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The "Sell in May" Effect: An Empirical Analysis from Turkey, Indonesia, France, and Germany

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Abstract:
This study aims to provide empirical insight into the "Sell in May" (SIM) effect in Turkey, Indonesia, France, and Germany stock exchange markets. We examined Turkey BIST All, BIST Dividend (XTM25), Indonesia IDX Composite, France CAC All (PAX), MSCI France High Dividend Yield (MSCIFRDIV), and Germany CDAX, DivDAX price indices, and individual stocks in dividend indices. Average monthly return data for January 2015 and December 2020 were used for the research. Linear, Quantile regression, and Autoregressive moving average (ARMA) models were employed. The Linear and Quantile regression results revealed no SIM effect for BIST All, MSCI France High Dividend Yield (MSCIFRDIV), CDAX, and DivDAX indices. Besides, regression results revealed no SIM effect for BIST Dividend (XTM25) and Indonesia IDX Composite indices. The Quantile regression model for individual stocks in the BIST Dividend (XTM25) index revealed significant positive SIM effects for KORDS, ANSGR, SISE, SAHOL, AKSA, AKGRT, and EREGL. There is no significant positive SIM effect for stocks in the IDX High Dividend (IDXHIDIV20) index. There are significant positive SIM effects for SCHN and SASY of MSCI France High Dividend Yield (MSCIFRDIV) and SIEGN of the DivDAX indices. We recommend for investment managers to closely follow stocks with a positive SIM effect and their forecasted values if they want to take advantage of the market anomaly. The traditional SIM period and dividend payout period coincide with each other. For this reason, the dividend index is a valuable variable that previous researchers did not consider. In our opinion, dividend index and individual stock level SIM inquiry for markets under review is new in the SIM research and leads to new knowledge discovery. Another original point of the article is that it reveals stocks with positive SIM effects and their forecasted values. Forecasting values charts for stocks in each market shed light on stock investors about the price movements of the stock in the years ahead.

Keywords: "Sell in May" effect, linear regression, quantile regression, autoregressive moving average, investment decisions, efficient market hypothesis.

«五月卖出”效应：来自土耳其、印度尼西亚、法国和德国的实证分析

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摘要:
本研究旨在为土耳其、印度尼西亚、法国和德国证券交易所市场的“五月卖出”（SIM）效应提供实证见解。我们检查了土耳其BIST全部、BIST分红（XTM25）、印度尼西亚IDX复合材料、法国CAC全部（帕克斯）、摩根士丹利资本国际法国高股息收益率(MSCIFRDIV)和德国CDAX、DivDAX价格指数以及股息指数中的个股。2015年1月和2020年12月的平均月回报数据用于研究。采用线性、分位数回归和自回归移动平均(ARMA)模型。线性和分位数回归结果显示BIST全部、摩根士丹利资本国际法国高股息收益率(MSCIFRDIV)、CDAX和DivDAX指数没有SIM效应。此外，回归结果显示BIST红利(XTM25)和印度尼西亚IDX综合指数没有SIM效应。BIST红利(XTM25)指数中个股的分位数回归模型揭示了科尔德、ANSGR、赛斯、萨霍尔、阿克萨、AKGRT和艾瑞格的显着正SIM效应。IDX高股息(IDXHIDIV20)指数中的股票没有显着的积极SIM效应。对摩根士丹利资本国际法国高股息收益率(MSCIFRDIV)的SCHN和SASY以及DivDAX指数的西恩有显着的正向SIM效应。如果投资经理想利用市场异常情况，我们建议投资经理密切关注具有积极SIM效应的股票及其预测值。传统的SIM期和派息期相互吻合。出于这个原因，股息指数是一个有价值的变量，以前的研究人员没有考虑过。我们认为，对所审查市场的股息指数和个股级别SIM查询在SIM研究中是新的，并导致新的知识发现。这篇文章的另一个原创点是它揭示了具有积极SIM效应的股票及其预测值。每个市场中股票的预测价值图表为股票投资者提供了有关未来几年股票价格走势的信息。

关键词:“五月卖出”效应、线性回归、分位数回归、自回归移动平均线、投资决策、有效市场假设。

1. Introduction

The efficient markets hypothesis asserts that security prices reflect available information in the market; securities are not traded at more or less than their value. Under these conditions, an investor will not earn a return above the market average. There are three forms of market efficiency. Markets are either weak-form, semi-strong form, or strong-form efficient based on efficiency strength. The distinction among these forms relates to what information prices reflect. If a market is strong-form efficient, all information is reflected in share prices. There is no inside information in this form. If a market is semi-strong-form efficient, all public information is reflected in the share price. For example, using financial statement information, an investment manager who tries to identify mispriced equities wastes time because the current price already reflects that information. Weak-form efficiency proposes that the current share price reflects past equity prices. In other words, analyzing past prices to determine mispriced securities is a useless effort in this form (Hillier et al., 2017: 307).

