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A Time Series Analysis on the Russian Red King Crab Auction Prices of the Korean Wholesale Seafood Markets

한국 수산물도매시장의 러시아산 레드 킹크랩 경매가격에 대한 시계열 분석

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A Time Series Analysis on the Russian Red King Crab Auction Prices of the Korean Wholesale Seafood Markets

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Abstract

The current paper aims to research auction prices for Russian Red King Crab (RKC) on South Korean wholesale seafood markets, using different time series analysis techniques, mainly for price forecasting purposes.

The study employs the Autoregressive Integrated Moving Average (ARIMA), Exponential Smoothing (ES) and Autoregressive Distributed Lag (ARDL) methods for auction price forecasting. The results indicate that ARIMA is more reliable than ES in short-run dynamic price forecasts. ARDL proved to be relatively effective for long-run forecasting, however this method requires a lot more additional estimated or predicted data.

In addition, linear Autoregressive Distributed Lag (ARDL) and non-linear Autoregressive Distributed Lag (NARDL) methods were applied to study the cointegration between average Russian RKC auction prices and several related exogenous variables. The obtained results indicate cointegrating long- and short run relationships between Russian RKC auction prices and several of the chosen variables.

The employment of machine learning, big data, or neural networks may be the next step in broadening the research topic and development of a functional auction price forecast model, however it will require much bigger data sets and a lot of research work.

KEY WORDS: Price forecasting; Cointegration; ARIMA; Exponential smoothing; ARDL; Seafood auction.

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초록

본 연구는 러시아산 레드 킹크랩의 경매 가격 예측을 위해 ARIMA (Autoregressive Integrated Moving Average), 지수평활법(Exponential Smoothing) 및 ARDL (Autoregressive Distributed Lag) 방법을 사용하였습니다. 결과는 단기 동적 가격 예측에서 ARIMA가 지수평활법보다 더 안정적임을 보여주고 있습니다. ARDL은 장기 예측에 상대적으로 효과적인 것으로 알려져 있지만 이 방법에는 훨씬 더 많은 추정 또는 예측 데이터가 필요합니다.

또한, ARDL 및 non-linear ARDL (NARDL) 방법을 적용하여 평균 러시아산 레드 킹크랩 경매 가격과 여러 관련 외생 변수 간의 공적분을 연구했습니다. 얻은 결과는 러시아 경매 가격과 선택된 변수 중 일부 사이의 장단기 관계가 존재함을 보여주고 있습니다.

Machine learning, big data 또는 neural networks 등으로 연구 주제를 확대하고 기능적인 수산물 경매 가격 예측 모델을 개발하는 방향으로 연구를 더욱 발전시킬 수 있을 것으로 생각되며 여기에는 훨씬 더 큰 데이터 세트와 추가적인 연구 작업이 필요할 것으로 생각됩니다.

KEY WORDS: 가격 예측; 공적분; ARIMA; 지수평활법; ARDL; 수산물 경매.

1. Introduction

1.1 The Research Background

The practice of harvesting and consuming seafood has been known to humanity since at least the Upper Paleolithic period (roughly between 50,000 and 10,000 years ago). It is undoubtful that by the time when early humans invented primitive fishing tools and founded the first fishing villages, they started bartering the excess catch with other settlements or outsiders.

The development of trade and social cooperation eventually led to the formation of seafood markets. In the course of time, such markets became more than just places for trade and barter. They became the places where large groups of people could meet to not only buy or sell, but also to socialize, share local news, and discuss recent events. The scale of seafood trade grew larger with humanity's scientific and economic progress.

Since seafood has a very limited shelf life, the first seafood markets were organized in river and coastal settlements. When people discovered that storing seafood in ice or snow could greatly delay its spoilage, they started organizing seafood markets in remote inland settlements that had stable trade connections with coastal regions. The later 19th century and the following 20th century were marked by invention and a rapid development of refrigeration equipment, as well as much faster means of transport than those that were available before. The technological progress eventually allowed people to build and organize seafood markets in almost any location.

However, since the major part of modern trade has shifted from traditional markets to retail shops, the great bulk of seafood and other groceries in the world is being sold through self-service supermarkets. Thus, the majority of modern seafood markets specialize in wholesale trade, while existing retail markets usually operate for the sake of tradition, not commerce. Both types of modern seafood markets often serve as tourist attractions.

With a total population of 52 million people and an average annual seafood consumption of 78.5 kilograms per capita[1), which is the world's highest seafood consumption rate, the Republic of Korea is one of the world's largest importers, consumers, and producers of seafood. Traditionally, Korean people eat seafood in various states: fresh, chilled, and lastly, frozen in that order of preference. Some types of seafood are consumed raw, and are usually sold at a premium price. Accordingly, live or fresh seafood is usually the most expensive and has the highest value for Korean consumers.

In general, Asian culinary traditions dictate that the most valuable and expensive seafood must be consumed fresh and often raw. Modern refrigeration technologies allow us to preserve even the most perishable and delicate seafood for a significant time, however any seafood, preserved by freezing, loses its gastronomic and/or physical qualities to a greater or lesser extent. That is why luxury seafood is usually carried alive on its way from fishing grounds to consumers' tables, and this requires additional costs and technologies. All the aforementioned factors stipulate the necessity of prompt and effective sales methods.

An average commoner will usually confuse a wholesale seafood market with a commodity exchange. At first glance, both these trade markets operate in the same way, however the difference is more significant than it seems. Wholesale seafood markets are not related either to commodity exchanges nor to stock exchanges, however similar they may seem. Their economic nature, legal status, and operation mechanisms are completely different.

In addition, unlike in commodity and stock markets, price fluctuations in fish markets may vary greatly for every party of the same good, depending only on its current qualities and buyers' preferences. Unlike in commodity and stock markets, a financial quote, i.e. the last price some commodity/security was traded at, do not matter for

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1) According to Joint Research Centre of the European Commission - https://ec.europa.eu/jrc/en/news/how-much-fish-do-we-consume-first-global-seafood-consumption-footprint-published. Accessed on February 23rd 2020

current price forming.

Wholesale seafood markets may be defined as market co-operatives, organized for buying out seafood catch from minor or major (sometimes international) fishing companies. Alternatively, it may be a partnership of several major fishing companies, united for promoting and distributing their goods on the market.

The necessity of such distribution methods usually arises in those countries, where minor fishing enterprises account for 60% ~ 80% of total catch, and the share of small-displacement fishing vessels amounts up to 90% of total fleet tonnage. In such countries like Australia, Japan, Norway, Iceland, Italy, Portugal, Spain, Italy, Greece, Chile, Ecuador, Brazil, and Peru small fishing businesses organize co-operative wholesale markets on a voluntary basis, due to the specific structure of fishing industries, traditions, and technological equipment of fishing fleets.

1.2. The Box-Jenkins Method and ARIMA

Every economic entity from simple households to transnational corporations and national governments must plan its economic activities in order to stay functional and effective. However, economic planning is impossible without a certain amount of forecasting. Therefore, the significance of economic forecasting on micro and macro levels must not be underestimated.

Forecasting is required in many situations: deciding whether to build another power generation plant in the next five years requires forecasts of future demand; scheduling staff in a call center for next week requires forecasts of call volumes; stocking an inventory requires forecasts of stock requirements. Forecasts can be required several years in advance (e.g. capital investments), or only a few minutes beforehand (e.g. telecommunication routing). Whatever the circumstances or time horizons involved, forecasting is an important aid to effective and efficient planning.[2]

Time series is the most common way of depicting a changing of economical or statistical parameters over a definite period of time. When forecasting time series, the

2) Hyndman, R.J., & Athanasopoulos, G., Forecasting: principles and practice (OTexts: Melbourne, Australia 2018) , 2nd edition, p.4.

mathematical model is used to predict future values based on previously observed values. Thus, for the purposes of time series analysis, making a good forecast means fitting an adequate mathematical model.

The Autoregressive Integrated Moving Average (ARIMA) model is one of the most popular and versatile stochastic models for time series forecasting. The ARIMA model is an element of the so-called Box-Jenkins method, named after George E. P. Box and Gwilym M. Jenkins, who originally proposed it in their textbook "Time Series Analysis: Forecasting and Control", first published in 1970. The ARIMA model can be applied when the time series is stationary (i.e. its statistical properties are constant over time) and there is no missing data within the time series.

Being a more complex version of a simple ARMA model with an added integration element, the ARIMA combines differencing, autoregression, and a moving average model. The general ARIMA model may be presented as:

$$y'_t = c + \phi_1 y'_{t-1} + \cdots + \phi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t \tag{1}$$

where y'_t is the differenced series (it may have been differenced more than once). The "predictors on the right hand side include both lagged values of y_t and lagged errors. This is called an ARIMA (p,d,q) model, where:

p – order of the autoregressive part (lag order);

d – degree of first differencing involved;

q – order of the moving average part.

As one of the most universal and powerful time series forecasting tools, the ARIMA can operate with data sets, which have trends, seasonality, cycles, errors and non-stationary aspects. However, the ARIMA usually works best for short-term forecasting with a sufficient amount of historical data points and a minimum number of outliers. For more information on the subject, please refer to the corresponding research works.

1.3 Exponential Smoothing

Since it is in the scope of the current research to find the most suitable and effective method for forecasting seafood auction prices, another popular time-series analysis method has drawn our attention - the Exponential Smoothing. Exponential Smoothing (ES) is a powerful forecasting tool, which is older than ARIMA, but is still often used as a viable alternative to the Box-Jenkins approach.

Exponential Smoothing was proposed in the late 1950s (Brown, 1959; Holt, 1957; Winters, 1960), and has motivated some of the most successful forecasting methods. Forecasts produced using exponential smoothing methods are weighted averages of past observations, with the weights decaying exponentially as the observations get older. In other words, the more recent the observation the higher the associated weight (i.e. priority, significance for the forecast). This framework generates reliable forecasts quickly and for a wide range of time series, which is a great advantage and of major importance to applications in industry. Exponential Smoothing techniques generally cope better with short-term forecasts, as longer term ES forecasts tend to be unreliable.

There are several types of exponential smoothing, suitable for applying to different data sets with or without trend and seasonality. However, considering the specifics of the current research’s data set (no clear trend or seasonal pattern), the most common form of exponential smoothing - the simple (or single) exponential smoothing is the most suitable for the purposes of the current research.

The Single Exponential Smoothing (SES) requires a single parameter, called alpha (a), which is also called a smoothing factor or a smoothing coefficient. This parameter controls the rate at which the influence of the observations at prior time steps decay exponentially. Alpha is often set to a value between 0 and 1. Large values mean that the model pays attention mainly to the most recent past observations, whereas smaller values mean more of the history is taken into account when making a prediction.

As it can be seen from our literature overview, most modern research works on time series price forecasting mostly rely on ARIMA, exponential smoothing, neural networks and other complicated machine learning algorithms. Unfortunately, in order to function properly and yield reliable results, neural networks and machine learning algorithms require a huge amount of data, much more than can be obtained from seafood wholesale markets' public databases. The required huge data set must also be preprocessed before integrating into machine learning algorithms. Therefore, it was decided to employ one more forecasting technique – the Autoregressive Distributed Lag model, which is usually used in cointegration studies, but is also able to solve prediction models.

1.4 ARDL and NARDL

However tempting the idea of a functioning seafood auction price forecasting model may be to both economists and market participants, it is also important to discover and understand the core principles and collateral economic values that define or influence the price-forming mechanisms in wholesale seafood auctions.

According to Granger, methods to analyze a single integrated (non-stationary) time series had been proposed previously by Box and Jenkins (1970) and others, but the joint analysis of pairs, or more, of such series was missing an important feature. It turns out that the difference between a pair of integrated series can be stationary, and this property is known as "cointegration." More formally, two smooth series, properly scaled, can move and turn, but slowly, in similar but not identical fashions, but the distance between them can be stationary.[3] The concept of cointegration, stipulated the development of appropriate methods and techniques, which help to determine long run relationships between non-stationary time series and reparametrize them into an Error Correction Model (ECM).

Before the introduction of cointegration tests, economists relied on linear regressions to find the relationship between several time series processes. However, Granger and Newbold argued that linear regression was an incorrect approach for analyzing time series due to the possibility of producing spurious correlation. A spurious correlation occurs when two or more associated variables are deemed causally related due to

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3) Clive W.J. Granger, Time Series Analysis, Cointegration, and Applications, Nobel Lecture, December 8, 2003, Department of Economics, University of California

either a coincidence or an unknown third factor. A possible result is a misleading statistical relationship between several time series variables. For further comprehensive reading on cointegration, see Granger (1981), Granger and Weiss (1983), Engle and Granger (1987).

The Autoregressive Distributed Lag (ARDL) approach was developed by Pesaran (1997), Pesaran and Smith (1998), and Pesaran et al. (2001) in their corresponding research works. The ARDL model is extensively used for modelling the relationship between (economic) variables in a single-equation time series setup. The method is able to estimate the long and short-run parameters of the model simultaneously for the avoidance of the problems posed by non-stationary time series data. In addition, ARDL does not require a prior determination of the order of the integration amongst the variables, unlike other approaches, which require that the variables pose the same order of integration.

The general expression of conventional (linear) ARDL model may be presented as:

$$\Delta y_t = \mu + \rho y_{t-1} + \theta x_{t-1} + \sum_{j=1}^{p-1} \alpha_j \Delta y_{t-j} + \sum_{j=0}^{q-1} \pi_j \Delta x_{t-j} + \epsilon_t \tag{2}$$

where △ represents the first difference operator, *yt* is the dependent variable in period *t*, μ denotes the intercept, *x* is a kx1 vector of regressors, and ρ and θ denote the long-run coefficients. Furthermore, α_j and π_j are the short-run coefficients, *p* and *q* represent the optimal lags for the dependent variable and the independent variables, respectively, and finally, ϵ_j is the error term for a time *t*. For more information, please refer to the corresponding research works by Pesaran and Pesaran (1997), Pesaran and Smith (1998), and Pesaran et al. (2001).

The popularity of the ARDL model also stems from the fact that cointegration of nonstationary variables is equivalent to an error correction (EC) process, and the model has a reparameterization in EC form (Engle and Granger, 1987; Hassler and Wolters, 2006). Thus, the existence of a long-run relationship or cointegration can be tested based on the EC representation and bounds testing results, in order to draw conclusive inference without knowing whether the variables are integrated of order zero or one, I (0) or I (1), respectively (Pesaran et al., 2001).

In the ARDL model, variables can cointegrate either positively or negatively, i.e. the model implicitly assumes "symmetry" when positive and negative variations of the explanatory variables have the same effect on the dependent variable. Hence the original ARDL model is sometimes called linear or symmetric ARDL,

The linear ARDL approach does not consider the possibility that negative/positive variations of the explanatory variables may have different "asymmetrical " effect on the dependent variable. Dependent variable may be more "sensitive" to explanatory variables' increases rather than decreases and vice versa.

Recently Shin et al. (2014) in their corresponding work have managed to improve the conventional ARDL model by adding the element of non-linearity (asymmetry) to it. According to them, the model is built around the following asymmetric long run equilibrium relationship:

$$y_t = \beta^+ x_t^+ + \beta^- x_t^- + u_t \tag{3}$$

where the equilibrium relationship between *y* and *x* is divided into positive $(\beta^+ x_t^+)$ and negative $(\beta^- x_t^-)$ effects, plus the error term (u_t) representing possible deviations from the long-run equilibrium.

