pooled one-step-ahead quarterly earnings predictions. This finding is inconsistent with time-series literature, where *ARIMA family models* outperform naïve models. However, the predictive power of tested models exhibits contextual predictive performance, dependent on firms' characteristics. They find that the *Griffin-Watts model* outperforms *random walk with drift model* for regulated firms. They also report the joint dominance of *random walk with drift* and *Griffin-Watts' models* over *seasonal random walk with drift*, *Foster's* and *Brown-Rozeff's models* for the default firms.

Following Brown and Kennelly (1972), Watts (1975), Griffin (1977), Foster (1977), Lorek (1979), Collins and Hopwood (1980), Bathke and Lorek (1984), Foster, Olsen and Shevlin (1984), Mendenhall and Nichols (1988), Bernard and Thomas (1990), Lorek and Willinger (2006), a broader set of models (univariate, Box and Jenkins models) is used to exploit time-series data efficiently. Table 1 presents forecasting performance of time-series models in prior research.

Table 1 summarizes average rank, Friedman's ANOVA S-statistic and *MAPE* of each prediction model for all quarters based on Foster (1977), Bathke and Lorek (1984) and Lorek and Willinger's (2006). Foster (1977) and Bathke and Lorek (1984) argue that seasonal outperform non-seasonal naïve models in terms of *MAPE* and average ranks. However, Lorek and Willinger (2006) report a significantly higher *MAPE* for

TABLE 1. Time-series Models in Prior Research

No.	Model	Research papers	MAPE	Average rank
1.	Seasonal random walk	Brown and Kennelly (1972); Foster (1977)	0.287**	3.847**
2.	Seasonal random walk with drift	Brown and Kennelly (1972); Beaver (1974); Bathke and Lorek (1984); Bernard and Thomas (1990), Lorek and Willinger (2006)	0.404* 0.283** 0.594***	3.49* 3.395** 3.18***
3.	Simple random walk	Bradshaw et al. (2013); Foster (1977); Lorek (1979)	0.346**	3.849**
4.	Simple random walk with drift	Foster (1977); Bathke and Lorek (1984), Lorek and Willinger (2006)	0.421* 0.346** 0.555***	3.17* 3.598** 2.93***
5.	Foster's model	Foster (1977); Lorek (1979), Collins and Hopwood (1980), Bathke and Lorek (1984), Lorek and Willinger (2006)	0.398* 0.258** 0.576***	3.02* 2.710** 2.98***
6.	Brown-Rozeff's model	Foster (1977); Brown and Rozeff (1979); Lorek (1979), Collins and Hopwood (1980), Bathke and Lorek (1984); Bernard and Thomas (1990), Lorek and Willinger (2006)	0.369* 0.563***	2.55* 3.00***
7.	Griffin -Watts' model	Watts (1975); Griffin (1977); Foster (1977) Lorek (1979); Brown and Rozeff (1979); Lorek (1979), Collins and Hopwood (1980), Bathke and Lorek (1984), Lorek and Willinger (2006)	0.397* 0.562***	2.76* 2.90***
		Friedman ANOVA S-statistic	46.84* 919.7** 187.25***	

* MAPE, Friedman ANOVA S-statistic and average rank for all quarters in Bathke and Lorek (1984).

** MAPE, Friedman ANOVA S-statistic and average rank for all quarters in Foster (1977).

*** MAPE, Friedman ANOVA S-statistic and average rank for all quarters in Lorek and Willinger (2006).

all models. They explore relatively new data compared to the data set used in Foster (1977), Brown and Rozeff (1987) and Bathke and Lorek (1984). Thus, contradiction in the findings is explained with the differences in the sample period. Bathke and Lorek (1984) argue that *Brown-Rozeff's model* outperforms other time-series models across all error metrics and quarters. Foster (1977) finds that *naive seasonal models* have lower ranks than *non-seasonal naive models*, and *Foster's model* has the lowest rank and the lowest MAPE compared to the remaining models. However, as it was mentioned before, Foster (1977) later agreed that this model does not fit the data well. Lorek and Willinger (2006) report the best performance for *Griffin-Watts' model* in terms of average rank and forecast errors.