An investment manager’s motto is to “Sell in May and Go Away”, which means selling assets in May and reinvesting in September. If this strategy outperforms the “buy and hold” approach, there is an uneven return distribution between the two periods. Uneven return distribution can be explained as a market abnormality. Market abnormality confronts the efficient market hypothesis because security prices reflect all publicly available information in efficient markets. The seasonal effect does not occur over long periods (Malkiel and Fama, 1970). After a seasonal effect becomes public knowledge in efficient markets, investors’ arbitrage activities will most probably lead to updated security prices, and the “Sell in May” (hereinafter referred to as SIM) effect will disappear. Dimson & Marsh (1999), Schwert (2003), Chordia et al. (2014), and McLean & Pontiff (2016) showed that many abnormalities in the market that diminish or even eliminate the information become part of the public information.

This empirical paper examines if a stock market abnormality known as a SIM effect exists in Turkey, Indonesia, France, and Germany markets at broad indices, dividend indices, and individual stock levels. Unlike other previous studies, we employed broad-based indices instead of benchmark indices in our study because we want to observe the existence of the SIM effect in the whole market in each country. Furthermore, we included dividend indices. Stocks in dividend indices distribute cash dividends regularly every year. We expect dividend-paying stocks have higher returns between November and May than other stocks because a corporation’s top management team can forecast year-end profit with high precision in November and estimate the dividend amount. Stockholders determine the actual dividend payout ratio and payment date at the general assembly meeting usually held in April. Stockholders are more eager to collect the cash dividend in addition to the principal appreciation and go away in May. For this reason, we expect to observe a significant SIM effect for dividend indices beyond seasonal market anomalies.

Moreover, we analyzed the SIM effect for each stock in dividend indices. Individual stock level analysis of the SIM effect is also unique for the markets under review. Finally, we calculated forecasting values for stocks with a positive SIM effect for 2021 and 2022 with the ARMA model and interpreted charts. Calculating forecasting values for stocks with a SIM effect is also distinctive in the literature. We list stocks with a positive SIM effect for each market under review with their 2022 forecasting values. This approach fills a gap in the literature, providing for portfolio managers and stock investors to focus on specific stocks and beat the market.

The following section explores the relevant literature body, section three presents the data, section four covers the empirical study, section five reveals the findings, and section six concludes the paper.

2. Literature Review

In the first academic analysis of this effect, Bouman and Jacobsen (2002) examined if, on average, returns during the winter (November-April) are higher than during the summer (May-October). They investigated thirty-seven markets (MSCI indices) between 1970 and 1998 and employed OLS regression with a dummy variable. They also examined the robustness of the January effect. They found higher returns in thirty-five of the thirty-seven markets in the November-April period than in the May-October period. November-April returns were significantly higher in twenty of the thirty-seven markets. Jacobsen and Visaltanachoti (2009) searched the nineteen developed markets (MSCI indices) and compared summer and winter returns between 1998 and 2007. They found a positive SIM effect in all developed markets under review. Haggard and Witte (2010) reviewed thirty-seven markets (MSCI indices) between 1970 and 2008. Again, they found that all markets show a strong positive SIM effect. They used OLS regression with dummy variables and examined the robustness of the outliers. Jacobsen and Zhang (2014) examined one-hundred-nine markets (indices with a broadened stock selection) from the availability of data (1693) to 2011. They also analyzed the SIM effect for smaller markets. They utilized OLS regression with dummy variables and examined the robustness of the time-varying volatility. They found the SIM effect in four-fifths of the markets, about a third with significant results. They also showed that the November-April period return is 4.5% above the May-October period return on average. Dichtl and Drobetz (2015) inquired about Europe, Germany, France, and United Kingdom markets. They reviewed primary stock indices from each market to exploit the SIM effect, such as EuroStoxx 50, DAX, FTSE 100, and CAC 40. They considered all available index data until 2012. They ran OLS regression with dummy variables and examined the robustness of the outliers, January effect, and time-varying volatility. They observed that the SIM effect weakens in recent years of the analysis. Carrazedo et al. (2016) looked into thirty-seven Dow Jones STOXX sector indices for the Eurozone and the Nordic region from 1992 to 2010. They used OLS regression with dummy variables and examined the robustness of the January and April effects. They identified that all indices show SIM effects with a two-thirds significant impact. However, the SIM effect weakened after the initial research done by Bouman and Jacobsen (2002).

We expect exploitable inefficiencies to be more common in emerging markets like Turkey and Indonesia (Hull and McGroarty, 2014). Lean (2011) studied daily stock market index returns of Malaysia, China, India, Japan, Hong Kong, and Singapore markets from 1991 to 2008, running OLS regression with dummy variables and examined the January effect's robustness and time-varying volatility. The researcher arrived at the SIM effect in all market indices except Hong Kong, and the effect was significant for Malaysia and Singapore. Guo et al. (2014) studied the SIM effect in the Chinese stock market utilizing the GTA CSMAR index of Chinese A-shares from 1997 to 2013. They used OLS regression with dummy variable methodology and examined the robustness of the January and February effects. They identified a significant SIM effect. In the Asian market, higher market efficiency weakens the SIM effect as time passes, as in European markets. Besides, there are no essential differences between developed and developing Asian markets. Tekin (2019) questioned whether the January and SIM effects are valid in Borsa İstanbul. He used the monthly data of the BIST100 index for the period 1990-2017. He found out that the SIM was valid in the Turkish market.