As can be seen from equation (2), the effect of the variable x can be decomposed into two parts - positive and negative:

$$x_t = x_0 + x_t^+ + x_t^- \tag{4}$$

where x_0 represents the random initial value and $x_t^+ + x_t^-$ denote partial sum processes, which accumulate positive and negative changes, respectively, and are defi ned as:

$$x_t^+ = \sum_{j=1}^{t} \Delta x_j^+ = \sum_{j=1}^{t} max(\Delta x_j, 0) \tag{5}$$

$$x_t^- = \sum_{j=1}^{t} \Delta x_j^- = \sum_{j=1}^{t} min(\Delta x_j, 0) \tag{6}$$

By combining equation (3) with the linear ARDL (p,q) model, which was specified previously in equation (2), the asymmetric error correction model can be obtained:

$$\Delta y_t = \mu + \rho y_{t-1} + \theta^+ x_{t-1}^+ + \theta^- x_{t-1}^- + \sum_{j=1}^{p-1} \alpha_j \Delta y_{t-j} + \sum_{j=0}^{q-1} (\pi_j^+ \Delta x_{t-j}^+ + \pi_j^- \Delta x_{t-j}^-) + \epsilon_t \tag{7}$$

The NARDL (Non-linear Autoregressive Integrated Moving Average) model not only allows us to detect the existence of asymmetric effects, but also permits testing for cointegration in a single equation framework. Moreover, this model presents some advantages, over traditional cointegration techniques: flexibility regarding the order of integration of the variables involved, the possibility of testing for hidden cointegration, avoiding to omit any relationship which is not visible in a conventional linear setting, and a better performance in small data samples.

In the context of the current paper, it should be noted that ARDL is not a dedicated forecasting technique. Its main purpose is testing multiple variables for level relationship (cointegration). However, estimations from ARDL modelling may still be used for forecasting purposes. The main and only limitation of ARDL-based forecasting is the fact that unlike single-variable prediction models (ARIMA, ES), functional ARDL forecasting model requires the presence of other exogenous variables (determinants).

Thus, it is impossible to obtain a forecast for a dependent variable without adding estimated or predicted future values (for the period of forecast) of independent variables into the model. In the current paper, in order to overcome the aforementioned limitations of ARDL, the “forecast” was obtained for the past period. At least this allowed us to analyze and compare forecasting reliability and error scores.

1.5 Literature Overview

1.5.1 ARIMA and ES

The ARIMA method is one of the most popular and effective for price forecasting. Despite the fact that researches on seafood auction price forecasting are not very popular amongst the researchers, ARIMA and its variants are extensively used for price forecasting of a wide array of industries and businesses.

Exponential smoothing is also one of the most popular time series forecasting methods for univariate data. It can also be modified to support data with a systematic trend or seasonal component.

As it can be observed from the list below, most modern forecasting researches are based on AR(I)MA, ES, and their derivatives, and also on Neural Networks (NN) and other machine learning algorithms. The following researches, based on the aforementioned methods, were studied during the work on the current paper.

Rangsan Nochai and Titida Nochai (2006) researched a model for forecasting of oil palm prices in Thailand. Using time series data from 2000-2004 the authors developed a functioning ARIMA model for forecasting of three types of oil palm prices (farm prices, wholesale prices, and pure oil prices) by considering the minimum value of mean absolute percentage error (MAPE) for each tested model. Each price type required a separate ARIMA model with different parameters.

Koutroumanidis et. al (2009) applied combined ARIMA-ANN (artificial neural network) in a hybrid model to predict the future selling prices of the fuelwood (from broadleaved and coniferous species) produced by Greek state forest farms. The use of the ARIMA-ANN hybrid model provided the optimum prediction results, thus enabling decision-makers to proceed with a more rational planning for the production and fuelwood market.

Ashuri and Lu (2010) studied the possibility of Construction Cost Index (CCI) short-term prediction using Holt and Holt-Winters exponential smoothing models. The results showed that both models provided high levels of forecasting accuracy right until the data had become discrete and volatile due to critical events on the market. The authors concluded that other, more accurate models could be researched for such critical scenarios.

Zhu and Wei (2012) proposed an innovative hybrid ARIMA/LSSVM (Least Squares Support Vector Machine) model for carbon price forecasting. Carbon prices simultaneously contain linear and nonlinear patterns due to a complex mechanism of their formation. Since ARIMA alone is unable to capture nonlinear patterns, the authors proposed an innovative hybrid methodology that exploits the unique combined strength of both ARIMA and LSSVM in forecasting carbon prices. The obtained results demonstrated that the proposed hybrid model was applicable for carbon price forecasting.

Ahmad and Ahmad (2013) compared ARIMA and exponential smoothing in forecasting with different amounts of data and different forecasting period lengths. They studied crude palm oil prices, currency exchange rates, and rubber price data. The study showed that ARIMA can yield more accurate forecasts in the long term with limited data, but is less accurate for short-term data sets. On the other hand, exponential smoothing was more accurate for short-term data sets and less accurate in the long-term.

Ishaque and Ziblim (2013) compared the performance of Holt-Winters and double exponential smoothing models in forecasting future prices of crops in the Upper East Region of Ghana. In their study, double exponential smoothing performed generally better than the Holt-Winters model. However, Holt-Winters model performed better in predicting prices for crops that were influenced by seasonal and trend factors.

Velásquez et al. (2013) compared the accuracy of the forecasts for the exponential smoothing (ES) approach and the Radial Basis Function Neural Networks (RBFNN) in the case when three nonlinear time series with trend and seasonal cycle were forecasted. They eventually came to the following conclusions: ES models had a better fit but lower predictive power than the RBFNN; detrending and deseasonality allowed the RBFNN to fit and forecast with more accuracy than the RBFNN trained with the original dataset; there were no evidence that combined forecasting models were more accurate than the RBFNN and ES models.

Ayodele Ariyo Adebiyi et al. (2014) examined the forecasting performance of conventional Box-Jenkins ARIMA model versus ANN (artificial neural networks) model with published stock data obtained from New York Stock Exchange. The empirical results revealed that both ARIMA and ANN models could achieve good forecast accuracy when applied to real-life problems and thus can be used for stock price prediction. However, the researchers also observed that the pattern of ARIMA forecasting models was directional, and the ANN-based approach demonstrated superior performance over the ARIMA models.

Xin James He (2014) researched the weekly crude oil price data from U.S. Energy Information Administration over the time period 2009 - 2017 to test the forecasting accuracy by comparing time series models such as simple exponential smoothing (SES), moving average (MA), and autoregressive integrated moving average (ARIMA) against machine learning support vector regression (SVR) models. The results proved that SES and MA showed reasonably acceptable forecasting accuracy, while ARIMA was more effective and accurate. The SVR machine-learning model was considered too difficult and overcomplicated for economic and business interpretation of the forecast results.

Sánchez Lasheras et. al (2015) examined the forecasting performance of ARIMA and two different kinds of artificial neural networks models (multilayer perceptron and Elman Neural Network) using published data of copper spot prices from the New York Commodity Exchange, (COMEX). The empirical results obtained showed a better performance of both neural networks models over the ARIMA model. The findings of this research were in line with some previous studies, which confirmed the superiority of neural networks over ARIMA models in relative research areas.

Abu Bakar and Rosby (2016) used the exponential smoothing and simple moving average models for long-term prediction of Malaysian oil companies’ share prices in 2012. They ultimately concluded that exponential smoothing method was more suitable for the studied data, as it showed more accurate forecasts.

Guha and Bandyopadhyay (2016) successfully applied the ARIMA model to forecast the future gold prices on the Indian market. Gold price ARIMA forecasting helps mitigating market risks and provides guidelines for market participants and potential investors.

Fauziah Nasir Fauziah et al. (2018) compared double exponential smoothing and artificial neural networks in local sugar prices forecasting. The authors concluded that artificial neural networks were more effective for average sugar price forecasting.

Garcia et. al (2018) developed the "Theory of transgenic time series", in their paper it was applied for forecasting of rare-earth element oxide prices. Their theory implies the existence of rare-earth metal price cycles and the presence of anomalous phenomena, which the theory allows to eliminate from the time series, improving the accuracy of the forecast. In order to establish the precise sequence of data from the original time series that should be eliminated or silenced in order to achieve a more accurate forecast, an algorithm based on ARIMA models was developed, focusing on the search of the data subset that presents the biggest adjustment capacity of the selected time series model.

Ohyver and Pudjihastuti (2018) used ARIMA model for forecasting medium quality rice prices on the Indonesian internal market and achieved a good level of forecast accuracy. The results can be used by the government organizations to predict and prevent rice supply shortages, which can happen due to sharp price fluctuations.

Zhao et. al (2018) used an autoregressive integrated moving average (ARIMA) model with historical Texas fuel cost data in development of a three-step-ahead fuel cost distribution prediction. First, the data from Form EIA-923 annual report fuel consumption and power plant report were explored and the natural gas fuel costs of Texas generating facilities were used to develop and validate the forecasting algorithm for the Texas example. Furthermore, the spot price associated with the natural gas hub in Texas was utilized to enhance the fuel cost prediction. The forecasted data were fit to a normal distribution and the Kullback-Leibler divergence was employed to evaluate the difference between the real fuel cost distributions and the estimated distributions. The comparative evaluation suggested the proposed forecasting algorithm was effective in general.

Thus, considering the significant amount of related research works, it can be concluded that ARIMA and ES are very popular, flexible, and relevant forecasting techniques.

1.5.2 ARDL and NARDL

ARDL type regression models have been in use for decades, but recently they have been shown to provide a very valuable specific tool for testing for the presence of long-run relationships between economic time-series. In addition, recently developed NARDL approach provides us with even more options for studying cointegration. While not very popular among the forecast researches, linear ARDL is still capable of forecasting, albeit it is less efficient than single-variable techniques.

The following related research works were studied, in order to better comprehend the methodology, practice, and the corresponding techniques.

Fatai et al. (2003) studied the demand for electricity in New Zealand by applying Engle and Granger's ECM and ARDL forecasting methods. ARDL forecasts showed better performance than ECM.

Adom and Bekoe (2012) applied Partial Adjustment Model (PAM) and ARDL for cointegration analysis and forecasting of electricity demand in Ghana. The ARDL approach was deemed superior over PAM for forecasting purposes.

Katrakilidis and Trachanas (2012) studied the dynamics between house prices and selected macroeconomic fundamentals in Greece. They applied the asymmetric ARDL cointegration methodology over the period from January 1999 to May 2011. The evidence suggested that ignoring the intrinsic nonlinearities might lead to misleading inference. The results revealed significant differences in the response of house prices to positive or negative changes of the explanatory variables in both the long- and short-run time horizons.

Hamuda et al. (2013) investigated the determinants of investments in Tunisia using annual data over the period of 1961-2011, using an ARDL modeling is employed to investigate the impact of the GDP, monetary base and trade openness on domestic investments. The results revealed that there was an equilibrium relationship between investments and monetary base, the influence of the other factor was insignificant or ambiguous.

Hanif and Malik (2015) compared forecasting performance of various models of inflation in the context of Pakistan economy. Forecast performance was analyzed in comparison to the best evaluation benchmarks – random walk, ARIMA and AR(1) models. The forecasts from ARDL and certain combinations of point forecasts were better than the best benchmark model - the random walk model. ARDL also proved to be more effective for long-run forecasting.

Chi Junwook (2016) employed the NARDL approach to investigate the short- and long-run impacts fuel price volatility on auto travel volumes in Korea. Using monthly data from January 2000 to December 2013, the results showed that travel responds differently depending on the fuel price changes. Auto travel volumes were significantly affected by fuel price decrease, and were irresponsive to fuel prices rising in the long run. Fuel price volatility had a negative long-run impact on demand for car travel, i.e. rising fuel prices compelled Korean drivers to reduce fuel consumption and drive distances. The GDP and the road lengths were found to be vital factors in determining demand for auto travel.

Hamid and Shabri (2017) studied palm oil prices cointegration and forecasting by comparing the forecasting effectiveness of ARIMA and ARDL models. The ARDL forecast model more accurate forecast results than ARIMA.

Shrestha and Bhatta (2017) in their work discussed the properties of time series data, compared common analysis methods and presented a methodological framework for time series analysis, including ARDL models. Nepal's money and price relationship was examined. Test results obtained were found to be more robust and reliable.

Siok Kun Sek (2017) applied linear and nonlinear ARDL to examine the symmetric and asymmetric pass-through effect of oil price changes on four domestic price indices in Malaysia. The results showed and evidence of symmetric and asymmetric pass-through effects of oil price changes on domestic prices across sectors. Oil price changes led to higher output growth but could cause increase of import and production prices in the long run. On the other hand, oil price changes had a limited effect on consumer prices in the long run. The impact of oil prices on consumer prices occurred indirectly through import prices and production costs. Oil-intensive economy sectors experienced a larger impact of oil price fluctuations.

Ekhlas et al. (2018) examined whether appreciation and depreciation in oil price, interest rate, exchange rate, industrial production, and inflation have the same effects on the stock market returns by using nonlinear ARDL model. Monthly data was utilized from January 1990 to November 2016 and from May 2000 to November 2016 for the aggregate market and the nine economic sectors, respectively. The bound test results showed strong evidence that all sectors (excluding plantation sector) including the aggregate market were cointegrated.

Lacheheb and Sirag (2018) examined the relationship between oil price changes and inflation rate in Algeria from 1970 to 2014. Using the NARDL approach the study was able to capture asymmetries in the relationship between oil price and inflation. The estimated model revealed the existence of a nonlinear effect of oil price on inflation. Specifically, they found a significant relation between oil price increases and inflation rate; whereas, a significant relation between oil price reduction and inflation was absent.

Eissa and Al Refai (2019) used linear and nonlinear ARDL models, to investigate the dynamic linkages between oil prices and agricultural commodities prices. The results from the linear ARDL model showed that barley, corn and rapeseed oil did not have long run cointegration with oil prices. NARDL showed that barley, corn and rapeseed oil cointegrated with oil prices in the long run. The NARDL model was more appropriate for describing the dynamic relationships.

Marques et al. (2019) analyzed the energy efficiency of the industrial sector for 11 European Union countries for a time span from 1997 to 2015, using NARDL model. The results indicated that additional industry investments increased energy efficiency and reduced greenhouse gas emissions. The same was for the Industrial Energy Price Index. To verify robustness, the Environmental Kuznets curve was estimated, using GDP per capita and the Industrial Production Index.

Gordon (2020) used ARDL as a basis for building a parsimonious and useful price forecasting model that characterizes both short-run dynamics and the long-run equilibrium price structure of the ex-vessel Canadian lobster market. The estimated ARDL/EC model was used to simulate the ex-vessel price of lobster under different policy scenarios that attempt to place reasonable upper and lower bounds on possible expected price outcomes. The model proved to be straightforward, simple to update, and could be used in simulating welfare and policy implications for lobster-fishing industry.

Judging by the amount of ARDL/NARDL researches on cointegration, it is obvious that the method is primarily used for discovering level relationships between the variables. However, those few works that applied ARDL for forecasting purposes, discovered its forecasting superiority over ECM, PAM, ARIMA, etc. by general consent, the current paper aims to prove this claim once again.

Table 1 Combined List of Relevant Studies.

