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PREDICTING BALTIC DRY INDEX WITH LEADING INDICATORS

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ABSTRACT

The Baltic Dry Index (BDI) is issued by the Baltic Exchange on a daily basis and it signals for the average cost of shipping raw materials on a number of shipping routes. Baltic Dry Index is considered by both the private and public authorities as an important indicator for freight rates, international trade and economic activity. Conducting a long-term prediction for dry bulk indices is challenging due to the high volatility of the dry bulk freight market; therefore, a linear prediction spanning a shorter time period offers both greater accuracy and can be used as a tool for speculation. The goal of this paper is to form a linear benchmark model through Box-Jenkins approach including explanatory variables selected rigorously to forecast Baltic Dry Index. Using monthly data between January 2010 and June 2017, the analysis results point out an ARIMAX (10,1,0) model with spot prices of gold and silver, United States 10-year bond yield and commodity price index composed of minerals, ores and metals.

Keywords: *Baltic Dry Index, ARIMAX model, forecast, freight market, time series.*

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BALTİK KURU YÜK ENDEKSİ'NİN ÖNCÜ GÖSTERGELER İLE TAHMİNİ

ÖZET

Baltik Kuru Yük Endeksi, Baltik Borsası tarafından günlük olarak yayımlanmakta ve farklı rotalar için ham madde taşıma maliyetini göstermektedir. Baltik Kuru Yük Endeksi hem kamu hem de özel sektör yetkilileri tarafından navlun oranları, uluslararası ticaret ve ekonomik faaliyetler için önemli bir gösterge olarak kabul edilmektedir. Kuru dökme yük navlun piyasasının çok dalgalı bir yapıya sahip olmasından ötürü kuru yük endeksleri üzerinde uzun vadeli tahminleme yapmanın oldukça zorlayıcı oluşu, daha kısa vadeli ve doğrusal tahminleme yapılması ile hem daha isabetli sonuçlar elde edilmesine hem de sonuçların spekülatif bir araç olarak kullanılabilmesine olanak vermektedir. Bu çalışmanın amacı Baltik Kuru Yük Endeksi'ni tahminlemek üzere seçilen açıklayıcı değişkenler içeren Box-Jenkins yaklaşımı ile bir kıyaslama modeli oluşturmaktır. Ocak 2010-Haziran 2017 verilerinin aylık bazda kullanılması ile elde edilen analiz sonuçları altın ve gümüş spot fiyatları, Amerika Birleşik Devletler 10 yıllık tahvil getirisi ile mineraller, cevherler ve metallere oluşan emtia fiyat endeksini içeren bir ARIMAX (10,1,0) modelini işaret etmektedir.

***Anahtar Kelimeler:** Baltik Kuru Yük Endeksi, ARIMAX modeli, tahminleme, navlun piyasası, zaman serisi.*

1. INTRODUCTION

The Baltic Exchange is a recognized independent source of maritime market information for the trading and settlement of physical and derivative shipping contracts. Recently, the Baltic Exchange houses 600 companies and more than 3000 individuals which makes it the most important market for shipping (Geman and Smith, 2012). With its large database and reflective status of the market, BDI is extensively studied through the years.

Baltic Dry Index (BDI) is a composite index that is calculated as the average of four sub-indices: Capesize, Supramax, Panamax and Handysize (Baltic Exchange, 2017). It incorporates the cost of transporting various raw materials worldwide. Furthermore, it is a fundamental indicator for direction of input prices and economic activity (Papailias et al., 2017) as average raw material prices such as coal, iron ore, cement and grains are embedded. Thus, it is closely related to economic conditions and therefore global trade. It is recognized as a predictor especially for economic crashes. In this context, it is critical to

find the appropriate variables which hold information for BDI and build a useful model for prediction. As the dry bulk shipping market is volatile and cyclical, companies are constantly searching for ways to evaluate the changes in freight rates, and reducing the business risk and uncertainties. Development of a prediction method using the historical BDI data could be an utmost importance for interested parties. In this paper, the concept of Autoregressive Integrated Moving Average with Explanatory Variables (ARIMAX) model is proposed for the prediction of BDI. With it, the forecast performance of leading indicators for BDI is thoroughly investigated. This study contributes to the literature by considering a more recent time horizon and a wide variety of leading indicators in modelling Baltic Dry Index.