Andrade, Chhaochharia, and Fuerst (2013) used MSCI stock market index total returns for the thirty-seven markets from 1998 to 2012. Again, they observed a strong and pervasive positive SIM effect. On average, stock returns are about ten percentage points higher for November –April half-year period than the May-October half-year periods. They ran OLS regression with a dummy variable. They defined the SIM effect as the half-year return for November–April minus the half-year return for May–October. Turkey and Indonesia markets also were in the sample. Indonesia's SIM effect was 15.90% (t-statistics: 1.45), whereas Turkey's SIM effect was 24.73% (t-statistics: 1.26). Hayati, Irman, and Agia (2020) found no significant differences between stock returns from May to October and returns from November to April on the IDX for two years through two cycles between 2015-2017.

3. Method

Previous studies on the SIM effect used benchmark indices such as BIST 100, IDX, CAC 40, and DAX in each country under review. However, we used broad-based indices for SIM analysis. Furthermore, this study contributes to the literature by examining the SIM effect for dividend indices for Turkey, France, and German markets. In addition, we have analyzed the SIM effect for each stock in dividend indices. Individual stock level analysis of the SIM effect is also unique for the markets under review. Investment managers can make a more accurate decision when they want to take advantage of the SIM effect after reading the findings of the article. Finally, we have employed Quantile regression in addition to linear regression. Quantile regression does not have any assumptions about the homogeneity of error variance and the distribution of errors. Thus, we accept it as a more flexible approach than linear regression. We used ARMA to forecast stocks' prices with a positive SIM effect.

3.1. Data

In this empirical paper, we used the broad-based (entire market) price indices data of Borsa Istanbul (BIST), Deutsche Börse (DAX), Euronext Paris (CAC), and Indonesia Stock Exchange (IDX) and dividend price indices data of Borsa Istanbul (BIST), Deutsche Börse (DAX), Euronext Paris (CAC). Besides, we used the companies' stock price data in each dividend indices, including the Indonesia Stock Exchange.

BIST All index consists of all corporations' stocks quoted at the Stock Exchange except Investment Trusts. BIST Dividend (XTM25) index consists of twenty-five stocks placed in the first 2/3 slice in the ranking of BIST Dividend (XTM25) index's constituents descending order according to dividend yield as of the review day and have the highest Median Free Float Market Value (BORSA Istanbul, 2018). The Dividend 25 Index consists of the stocks traded on the Stars, Main, and Sub Market, all having distributed cash dividends in the last three years (BORSA Istanbul, 2018).

IDX Composite index gauges all quoted corporations of the Indonesia Stock Exchange (ISE, 2019). IDX High Dividend (IDXHIDIV20) is an index that measures the stock price performance of 20 stocks that have distributed cash dividends every year over the past three years and have relatively high dividend yields. Besides, stocks have a daily trading value of at least IDR 1 billion in the regular market over the past three months, six months, and twelve months. We used the top ten constituents (companies) stock prices, 81.21% of index weight (ISE, 2021).

CDAX index consists of stocks of all German companies. Thus, CDAX gauges the performance of the entire German stock market and is ideal for analysis purposes. DAX indices are calculated as free-float market-capitalization-weighted (STOXX Ltd, 2019).

The DivDAX index comprises the 15 companies with the highest dividend yields. It is calculated by dividing the dividend paid by the closing price of the share on the day before the distribution. The DivDAX traces companies with a robust and solid economic performance by selecting constituents according to the dividend yield. DivDAX pursues Deutsche Börse's rules of selection indices. Its composition is reassessed every September. Weighting depends on the market capitalization of freely tradable shares, i.e., free float. Weightings are modified every three months. No single stock may account for more than ten percent of the index. CAC All (PAX) index gauges all quoted corporations' performance in the Stock Exchange Market (EURONEXT, 2019).

The MSCI France High Dividend Yield (MSCIFRDIV) includes large and mid-cap stocks. It reflects equities' performance with higher dividend income and quality characteristics, both sustainable and persistent. The index also applies quality screens and reassessments twelve months past performance to discard stocks that will reduce dividends.

We excluded NUHCM, ISDMR, and ENJSA stocks in BIST Dividend (XTM25) and UNTR stock in the IDX High Dividend (IDXHIDIV20) indices due to missing data on an individual stock level analysis of the SIM effect.

We obtained the data from the investing.com website and analyzed the Eviews 9 program using the average monthly return series from January 2015 to December 2020.

3.2. Empirical Study

In this empirical study, we have included the average return for a total of seventy-two months in the analysis. In the first step, we have used the formula (P_t - P_{t-1}) / P_{t-1} * 100 to obtain the returns series. In the second step, we have employed Linear and Quantitative regression models and added the dummy variable (value of 1 from April to November and 0 for the other months) representing the SIM effect to these models as the explanatory variable. In the last step, we have utilized the Autoregressive moving average (ARMA) model as a linear stationary stochastic forecasting model.

3.2.1. Regression Models

Regression analysis examines the functional relationship between the dependent and independent variable (s) and aims to estimate the mathematical model's parameters expressing this relationship. The Least Squares (OLS) estimators, commonly used in regression analysis, are effective, and the obtained model can be used for inference depending on some assumptions. These assumptions can be listed as being independent of errors, having zero mean and constant variance, having normal distribution, and not having multiple linear relationships between independent variables (Vining et al., 2013).