Studies	Researched subject	Method
Fatai et al.(2003)	Demand for electricity in New Zealand	ARDL Engle and Granger' s ECM
Rangsan Nochai and Titida Nochai (2006)	Oil palm prices (farm prices, wholesale prices, and pure oil prices) in Thailand in 2000-2004.	Conventional Box-Jenkins ARIMA model
Koutroumanidis et. al (2009)	Selling prices of the fuelwood (from broadleaved and coniferous species) produced by Greek state forest farms	ARIMA/Artificial Neural Network hybrid model
Ashuri and Lu (2010)	Construction cost index	Holt Exponential Smoothing Holt-Winters Exponential Smoothing
Adom and Bekoe (2012)	Electricity demand in Ghana	Partial Adjustment Model ARDL
Katrakilidis and Trachanas (2012)	House prices and selected macroeconomic fundamentals in Greece	NARDL
Zhu and Wei (2012)	Carbon prices	Hybrid ARIMA/LSSVM (Least Squares Support Vector Machine) model
Hamuda et al. (2013)	Investments in Tunisia using annual data over the 1961-2011 period	ARDL
Velásquez et al. (2013)	Electricity contract prices Electricity demand Paper sales	Exponential Smoothing RBFNN (Radial Basis Function Neural Network)

Ishaque and Ziblim (2013)	Crops prices	Double Exponential Smoothing Holt-Winters ES
Ahmad and Ahmad (2013)	Crude palm oil prices Currency exchange rates Rubber prices	ARIMA Exponential smoothing
Ayodele Ariyo Adebiyi et al. (2014)	New York Stock Exchange stock data	Conventional Box-Jenkins ARIMA model ANN (Artificial Neural Networks) model
Xin James He (2014)	Crude oil prices	Simple Exponential Smoothing ARIMA SVR (Support Vector Regression)
Hanif and Malik (2015)	Inflation rates in Pakistan	ARIMA ARDL-based forecasting
Sánchez Lasheras et. al (2015)	Copper spot prices from the New York Commodity Exchange (COMEX)	Box-Jenkins ARIMA Multilayer perceptron ANN model Elman NN model
Chi Junwook (2016)	Short- and long-run impacts of fuel price volatility on auto travel volumes in Korea	NARDL
Guha and Bandyopadhyay (2016)	Gold prices on the internal Indian market	Conventional Box-Jenkins ARIMA model
Abu Bakar and Rosby (2016)	Oil companies' share prices	Simple Moving Average Exponential Smoothing
Hamid and Shabri (2017)	Palm oil prices	ARIMA ARDL-based Forecasting
Siok Kun Sek (2017)	Symmetric and asymmetric pass-through effect of oil price changes on four domestic price indices in Malaysia	Linear ARDL NARDL
Shrestha and Bhatta (2017)	Methodological framework for time series analysis	ARDL
Ekhlas et al. (2018)	Effects of oil price, interest rate, exchange rate, industrial production, and inflation on the stock market returns	NARDL
Fauziah Nasir Fauziah et al. (2018)	Sugar prices	Double Exponential Smoothing Artificial Neural Networks
Garcia et. al (2018)	Rare-earth element oxide prices	ARIMA-based algorithm for «transgenic» time series
Ohyver and Pudjihastuti (2018)	Medium quality rice prices on the Indonesian internal market	Conventional Box-Jenkins ARIMA model

Lacheheb and Sirag (2018)	Oil price changes and inflation rate in Algeria from 1970 to 2014	NARDL
Zhao et. al (2018)	Texas fuel cost data in development of a three-step-ahead fuel cost distribution prediction.	Conventional Box-Jenkins ARIMA model
Eissa and Al Refai (2019)	Oil prices and agricultural commodities prices	Linear ARDL NARDL
Marques et al. (2019)	Energy efficiency of the industrial sector for 11 European Union countries for a time span from 1997 to 2015	NARDL Environmental Kuznets Curve
Gordon (2020)	Ex-vessel Canadian lobster prices	ARDL-based Forecasting Framework

1.6 Research Objectives

Considering the magnitude of seafood trade between Russia and South Korea, and the importance of Red King Crab for Korean consumers and businessmen, the topic of this research is deemed significant enough from both academic and practical points of view. Given all of the above, the objectives for the current research may be stated as follows:

1. By applying ARIMA, ES, and ARDL methods, obtain forecasts of Russian Red King Crab wholesale auction prices in 2014-2019.

2. Find out, which time series analysis method is more suitable and accurate for seafood auction price forecasting - ARIMA, ES or ARDL.

3. Using linear and non-linear ARDL techniques, perform a cointegration analysis of Russian RKC auction prices and several related exogenous variables, which possibly affect the market situation, in order to find long- and short run cointegrating relationships.

For better comprehension of the research topic, a general description of wholesale seafood auctions, Russian-Korean seafood trade, and crab catching industry’ s features will be presented in the current research.

The potential results of the current research, besides having a purely academic importance, may also yield valuable economical and decision-making information for market participants and policy makers.

2. Russian-Korean Crab Trade and Wholesale Seafood Auctions

2.1 Wholesale Seafood Auctions

Auctions are often used to organize fish markets around the world, particularly at the port and wholesale levels of the value chain. Mostly because auctions usually bring many sellers and buyers together, and a great variety of seafood species is generally available in various sizes, quantities, and qualities.

Traditionally, fish markets have been organized with financial funding of all its participants in a form of partnerships. In this regard, Korean wholesale fish auctions stand out among other wholesale fish markets, because they do not become the owners of distributed seafood. The only distribution form in Korean wholesale seafood markets is auction, which is always preceded by thorough examination and inspection of every seafood lot for sale. Electronic sales without preliminary quality control are forbidden, as well as any futures contracts.

For the purposes of the current research, and in order to understand the specifics of Korean fish markets, the oldest and largest fish market in Korea – the Noryangjin Fisheries Wholesale Market known commonly as the Noryangjin Fish Market (노량진 수산시장) was chosen. Established in Seoul in 1927, this fish market became not only the largest wholesale seafood market in Korea, but also a major tourist attraction.

Traditionally, all seafood auctions in South Korea begin at night – from 1.00 AM to 3.00 AM, and the trade lasts for several hours. This is probably due to the perishable nature of seafood, so the market traders make sure the goods are fresh and ready to be shipped by the beginning of a new day's business opening hours.

The price-setting process is highly influenced by the freshness and culinary qualities of the goods. Of course, different seafood types are not equal to each other – some are more valuable/expensive, while others are less so. Freshness, however, will always be the ultimate factor in the price setting of seafood. Fishing methods and equipment often define the final quality/price of seafood for sale, since some fishing gear (e.g. trawls, knotted nets) inflict more damage to fish and other gear (like knotless nets and some traps) inflict less damage.

There are several main auction types, more or less suitable for selling different goods, however wholesale seafood auctions traditionally employ the so-called Dutch auction model, also known as an open descending price auction. In the traditional Dutch auction, the auctioneer begins with a high asking price for some quantity of similar items. The price is lowered until a participant is willing to accept the auctioneer's price for some quantity of the goods in the lot, or until the bids reach the reserve price (i.e. a secret lowest price a seller is willing to accept).

If the first bidder does not purchase the entire lot, the auctioneer continues lowering the price until all of the items have been bid for, or up until the reserve price is reached. Items are allocated based on bid order - the highest bidder selects their item(s) first, followed by the second highest bidder, and etc. In some Dutch auctions, all of the winning participants pay only the last announced price for the items they bid on.

The Dutch auction is named after its best-known example; the Dutch tulip auctions. In addition to flower sales in the Netherlands, Dutch auctions have also been used worldwide for perishable commodities, such as seafood or tobacco.

Recently, however, due to the development of digital technologies, South Korean fish markets have shifted to electronic auction trade. It is a system, where bids from multiple different auction participants are simultaneously sent via wireless communication into the mainframe, which analyzes the bids and chooses the winner. Modern computer and communication technologies made electronic auctions faster and more accurate than traditional ones. It is also much easier to obtain price and bid statistical data, which allows easier conducting of economical and statistical research, as well as adjusting pricing policies.

Figure 1 shows a general example of a large Korean wholesale seafood market’s operation scheme.

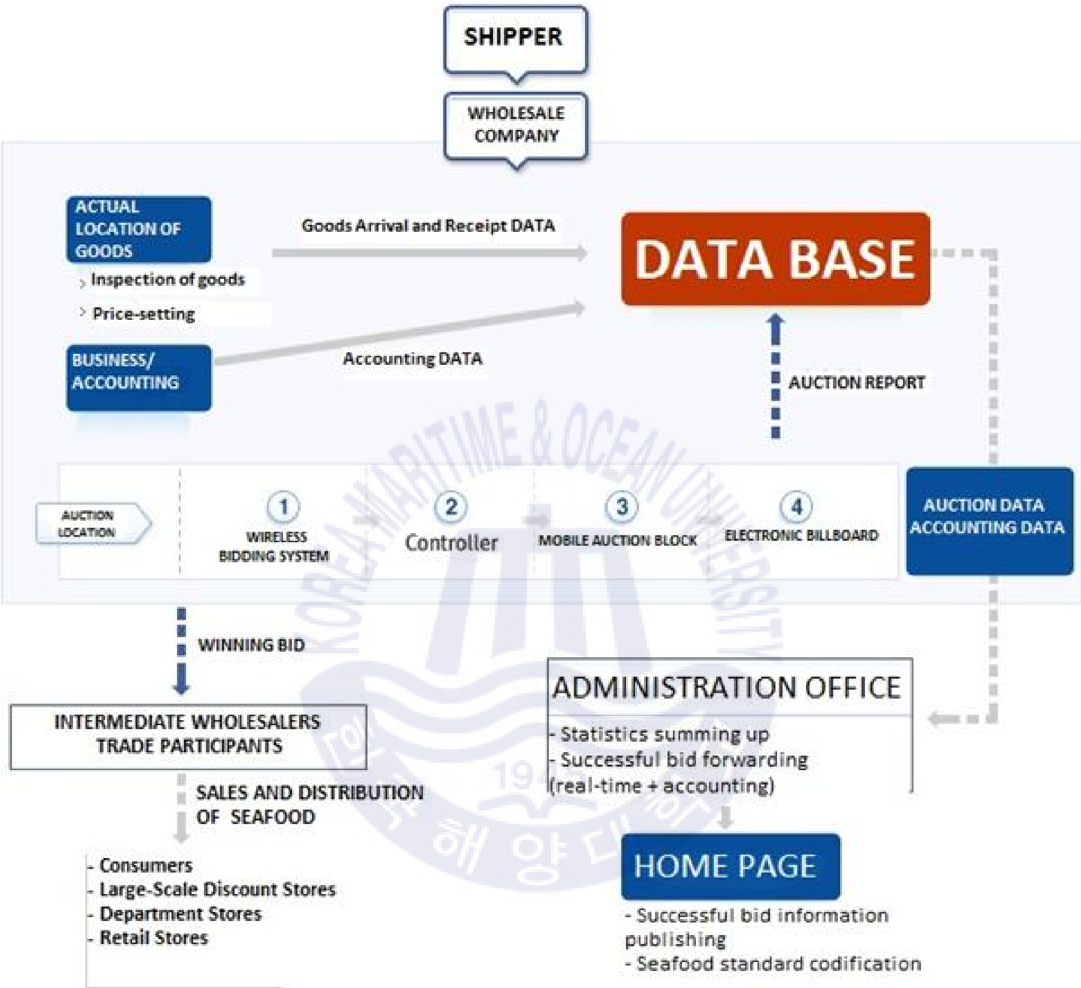

Fig. 1 An Example of a Major Korean Wholesale Seafood Market Operation Scheme

Some elements of this operation scheme require further clarifying. A shipper is a fishing company or a group of companies that supply different aquatic products to wholesale seafood markets, and which are enrolled and registered in accordance with rules and regulations of the market’s administration. All shippers must comply with the market administration’s requirements and code of conduct, especially when it concerns proper quality and quantity of the goods.

A wholesale company is a legal entity, which is officially entrusted by shippers to present and sell seafood to intermediate wholesalers and/or other trade participants. As a payment for their services, wholesale companies charge a commission, which is defined as a percentage from the final selling price of goods. Thus, both shippers and wholesale companies are interested in selling their goods at a highest possible price. Wholesale companies must operate on the principles of impartiality and integrity, without unfair discrimination of entrusted goods, shippers, other market participants, and business associates.

An intermediate wholesaler is a legal entity, authorized by the fish market administration, which is directly involved or mediates on some other entity's behalf in the seafood trade on the market. In order to participate in fish market activities, an intermediate wholesaler must be qualified and receive permission from the market administration.

Trade participants are processed goods manufacturers, seafood retailers, exporters, and other consumer entities who are authorized by the market administration and are eligible for direct buying of seafood on the market. However, they are specifically prohibited from selling goods on the market.

2.2 Russian-Korean Seafood Trade and Aquatic Production

According to the Food and Agriculture Organization of the United Nations (FAO) 2017 statistics yearbook, the world's total aquatic production in 2016 was 79.28 million tons. In the same year, the largest producers of aquatic products were China (15.25 million tons, accounting for 19.2% of the world's total production), Indonesia (6.1 million tons, 7.7%), USA (4.9 million tons, 6.1%), and Russia (4.46 million tons, 5.6%). Republic of Korea ranked 14th in the world aquatic fisheries, with 1.7% of the world's total output at 1.37 million tons. The relevant world statistics is presented in Table 2.

Korean and Russian capture fisheries trends are presented in Figure 2. The Korean fisheries production trend is rather stable, however, a slow decline may be observed in the recent years. The Russian capture fisheries production trend has been going upward since 2004.[4)]

Table 2 2005-2016 World Seafood and Aquatic Capture Production

Country	Production (t)			Annual change (%)	Annual change (t)
	Avg. in 2005-2014	2015	2016		
China	13 189 273	15 314 000	15 246 234	-0.4	-67 766
Indonesia	5 074 932	6 216 777	6 109 783	-1.7	-106 994
USA	4 757 179	5 019 399	4 897 322	-2.4	-122 077
Russia	3 601 031	4 172 073	4 466 503	7.1	294 430
Peru Total	6 438 839	4 786 551	3 774 887	-21.1	-1 011 664
(excl. Anchovetta)	989 918	1 016 631	919 847	-9.5	-96 784
India	3 218 050	3 497 284	3 599 693	2.9	102 409
Japan	3 992 458	3 423 099	3 167 610	-7.5	-255 489
Vietnam	2 081 551	2 607 214	2 678 406	2.7	71 192
Norway	2 348 154	2 293 462	2 033 560	-11.3	-259 902
Phillipines	2 155 951	1 948 101	1 865 213	-4.3	-82 888
Malaysia	1 387 577	1 486 050	1 574 443	5.9	88 393
Chile Total	3 157 946	1 786 249	1 499 531	-16.1	-286 718
(excl. Anchovetta)	2 109 785	1 246 154	1 162 095	-6.7	-84 059
Morocco	1 074 063	1 349 937	1 431 518	6.0	81 581
Republic of Korea	1 746 579	1 640 669	1 377 343	-16.0	-263 326
Thailand	1 830 315	1 317 217	1 343 283	2.0	26 066
Mexico	1 401 294	1 315 851	1 311 089	-0.4	-4 762
Myanmar	1 159 708	1 107 020	1 185 610	7.1	78 590
Iceland	1 281 597	1 318 916	1 067 015	-19.1	-251 901
Spain	939 384	967 240	905 638	-6.4	-61 602
Canada	914 371	823 155	831 614	1.0	8 459
Taiwan	960 193	989 311	750 021	-24.2	-239 290
Argentina	879 839	795 415	736 337	-7.4	-59 078
Ecuador	493 858	643 176	715 357	11.2	72 181
UK	631 398	698 996	701 749	-0.4	-2 753
Denmark	735 966	868 892	670 207	-22.9	-198 685
Total 25 major countries	65 451 506	66 391 560	63 939 966	-3.7	-2 451 594
World TOTAL	79 778 181	81 247 842	79 276 848	-2.4	-1 970 994

Source: FAO 2019. Fishery and Aquaculture Statistics 2017, Rome

4) According to World Bank statistics, https://data.worldbank.org/indicator/ER.FSH.CAPT.MT?end=2016&locations=KR-RU&name_desc=false&start=1991. Accessed on May 1st 2020.