In the period from 1968 to 1987, when financial analysts' coverage of the firms was increasing, the research asked whether analysts' forecasts are superior to time-series forecasts. After Brown (1987) reported the superiority of analysts' forecasts over time-series forecasts, the research on properties of time-series forecasts experienced a deep decline. Further research (Brown & Rozeff, 1978; Collins & Hopwood, 1980; Mendenhall & Nichols, 1988; Kross, Ro, & Schroeder, 1990; Abarbanell, 1991; Lobo 1992; Branson, Lorek, & Pagach, 1995; Walther, 1997; Kothari, 2001; Peek, 2005; Bradshaw, Drake, Myers, & Myers, 2013, etc.) compares analysts' and time-series models forecasting performance and in most of the cases they prove analysts' forecasts to be superior. A great number of studies, including Brown et al. (1987), investigate the sources of superiority of the analysts' forecast. One source of analysts' forecast superiority is related to *timing advantage*, because the experts process the information obtained between the date on which time-series forecast is done and the date on which the analysts' forecast is done. However, Kross et al. (1990) provide evidence that financial analysts' forecasts are negatively correlated with the forecast horizon, which is consistent with Bradshaw et al. (2013) findings, who prove time-series forecasts to be superior over the analysts' forecasts for longer horizons. The other source of analysts' forecast superiority stems from information advantage, because analysts have access to accounting and non-accounting information sources. O'Brien (1988) explores forecasting ability of time-series models and analysts' forecasts and argues that the latter are superior, because analysts use time-series modeling along with a wide range of other information sources, such as macroeconomic releases, management releases on sales, production, acquisitions, and other analysts' forecasts. However, Jung (2005) argues that forecast timing (forecast horizon, recency, and frequency) and information availability (firm size, analyst coverage, and brokerage size) may result in the limited forecast accuracy. He assumes inefficient information incorporation by both analysts and investors that leads to discrepancies in market's expectations of earnings and analysts' earnings forecasts. Controversy in prior research findings suggests that time-series predictions taken as proxies for market's earnings expectations are not worse than analysts' forecasts depending on the forecasting horizon, period and/or markets viewed. Branson et al. (1995) report that analysts' forecasts exhibit more accurate performance for large firms and time-series forecasts perform better for small firms without analysts' following. Recent accounting literature seems to come back to the examination of regression-based earnings forecast. Hou et al. (2012) provide evidence that cross-sectional ordinary least squares (OLS) regressions provide relatively well-behaved forecasts of the level of earnings. Gerakos and Gramacy (2013) provide a comprehensive examination of regression-based earnings forecasts and find that earnings forecasts generated using ordinary least squares and lagged net income are more accurate. Moreover, at a one year horizon, random walk model performs as well as modern sophisticated methods that use larger predictor sets. Recent research also looks at new aspects of regression-based earnings forecasting performance. Fama and French (2000) and Gerakos and Gramacy (2013) explore how market volatility affects

forecasting performance of time-series models. During volatile times, *random walks* provide accurate forecasts of accounting data and during stable times, they suggest including predictors into regression.

The overview of prior and recent research shows that time-series forecasts are superior to analysts' forecasts in predicting quarterly earnings of small firms without financial analysts' following in emerging stock markets with limited liquidity and thin trading characteristics. The reasoning is the following:

- Time-series models perform better for longer periods. Time-series models require at least 10 years of data (data set contains 39 observations of quarterly earnings).
- Time-series forecasts are accurate at both short and long forecast horizons. The early research uses at least one quarter ahead in quarterly setting, and they perform better for longer horizons.
- Although in general analysts' forecasts perform better, the economic magnitude of the difference between analysts' and time-series forecasts is modest.
- Time-series models exhibit better performance for small firms (all Baltic firms are characterized as small, young and without analysts' following).
- Sufficiently large panel of analysts' coverage for Baltic firms is not available.

The above-mentioned arguments suggest employing time-series models to forecast quarterly earnings. The data description and methodology are presented in the next section.

Data and Methodology considerations

Quarterly earnings data are taken from the quarterly financial statements of 40 Baltic firms over the period from 2000 through 2009. All sample firms are characterized as small-size, young and not followed by financial analysts. Therefore, time-series models forecasting performance is compared in terms of average ranks and forecast errors.

The Baltic stock market investors are assumed to use less accurate naïve models to form their expectations rather than the more complicated ARIMA family time-series models. The study employs *seasonal random walk model (SRW)*, which assumes seasonality in quarterly data:

$$E(Q_t) = Q_{t-4} \tag{1}$$

Where:

Q_t - is a quarter t of a given year.