The Efficient Market Hypothesis (EMH) suggests that the prices respond only to information available in the market, which is possessed by all the market participants (Fama, 1970). This situation removes the market participants' possibility of out-profiting each other. Fama (1970) also points out that in efficient markets prices follow a random walk process and are indeed not predictable. In order to conduct a prediction on BDI, existing literature on dry bulk shipping market efficiency is also examined in Section 2.

The remainder of this paper is organized as follows: Section 2 includes the review of BDI modelling, forecasting and its market efficiency related literature; Section 3 presents data for BDI and other leading indicator series information and Section 4 explains construction of the time series model with Box-Jenkins methodology ARIMAX (p,d,q); Section 5 presents the empirical results and discussions; and Section 6 gives conclusions and recommendations for future research.

2. LITERATURE REVIEW

There are various studies which tested EMH upon the shipping markets. Evans (1994) conducted an analysis on the market efficiency of dry bulk shipping by employing marginal cost approach in both short term and long term perspectives. His empirical evidence suggests that even though short term properties of the market show somewhat similarities to efficiency, in the long run the market is considered an inefficient one. Various authors applied the Expectation Hypothesis for determining market efficiency in shipping. If expectations in the freight markets are rational, expectation hypothesis imply that it is not possible to forecast the excess earnings on consecutive short-term charters over

long-term charters. Failure of this relationship might imply market inefficiency or incorrect expectations of agents (Kavusannos and Alizadeh, 2002). Studies conducted for the dry bulk market by Hale and Vanags (1989), Veenstra (1999), Kavusannos and Alizadeh (2002), Adland and Cullinane (2005) broadly reject the validity of the relationship, implying existence of inefficient market structure. As a different point of view Adland and Stradenes (2006) argue that the traditional form of EMH cannot be applied on short-term/spot freight rates due to their inability to be traded and stored. Therefore, they generate an alternative test of market efficiency in the freight market with a kernel smoothing technical analysis which gives mixed results, suggesting both inconsistencies with market efficiency and indications of weak-form efficiency for VLCC freight market. It can be understood from the overall literature upon market efficiency of shipping that prediction is applicable for dry bulk freight industry.

Regarding the literature on dry bulk freight rates, a vast number of studies have analyzed the time series properties of the industry. Studies about prediction of BDI mainly utilize two general types of methodological approaches.

The first approach consists of linear time series models in BDI modelling focusing on the relationship of BDI with economic growth and financial markets. As an early study about dry bulk sector, Marlow and Gardner (1980) develops a theoretical framework for supply and demand in shipping sector and then analyzes the effects of government intervention through subsidies. Papers which focus on prediction of BDI dates back to early 1990's. For predicting the future movements of the Baltic Freight Index (BFI) -later changed to BDI- Cullinane (1992) employs Box-Jenkins approach using daily series between January 1985 and December 1988 to deduce a model which yields accurate predictions over short term. An autoregressive model, namely AR (3) is concluded as the best fitted model with a short forecasting horizon being optimal. The purpose of such an exercise is specified as forming a useful model to develop speculative strategies in the market. Furthermore, Cullinane et al. (1999) develops an autoregressive integrated moving average (ARIMA) model to provide short term forecasts of BFI. As the results of the study, it is stated that although the model can capture characteristics of the index, it falls short in terms of specification and the number of its parameters. Bakshi et al. (2011) investigates BDI growth rate as a tool for predicting the global stock markets and global real economic activity. Overlapping returns are analyzed through both one-month and multi-

month horizons for the study and predictive ability of BDI growth is documented. By the same token, Geman and Smith (2012) conduct a financial analysis on BDI to present its key features and its relationship with the world economy. BDI behavior is found to be strongly different from behaviors of stocks, bonds and most commodities via a mean-reverting form of the Constant Elasticity of Variance (CEV) model.