According to FAO, live, fresh, or chilled seafoods are the most preferred and highly priced forms of fish consumption. This represents the largest share of fish for direct human consumption (45% in 2016), followed by frozen (31%), prepared and preserved (12%), and cured (i.e. dried, salted, in brine, fermented, smoked – 12%). Freezing represents the main method of processing fish for human consumption; it accounted for 56% of total processed fish for human consumption and 27% of total fish production in 2016.

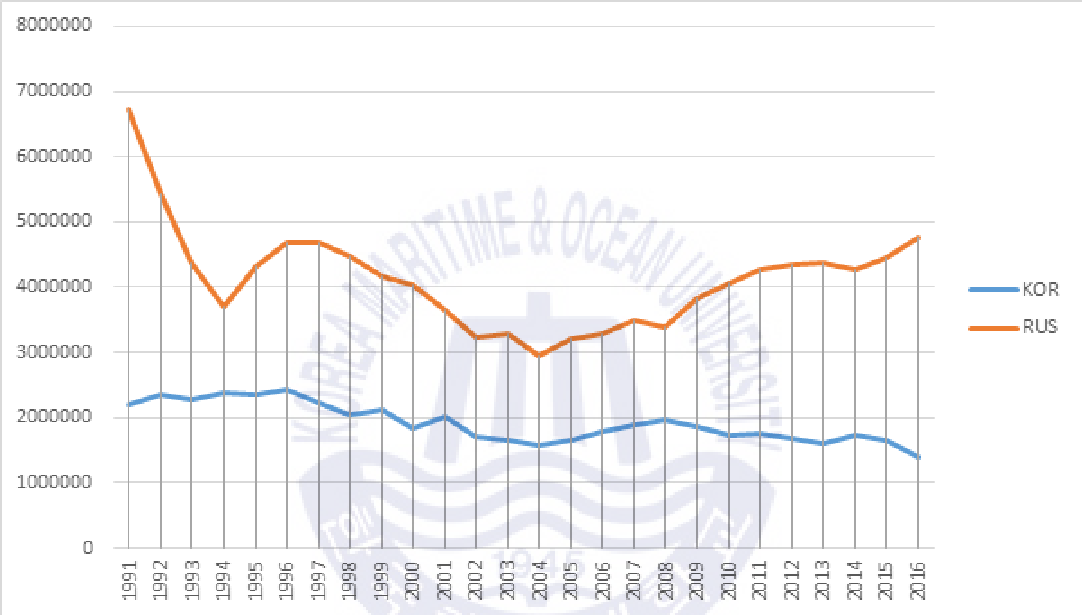

Fig. 2 Capture Fisheries Production of South Korea and Russia in 1991-2016 (tons)

Live fish is especially appreciated in Eastern and Southeastern Asia and in niche markets in other countries with strong Asian immigrant communities.[5] Commercialization of live fish has grown in recent years due to technological developments, improved logistics, and increased demand. Systems for live fish transporting range from primitive home-made systems of plastic bags filled with an oxygen saturated water, to specially designed or modified tanks and containers, and onto sophisticated systems installed in trucks and other vehicles that regulate

5) FAO. 2018. The State of World Fisheries and Aquaculture 2018 – Meeting the sustainable development goals. Rome.

temperature, filter and recycle water, and also enrich it with oxygen.

2.3 Russian Red King Crab Production and Trade Specifics.

The Red King Crab (RKC), also known as Kamchatka Crab or Alaskan King Crab (Paralithodes Camtschaticus) is one of the most important goods for both Russian and South Korean seafood markets. It is one of the largest species of king crabs in the Far East. The largest species can reach a carapace width of up to 28 cm, a leg span of 1.5-1.8 m, and an average weight of 3-5 kg (the largest known male specimen had a record weight of 12.7 kg).

The crab fishing business is sometimes called the "Golden rush" of the Far Eastern seas. The Red King Crab lives in the cold waters of the Sea of Okhotsk and the Bering Sea. Crab fishermen usually work in extreme weather and labor conditions in order to supply the delicious seafood to consumers, who are willing to pay handsomely for it. The profession of a crab fisherman is one of the most dangerous in the world - all kinds of accidents, injuries, and even deaths may occur during the fishing voyage. Falling overboard is one of the most common fatal accidents that may happen.

Crustaceans are a valuable biological resource. The crab fishing industry is legally obliged to adhere to individually established fishing quotas. All fishing grounds are divided into different fishing zones that are strictly specified geographically. The scientists from fishing scientific institutions are always monitoring the important biological parameters: share of females in the total population, growth rates of the young, food reserves, etc. If any threat to the crab population occurs, all fishing is forcibly stopped by the authorities.

In the end of the 1990s, Red King Crab fishing in the Sea of Okhotsk was almost completely illegal - both Russian and foreign poachers operated extensively in the region. Eventually, the government, being unable to control the situation, had prohibited any kind of crab fishing in the region for the next several years.

The RKC fishing season usually starts in October, however due to biological conditions and shifting market situation, the season start can be postponed up until

January. All RKC fishing vessels must operate according to their licenses and within their allowed fishing grounds.

Russian RKC catching vessels are usually from 18 to 50 meters in length. A standard Russian fishing deck crew consists of a fishing foreman, bosun, and 8-9 sailors. A ship's master is responsible for everything that happens onboard, and especially for catching and yield. The ship's master, fishing foreman, and bosun supervise all topside and fishing operations.

All Russian RKC fishing vessels are equipped with onboard processing plants and refrigeration equipment, which provides at least a basic level of seafood processing - leg separation, washing, cleaning, boiling, chilling, freezing, packing etc. However, the most valuable type of crab catch is live crab. Live RKC fishing requires a completely different (and much more expensive) set of onboard equipment, including large seawater tanks, seawater chilling and circulation pumps, and support machinery.

Russian RKC crab fishing is traditionally performed with crab pots - i.e. traps, made of welded metal carcass and netting, which are usually rectangular or conical in shape. Largest heavy duty rectangular traps weigh about 300-400 kg each; crab fishing vessels can be equipped with approximately 40-250 traps, depending on the size of a vessel and catching method. Inside every trap there is a plastic bait can that contains a piece of slightly rotten herring, cod or sardine. Crabs, attracted by the smell of the bait, enter the pot, but cannot leave it because of the special form of the pot entrance.

Tens of traps with bait cans and buoys attached are interconnected with a mainline - a very (up to several kilometers) long polypropylene rope, 20-24 mm in diameter. The whole construction is gradually cast into the water in a catching area of approximately 100 square kilometers. Crab pots submerge to a depth of 120 meters. After a while, full pots are lifted onboard with a special grappling hook and a drum winch conveyor mechanism. Fishermen manually clear the pots of caught crustaceans and other sea life and send them to the factory deck of the vessel. It should be noted that only fully grown male crabs are allowed to be caught. Females and youngsters must be released back into the water. Every vessel works until all cargo holds/seawater tanks are full with crabs either frozen and packed or alive. One fishing cycle usually takes 3 days; if the crew is inexperienced or just unlucky, the fishing cycle may take up to 8-9 days.

Frozen crabs are transferred to reefer vessels that haul the cargo to a nearest seaport, capable of organizing refrigeration logistics. It is very cumbersome and risky to transfer live crabs to transport vessels, since many crabs may perish in the process. Thus, live crab catching vessels usually transport their haul to ports independently on their own.

If even a single crab dies in a water tank, its decomposing body starts to produce deadly toxins, which in turn may poison other crabs and eventually lead to a loss of the whole catch. Live crabs may die of different causes - contaminated or excessively warm water in a tank, insufficient water salinity etc. In addition, the seawater in a tank must always circulate, since crabs would perish faster in a dead water than without any water at all. All these troubles of keeping the RKC catch alive are greatly rewarded, since prices for live crab are exorbitant in comparison to frozen crabmeat.

Apart from obviously being dangerous and exhausting for the crew, the RKC fishing is also a very complicated process by itself. Since RKC are bottom-dwelling creatures, an echo sounder is useless in finding large clusters of them. They also randomly migrate every year on different routes. That is why a crab catching ship’s master must rely only on his professional experience and intuition in order to have a successful fishing.

During the RKC fishing season crew members have to work in extreme conditions - low temperatures, strong winds up to 100 km/h, and 15 meters high storm waves. Besides, crewmen can have only 3-4 hours of sleep a day. Cold seawater, strong winds and low temperatures inevitably cause a massive ice formation on a ship’s hull. In order to prevent capsizing, the sailors have to stop all fishing operations and manually crack the ice. In such conditions people often suffer from hypothermia and viral infectious diseases, which in turn severely cripple the crew’s performance and may lead to work accidents.

However, it should also be noted that salary levels on crab catchers are one of the highest in the Russian fishing industry, that is why officers and sailors are usually content with extremely hard labor conditions, and many young specialists seek employment in crab catching fleets.

Considering all the stated above, frozen or live RKC is a very expensive and precious commodity, not due to its exoticism or rarity, but mostly due to the expensive, dangerous, and labor-consuming catching process.

Due to its rich nutritional and taste qualities, RKC is in high demand in Asian seafood markets, it is also the most valuable export commodity of the Russian fishing industry. Russia is the largest Red King Crab producer, accounting for 63% of global supply, in which 45% accounts for legal harvests and a conservative estimate of 18% accounts for illegal, unreported, or undocumented fishing activity. More than 95% of Russian total Red King Crab catch goes for export to the markets of China, Japan and, of course, South Korea.

According to Korea Customs Service, in 2018 Korea's total imports of crustaceans (HS code 0306) from all origins reached 134,000 tons (121,781 ton in 2017 – 10.7% increase) with a total value of $1.17 billion ($1.03 billion in 2017 - 13.5% increase).

The largest importers of crustaceans on Korean markets in 2017 were China and Russia. China's total import weight reached 42,200 tons (41,900 tons in 2017 – 0.7% increase) with an import value of $154.5 million ($133.7 million in 2017 – 15.5% increase). Russian imports amounted to 15,500 tons (14,300 thousand tons in 2017 – 8.4% increase), however due to more expensive imported aquatic life forms that comprise Red King Crab, total Russian import value was significantly higher than Chinese, reaching $367 million ($301.3 million in 2017 – 22% increase).[6)]

As it can be seen from Table 3 and Figures 3 and 4, Russian live crab is an extremely valuable and important commodity for the Russian-Korean seafood trade. Import growth rates and values in the early 2000's were tremendous in both absolute and monetary values. Since the absolute majority of the Russian crab catch

6) Korea Customs Service database https://unipass.customs.go.kr:38030/ets/index_eng.do – Accessed on May 1st 2020

traditionally goes for export, Russian crab fishing enterprises have been receiving extreme profits since the early 1990's.

Table 3 Total Annual Values of Russian Live/Fresh/Chilled Crabs (HS Codes 030624/030633), Imported to South Korea in 1999-2019

Year	Total import value (USD thousands)	Annual total value change (%)	Total import weight (t)	Annual total weight change (%)
1999	33	n/a	5.60	n/a
2000	316	858	73.60	1214
2001	4 812	1423	1 405.40	1810
2002	40 389	739	11 870.40	745
2003	45 117	12	12 418.07	5
2004	55 540	23	13 629.70	10
2005	57 150	3	12 096.70	-11
2006	75 629	32	15 522.20	28
2007	84 109	11	15 738.48	1
2008	57 440	-32	9 322.30	-41
2009	61 098	6	10 823.61	16
2010	24 234	-60	3 091.05	-71
2011	37 994	57	2 721.55	-12
2012	74 468	96	5 630.80	107
2013	65 770	-12	4 007.40	-29
2014	134 388	104	6 154.37	54
2015	174 150	30	9 415.18	53
2016	178 953	3	8 433.56	-10
2017	261 415	46	11 654.80	38
2018	317 889	22	12 443.00	7
2019	375 107	18	13 987.40	12

Source: Korea Customs Service database

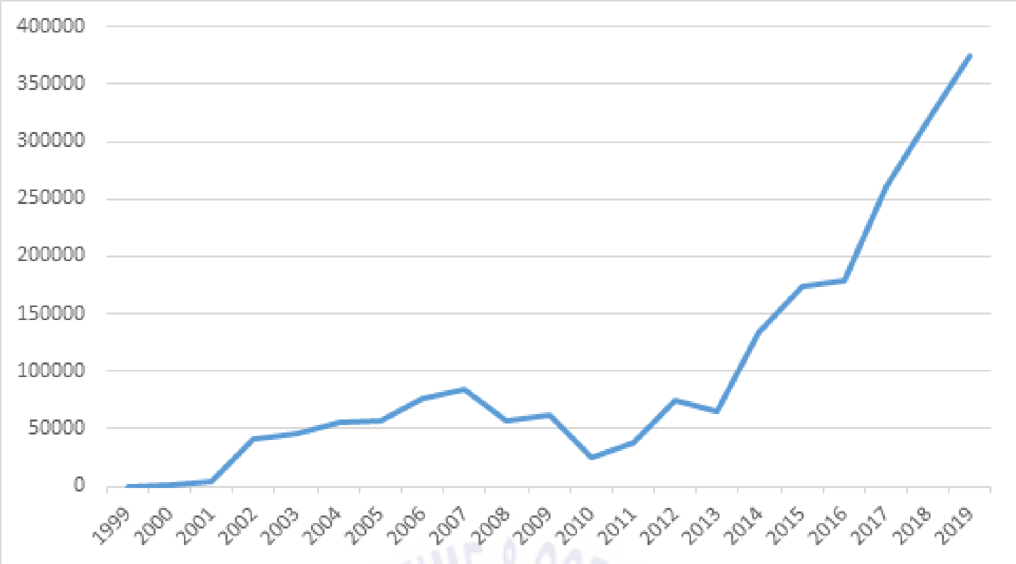

Fig. 3 Annual Russian Live Crab Values, Imported in South Korea in 1999-2019 (USD thousands)

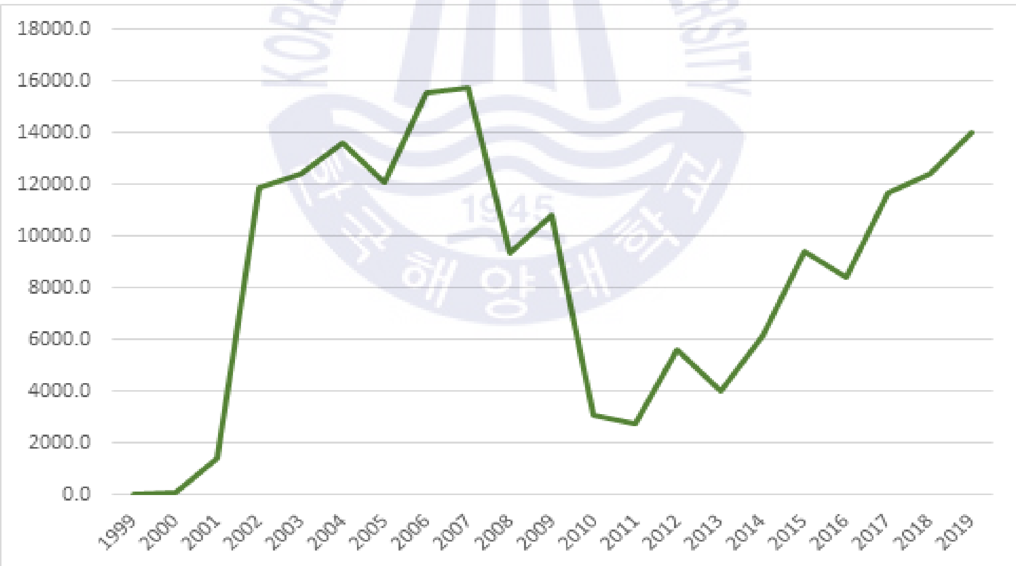

Fig. 4 Annual Russian Live Crab Values, Imported in South Korea in 1999-2019 (tons)

Nevertheless, several sharp drops in import values are also present, as can be seen from Figures 3 and 4. These declines were most likely caused by internal problems of the Russian fishing industry over recent years: high levels of corruption, business criminalization and smuggling, high competition, hardening of customs and taxing regulation policies, obsolete Soviet-era fishing fleet and coastal facilities, underdeveloped shipbuilding and repair capabilities, etc. In addition, a significant downward trend, which existed from 2008 to 2011, may be the result of the 2008 financial crisis that greatly impaired the Russian economy in particular and its foreign trade partners' solvency in general.