Lakonishok and Smidt (1988) and Sullivan et al. (2001) emphasized that the results of calendar effect studies can be significantly influenced by methodological issues, especially with the econometric model and estimation technique chosen. Therefore, we will interpret the results using different approaches such as linear and quantile regression.

The first model used is the Linear regression model estimated by the least-squares method. Specifically, to test for a SIM effect, we estimate the model:

$$r_t = \mu + \beta_1 S_t + \varepsilon_t$$
$$\varepsilon_t \sim N(0, \sigma^2),$$

where r_t is the monthly average return of the stock analyzed, S_t is the SIM dummy variable that takes the value from April to November, and 0 otherwise. The μ parameter represents the average summer months return, while β_1 is the SIM coefficient reflecting the average surplus return of winter over the summer. Thus, the average return for the winter months is given by the sum of $\mu + \beta_1$. ε_t is a classic error term that follows a normal distribution with zero mean and σ^2 variance. A

SIM impact test will be conducted in this model (and all subsequent models) by evaluating the economic dimension and statistical significance of β_1.

The main reason for the widespread use of the OLS method in regression analysis is that it is easier to calculate than other regression methods. The purpose of the OLS method is to minimize the sum of squares of errors. Besides, when the errors are normally distributed, the predictor with minimum variance among the non-biased estimators is the OLS estimator. Especially when errors are not suitable for normal distribution and contain outliers, OLS estimators lose their efficiency. In these cases, alternative regression techniques should be used. One of the alternative regression techniques is Quantile regression. Since the error term is not normally distributed in models with financial series, the Quantile regression model can be used as an alternative model to the Linear regression model.

Quantile regression was developed to estimate the functional relationship between any quantile in the distribution of the dependent variable and independent variables. Quantile regression is instrumental where conditional quantiles vary. Regression coefficients are determined depending on the quantiles (Chen and Wei, 2005). Quantile regression first emerged as a robust regression method that neglects the normal distribution of error terms from classical assumptions in regression (Chen and Wei, 2005). The Quantile regression model is more flexible than the OLS method and allows examining the covariance effects of the dependent variable's distribution. The Quantile regression model offers a complete model than the traditional mean regression (Yu et al., 2003).

As in other regression models, the purpose of this method is to explain the relationship between variables. Quantile regression is developed for selected quantiles of the conditional distribution of the dependent variable. Unlike the classical regression model, it does not have any assumptions about the homogeneity of error variance and the distribution of errors. Because of these situations, it can be accepted as a more flexible approach than Linear regression. While classical regression looks for a model for the conditional expected value of the dependent variable, the Quantile regression determines the model for the quantiles chosen in the dependent variable's conditional distribution. While the classical regression is based on minimizing the dependent variable's conditional mean and the residual sum of squares, the Quantile regression functions are based on minimizing the weighted sum of absolute residuals.

Quantile regression model is expressed in the following form:

$$y_i = x_i\beta_\theta + u_{\theta i}$$

where the x_i $(kx1)$ dimension is the vector of independent variables. It shows the Linear regression between the independent variables and the θ^{th} quantile of the conditional distribution of the dependent variable y_i; β_θ, is the parameters vector for the θ^{th} quantile regression and $u_{\theta i}$ is the error vector.

While OLS regression gives information about the mean of the conditional distribution of y, the Quantile regression provides information about the entire conditional distribution of y to x for different quantile values. Quantiles are stable against deviating values in y. When the error term is not normally distributed, Quantile regression estimators can be much more efficient than OLS estimators. While the variances of the error terms are assumed to be homogeneous in the OLS regression model, the variability of the error terms is allowed in the Quantile regression model, and there is no assumption about the variance structure.

The traditional Box-Jenkins method is generally used in the literature when estimating assets' future values. Box-Jenkins try to demonstrate a financial asset behavior with historical data and predict that this structure will continue in the future.

We examined the time-series properties of stocks in DivDAX, BIST Dividend (XTM25), IDX High Dividend (IDXHIDIV20), MSCI France High Dividend Yield (MSCIFRDIV) indices to determine a model and predict future return for the next twenty-four months. We choose autoregressive moving average models for forecasting. The time series must first be stationary to apply the Box-Jenkins method, which consists of autoregressive (AR) and moving averages (MA). Stationarity, the sum of random variables ordered according to time, is called a random or stochastic process (Gujarati.2004). If the mean and variance of the stochastic process are constant and the covariance value between two time periods depends on the distance between two periods. In that case, the stochastic process is stationary (Gujarati.2004).

The return on a financial asset provides complete and unit-of-measure summary information regarding investment opportunities for any investor. The statistical properties of the return series are more informative than the price series. Asset returns are close to the average, and they only deviate temporarily from the average in short time frames. Therefore, the return series are generally stationary. Since we have used average monthly returns, the series graphs are stable in average and variance.

3.2.2. Linear Stationary Stochastic Estimation Models

Linear stationary stochastic forecasting models are autoregressive (AR), moving average (MA), and autoregressive moving average (ARMA) models.

Autoregressive Models (AR) express the observation value of a time series in any period and a linear combination of the observation values and error terms of a certain number of previous periods. The AR (p) model does not reveal the relationship between the dependent and independent variables, as in the multiple regression model. It differs from the multiple regression model because it explains the relationship between the observed value of a variable for a certain t period and the previous periods' observation values and is called the "autoregressive model".