A second set of studies engages in non-linear methods. Thalassinos et al. (2013) propose that the prediction of Baltic Dry Indices is possible by applying algorithms used in physical sciences. Due to the shipping indices' similarities to chaotic systems such as their sensitivity to crises and irregular shocks, chaotic methodology is found to be the optimum forecasting method. The study suggests that Baltic Dry Indices are characterized as high dimension chaotic systems although the predictive power is limited by the properties of the original system and the series alone. By the same token, Chou (2008) applies a fuzzy time series model with 4.278% root-mean squared error (RMSE) for one-step ahead forecasting of BDI. Papailias et al. (2017) exert a cyclical analysis of the BDI, which resulted in finding of a strong and relatively stable cyclical pattern with cycle durations between 3 and 5 years. It is also suggested that linear models are more suitable for mid-to-long term forecast horizon whereas for the short term forecasting a trigonometric regression model is recommended for more robust and more accurate predictions.

There is considerable effort to predict BDI in the literature. However the predictive performance can be improved when explanatory variables associated with BDI are taken into account in a model as indicated by Cullinane et al. (1999). In that sense, this paper attempts to set up a reliable linear model regarding predictive capacity of possible leading indicator data series. Following Cullinane (1992), a linear model is constructed with the aim to develop a base model for BDI forecasting. Besides, in line with Papailias et al. (2017) this study tries to generate a concrete model for multiple-step ahead prediction.

3. DATA

In order to investigate the forecast performance of leading indicators for BDI, empirical analysis is conducted using monthly data covering the period of January 2010 and June 2017. BDI data which represents the last price of each month, is taken from Bloomberg Database (Bloomberg, 2017). To enhance prediction performance of the model, leading macroeconomic and financial indicators are included.

These indicators are commodity price index for minerals, ores and metals; commodity price index for food; crude oil prices; US 10-year bond yield; world industrial production; S&P 500 index, world consumer price index, gold spot prices, silver spot prices and exchange rate for US\$/Special Drawing Rights.

Crude oil prices are essential input for cost of transportation for dry bulk cargo. Thus, cost side is represented with crude oil prices data as the average of Brent, West Texas and Dubai Fateh spot rates nominated in \$/barrel. As minerals and iron ore are products shipped in bulks, demand for dry bulk is determined by price of these products to a large extent (UNCTAD, 2017a). Besides, the relationship between BDI and various commodities including iron, copper, tin and wheat are investigated in a recent study by Papailias et al. (2017). As a result, commodity price index for minerals, ores and metals is included in this study due to its comprehensive structure for representing demand side with especially iron ore and phosphate prices as well as copper, zinc, nickel and primary aluminium prices. Besides, commodity price index for food is also considered as it refers to prices of wheat, rice, maize, sugar, banana, pepper which are in the categories of dry bulk cargo.

Gold and silver prices in terms of US\$/troy ounce are other commodities taken into account following Theodoulidis and Diaz (2009). Another indicator is Special Drawing Rights (SDR) which is formed as an international reserve asset to better reflect trade growth and financial flows (IMF, 2016). After Papailias et al. (2017) investigate the relationship between exchange rates and BDI, US\$/SDR exchange rate is included in the set of explanatory variables. Commodity price indices for minerals, ores and metals along with for food are sourced from UNCTAD (2017b). Gold and silver spot prices, crude oil prices, and US\$/SDR exchange rate are taken from UNCTAD (2017c).

Industrial production and world consumer price index data are also taken as signals of theoretical framework of supply and demand relationship outlined by Stopford (2009). BDI level is closely related to merchandise production and consumption worldwide along with global economic growth. Moreover, potential relationship between business cycles and BDI is a phenomenon which is addressed in studies by Papailias et al. (2017), Theodoulidis and Diaz (2009). So, this study considers industrial production to capture economic activity in line with Bakshi et al. (2011). Data for world consumer price index (for OECD total as a proxy for world inflation rate) and seasonally adjusted industrial

production growth series are sourced from OECD (2017a, 2017b). Besides, in line with Bakshi et al. (2011) and Theodoulidis and Diaz (2009), S&P 500 Index as the closing price of the first day of each month is downloaded from Yahoo Finance (2017). The index is considered in order to capture the financial outlook and to apprehend the capital-intensive nature of shipping sector. US 10-year bond yield taken from Federal Reserve Bank of Saint Louis (2017) is also included as a variable representing liquidity in the global economy and bond market.