As it has been already mentioned in the previous chapters, the question of seasonality is an important aspect when it comes to choosing a forecasting technique for a particular set of data. In reality, demand for seafood may sway during different seasons, which causes the prices to follow these seasonal changes. However, when it comes to RKC auction trade in particular and other seafood auction trade in general, there is no strict correlation between seasonal factors and seafood auction price and consumption changes, unlike with electric power or district heating consumption, for example. Seafood auction prices greatly depend on quality and available quantity of the goods. Modern storage and transport technologies as well as effective logistics schemes help to mitigate natural and seasonal conditions.

Red King Crab fishing season in the Russian Far East usually starts on September 1 and lasts up until December 31. During the season, Red King Crab carrier vessels unlade every week in Korean ports of Sokcho (속초), Donghae (동해) and Russian port of Zarubino (Зарубино). After that importers' reefer and live fish tank trucks transport the catch to their designated facilities, including seafood markets and commercial cold storages, from where it can be distributed to wholesalers through auctions.

It takes approximately one month for fresh or frozen Red King Crab to reach seafood market facilities. Effective logistics chains and modern equipment can guarantee that frozen Red King Crabs keep their original taste and nutritional qualities for up to two years after being frozen. Live crabs can be stored in special live fish tanks for approximately one month. Such preserved products can be put up on an auction sales almost year-roundly, and any selling risks are minimal.

Sometimes prices may rise during summer vacation season in Korea (usually from

June to August), when seafood restaurants are in high demand for people on vacation. Sometimes prices may fall due to oversupply on the market. Especially in the recent years, fishing companies from Europe and the US are trying to compete with Russian fisheries for the Korean Red King Crab market.

Crab quality also affects price. There is even a special parameter that defines the amount of flesh inside crabs' legs - the so-called "meat content" measure. This parameter is very important for price forming. Live crabs must have all their legs in place, missing legs, and/or any shell damage is unacceptable. Obviously, lower quality crabs cannot be sold at high price.

Catching conditions and regulations also play a significant role in seafood price forming. Historically the Russian government has been distributing crab-catching rights among the fishing companies in the form of quotas, which represent a percentage of a TAC (Total Allowable Catch) value, also established by the government for every seafood type in every catching zone. However, the crab-catching rights distribution system has changed recently. Starting from 2019, 50% of all TAC shall be distributed for a 15-years period between the market participants through an auction, where the highest bidder gets more quotas. The auction winners are also obliged by the Russian government to build new crab-catching vessels as a part of the auction bargain.

Naturally, most market participants were against the auction distribution, due to its obvious contradiction to the principles of fair market competition, since it means that major fishing companies (usually with government participation or support) will be able to obtain more quotas than independent medium-sized and small-sized enterprises. Unfortunately for the latter two categories, the government is particularly interested in making crab quota auctions a permanent tradition, since all auction bid income goes directly to the state treasury. In 2019 the total crab quota auction bid income amounted to almost $2.4 billion. The largest fishing companies also have a very strong lobby presence in the Russian government and both chambers of the Russian parliament.

In recent years the largest Russian fishing companies, which did not specialize in crab fishing before, made considerable efforts in entering the crab fishing market of the Russian Far East through acquisition (sometimes involuntary), merging, and consolidating smaller enterprises into large ones. Considering all the aforementioned and high levels of corruption in both the Russian economy and fishing industry, it is highly likely that eventually only a handful of the largest enterprises will stay in the market. This will undoubtedly influence imported Russian seafood price forming in South Korea, since it is one of the most important export destinations for the Russian fishing industry.

There is absolutely no doubt that the seafood trade in South Korea is very important from both economic and consumer's points of view. Taking into consideration that Russian Red King Crab is one of the most valuable and important commodities on the market, it is of great interest for us to research the possibilities of the Red King Crab auction price forecasting. A valid Red King Crab auction price forecasting model may prove useful for all of the involved parties - importers and producers, auction brokers, intermediate wholesalers, distributors, even for retailers and restaurant owners. Moreover, it is of great academic interest to determine what time series forecasting models are more accurate and reliable for seafood auction price forecasting in general.

Moreover, the price forming mechanism for such valuable products must be definitely governed by more than just local market situation and supply/demand ratio. National micro- and macroeconomic situation may also play a significant role. Wholesale seafood trade is not limited to only Russian crabs, there are also other highly demanded species from both economic and gastronomic points of view, and Russia in not the only Red King Crab importer on the market. Thus, in order to "dissect" the seafood auction price-forming and determine the level of involvement of other contributing economic factors, cointegration techniques must be employed to find long- and/or short run relationships between the dependent and exogenous variables.

3. Data and Analysis

3.1 Price Data and Forecasting

3.1.1 ARIMA/ES Weekly Data Set

For the single-variable techniques (ARIMA, ES) forecasting purposes, statistic data for fresh Russian Red King Crab average auction prices in 2014-2019 was obtained from Noryangjin Fisheries Wholesale Market's electronic database[7]. The obtained data was reprocessed into time series for the purposes of the current research. For our single-variable forecast modelling purposes, weekly average RKC auction prices were obtained. The statistical software package, used for ARIMA/ES forecast modelling, was STATA/SE ver. 14.2.

The data covers the period from the 1st week of 2014 to the 26th week of 2019, with a total number of 287 observations. The studied variable was defined as: Avg_P_KRW - average weekly auction price per 1 kg of fresh Russian Red King Crab (₩).

The descriptive overview of the data set is presented in Table 4:

Table 4 Forecast Data Set Descriptive Statistics

Value	Number of observations	Mean	Std. Dev	Min	Max
Avg_P_KRW (₩)	287	15 625.44	5 992.89	2 000	40 400

Source: Author's own calculations in Stata ver. 14.2.

7) https://www.susansijang.co.kr/nsis/mim/info/mim9030

3.1.2 Configuring the Parameters of the ARIMA (p, d, q) Model

Graphical representation of a time series data is an important preliminary step where data stationarity may be confirmed or denied. In general, a stationary time series will have no predictable patterns in the long-term, i.e. no distinct trend or seasonal component. Time plots will show the series to be roughly horizontal (although some cyclic behavior or insignificant number of outliers is possible), with constant variance.

As can be seen from Figure 5, there is no evident trend or seasonality pattern in the data. However, visual assessment may not be enough to confidently reject the probability of non-stationarity. Additional econometric assessment methods must be employed for a final conclusion.

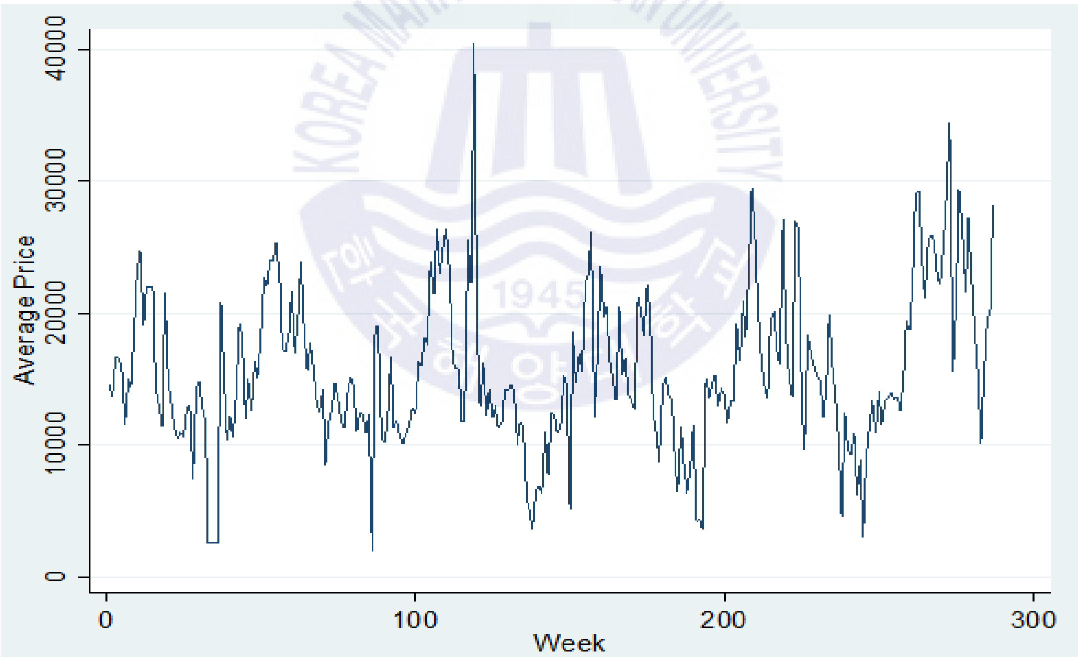

Fig. 5 Time Series Graph of Average Russian RKC Weekly Auction Price in 2014-2019

In order to definitively reject the probability of non-stationarity of the data, the Dickey-Fuller test must be employed, it helps to examine the (non)stationarity in time series data. An important assumption of this test is that the error term is uncorrelated. Therefore, an Augmented Dickey Fuller (ADF) test must be conducted. It checks the correlation in error term by adding lags.

Before applying the test, the null-hypothesis that the time series data set is non-stationary should be stated.

Table 5 Forecast Data Set ADF Results

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-7.314	-3.989	-3.429	-3.130
MacKinnon approximante p-value for Z(t) = 0.0000				

Source: Author’ s own calculations in Stata ver. 14.2.

The Augmented Dickey Fuller test results are shown in Table 5. Since the acquired ADF Test Statistic’ s absolute value is bigger than 1%/5%/10% critical values, and the Mackinnon approximate p-value for *Z(t)* equals zero, it can be safely assumed that there is no unit root, and the null hypothesis can be rejected. Thus, the data set is stationary.

In order to double check the aforementioned stationarity assumption under ADF, the modified version of the ADF test - the DF-GLS test (Dickey-Fuller Generalized Least Squares test) was executed (Table 6).

The DF-GLS test was proposed by Elliott, Rothenberg, and Stock (1996) and is essentially an ADF test, except that the time series is transformed via a generalized least squares (GLS) regression before performing the test. Elliott, Rothenberg, and Stock (1996) as well as later studies have shown that this test has significantly greater power than the previous versions of the ADF test.

The max lag parameter was chosen by the Schwert criterion. The obtained DF-GLS results also showed that the null hypothesis can be rejected and the data set is stationary. The null of a unit root was rejected at the 5% and 10% levels for all 15 lags. Therefore, there is no need in differencing the data set in order to perform the ARIMA modelling.

Table 6 Forecast Data Set DF-GLS Results

Lags	DF-GLS tau Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
15	-4.326	-3.480	-2.813	-2.533
14	-3.719	-3.480	-2.821	-2.54
13	-3.403	-3.480	-2.829	-2.548
12	-3.332	-3.480	-2.837	-2.555
11	-3.176	-3.480	-2.844	-2.562
10	-3.203	-3.480	-2.851	-2.568
9	-3.220	-3.480	-2.859	-2.575
8	-3.242	-3.480	-2.865	-2.581
7	-3.296	-3.480	-2.872	-2.587
6	-3.523	-3.480	-2.878	-2.593
5	-3.692	-3.480	-2.885	-2.598
4	-3.799	-3.480	-2.890	-2.604
3	-4.133	-3.480	-2.896	-2.609
2	-4.825	-3.480	-2.901	-2.613
1	-5.722	-3.480	-2.907	-2.618
Opt Lag (Ng-Perron seq t) = 15 with RMSE 4237.49				
Min SC = 16.82567 at lag 1 with RMSE 4412.343				
Min MAIC = 16.94963 at lag 7 with RMSE 4343.491				

Source: Author' s own calculations in Stata ver. 14.2.

The parameters p and q of the ARIMA model can be determined by analyzing the autocorrelation function and the partial autocorrelation function (Figures 6, 7). To determine autocorrelation, it should be defined, which of the lines are coming out of the shaded region. The shaded region indicates the acceptance region and the lines indicate different lags. As can be seen from Figure 6, for the first 9 lags, the lines are coming out of shaded region, the series of Avg_p_KRW is autocorrelated with its lagged series at lags 1, 2, 3, 4, 5, 6, 7, 8 and 9. Therefore, the MA value of ARIMA model can take the value from 1 to 9.