The model was estimated by Brown and Kennelly (1972), Foster (1977), Foster et al. (1984), Brown et al. (1987), Mendenhall and Nichols (1988), Han and Wild (1990), Bamper and Cheon (1995), Rangan and Sloan (1998), Walther (1997), Battalio and Mendenhall (2005), and Demers and Vega (2010).

The other time-series model, which captures seasonality patterns in quarterly earnings, is *seasonal random walk with drift (SRWD)*. It is estimated as follows:

$$E(Q_t) = Q_{t-4} + \delta \quad (2)$$

Where:

Q_t - is a quarter t of a given year;

δ - drift term, calculated over the quarter of interest.

This model is included because it was extensively used in prior research (Brown & Kennelly, 1972; Lorek, 1979; Bathke & Lorek, 1984; Foster et al., 1984; Mendenhall & Nichols, 1988; Bernard & Thomas, 1990; Han & Wild, 1990; Ball & Bartov, 1996; Bernard, Thomas, & Whalen, 1997; Lorek & Willinger, 2006; Jegadeesh & Livnat, 2006; Kama, 2009). It appeared to be a good proxy for market expectations of quarterly earnings. Its expectations are based entirely upon seasonal patterns in the data. Furthermore, it does not require firm-specific parameter estimation aside from the deterministic trend constant and is relatively parsimonious in nature.

Simple random walk (RW) ignores any seasonality in quarterly data. It was previously used in Foster (1977), Lorek (1979), Van Huffel et al. (1996), Burgstahler, Jiambalvo and Shevlin (1999), Haw, Qi and Wu (2000), Gerakos and Gramacy (2013), and Bradshaw et al. (2013). It is calculated as follows:

$$E(Q_t) = Q_{t-1} \quad (3)$$

Where:

Q_t - is a quarter t of a given year.

Following Foster (1977), Lorek (1979), Bathke and Lorek (1984), Lorek and Willinger (2006), *simple random walk with drift model (RWD)*, which suppresses any seasonality, is used:

$$E(Q_t) = Q_{t-1} + \delta \quad (4)$$

Where:

Q_t is a quarter t of a given year;

δ - drift term, calculated over the quarter of interest.

RW serves as a benchmark model, which bases its expectations exclusively on adjacent (quarter-to-quarter) effects. This model does not require the firm-specific parameter estimation aside from the deterministic trend constant, and serves as a control against potential structural changes in the holdout period. After discussing benchmark naïve models, more complicated Box Jenkins ARIMA family models must be explored.

Literature analysis (Foster, 1977; Lorek, 1979; Collins & Hopwood, 1980; Bathke & Lorek, 1984; Foster et al., 1984; Mendenhall & Nichols, 1988; Lorek & Willinger, 2006) shows that *Foster's model* exhibits better results in forecasting quarterly earnings. *Foster's model* is defined as a seasonally differenced first-order autoregressive model with a constant drift term. In terms of customary (pdq) x (PDQ) Box-Jenkins (1970) terminology, where: p, P represent autoregressive and seasonal autoregressive parameters; d, D represent consecutive and seasonal differencing; q, Q represent

moving average and seasonal moving average parameters, this model is identified as $(1, 0, 0) \times (0, 1, 0)$ and is calculated as follows:

$$E(Q_t) = Q_{t-4} + \varphi_1(Q_{t-1} - Q_{t-5}) + \delta \quad (5)$$

Where:

Q_t - is a quarter t of a given year;

δ - drift term, calculated over the quarter of interest;

φ_1 - autoregressive parameter.

The main drawback of the model is the assumption that first-order autoregressive process describes time-series behavior of the fourth differences in quarterly data of all firms. Basically, *Foster's model* fails to incorporate a systematic seasonal lag (a seasonal moving average component).

Brown and Rozeff (1979) addressed the *Foster's model* issue by supplementing autoregressive process with a seasonal moving-average parameter, which accounts for seasonality. In terms of Box-Jenkins terminology, the *Brown-Rozeff's model (BR)* is identified as $(1, 0, 0) \times (0, 1, 1)$ and is estimated as follows:

$$E(Q_t) = Q_{t-4} + \varphi_1(Q_{t-1} - Q_{t-5}) - \bar{\theta}_1 a_{t-4} \quad (6)$$

Where:

Q_t - is a quarter t of a given year;

φ_1 - autoregressive parameter;

$\bar{\theta}_1$ - seasonal moving average parameter;

$\bar{\theta}_1 a_{t-4}$ - disturbance term at time $t-4$.