According to Carnot et al. (2005), pth degree autoregressive process is expressed as follows:

$$Y_t = \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \dots + \alpha_p y_{p-1} + \varepsilon_t,$$

where ε_t expresses white noise, the coefficients from α_1 to α_p express unknown parameters (Heij et al., 2004).

Moving Average Models (MA) are models in which the observation value in any period of a time series is expressed as a linear combination of the same period’s error term and the error terms of a certain number of past periods.

In the moving average (MA) model, the dependent variable is explained only in unobservable shocks. It is impossible to predict the model with unobservable data, but previous errors can be used. One lagged moving average model (MA (1)) uses the last prediction error, while two lags (MA (2)) use the last two prediction errors (Evans.2003). The moving average of q degrees (MA (q)) is expressed as follows (Carnot et al.2005):

$$y_t = \varepsilon_t + b_1\varepsilon_{t-1} + b_2\varepsilon_{t-2} + \dots + b_q\varepsilon_{q-1}$$

Autoregressive Moving Average Models (ARMA) are used to model stationary time series and combine AR and MA models. In these models, the observation value for any time series period is expressed as a linear combination of the certain previous number of observation values and error terms.

If the ARMA model is a combination of the p-term AR and the q-term MA model, it contains p + q terms and is written as ARMA (p, q). ARMA (p, q) model is expressed as below (Carnot et al.2005):

$$y_t - \alpha_1 y_{t-1} - \alpha_2 y_{t-2} - \dots - \alpha_p y_{p-1} = \varepsilon_t + b_1\varepsilon_{t-1} + b_2\varepsilon_{t-2} + \dots + b_q\varepsilon_{q-1}$$

After deciding on the Box Jenkins models group, we determined model type. The model is named a “temporary suitable model”. First, the degree of the temporal model, namely p in the AR (p) model, q in the MA (q) model, p and q in the ARMA (p, q) model, is determined. Then the temporary parameter values are estimated. First, the autocorrelation and partial autocorrelation functions of the series to be analyzed are determined, and their correlogram is drawn to choose between stationary models. These correlograms are examined together, and the type of the appropriate model is determined according to the following criteria.

The model can be used for forecasting after determining the appropriate model for a time series and estimating the parameters. Forecasting estimates the likelihood of future time series values using current and past period information for a time series. Forecasting is an essential application of time series, especially ARMA models. The primary purpose of ARMA Models is to predict the future values of the time series. Forecasting is to estimate the future value of rt from a specific model. As the prediction time gets longer for stationary series, the predictions approach the mean of the series. Moving average models have finite memory, so the model point predictions quickly approach the series average (Yavuz, 2015).

4. Findings

We assessed and analyzed Linear, Quantile regression, and ARMA results in this part. Eviews software is used for the data analysis.

4.1. Regression Results

Tables 1, 2, 3 and 4 depict the SIM effect with Linear and Quantile regression models using the average monthly returns of BIST All, BIST Dividend (XTM25), IDX Composite, CAC All (PAX), MSCI France High Dividend Yield (MSCIFRDIV), CDAX and DivDAX indices. Besides, it illustrates the SIM effect for individual stocks in the dividend indices of each market under review.

The coefficient of the dummy variable expresses the SIM effect in the BIST All and BIST Dividend (XTM25) indices, and the SIM coefficient is statistically insignificant in the linear regression. This result is expected and is similar to Guo et al. (2014) in the literature section.

Table 1. Linear and quantile regression results for BIST All, BIST Dividend (XTM25) indices along with individual stocks in the dividend index