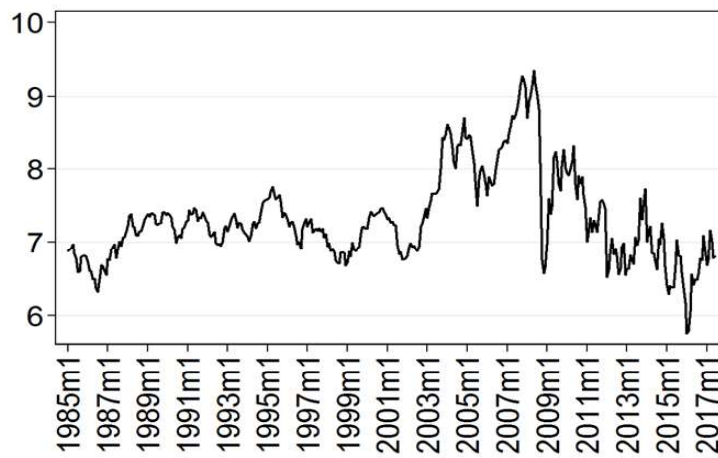


Figure 1: BDI Series in Logarithmic Value (January 2010 - June 2017)
Source: Bloomberg, 2017

Monthly BDI series in natural logarithms are depicted in Figure 1 for the period between January 1985 and June 2017, i.e. since the beginning of the index. Cyclical and seasonal patterns are obvious in the data. Starting from 2000's, data reveal more volatile characteristics. After 2010, the industry follows a relatively stable pattern with the only exception of January 2016. Modeling and prediction efforts are exercised for the period spanning from January 2010 to June 2017 in seeking of better predictive performance.

As an introductory investigation, unit root tests are conducted for all variables. In the analysis, each variable is denoted in the form in parenthesis: BDI (lnbdi); US 10-year bond rate (lnbond); food commodity price index (lnfood); minerals, ores and metals commodity price index (lniron); crude oil prices (ln crude); S&P 500 index (lnsp500); world consumer price index (lnwcp); world industrial production

(product); gold prices (lngold); silver prices (lnsilver) and US\$/SDR exchange rate (lnexch).

4. METHODOLOGY

4.1. The Linear Model

By definition, time series is a sequence of measurements observed over time. The purpose of conducting a time series analysis is usually twofold. First and foremost, the reason is to model and understand the stochastic mechanism that lies behind the observed series. Secondly it aims to estimate the series by examining its past values. Box and Jenkins (1970) proposed a general approach on time series, which has been widely used in the literature due to its simplicity and performance ever since. Random-walk, AR models, exponential smoothing models and ARIMA models are all different versions of this approach adopted from the foundation set by Box and Jenkins (1970).

In this study a special type of ARIMA model which contains exogenous variables is employed. The general notation of such models are in the form of ARIMAX (p,d,q) and p refers to order of AR component, q is the order of integration and q stands for order of MA component. For an ARIMAX model, the general equation is in the form:

$$Y_t = \mu + \phi_1 Y_{(t-1)} + \phi_2 Y_{(t-2)} + \phi_3 Y_{(t-3)} + \dots + \phi_p Y_{(t-p)} + \gamma_1 x_1 + \gamma_2 x_2 + \gamma_3 x_3 + \dots + \gamma_k x_k + \alpha_1 \varepsilon_{(t-1)} + \alpha_2 \varepsilon_{(t-2)} + \alpha_3 \varepsilon_{(t-3)} + \dots + \alpha_q \varepsilon_{(t-q)}$$

where Y_t is the dependent variable, μ is the constant term, $Y_{(t-1)} \dots Y_{(t-p)}$ are the autoregressive components with lags up to order p, $x_1 \dots x_k$ are k number of stationarized dependent variables, $\varepsilon_{(t-1)} \dots \varepsilon_{(t-q)}$ refer to moving average components with lags up to order q.