This model appears to be superior over other time-series forecast models used in Lorek (1979), Collins and Hopwood (1980), Bathke and Lorek (1984), Bernard and Thomas (1990), Mendenhall and Nichols (1988), Brown and Han (2000) and Lorek and Willinger (2006). Brown and Rozeff (1979) compared their model with the *Box-Jenkins*, *Foster and Griffin-Watts models*. They conclude that their model as well as the *Griffin-Watts model* outperform *Foster's model* on the basis of goodness-of-fit statistics. Brown and Rozeff (1978) obtain *MAPE* for one-, five-, and nine-quarter-ahead forecasts for each model and conclude that their model outperforms *Foster's model* at all time horizons and also outperforms *Griffin-Watts'* and *Box-Jenkins'* models at longer horizons.

Finally, the paper uses the *Griffin -Watts model (GW)*, which is calculated as follows:

$$E(Q_t) = Q_{t-4} + (Q_{t-1} - Q_{t-5}) - \theta_1 a_{t-1} - \bar{\theta}_1 a_{t-4} - \theta_1 \bar{\theta}_1 a_{t-5} \quad (7)$$

Where:

Q_t - is a quarter t of a given year;

θ_1 - regular moving average parameter;

$\bar{\theta}_1$ - seasonal moving average parameter;

$\bar{\theta}_1 a_{t-4}$ - disturbance term at time $t-4$.

Watts (1975) and Griffin (1977) report that cross-sectional autocorrelation function (ACF) and partial autocorrelation function (PACF) could be modeled by the (0, 1, 1) x (0, 1, 1) model. *Griffin-Watts' model* is defined as a consecutively and seasonally differenced first-order moving average and seasonal moving average model. It was estimated in Watts (1975), Griffin (1977), Lorek (1979), Brown and Rozeff (1979), Collins and Hopwood, 1980; Bathke and Lorek (1984), Mendenhall and Nichols (1988), Lorek and Willinger (2006), and Gerakos and Gramacy (2013).

Forecasting performance of the above-mentioned models is tested by calculating the mean absolute percentage error (*MAPE*). *MAPE* is calculated as follows:

$$MAPE = \frac{1}{n} \sum \left(\frac{Q_t - E(Q_t)}{Q_t} \right) \quad (8)$$

This error metric was previously used in many studies (Foster, 1977; Griffin, 1975; Lorek 1979; Brown & Rozeff, 1978; Bathke & Lorek, 1984; Mendenhall & Nichols, 1988; Bernard & Thomas, 1990; Lorek & Willinger, 2006, etc.).

Average ranks also allow us to compare forecasting performance across models. For every quarter/firm combination, forecast errors from the above-mentioned models are ranked in terms of accuracy. The model with the most accurate forecast for a particular quarter/firm is given a rank of 1; the model that gives the least accurate forecast is given a rank of 7. Then the average rank of each model over all firms and all quarters is estimated. Employing *ANOVA* two-way analysis, the null hypothesis that the average rank of all seven models is the same against the alternative hypothesis that average rank is not the same is examined. The next section presents the results of the above-mentioned methodology.

Empirical results and discussions

Building on the prior literature the paper employs four benchmark expectation models: *random walk (RW)*, *random walk with drift (RWD)*, *seasonal random walk (SRW)* and *seasonal random walk with drift (SRWD)* and 3 premier ARIMA family models that include *Foster's (F)*, *Brown-Rozeff's (BR)* and *Griffin-Watts' (GW)* models. The regression parameters and their significance level for premier ARIMA family models are available upon request. The regression coefficients of *Foster's model* were economically and statistically significant for 55% of all firms. The autoregressive parameter of *Brown-Rozeff's model* was significant for 60 % of firms and the seasonal moving average parameter was significant accordingly for 77.5% of firms. The regular moving average parameter and the seasonal moving average parameter of the *Griffin-Watts model* were significant for 82.5% and 62.5% of all firms respectively. Using earnings for the period of 2000 Q1 through 2008 Q3, quarterly earnings of the subsequent period of 2008 Q4 through 2009 Q3 are forecasted ². The observed high diversity in forecast errors³

² The forecast earnings four-quarter ahead for each firm are available upon request.