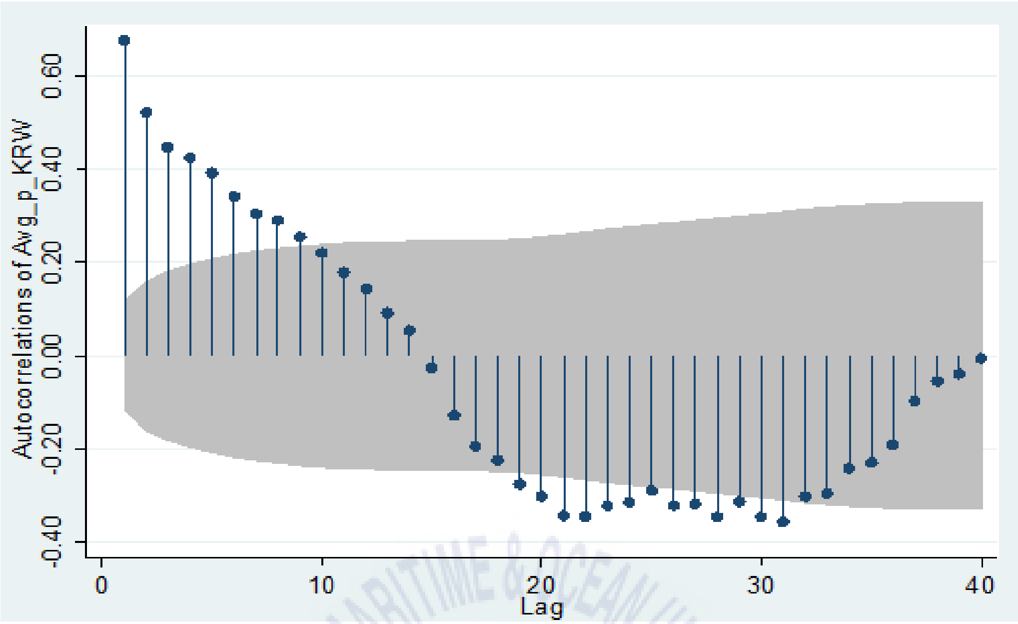

Fig. 6 Autocorrelation Plot of Avg_p_KRW (Obtained in Stata ver. 14.2)

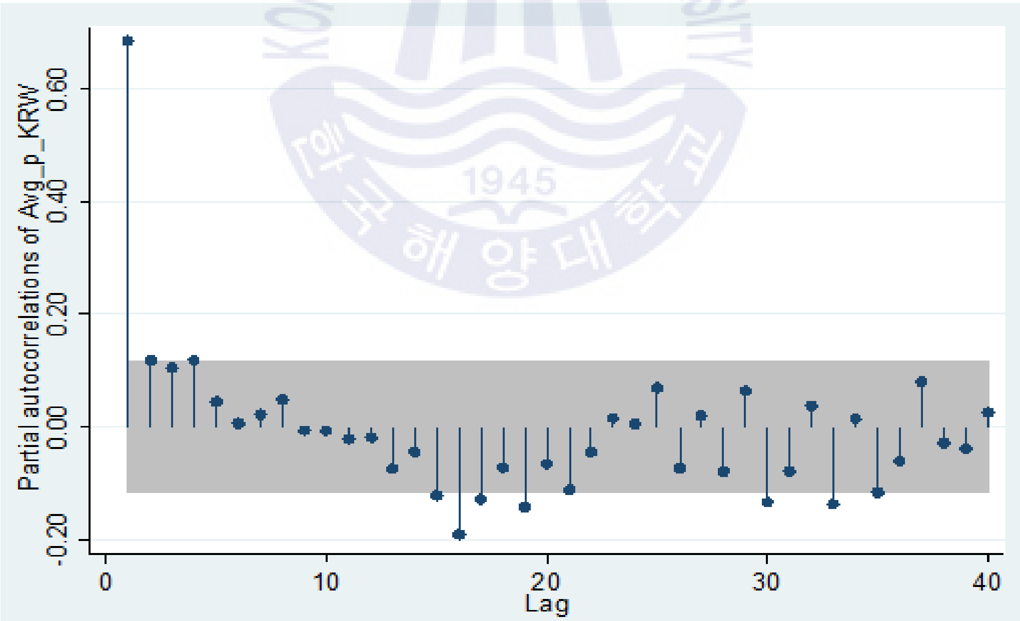

Fig. 7 Partial Autocorrelation Plot of Avg_p_KRW (Obtained in Stata ver. 14.2)

On the partial autocorrelation plot (Figure 7) only the first lag comes out of the acceptance region, i.e. the series of Avg_P_KRW partially auto correlates with its lagged series at lag 1. Therefore, the AR value of ARIMA model can take the value of 1.

Since our data was stationary from the very beginning and no differencing was necessary, it can be safely assumed that I parameter of our model equals 0 for every AR and MA value. All the discovered model parameters are summarized in the Table 7 below:

Table 7 Summary of Possible ARIMA Model Parameters

S. No	AR	I	MA	ARIMA
1	1	0	1	(1,0,1)
2	1	0	2	(1,0,2)
3	1	0	3	(1,0,3)
4	1	0	4	(1,0,4)
5	1	0	5	(1,0,5)
6	1	0	6	(1,0,6)
7	1	0	7	(1,0,7)
8	1	0	8	(1,0,8)
9	1	0	9	(1,0,9)

3.1.3. ARIMA Forecast

The ARIMA modelling has been executed for nine times in total, every time using different (p,d,q) parameters. The log likelihood component of ARIMA model should be relatively high. The model with the highest log likelihood value is better for forecasting.

The coefficient of AR should be less than 1 at least 5% level of significance. In addition to the ARIMA calculation, another operation is required to find the most effective forecast model – the calculation of Akaike's and Schwarz's Bayesian information criteria (AIC/BIC). The model with lowest AIC/BIC values will be more appropriate for forecasting. The results for every ARIMA modelling configuration are presented in Table 8 below:

Table 8 Summarized ARIMA Model Results (the optimal parameters are highlighted)

Models	Log likelihood	L1 AR	L1 MA	L2 MA	L3 MA	L4 MA	L5 MA	L6 MA	L7 MA	L8 MA	L9 MA	AIC	BIC
(1, 0, 1)	-2811.427	0.816	-0.263									5630.854	5645.492
P>|z|		0.000	0.001										
(1, 0, 2)	-2809.189	0.892	-0.330	-0.147								5628.378	5646.676
P>|z|		0.000	0.000	0.018									
(1, 0, 3)	-2808.890	0.903	-0.330	-0.138	-0.049							5629.780	5651.737
P>|z|		0.000	0.000	0.028	0.507								
(1, 0, 4)	-2808.644	0.896	-0.326	-0.139	-0.061	0.040						5631.288	5656.904
P>|z|		0.000	0.000	0.027	0.427	0.524							
(1, 0, 5)	-2808.537	0.891	-0.321	-0.139	-0.067	0.318	0.028					5633.074	5662.350
P>|z|		0.000	0.001	0.029	0.381	0.617	0.703						
(1, 0, 6)	-2808.536	0.892	-0.321	-0.139	-0.066	0.032	0.029	-0.002				5635.072	5668.008
P>|z|		0.000	0.001	0.036	0.385	0.612	0.703	0.974					
(1, 0, 7)	-2808.515	0.891	-0.323	-0.139	-0.067	0.030	0.026	-0.004	0.013			5637.031	5673.626
P>|z|		0.000	0.003	0.044	0.380	0.632	0.728	0.956	0.865				
(1, 0, 8)	-2806.993	0.888	-0.347	-0.158	-0.081	0.015	0.026	-0.003	0.026	0.146		5635.987	5676.241
P>|z|		0.000	0.000	0.009	0.263	0.818	0.722	0.965	0.709	0.039			
(1, 0, 9)	-2805.317	0.861	-0.326	-0.160	-0.091	0.022	0.031	0.007	0.047	0.145	0.116	5634.635	5678.548
P>|z|		0.000	0.000	0.008	0.188	0.734	0.645	0.912	0.495	0.034	0.122		

Source: Author's own calculations in Stata 14.2

Judging by the optimal parameters, it can be observed that ARIMA (1,0,1) is the most optimal model for the researched data set. Using the ARIMA (1,0,1), a short-term (12 weeks) dynamic forecast was obtained (Figure 8)

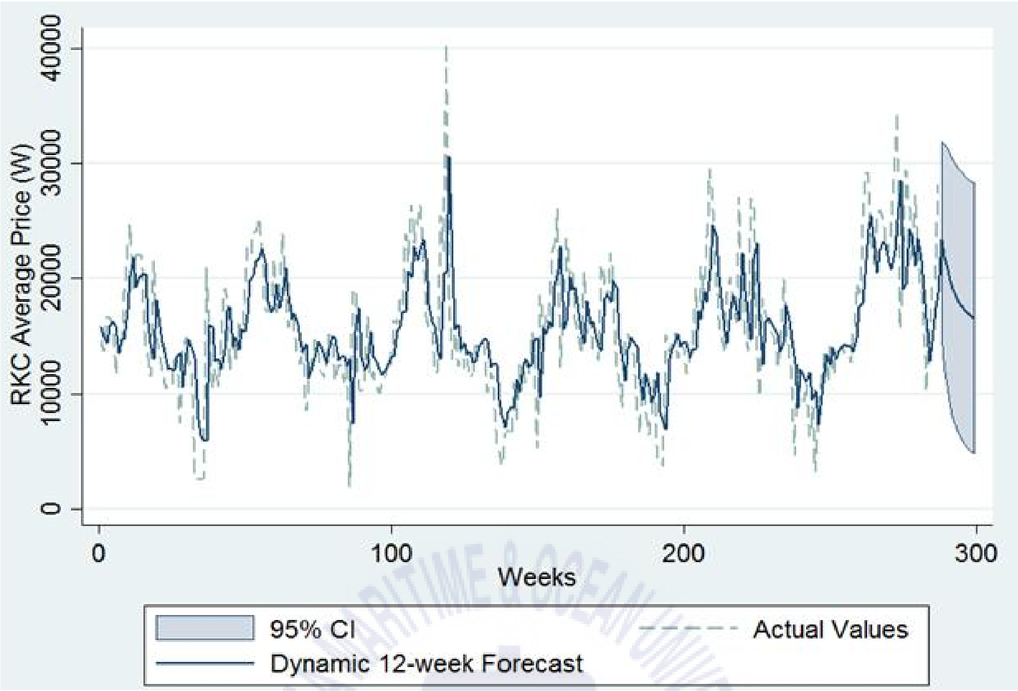

Fig. 8 ARIMA (1,0,1) Average Price 12-Week Dynamic Forecast
(Obtained in Stata ver. 14.2)

The forecasted values for a 12-week period (weeks 288-299) are summarized in Table 9 below:

Table 9 ARIMA (1,0,1) Forecast Values for Weeks 288-299

Week	ARIMA (1,0,1) Forecasted Price (₩)	Week	ARIMA (1,0,1) Forecasted Price (₩)
288	23358.91	294	17993.24
289	21956.95	295	17580.4
290	20813.43	296	17243.66
291	19880.71	297	16968.99
292	19119.93	298	16744.96
293	18499.39	299	16562.23

Source: Author's own calculations in Stata 14.2

3.1.4. Exponential Smoothing Forecast

Since the current data set is devoid of trend or a seasonal component, a single exponential smoothing is more appropriate for the task. A simple exponential smoothing model adjust forecasts according to the sign of the forecast error. The smoothing parameter is known as alpha and it is a number between 0 and 1. The smaller the alpha, the less the forecast will change, so the more significant the changes in the time series are, the higher the alpha should be.

The optimal value of smoothing parameter (alpha) was chosen according to its mean of square errors (MSE) value. For our data set, the value of 0.5263 was the optimal one, since it' s MSE value was the smallest (4487.8567).

The results of the single exponential smoothing forecast with an alpha of 0.5263 are shown in Figure 9:

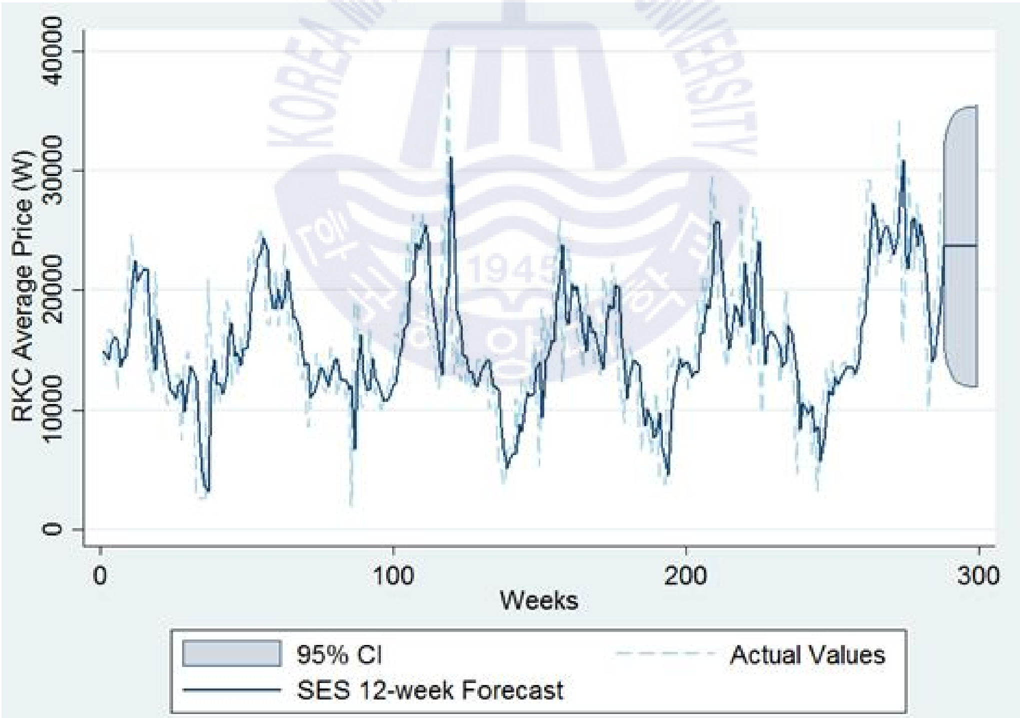

Fig. 9 Simple Exponential Smoothing (Alpha=0.5263) 12-Week Dynamic Forecast (Obtained in Stata ver. 14.2)

The obtained simple exponential smoothing forecast results are summarized in Table 10 below:

Table 10 Simple Exponential Smoothing (Alpha=0.5263) Forecast Values for Weeks 288-299

Week	SES Forecast values (₩)	Week	SES Forecast values (₩)
288	23675.25	294	23675.25
289	23675.25	295	23675.25
290	23675.25	296	23675.25
291	23675.25	297	23675.25
292	23675.25	298	23675.25
293	23675.25	299	23675.25

Source: Author's own calculations in Stata 14.2

Having obtained ARIMA and ES results, the forecasted values plotted on a graph in comparison to actual average auction Russian RKC prices that took place during weeks 288-299 of 2019 (Figure 10).

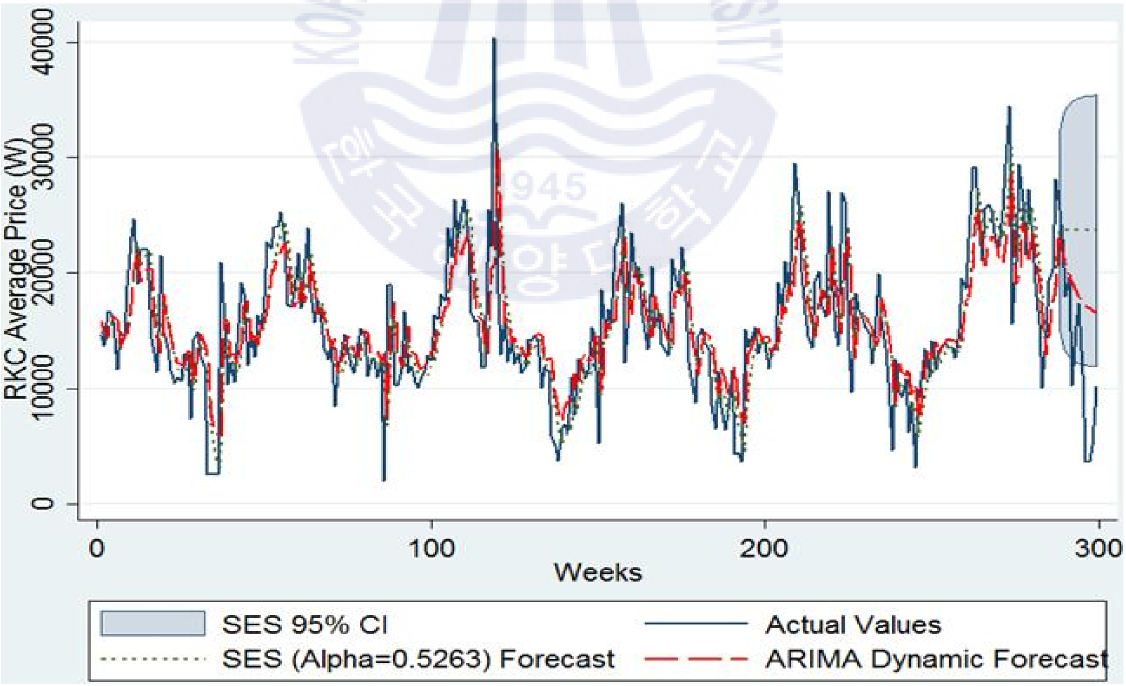

Fig. 10 SES, ARIMA Forecast Results versus Actual Values

The forecast results for ARIMA and ES, along with the corresponding errors are summarized in Table 11:

Table 11 ARIMA and ES Forecast Results and Accuracy Statistics (extreme forecast deviations are marked with an *)

Week	ARIMA (1,0,1) Forecast	SES Forecast	Actual Values	Absolute Percentage Error	
				ARIMA	SES
288	23358.91	23675.25	25500	8.40	7.16
289	21956.95	23675.25	23000	4.54	2.94
290	20813.43	23675.25	18000	15.63	31.53
291	19880.71	23675.25	19600	1.43	20.79
292	19119.93	23675.25	10300	85.63*	129.86*
293	18499.39	23675.25	15400	20.13	53.74
294	17993.24	23675.25	17400	3.41	36.06
295	17580.4	23675.25	11200	56.97*	111.39*
296	17243.66	23675.25	3600	378.99*	557.65*
297	16968.99	23675.25	3600	371.36*	557.65*
298	16744.96	23675.25	5000	234.90*	373.51*
299	16562.23	23675.25	10200	62.37*	132.11*
			MAPE	**103.65**	**167.86**

Source: Author's own calculations in Stata 14.2

Judging by the error scores, the ARIMA model had produced more reliable forecast results than the SES model. Although ARIMA results were not 100% accurate, they were at least able to grasp the general price trend for the period of forecast. ARIMA forecast results also have a lower MAPE score.