4.2. Modeling Procedure

As stressed in previous chapters, BDI prediction is crucially important in terms of signaling for global economy and can also be used as a notable input for investment decisions in such a capital-intensive business. In this study, in order to generate a useful model, several steps have been followed. First of all, possible variables are identified in the

light of literature and economic theory. Then the dependent variables along with BDI series are examined in terms of stationarity and necessary processes are applied to make them stationary. The second step deals with a search for a proper model to predict BDI. Identifying the most influential indicators within a set of variables from various origins to be embodied in modeling is essential in forecasting. The third step encompasses a few sub-steps. Firstly, p and q , order of AR component and order of MA component respectively, are ascertained to set an ARIMAX (p,d,q) model. The procedure for determining d -order of integration is already completed during the stationarization process as BDI is first differenced stationary. AR and MA orders are determined using an automated search over all possible models considering up to 12 orders for both AR and MA parts by means of an automated search with the framework outlined by Hyndman and Khandakar (2008). The search is set to minimization of Akaike Information Criterion characterized as;

$$AIC = -2LL + 2n_p \quad (2)$$

where LL is the log-likelihood value and n_p is the number of parameters.

To be more specific, some details of the process are briefly articulated. Stationarity tests are realized via Augmented Dickey Fuller test (Dickey and Fuller, 1979) following a backward elimination approach with a maximum lag of 12 as monthly observations are utilized. As shown in Table 1, all variables are non-stationary in levels with the exception of product and they are stationarized through first differencing. For the remainder of the paper, all leading indicators along with BDI series are in first differences except for product.

As for AR and MA orders, the search has given the order of AR as 10, the order of MA as 0. Overall, the modelling process has yielded an ARIMAX (10,1,0) model. With respect to leading indicators, initially all of the variables are included in the ARIMAX (10,1,0) regression and the optimal model is determined via elimination of insignificant variables step-by-step.

Table 1: ADF Unit Root Tests

| Variables | Level | p | First Difference | p |
|----------------------------|--------------|--------|------------------|--------|
| lnbdi | -2.27 | [0.45] | -6.29*** | [0.00] |
| lnbond | -2.38 | [0.39] | -4.30*** | [0.00] |
| lnfood | -2.57 | [0.30] | -6.03*** | [0.00] |
| lniron | -3.31 | [0.07] | -6.69*** | [0.00] |
| lncrude | -2.6 | [0.28] | -5.57*** | [0.00] |
| lnsp500 | -2.87 | [0.18] | -4.97*** | [0.00] |
| lnwepi | -3.26 | [0.08] | -5.33*** | [0.00] |
| lngold | -2.62 | [0.27] | -7.34*** | [0.00] |
| lnsilver | -3.26 | [0.08] | -7.38*** | [0.00] |
| lnexch | -2.36 | [0.39] | -7.49*** | [0.00] |
| product | -10.36* | [0.00] | - | |
| Critical Value (5%) | -3.46 | | -3.46 | |

Note: *** refers to rejection of the null hypothesis for non-stationarity at 1%.

4. PREDICTION RESULTS AND DISCUSSION

The modeling procedure aforementioned in the previous chapter has resulted in ARIMAX (10,1,0) model and the parameter estimates are presented in Table 2. As shown below; lnbond, lngold, lnsilver and lniron are included in the model as well as autoregressive components ordered up to 10 followed by the processed given above.

Table 2: ARIMAX (10,1,0) Estimation Output

| <i>Var.</i> | <i>Coefficient</i> | <i>P-value</i> | <i>Var.</i> | <i>Coefficient</i> | <i>P-value</i> |
|---------------------------|--------------------|----------------|-------------|--------------------|----------------|
| lnbond | 1.1860* | [0.02] | AR(4) | -0.4891* | [0.00] |
| lngold | 2.6613** | [0.10] | AR(5) | -0.3084* | [0.02] |
| lnsilver | -1.6763* | [0.01] | AR(6) | -0.2886** | [0.09] |
| lniron | 0.8910 | [0.21] | AR(7) | -0.2349* | [0.02] |
| AR(1) | -0.2899** | [0.06] | AR(8) | -0.3347* | [0.02] |
| AR(2) | -0.3507* | [0.01] | AR(9) | -0.3250* | [0.01] |
| AR(3) | -0.2484* | [0.02] | AR(10) | -0.2849* | [0.02] |
| <i>Summary Statistics</i> | | | | | |
| Log-likelihood | | | | 8.75 | |
| AIC | | | | 11.51 | |
| R ² | | | | 28% | |
| Het. test | | | | 0.72 | [0.58] |

Note: * refers to significance at 5% and ** refers to significance at 10%.