³ Forecast errors across all firms in the sample for the forecast period are available upon request.

across firms/quarters, affect *MAPE* metrics for the four-step-ahead quarterly earnings predictions⁴ across seven time-series models for each individual quarter (1st, 2nd, 3rd, 4th), as well as on a pooled basis across all quarters and years. Table 2 also summarizes average ranks for each individual quarter and on a combined basis.

TABLE 2. Summary Statistics on Forecasts Errors and Average Ranks

<i>Panel A: Summary statistics on forecast errors: 2000-2009</i>										
Model/ quarter	All quarters		Q1		Q2		Q3		Q4	
	MAPE	Average rank	MAPE	Average rank	MAPE	Average rank	MAPE	Average rank	MAPE	Average rank
Seasonal random walk (SRW)	370.66	3,969	276.63	3,950	370.93	3,875	597.05	4,050	238.03	4,000
Simple random walk (RW)	293.71	3,769	353.06	4,025	308.98	3,800	271.10	3,250	241.69	4,000
Seasonal random walk with drift (SRWD)	353.78	3,663	266.17	3,700	347.95	3,625	572.88	3,900	228.13	3,425
Simple random walk with drift (RWD)	292.46	3,688	351.04	3,925	309.31	3,600	272.09	3,350	237.40	3,875
Foster's model (F)	458.27	4,308	365.01	4,359	483.74	4,359	721.24	4,564	263.10	3,949
Brown-Rozeff's model (BR)	423.77	3,619	314.05	3,450	463.15	3,400	652.65	3,475	265.23	4,150
Griffin -Watts' model (GW)	713.93	4,919	532.12	4,525	696.95	5,275	1150.34	5,350	476.30	4,525

<i>Panel B: Paired comparisons – all quarters</i>						
	SRW (3,969)	RW (3,769)	SRWD (3,663)	RWD (3,688)	F (4,308)	BR (3,619)
RW (3,769)	RW					
SRWD (3,663)	SRWD	SRWD				
RWD (3,688)	RWD	RWD	SRWD			
F (4,308)	SRW	RW	SRWD	RWD		
BR (3,619)	BR	BR	BR	BR	BR	
GW (4,919)	SRW	RW	SRWD	RWD	F	BR

Panel A summarizes *MAPE* metrics and average ranks for the four-step-ahead quarterly earnings predictions across seven models for each individual quarter (1st, 2nd, 3rd, 4th), as well as on a pooled basis across all the quarters and years. The prediction model yielding the smallest absolute percentage error was given a rank of one. The next

⁴ Quarterly earnings predictions are available upon request.

smallest error was given a rank of two and so on until the model yielding the largest error was given a rank of 7. Conclusions on the accuracy of forecasts for each time-series model are based on the given MAPE and average ranks.

Consistently with findings in Bathke and Lorek (1984), *Brown-Rozeff's model* outperforms the remaining models for all quarters, for the 1st, 2nd and 3rd quarters but not for the 4th quarter in terms of average ranks. However, the rank of 3,619 for all quarters across firms is higher than in Bathke and Lorek (1984). They obtained 2,55 for all the quarters across all sample firms. For the 4th quarter *RWD* and *SRWD* outperform *Brown-Rozeff's model*. *RW* and *SRW* models outperform *Foster's* and *Griffin-Watts' models*. Table 2 documents the highest average rank for *Griffin-Watts' model* (4,919), whereas in Bathke and Lorek (1984) and Lorek and Willinger (2006) this model performs well in terms of the average ranks. *RW*, *RWD*, *SRW*, *SRWD* appeared to be quite accurate forecasting models for Baltic firms' quarterly earnings, as average ranks are significantly lower than using *Foster's* and *Griffin-Watts' model*, which is in contrast with prior research. However, consistently with Ball and Bartov (1996), the results suggest that the Baltic market investors act as if they are aware of the existence and form of serial correlation. To summarize, naïve models perform quite well for each quarter and for all quarters and this evidence suggests that investors in the Baltic stock market resemble less accurate naïve models to form their expectations rather than more complicated.