Single exponential smoothing on the other hand has failed to deliver robust forecast results with its much bigger MAPE score. Moreover, some average price actual values even fell beyond the SES 95% forecast confidence interval bounds.

Considering all the aforementioned, of the single-variable forecast methods, ARIMA proved to be more accurate than exponential smoothing for seafood auction price forecasting.

3.1.5 ARDL Forecast

It should be noted, that direct comparison of ARIMA, ES and ARDL forecasting power in a single time series data set would be ill-posed due to a number of reasons.

First and foremost, ARIMA and ES are both univariate methods – i.e. require only a single variable time series for proper modelling, while ARDL, on the other side, is a multivariate analysis method, i.e. it requires at least two variables for a proper implementation.

Secondly, ARIMA and ES are specialized forecasting techniques, which behave better in bigger data sets (the more the better), hence our choice of weekly interval that was employed for ARIMA/ES forecasting in the current research. ARDL works adequately even with smaller data sets (several tens of observations), because its main purpose is cointegration analysis, and forecasting is just a secondary function.

Besides, ARDL requires equally long time series for all the variables included. Some exogenous variables are impossible (or too hard) to be obtained correctly on a weekly basis – e.g. GDP, inflation, some prices and indices etc.

Thirdly, ARDL-based forecasting models require at least approximately estimated exogenous variables for the period of forecast to be present in the data set, i.e. in order to forecast the independent variable, exogenous variables for the forecast period must already be specified – either by forecasting or estimation. This fact makes the ARDL forecasting procedure more difficult and cumbersome than in single-variable techniques like ARIMA, ES, etc.

And lastly, ARDL forecasts cannot be performed independently, since they are always based on estimations and error correction representations from cointegration analysis models. Thus, a proper ARDL analysis must be executed before forecasting anything at all.

Thereby, in order not to break the logical structure of this research, the data set along with cointegration analysis results and estimations from subchapter 3.2 was used as a basis for obtaining a long-run 12-month forecast of Russian RKC average auction prices. In order not to estimate or forecast other exogenous variables and for experimental convenience, it was decided to perform forecasting for the past period of January 2019 – December 2019. The obtained results are presented in Table 12:

Table 12 ARDL Forecast Results and Accuracy Statistics
(extreme forecast deviations are marked with an *)

Month	ARDL Forecasted Values	Actual Values	Absolute Percentage Error
Jan 2019	20872.592	24300	14.10
Feb 2019	20435.137	24500	16.59
Mar 2019	20063.721	22900	12.39
Apr 2019	20404.563	24400	16.37
May 2019	20795.229	17100	21.61
Jun 2019	20991.865	17300	21.34
Jul 2019	21585.078	16300	32.42*
Aug 2019	20699.357	12700	62.99*
Sep 2019	24255.943	10200	137.80*
Oct 2019	25433.166	15500	64.08*
Nov 2019	26424.723	20700	27.66
Dec 2019	26822.625	27300	1.75
MAPE			**35.76**

Source: Author’ s calculatons in Stata 14.2

The results indicate that ARDL forecast yields relatively reliable and results. Marginal Absolute Percentage Error value (35.76) is much lower than in ARIMA (103.65) and ES (167.86) cases, even considering the difference in time series intervals – weeks versus months. It should be noted that ARDL seems to give more accurate forecasts when closer to the beginning and to the end of the forecast period.

For the best visualisation, the forecasted ARDL values were plotted on a graph versus actual values for the forecast period (Figure 11):

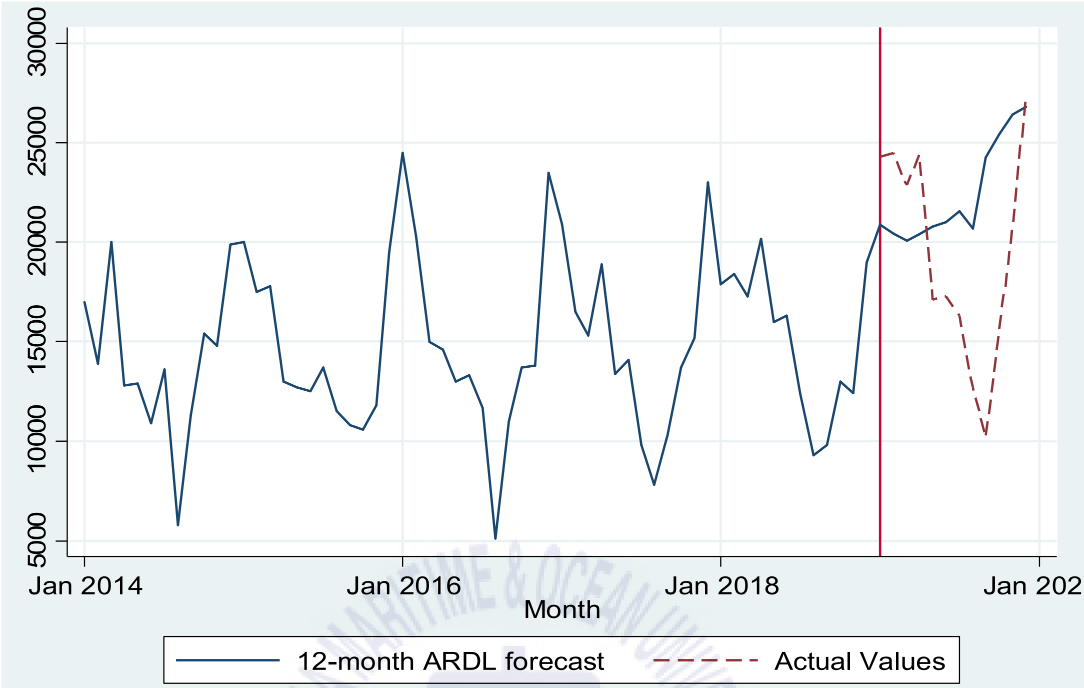

Fig. 11 ARDL Forecasted Values versus Actual Values Comparison Plot (Obtained in Stata 14.2)

Considering all of the above, it can be concluded that ARIMA proved to be more effective in forecasting seafood auction prices than ES in the current research case, and especially in the short run. On the other side, ARDL-based forecasting, even with all its limitations, provided a much better MAPE score and looks more appropriate for long-run forecasting.

In any case, all models showed critical forecast errors, when actual average prices dropped sharply. This reflects the highly volatile nature of seafood auction trade, which is influenced by a vast array of external and internal factors, most of which are impossible to include into mathematical modelling. Such factors include but are not limited to: current crab qualities and biological condition, current environmental laws and regulations, marine life population fluctuations, climate changes, abrupt market demand and consumption changes, trade and customs tariff policies, sanctions and trade wars etc.

3.2 Russian RKC Auction Price Cointegration Analysis

3.2.1 Cointegration Data Set

For the purposes of the cointegration research, monthly statistics for fresh Russian Red King Crab, fresh Norway Red King Crab and fresh Russian Opilio Crab in 2014 – 2019 was obtained from Noryangjin Market’ s electronic database.

In order to perform the cointegration analysis, several other relevant exogenous variables for the same time period were and included into the model. The data used in this study covers the period from January 2014 to December 2019, with a total number of 72 observations.

The studied variables were:

RKC_AVG_P – dependent variable, average monthly auction price per 1 kg of fresh Russian RKC (₩)

∆INFLATION – monthly inflation growth rate based on Consumer Price Index (%)

∆GDP – quarterly GDP percentage change (%)

USD_KRW_EXC_RT – USD to KRW mid-market exchange rate (₩)

RUS_CRAB_IMPORT – total monthly import of fresh/freshly frozen Russian crab (all types and species, HS codes 030624, 030633) to South Korea (tons)

RUS_OPILIO – monthly auction traded amount of fresh Russian Opilio Crab (kg)

NOR_KC – monthly auction traded amount of fresh Norwegian RKC (kg)

Inflation, GDP and national currency to dollar exchange rate values were chosen as important general domestic economic indicators that may directly influence the welfare of both consumers and wholesale seafood market participants.

Total Russian crab (fresh/freshly frozen) import values may influence the availability of fresh RKC (along with any other substitutes or complementary crab species) on Korean wholesale seafood markets and, consequently, impact average auction prices.

Fresh Russian Opilio Crab auction trade volumes must be analyzed, in order to define if consumption of the second most valuable (both economically and gastronomically) imported crab species may cointegrate with availability, demand for, or price of Russian RKC.

Finally, the availability of the direct substitute - Norwegian RKC may also prove to have a cointegrated relationship with Russian RKC prices.

The data set’ s descriptive statistics is summarized in Table 13 below:

Table 13 Cointegration Data Set Descriptive Statistics

	Number of observations	Mean	Std. Dev	Min	Max
RKC_AVG_P (₩)	72	15462.5	4670.598	5100	27300
⊿Inflation (%)	72	1.126389	0.614623	-0.43	2.49
⊿GDP (%)	72	0.6889167	0.4312318	-0.37	1.523
USD_KRW_EXC_RT (₩)	72	1121.069	49.24993	1011.16	1231.23
RUS_CRAB_IMPORT (t)	72	862.3389	313.2144	224.2	1777.6
RUS_OPILIO (kg)	72	5166.736	2897.829	1354	14747
NOR_KC (kg)	72	2601.903	2866.035	120	12901

Source: Author’ s own calculations in Stata 14.2

3.2.2 Preparing the ARDL Model

In order to run ARDL modelling with our data, several requirements must be met:

1. Dependent variable must be non-stationary in order for the model to behave better (defined by ADF test);

2. None of the variables should be I(2) under normal conditions (defined by ADF test);

3. None of the variables should be I(2) in a structural break (defined by Zivot-Andrews test).

In order to confirm that none of the variables is I(2), the combined ADF test was employed. The results are presented in Table 14.

Table 14 ADF Test Results

Variable	Z(t)	1% crit. value	5% crit. value	10% crit. value	p-value	Order of Integration	Stationarity
⊿Inflation (%)	-1.841	-4.121	-3.487	-3.172	0.6844	I(1)	Non-stationary
⊿GDP (%)	-2.397	-4.119	-3.486	-3.172	0.3810	I(1)	Non-stationary
USD_KRW_EXC_RT (won)	-2.305	-4.106	-3.480	-3.168	0.4313	I(1)	Non-stationary
RUS_CRAB_IMPORT (t)	-1.8	-4.130	-3.491	-3.175	0.7034	I(1)	Non-stationary
RKC_AVG_P (won)	0.506	-4.13	-3.491	-3.175	0.9969	I(1)	Non-stationary
RUS_OPILIO (kg)	-4.31	-4.106	-3.480	-3.168	0.0030	I(0)	Stationary
NOR_KC (kg)	-1.37	-4.128	-3.490	-3.174	0.8699	I(1)	Non-stationary

Source: Author’s own calculations in Stata 14.2

None of the variables were in second order of integration I(2), however, RUS_OPILIO variable showed the signs of stationarity. One of the most important advantages of ARDL method is that it can safely operate with mixed variables of I(0) and I(1) orders of integrations, therefore it should not be a problem in our case.

The next step is to check if the variables are sensitive to structural break, which means testing for unit root through the Zivot-Andrews Test. The combined Zivot-Andrews test results are shown in Table 15 below.

Table 15 Zivot-Andrews Test Results

Variable	Minimum T-statistic	1% crit. value	5% crit. value	10% crit. value	Structural Break Date
⊿Inflation (%)	-2.444	-5.570	-5.080	-4.820	May 2018
⊿GDP (%)	-2.559	-5.570	-5.080	-4.820	Aug 2016
USD_KRW_EXC_RT (won)	-2.876	-5.570	-5.080	-4.820	Nov 2017
RUS_CRAB_IMPORT (t)	-3.329	-5.570	-5.080	-4.820	Jan 2016
RKC_AVG_P (won)	-3.850	-5.570	-5.080	-4.820	Nov 2018
RUS_OPILIO (kg)	-4.699	-5.570	-5.080	-4.820	Jan 2018
NOR_KC (kg)	-2.645	-5.570	-5.080	-4.820	Jun 2016

Source: Author’s own calculations in Stata 14.2

Once it is proved that none of the variables is I(2) under structural breaks, the next step of the ARDL modelling can be undertaken. For the purposes of the current research, the Microfit 5.5 econometrics software package was used. Made by Bahram Pesaran and M. Hashem Pesaran, it is one of the best free software packages in the market, which is particularly effective at calculating ARDL models.

3.2.3 ARDL Model Results and Interpretation

The model was specified as ARDL (1,0,0,1,0,0,0), the choice of optimal lags was based on Schwarz Bayesian Criterion, as it proved to be the most appropriate for our model and data. The obtained estimated long run ARDL coefficients are shown in Table 16.

Table 16 Estimated ARDL Long Run Coefficients

Regressor	Coefficient	Std.error	T-ratio [prob.]	
DGDP	-1523.1000	2326.1000	-0.65479 [0.515]	
DINF	-868.5794	1537.7000	-0.56487 [0.574]	
RUSCIMP	22.9362	8.3527	2.7460 [0.008]	
USDKRWER	12.0522	4.3023	2.8014 [0.007]	
RUSOPILIO	-1.1708	0.5561	-2.1055 [0.039]	
NORRKC	-0.7230	0.3828	-1.8888 [0.064]	
TREND	-204.1962	105.9560	-1.9272 [0.059]	
F-statistic	*95% Lower Bound*	*95% Upper Bound*	*90% Lower Bound*	*90% Upper Bound*
4.8179	2.6139	3.9376	2.2460	3.4337
W-statistic	*95% Lower Bound*	*95% Upper Bound*	*90% Lower Bound*	*90% Upper Bound*
33.7251	18.2975	27.5629	15.7219	24.0362

Source: Author’s own calculatons in Microfit 5.5

Since the F-statistic value lies above the upper bounds, the null hypothesis of no existing level effect (i.e. no cointegration) can be safely rejected.

As can be seen from the regressor coefficients there are several variables, which cointegrate with the independent variable in the long run: total Russian fresh/freshly frozen crab imports, mid-market USD-KRW exchange rate, total Russian Opilio Crab sold by auction and total Norwegian RKC sold by auction.

Judging by the ARDL results, it can be stated that total Russian fresh/freshly frozen crab import values and mid-market USD-KRW exchange rates have a positive and statistically significant impact on Average Russian RKC auction price at 5% level, while quantities of Opilio Crab and Norwegian RKC, sold by action, have a negative impact (however much less statistically insignificant) on average Russian RKC auction prices at 5% level in the long run. It should be noted that at this step, any variables that show insignificant or ambiguous coefficients may still influence the dependent variable in the short run.