The positive sign of \ln_{bond} estimate can be explained by the risk-taking mechanism in financial markets. US treasury bonds are ‘risk-free assets’ in financial terms and their demand goes up in times of low market confidence. When investors have high market confidence, they prefer to invest in riskier assets which offer higher returns resulting in declining price and rising yield of US treasury bonds. The positive relationship between \ln_{gold} and \ln_{bdi} signals for hedging properties of gold as it is a very liquid and easily traded asset along with being used as a policy tool like interest rates (Soytas et al. 2009). Considering the cyclical behavior of Baltic Dry Index market, investors and market participants protect their business against market risk with inclusion of gold in investment strategies. In this way, gold provides diversification in the portfolio as well. With regard to silver, it is a fundamental input in industrial production and it is a highly speculative asset. The negative estimate of \ln_{silver} highlights that silver and BDI are used as substitutions in portfolios as both are highly volatile as a result of being connected to trade and industrial production. Another point is worth to mention about these metals. The reason for \ln_{brent} being insignificant despite of being a main cost item in freight market can be linked to the strong relationship between crude oil prices and the metals, specifically gold. This relationship is investigated by studies like Baffes (2007), Hammoudeh and Yuan (2008) in the literature. As a last remark on the parameters, \ln_{iron} is included as it enhances the power of the model based on minimization of AIC and maximization of log-likelihood measures.

The value of R^2 indicates that the model explains 28% of variation in BDI. The p value of Breusch-Pagan-Godfrey test indicates that the model has homoscedastic variance. Parameter estimates are coherent with the relationship of freight market with commodity and financial markets. Modeling procedure based on AIC and log-likelihood criteria have ended up with a functional model with appealing statistical diagnostics. In Figure 2, the graph of actual and fitted values is given for visual examination.

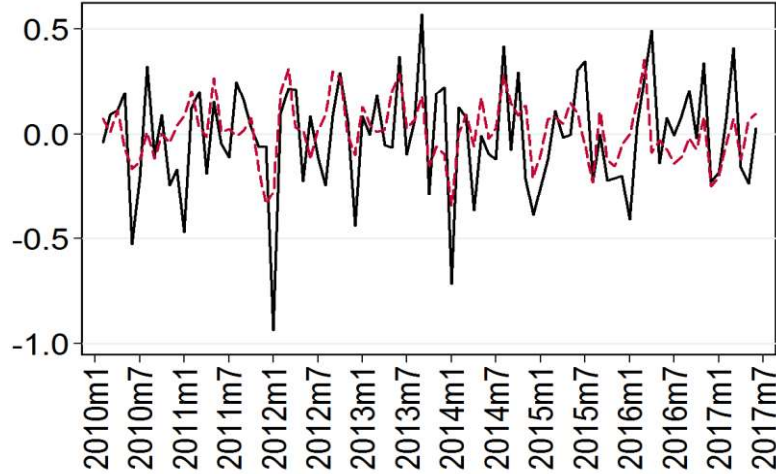


Figure 2: Comparison Between Actual and ARIMAX (10,1,0) Fitted Values

5. CONCLUSION

This paper focuses on forecasting of BDI with an attempt to choose the factors which influence the index from a various background including financial markets, stock markets, commodity markets and economic indicators. The literature on market efficiency of dry bulk shipping indicates an inefficient one, therefore rendering employment of a prediction model as an applicable approach for the matter. The build-up literature to model BDI has been extended with this study by a linear model incorporating various predictors from a diverse range of categories. The series from January 2010 until June 2017 are exploited in the analysis. This is due to the fact that BDI shows cyclical patterns along with high volatility. After examination of BDI time series, a more recent period with a relatively narrow band is purposefully chosen to get a robust model. In the modeling process, a search for optimal AR and MA orders are found out with the stationarized series. Finally, inclusion of leading indicators is assessed based on AIC by eliminating stepwisely. Finally, a benchmark model, ARIMAX (10,1,0) with explanatory variables of \ln bond, \ln gold, \ln silver and \ln iron has been proposed as a useful tool to monitor both freight markets and economic conditions. The model can serve as a reliable analytical tool for decision makers in shipping business, where certain actors can out-play and out-profit other actors due to market inefficiency. As a further study, construction of a

linear benchmark model can be applied to other freight indices related to dry bulk business.

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