In terms of forecast errors, naïve models outperform ARIMA family models for the 1st, 2nd, 3rd and 4th quarters. For the 1st quarter, the best performing model is *SRWD* model, and the worst is *GW* model (inconsistently with prior research). For the 2nd, 3rd and for all quarters *RW* and *RWD* models produce the smallest MAPE. This finding is consistent with Lorek and Willinger (2006). They find that *RWD* outperforms the remaining models for the 2nd, 3rd 4th and for all quarters. In this paper, *SRWD* outperforms the remaining models for the 4th quarter. However, Lorek and Willinger (2006) find that *SRWD* produces the highest *MAPE* among the above-mentioned models on a pooled basis. In this paper, the best performing model is *SRWD* and the worst is *RW* model for the 1st and 4th quarters. It should be noted that for the 2nd and 3rd quarters *SRW* and *SRWD* models perform significantly worse than *RW* and *RWD* models, as their forecast errors are significantly higher. *Griffin-Watts' model* produces the largest errors in quarterly earnings forecasts. The findings are inconsistent with prior empirical studies (Lorek & Bathke, 1984).

GW model was found to have the strongest predictive power in prior research, but for Baltic firms accounting data it is the worst performing model across all the quarters. In general, benchmark models that are defined as short-memory models show better performance than premier or long-memory models for each quarter and on the pooled basis.

It also should be noted, that for the 4th quarter forecast errors are significantly lower compared to those for the remaining quarters and for all the quarters. The differences across forecasting models are the smallest in the 4th quarter, which is in line with Lorek

and Bathke (1984). They find that *RWD* outperforms *SRWD*, *Foster*, and *GW models*, although it completely ignores seasonal relationships. However, in this study these seasonal relationships seem to be taken into account and, therefore, *SRWD* outperforms the remaining models.

MAPE for all models is quite large when compared with forecast errors in prior research, but it can be explained by the large deviations of quarterly earnings of some analyzed firms during the last two years due to worsening economic conditions in the Baltic market and due to the dominant pessimism in the market. The same tendency was proven in prior literature. Lorek and Willinger (2006) also report much higher *MAPE* than reported in previous empirical studies. The early research mostly explored the data before 1974. Quarterly earnings were not so much volatile during that period and, therefore, the forecast errors are relatively low.

Panel B contains pair comparisons of average ranks of each time-series model for all quarters. Given that lower rankings imply a lower *MAPE* and greater predictive ability, it is found that *GW model* was outperformed by all models. *RWD* outperforms all but *BR* and *SRWD* models. *SRWD* outperforms all naive models, which is consistent with prior research and resembles the idea that the majority of firms exhibit a seasonal component in their quarterly earnings series. *Foster's model* also shows a poor predictive ability. However, its forecasting performance is more accurate when compared to *GW model*. This finding is in a marked contrast with Foster (1977), who proves *Foster's model* to have the lowest rank and, therefore, the best predictive ability among the other time-series models. *BR model* exhibits the best predictive ability for all quarters. This is because it supplements autoregressive process with a seasonal moving-average parameter and tracks the adjacent quarter-to-quarter serial correlation in the quarterly earnings series which is ignored by *SRWD*. This finding is consistent with Bathke and Lorek (1984). They also argue that *BR* outperforms *GW* and *Foster's models*.

In general, the more sophisticated models do not perform well in the Baltic market. The findings suggest that investors use naïve models to form their expectations. They are not sufficiently sophisticated to use premier models.

Pooled results across all quarters and years differ from those for individual quarters. Therefore, on the later stage of research, it is necessary to compute the average ranks for each quarter individually and perform Friedman two-way ANOVA test to check for accuracy of results. Table 3 summarizes ANOVA Friedman test results.

ANOVA two-way Friedman test shows that for the 1st and 4th quarters there are no significant differences across applied time-series models in predicting quarterly earnings in the Baltic stock market. However, for the 2nd and 3rd quarters the differences are significant at 0.01 significance level. The reported F-statistics values are significantly lower compared to ones provided in prior research. Pair comparison of average ranks of time-series model for the 1st quarter shows significant differences in predictive ability of *RW* and *RWD*. They outperform *SRW* at 0.1 and 0.05 significance level respectively. Forecasting performance of the remaining models does not exhibit significant differences for the 1st quarter. For the 2nd quarter *RW*, *RWD*, *SRW* and