TURKEY											
	Linear Regressions					Quantile Regressions					
Index / Stocks	Cons.	t-value	Sell in May Coef.	t-value	Prob	Cons.	t-value	Sell in May Coef.	t-value	Prob	Quartile Value
BIST All	-0,05	-0,75	0,02	0,31	0,76	0,38	3,71	-0,05	-0,42	0,67	
BIST Dividend (XTM25)	-0,04	-0,86	0,03	0,36	0,71	-0,51	-6,23	0,20	1,90	0,06	0,10
YGGYO	0,10	1,88	-0,13	-1,53	0,13	0,27	3,95	-0,15	-1,90	0,06	0,80
ALGYO	0,53	1,16	-0,64	-0,99	0,32	0,76	2,76	-0,22	-0,75	0,45	
ALKIM	0,63	-0,17	0,71	0,92	0,36	-0,43	3,93	0,04	0,28	0,77	
TKFEN	-0,06	-0,74	0,04	-0,36	0,72	1,02	3,17	-0,52	-1,56	0,12	
KORDS	-0,12	-1,51	0,11	0,97	0,33	-0,89	-4,44	0,37	1,68	0,09	0,10
TCELL	-0,02	-0,24	0,03	0,40	0,69	0,58	4,41	-0,13	-0,83	0,40	
ANSGR	-0,15	-3,90	0,08	1,60	0,11	-0,35	-5,22	0,20	2,68	0,00	0,20
ISMEN	-0,20	-2,69	-0,04	0,46	0,64	-0,86	-3,86	0,23	0,98	0,33	
BIMAS	0,11	0,07	0,02	0,14	0,89	-0,37	-4,53	-0,15	-1,58	0,11	
SISE	-0,08	-1,11	0,09	0,98	0,32	-0,41	-4,88	0,22	1,88	0,06	0,20
EGEEN	-0,14	-1,12	0,05	0,31	0,76	-0,83	-4,21	0,36	1,57	0,12	
SAHOL	-0,03	-0,46	0,08	0,80	0,42	-0,40	-4,04	0,21	0,73	0,08	0,20
OTKAR	-0,14	-1,46	0,15	1,16	0,24	-0,71	-3,47	0,03	0,14	0,89	
VESBE	-0,08	-0,65	0,05	0,32	0,74	-0,65	-3,20	0,21	0,85	0,40	
AKSA	-0,21	-2,01	0,17	1,39	0,17	-1,01	-5,66	0,47	2,29	0,02	0,10
AKGRT	0.12	0.98	-8,00	-4,4	0,66	-0,55	-5,19	0,30	2,21	0,03	0,20
CCOLA	5,11	2,91	-5,06	-2,03	0,04	44,85	2,71	-44,30	-2,67	0,00	0,90
ENKAI	0,38	2,84	-0,44	-2,29	0,02	0,44	2,77	-0,35	-2,11	0,03	0,80
TOASO	1,76	2,47	-1,27	-1,26	0,21	16,07	2,63	-15,52	-2,52	0,01	0,90
FROTO	0,02	0,19	-8,08	-0,68	0,50	0,65	3,87	-0,20	-0,99	0,32	
EREGL	-0,11	-1,47	0,12	1,03	0,30	-0,85	-6,01	0,34	2,05	0,04	0,10
AEFES	-0,06	-0,08	0,04	0,48	0,62	0,44	4,48	0,20	1,32	0,18	

The Linear regression model for individual stocks in the BIST Dividend (XTM25) index revealed significant negative SIM effects for ENKAI and CCOLA.

According to the Quantile regression model results, we have observed that the positive SIM coefficient is statistically significant at the 10% significance level for BIST Dividend (XTM25) index. However, the SIM coefficient is not statistically significant for BIST All index. We have shown the quartile values of the index and the stocks in the last column of Table 1. The Quantile regression model for individual stocks in the BIST Dividend (XTM25) index revealed significant positive SIM effects for KORDS, ANSGR, SISE, SAHOL, AKSA, AKGRT, and EREGL and negative SIM effects for YGGYO, CCOLA, ENKAI, and TOASO. KORDS, ANSGR, SISE, SAHOL, AKSA, AKGRT and EREGL has a 0.37%, 0.20%, 0.22%, 0.21%, 0.47%, 0.30% and 0.34% respectively higher return in November and April periods than May and October periods. YGGYO, CCOLA, ENKAI, and TOASO have -0.15%, -44.30%, -0.35%, and -15.52%, respectively, lower returns in November and April periods than May and October periods.

Table 2. Linear and quantile regression results for IDX Composite index along with individual stocks in IDX High Dividend (IDXHIDIV20) index

INDONESIA

	Linear Regressions					Quantile Regressions					
Index / Stocks	Cons.	t-value	Sell in May Coef.	t-value	Prob	Cons.	t-value	Sell in May Coef.	t-value	Prob	Quartile Value
IDX Composite	0,04	0,92	-0,09	-1,53	0,13	0,34	3,87	-0,18	-1,85	0,07	0,90
BBRI	-0,05	-0,08	-0,04	-0,40	0,70	0,54	3,77	0,09	0,04	0,96	
TLKM	-0,02	-0,55	-0,04	0.62	0,54	0,42	4.04	-0,06	-0,52	0,60	
BMRI	-0,42	1,74	-1,41	-0,99	0,32	-0,15	-1,70	0,08	0,69	0,49	
BBCA	-0,06	-1,10	1,74	0,05	0,96	-0,33	-5,06	-0,05	-0,63	0,53	
ASII	0,09	1,19	-0,12	-1,13	0,48	-0,30	-4,63	-0,41	-1,81	0,07	0,10
BBNI	0,04	0,38	-0,03	-0,22	0,83	0,41	2,51	0,20	0,97	0,34	
INTP	0,17	1,52	-0,15	0,29	0,29	0,76	4,30	-0,10	-0,48	0,63	
INDF	2,22	1,74	-2,22	-1,42	0,16	0,74	2,35	-0,20	-0,62	0,54	
PTBA	3,77	1,74	-3,76	-1,42	0,16	0,66	3,69	0,11	0,50	0,62	
UNTR	-0,03	-0,05	0,10	1,02	0,31	0,37	3,17	0,10	0,60	0,55	

The Linear regression for the IDX Composite is not statistically significant. The Linear regression results reveal no SIM effect for IDX High Dividend (IDXHIDIV20) stocks on individual stock levels. This result is expected and is similar to Guo et al. (2014) in the literature section.