To further prove the model's stability and lack of Recursive Residuals the CUSUM and CUSUMSQ tests were employed (Figures 12, 13).

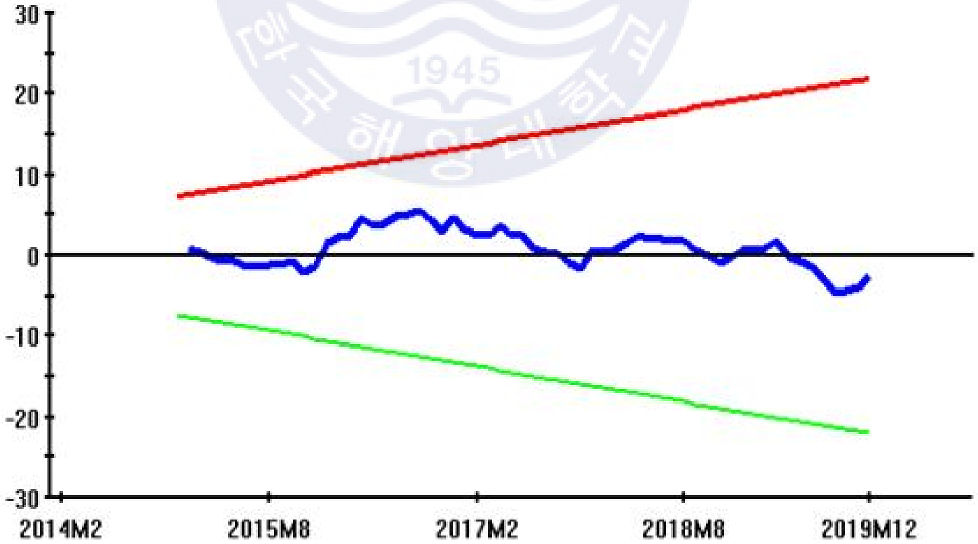

Fig. 12 Plot of Cumulative Sum of Recursive Residuals (Obtained in Microfit 5.5)

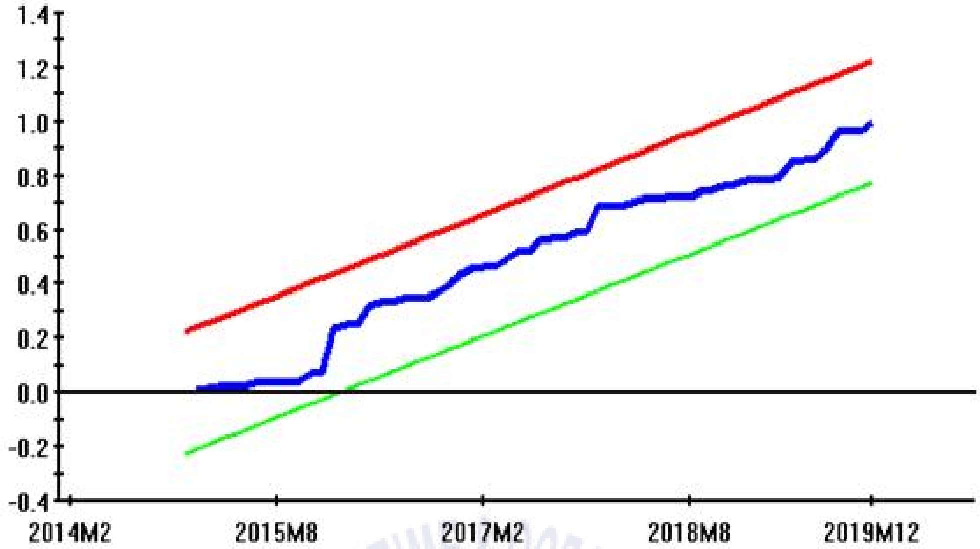

Fig. 13 Plot of Cumulative Sum of Squares of Recursive Residuals (Obtained in Microfit 5.5)

Straight lines represent critical bounds at 5% significance level. Since both CUSUM and CUSUMSQ plots stay inside the 5% critical bounds, it can be assumed that there is no issue of recursive residuals in terms of both mean (CUSUM) and variance (CUSUMSQ).

The most important part of the ARDL cointegration analysis is the bounds test. One of the main reasons for ARDL for being so popular among the researchers is the fact that cointegration of nonstationary variables is equivalent to an error-correction (EC) process, and the ARDL model has a reparameterization in EC form (Engle and Granger, 1987; Hassler and Wolters, 2006).

The existence of a long-run cointegrating relationship can be tested based on the EC representation. A bounds testing procedure is available to draw conclusive inference without knowing whether the variables are integrated of order zero or one, I (0) or I (1), respectively (Pesaran, Shin, and Smith, 2001).

The model’ s error correction analysis is represented below in Table 17.

Table 17 Error Correction Representation

Regressor	Coefficient	Std.error	T-ratio [prob.]
dDGDP	-582.9361	899.3246	-0.64819 [0.519]
dDINF	-332.4332	588.9899	-0.56441 [0.574]
dRUSCIMP	3.9467	2.0772	1.9000 [0.062]
dUSDKRWER	4.6128	1.9979	2.3089 [0.024]
dRUSOPILIO	-0.4481	0.1472	-3.0451 [0.003]
dNORRKC	-0.2767	0.1442	-1.9183 [0.060]
dTREND	-78.1524	31.8118	-2.4567 [0.017]
ecm(-1)	-0.3827	0.0957	-3.9996 [0.000]
R-squared		0.4802	
F-stat.		F (7,63) 8.1823 [0.000]	

Source: Author's calculatons in Microfit 5.5

The EC results indicate that short run coefficients for total Russian crab import and USD-KRW exchange rates are statistically significant at the 5% level and the coefficient of error correction term ecm(-1) is negative and highly significant (-0.3827), indicating that in the short run changes in total Russian crab import values and USD-KRW exchange rates are associated with an increase of Russian RKC average auction prices.

The estimated value of the ecm(-1) coefficient indicates that about 38.3% of the disequilibrium in Russian RKC average price values is offset by the short run adjustment in the same month.

The negative and significant coefficient of ecm(-1) (-0.3827) lets us assume that there is convergence in the model, which may mean that there is at least one significant long run relationship between the variables. Significant R-squared and F-statistics values let us assume the overall fitness of the model.

3.2.4 Non-linear ARDL Model Results and Interpretation

Since Stata 14.2 and Microfit 5.5 do not have a built-in NARDL module, a custom NARDL computation package for Stata 14.2, made by Marco Sunder from Leipzig University[8] was employed. The obtained estimated NARDL coefficients are shown in Table 18.

Table 18 NARDL Model Results

Exogenous variable	Cointegtation t-statistics	Long-run Effect [+]	Long-run Effect [-]	Long-run Asymmetry		Short-run Asymmetry	
				F-stat.	P>F	F-stat.	P>F
ΔInflation	2.9600	-1196.7230	1826.3400	6.5690	0.0140	0.0626	0.8040
ΔGDP	0.9241	1730.7880	-2427.9120	0.0510	0.8230	0.8437	0.3650
USD-KRW Exc. Rate	1.5279	16.0600	-15.8780	0.0032	0.9550	0.0402	0.8420
Total RUS Import	3.8507	-4.1440	3.8400	0.0751	0.7850	1.6730	0.2030
RUS_Opilio	2.3575	0.1840	-0.1850	0.0002	0.9880	1.3380	0.2540
NOR_RKC	1.8184	2.5070	-1.9580	0.1760	0.8950	1.6380	0.2080

Source: Author's calculatons in Stata 14.2

In general, NARDL cointegration results are in accordance with ARDL results – USD-KRW exchange rate and total Russian crab imports showed a cointegrating relationship with average Russian RKC auction prices.

According to the test results, in the long run for every 1% of increase in USD-KRW exchange rate, average Russian RKC auction prices increase by 16.06%, and for every 1% of decrease in USD-KRW exchange rate, average RRKC auction prices decrease by 15.88%. In this case both long-run and short run asymmetries are insignificant, since their F-stat. scores are very low (0.0032 and 0.0402 respectively).

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Taking into consideration the specifics of Russian-Korean seafood action trade, it should be noted that the aforementioned discoveries are logical. Russian fishing companies enter Korean seafood auctions through Korean intermediates (auction agents) and negotiate all prices in USD. However auction lot price-setting and auction trade itself must be held in Korean currency, as facilitated by local laws. That is why current exchange rate fluctuations may influence auction prices.

In the long run, for every 1% of increase in total Russian crab imports, average Russian RKC auction prices decrease by 4.14%, and for every 1% of decrease in total Russian crab imports, average Russian RKC auction prices increase by 3.84%. Long-run and short run asymmetries are insignificant as well (0.0751 and 1.6730 respectively). Judging by these results, it can be said that in the long run, increasing supply of Russian crabs to Korean seafood markets can lead to decreasing average auction prices, and vice versa - decreasing imports lead to increasing prices.

It should be noted that both ΔGDP and ΔInflation values showed very contradictory and inconsistent results in both ARDL and NARDL models. Their long-run effect coefficients were enormous and somewhat ambiguous - inflation decrease leads to increase in average auction prices for consumer goods, and GDP growth also leads to price increase. It is highly likely that mixed absolute and percentage variables in a single ARDL/NARDL model may lead to inconsistent results.

In the NARDL modelling, quantities of sold Russian Opilio Crab proved to be statistically insignificant in their influence on average Russian RKC auction prices.

Auction-sold Norwegian RKC, however, showed a more peculiar result. In the long run, for every 1% of increase in Norwegian RKC sold quantities, average Russian RKC auction prices increase by 2.5%, and for every 1% of decrease, average Russian RKC auction prices also decrease by 1.95%. Both long-run and short run asymmetries were insignificant, due to their low F-stat. scores (0.176 and 1.638 respectively).

It should be noted that both Russian- and Norwegian-imported red king crabs are in fact the same species with equal biological and gastronomical qualities. Red king crabs, originated from Kamchatka, were artificially introduced into the Barents Sea by Soviet biologists in 1961-1969. By 1977 red king crabs reached Norwegian fishing grounds, since then red king crabs have been breeding extensively in Norwegian waters.

The positive long-run cointegration between the two can possibly be explained by "reversed causality" – i.e. Russian RKC auction prices increase due to other exogenous factors, this fact, in turn, compels some intermediate wholesalers to buy cheaper Norwegian RKC, hence the sales volume increase.

The negative long-run cointegration is hard to explain. It can happen due to monthly price volatility, supply fluctuations or current quality of every sold auction lot. Also Norwegian and US red king crabs are usually sold at a lower auction price and in smaller quantities than Russian red king crabs. Norwegian crab-catching and export volumes are also much lower than Russian volumes.

In general, NARDL modelling results confirm the results of linear ARDL modelling, and no variables showed distinct signs of cointegration asymmetry.

4. Conclusion

4.1 Summary

The current study employed ARIMA, exponential smoothing and ARDL techniques for forecasting average Russian RKC auction prices on Korean wholesale seafood markets. According to the obtained results, ARIMA gave more accurate short-run forecast, than exponential smoothing. It can be safely assumed, that ARIMA is a very reliable univariate method for auction price forecasting, especially in the short run.

ARDL, despite not being a specialized forecasting technique, showed better MAPE scores than both ARIMA and ES. Even considering its multivariate nature and additional requirements, it is still a powerful forecasting instrument, especially for long-run forecasts. In case when reliable forecasted or estimated exogenous variables are available, it is recommended to use ARDL instead of univariate techniques.

It should be noted that discoveries of the current research match the results of other ARDL-based forecasting works – Fatai et. al (2003), Adom and Bekoe (2012), Hanif and Malik (2015), Hamid and Shabri (2017). The existing relevant research papers assume that ARDL-based forecasting is more accurate than ARIMA or other single-variable techniques, however its forecasting applicability is hampered by its multivariate nature.

The ARDL cointegration modelling, executed for the purposes of the current research, discovered a level relationship between average Russian RKC auction prices and several of the chosen independent variables. In the long run, changes in total Russian crab import values and USD-KRW exchange rates have a positive statistically significant impact on average Russian RKC auction prices at 5% level. Changes in quantities of sold Opilio Crab and Norwegian RKC have a negative impact (however much less statistically significant) on average Russian RKC auction prices at 5% level.

In the short run, changes in total Russian crab import values and USD-KRW exchange rates are associated with an increase of average Russian RKC auction prices.

The NARDL cointegration results were in accordance with those from ARDL modelling – USD to KRW exchange rates and total Russian crab import showed a cointegrating (albeit symmetrical) relationship with average Russian RKC auction prices. The discovered cointegration can be logically explained in accordance with the actual market practices and specifics.

Russian Opilio Crab auction-sold quantities were statistically insignificant in their influence on average Russian RKC auction prices. Auction-sold Norwegian RKC showed a strange cointegration, which probably happened due to monthly price volatility, supply fluctuations and/or current quality of every sold RKC auction lot.

The studied ΔGDP and ΔInflation variables showed very contradictory and inconsistent results in both ARDL and NARDL models. The cointegration coefficients were too large and ambiguous in their relationships. It is highly likely that mixing both absolute and percentage variables in a single ARDL/NARDL model may lead to inconsistent results. Further research may be necessary to clarify the problem.

Generally, the NARDL modelling showed no signs of asymmetry for any of the cointegrating variables.

4.2 Suggestions and Implications

The current research paper, besides pure academic interest, contains potentially valuable discoveries for all Russian-Korean seafood trade and wholesale auction participants.

Currently, there is no system (mathematical or not), which would allow seafood auction participants to even roughly predict future auction prices. Their only working method is constant market monitoring for supply/demand fluctuations, backed up by their own experience and professional intuition. However, modern forecast and cointegration techniques may shed some more light on the process of seafood auction price-forming.

The current research was just a first attempt at comprehension of seafood auction price forecasting, nevertheless its humble results may prove useful for market participants and seafood auction traders. However, in order to develop a universal complex seafood price forecast model, more extensive research is necessary, more data should be involved, and more complex techniques (like neural networks) must be applied.

4.3 Policy Recommendations

Considering the results of the current research paper, and until more precise results from more complicated researches are available, it is recommended for the market participants to pay closer attention to currency exchange rates and total fresh/live Russian crab import quantities, while considering the future pricing of auction-sold Russian RKC, at least in the long-run perspective.

4.4 Limitations

Since seafood auction price-forming mechanism is very complicated and is directly or indirectly influenced by a plethora of exogenous and endogenous factors, simple univariate forecast techniques (ARIMA, ES) prone for extreme forecast errors in case of abrupt market situation changes.

Multivariate ARDL-based forecasting gives better forecast error scores, however it suffers from its own multi-variable nature when it comes to forecast modelling. Some exogenous variables (like auction-sold amounts of different crab species, currency exchange rates etc.) cannot be accurately predicted or estimated without a discrete single-variable forecasting, but making individual forecasts of exogenous variables to make forecast of an endogenous variable seems unnecessarily overcomplicated, and the obtained results are highly likely to be inaccurate and not reliable for practical purposes.

Nevertheless, the practical part of the current research may be extended by adding more price data and/or seafood types into the research, or by using more complex forecast and cointegration analysis techniques, especially those that involve machine learning solutions. Unfortunately, the necessary data volumes will be immense and hard to obtain for the researchers, who are operating outside the wholesale seafood auction system. Involving seafood market participants and auction traders into the research activities will be most welcome.

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