TABLE 3. ANOVA Friedman Test Results

	<i>Source of Variation</i>	<i>SS</i>	<i>df</i>	<i>MS</i>	<i>F</i>	<i>Prob>F</i>
1th quarter	Between Groups	32.068383	6	5.34473049	1.35	0.2363
	Within Groups	1078.89936	272	3.96654176		
	Total	1110.96774	278	3.99628684		
2th quarter	Between Groups	98.668383	6	16.4447305	4.42	0.0003
	Within Groups	1012.29936	272	3.72168882		
	Total	1110.96774	278	3.99628684		
3th quarter	Between Groups	136.202998	6	22.7004997	6.33	0.0000
	Within Groups	974.764744	272	3.58369391		
	Total	1110.96774	278	3.99628684		
4th quarter	Between Groups	25.845306	6	4.30755101	1.08	0.3748
	Within Groups	1085.12244	272	3.98942072		
	Total	1110.96774	278	3.99628684		

Note: we test if there are significant differences in average ranks of 7 time-series models across all firms/quarters. We reject the null if there is a 5% chance that at least one of the post tests will have $P < 0.05$. P-value will be very small, if the sums are very different. The 5% chance does not apply to each comparison but rather to the entire family of comparisons.

SRWD outperform *GW model*. *RW* and *SRW* outperform *GW model* at 0.05 significance level, whereas *RWD* and *SRWD* outperform *GW* at 0.01 significance level. *GW* exhibits significantly (at 0.01 significance level) higher predictive ability than *BR model* for the 2nd quarter. Comparing forecasting ability of naïve models, it is found that *RW* outperforms *SRW* and *RWD* outperforms *SRWD* at 0.1 and 0.05 significance level respectively. *GW* outperforms *BR model* at 0.01 significance level for the 3rd quarter. *RW* and *RWD* exhibit a higher predictive ability than *Foster's model* at 0.05 and at 0.1 significance level respectively. All naïve models significantly outperform *GW model* for the 3rd quarter, but no significant differences in forecasting ability among naïve models are found. For the 4th quarter *RW*, *RWD*, and *SRW* significantly outperform a predictive ability of *Foster's model*. In general, almost no differences in forecasting performance of naïve models are found for the 2nd and 3rd quarters. However, *SRW* exhibits significantly better forecasting performance compared to *RW* for the 4th quarter, which is suggestive of the presence of a seasonal component in firm quarterly earnings series.

Conclusions

This paper explores time-series properties of quarterly earnings of 40 Baltic firms over the period from 2000 through 2009. It provides quarterly earnings forecasts based on seven time-series models: four naïve (*simple and seasonal random walk with and without drift*) and three premier ARIMA family (*Foster's, Brown-Rozeff's, and Griffin-Watts'*) models. Quarterly earnings follow simple and seasonal random walk process that appears to adequately describe quarterly earnings in the Baltic stock

market. Consistently with Foster (1997), each quarterly earnings series proves to have seasonal and adjacent quarter-to-quarter components. This conclusion comes from the inspection of four-step-ahead forecasting results. *Brown-Rozeff's model*, which supplements an autoregressive process with a seasonal moving-average parameter, accounts for the seasonality and exhibits the best performance for Baltic firms' data set on a combined basis. Forecasting performance of naïve time-series models outperform premier ARIMA family models in terms of mean absolute percentage errors and average ranks. The findings suggest that investors use naïve time-series models to form their expectations. They are not sufficiently sophisticated to use premier Box Jenkins ARIMA family models.

There are several limitations related to the research framework. First, the sample for the period of 2000–2009 is subject to a survivorship bias that is present in most of the time-series research. Second, the paper explores a wide range of ARIMA family models and naïve expectations models. However, the other expectations-based models can provide different results.

This paper focuses on univariate analysis, when each firm's earnings are examined separately. The natural extension of the current research will be a joint quarterly earnings analysis. It would allow us to compare forecasting accuracy of individually identified and generally identified models. This research can be extended by exploring how time-series models approximate stock market expectations that are highly dependent on the accuracy of time-series predictions. Therefore, the next step in this research is to use the above-mentioned models to explore market responses to quarterly earnings. Lorek and Willinger (2006) empirical study calls for further research on the contextual nature of predictive power of time-series models in forecasting quarterly earnings of firms with different characteristics. However, the small sample problem arises especially if the research is going to be done in small emerging markets with limited liquidity and thin trading characteristics.

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