Table 3. Linear and quantile regression results for CAC All (PAX), MSCI France High Dividend Yield (MSCIFRDIV) indices along with individual stocks in dividend index

FRANCE

	Linear Regressions					Quantile Regressions					
Index / Stocks	Cons.	t-value	Sell in May Coef.	t-value	Prob	Cons.	t-value	Sell in May Coef.	t-value	Prob	Quartile Value
CAC All(PAX)	**-0,03**	**-0,8**	**0,03**	**0,51**	**0,06**	**-0,32**	**-5,74**	**0,13**	**1,87**	**0,06**	0,1
MSCIFRDIV	0,10	1,49	-0,11	-1,42	0,16	0,47	3,02	-0,22	-1,38	0,17	
SCHN	-0,05	-1,05	0,04	0,54	0,59	-0,10	-1,61	0,16	1,67	0,09	0,6
DANO	-0,03	0,49	0,05	0,92	0,36	-0,38	-4,37	-0,06	-0,86	0,39	
SASY	0,03	0,15	-0,03	-0,53	0,97	0,13	-4,80	0,15	1,71	0,09	0,1
BOUY	0,04	0,58	-0,05	-0,57	0,57	-0,29	-3,45	0,06	0,62	0,54	
EXHO	0,15	1,92	-0,19	-1,98	0,05	0,51	3,72	-0,18	-1,15	0,25	
AKE	0,03	0,42	-0,08	-0,81	0,42	0,61	2,63	-0,18	-0,72	0,48	

The Quantile regression results reveal a negative significant SIM effect for the IDX Composite index. The index has a 0.18% lower return in November and April than in May and October. The Quantile regression results reveal a negative SIM effect for ASII in IDX High Dividend (IDXHIDIV20) index on individual stock levels. ASII has a 0.41% lower return in November and April than the May and October (quartile value of 0.10) periods.

The Linear regression results reveal a positive SIM effect for the CAC All (PAX) index and a negative SIM effect for EXHO stock of MSCI France High Dividend Yield (MSCIFRDIV) index. The SIM coefficient is statistically insignificant for MSCI France High Dividend Yield (MSCIFRDIV) index. The CAC All (PAX) index has a 0.03% higher return; however, EXHO has a -0.19% lower return in November and April than the May and October periods.

The Quantile regression results reveal a positive SIM effect for the CAC All (PAX) index and SCHN and SASY stocks of the MSCI France High Dividend Yield (MSCIFRDIV) index on individual stock level. The SIM coefficient is statistically insignificant for MSCI France High Dividend Yield (MSCIFRDIV) index. This result is expected and similar to Dichtl and Drobetz (2015) and Carrazedo et al. (2016). CAC All (PAX) index, SCHN and SASY have a 0.13%, 0.16%, and 0.15% higher return in November and April periods, respectively, than in May and October periods.

The Linear and Quantile regression results reveal no SIM effect for Germany's CDAX and DivDAX indices. The SIM coefficients are insignificant in both regressions. This result is expected and similar to Dichtl and Drobetz (2015) and Carrazedo et al. (2016). The Quantile regression results reveal a positive SIM effect for SIEGN of DivDAX index on individual stock level. SIEGN of DivDAX has a 0.19% higher return in November and April periods than May and October periods.

Table 4. Linear and quantile regression results for CDAX and DivDAX indices along with individual stocks in dividend index

GERMANY

	Linear Regressions					Quantile Regressions					
Company	Cons.	t-value	Sell in May Coef.	t-value	Prob	Cons.	t-value	Sell in May Coef.	t-value	Prob	Quartile Value
CDAX	**0,04**	**1,14**	**-0,02**	**-0,44**	**0,65**	**0,35**	**5,81**	**-0,06**	**-0,78**	**0,44**	
DivDAX	-0,02	-0,05	0,05	0,08	0,94	0,43	3,35	-0,17	-1,26	0,21	
ALVG	0,06	0,87	-0,11	-1,24	0,22	0,48	3,55	-0,03	-0,21	0,84	
BASF	0,02	0,95	0,04	0,48	0,64	0,57	3,94	-0,24	-1,58	0,12	
BAYER	0,09	1,00	-0,02	-0,18	0,85	0,61	3,86	0,11	0,50	0,62	
BMW	0,12	1,40	-0,14	-1,27	0,21	0,65	4,14	-0,19	-1,08	0,28	
DAIGN	0,13	1,34	-0,15	-1,19	0,24	0,84	3,60	-0,39	-1,61	0,11	
DPWGN	0,16	0,26	-0,05	-0,60	0,54	0,63	2,69	-0,14	-0,47	0,64	
DTEGN	0,05	0,75	-0,07	-0,87	0,39	0,34	3,66	0,03	0,19	0,85	
EON	-0,01	-0,07	0,07	0,75	0,46	-0,43	-3,91	0,10	0,79	0,43	
LHAG	0,05	0,58	-0,40	-0,03	0,97	0,76	2,93	-0,01	-0,41	0,96	
PSMGN	0,13	0,97	-0,07	-0,40	0,69	-0,31	-2,41	0,16	1,00	0,32	
SIEGN	0,07	1,12	-0,16	-1,18	0,85	-0,04	-0,70	0,19	1,78	0,07	0,6
VNAN	-0,07	-1,20	0,05	0,67	0,51	-0,39	-6,42	0,05	0,59	0,56	

Regression results reveal that the seasonal effect does not occur over long periods. After a seasonal effect becomes public knowledge in efficient markets, investors' arbitrage activities will most probably lead to updated security prices, and the SIM effect will disappear (Malkiel and Fama, 1970). Dimson and Marsh (1999); Schwert (2003); Chordia, Subrahmanyam, and Tong (2014); McLean and Pontiff (2016) have also shown that many abnormalities in the market diminish or even disappear the information becomes part of the public information.

4.2. ARMA Results

In this study, first, autoregressive moving average models were chosen for forecasting. Second, the temporary model type was preferred after deciding on the Box Jenkins models group. Third, the degree of the temporary model was determined, namely p and q values. Fourth, since we could not determine p and q values from the correlogram of the returns, we determined suitable ARMA models according to AIC values by the automatic forecasting method. Finally, we presented the results in Table 5.

Table 5. Forecasting model and AIC values

	TURKEY			INDONESIA			FRANCE			GERMANY	
Stocks	Selected ARMA Models	AIC Value	Stocks	Selected ARMA Models	AIC Value	Stocks	Selected ARMA Models	AIC Value	Stocks	Selected ARMA Models	AIC Valu e
YGGYO	(0,0)(0,0)	0,94	BBRI	(3,3)(0,0)	1,3	SCHN	(2,3)(0,0)	0,81	ALVG	(3,3)(0,0)	0,85
ALGYO	(0,0)(0,0)	4,80	TLKM	(2,2)(0,0)	0,69	DANO	(0,0)(0,0)	0,38	BASF	(3,3)(0,0)	1,16
ALKIM	(0,0)(0,0)	5,40	BMRI	(0,0)(0,0)	15,82	SASY	(0,0)(0,0)	0,3	BAYER	(4,4)(0,0)	1,28
TKFEN	(0,0)(0,0)	1,78	BBCA	(0,0)(0,0)	0,37	BOUY	(0,0)(0,0)	1,05	BMW	(2,2)(0,0)	1,26
KORDS	(4,3)(0,0)	1,57	ASII	(3,3)(0,0)	1,54	EXHO	(4,4)(0,0)	1,08	DAIGN	(1,1)(0,0)	1,65
TCELL	(0,0)(0,0)	1	BBNI	(4,4)(0,0)	1,87	AKE	(0,0)(0,0)	1,19	DPWGN	(2,2)(0,0)	1,01
ANSGR	(4,4)(0,0)	-0,14	INTP	(0,1)(0,0)	1,78				DTEGN	(1,2)(0,0)	0,55
ISMEN	(0,1)(0,0)	1,19	INDF	(0,0)(0,0)	15,9				EON	(4,0)(0,0)	1,01
BIMAS	(3,2)(0,0)	2,74	PTBA	(0,0)(0,0)	15,96				LHAG	(0,0)(0,0)	1,72
SISE	(4,4)(0,0)	1,05	UNTR	(3,2)(0,0)	1,28				PSMGN	(2,0)(0,0)	2,15
EGEEN	(0,0)(0,0)	2,07							SIEGN	(3,4)(0,0)	0,91
SAHOL	(3,2)(0,0)	1,01							VNAN	(1,1)(0,0)	0,41
OTKAR	(0,0)(0,0)	1,78									
VESBE	(3,4)(0,0)	2,22									
AKSA	(2,3)(0,0)	1,47									
AKGRT	(0,1)(0,0)	1,99									
CCOLA	(1,0)(0,0)	6,44									
ENKAI	(3,2)(0,0)	1,92									
TOASO	(1,0)(0,0)	4,63									
FROTO	(2,2)(0,0)	1,68									
EREGL	(0,0)(0,0)	1,67									
AEFES	(4,4)(0,0)	0,99									

We have selected the best models with the lowest AIC value by optimizing the model’s parameters for each stock and generated point estimates using the best model in Table 5.

The stock’s forecasting values are presented in BIST Dividend (XTM25) between January 2021 and December 2022 in Table 6.

Table 6. Forecasting values for stocks in the BIST Dividend (XTM25)

DATE	YGGYO	ALGYO	ALKIM	TKFEN	KORDS	TCELL	ANSGR	ISMEN	BIMAS	SISE	EGEEN
2021M01	0,23	-1,98	-0,26	-0,11	-0,74	-0,33	-0,36	-0,61	-0,45	-0,29	-0,45
2021M02	0,09	-5,53	-0,08	-0,13	0,18	0,07	-0,30	-0,25	-0,27	-0,53	0,23
2021M03	0,08	-5,62	0,08	0,35	0,37	0,18	0,24	-0,01	0,38	0,75	-0,05
2021M04	-0,08	-5,68	4,19	-0,33	-0,37	-0,02	-0,18	-0,78	-0,45	-0,29	0,07
2021M05	-0,24	-5,68	-0,03	-0,08	0,44	0,18	0,09	-0,51	0,10	0,36	0,28
2021M06	0,00	-5,72	0,07	-0,21	-0,28	-0,22	-0,16	-0,23	1,23	-0,18	-0,18
2021M07	-0,03	-5,76	-0,07	0,04	0,25	0,01	-0,13	-0,57	0,20	-0,40	-0,32
2021M08	0,04	-5,79	0,10	0,06	-0,09	0,36	-0,16	-0,50	0,03	0,54	0,24
2021M09	0,10	-5,81	-0,20	-0,03	-0,01	-0,01	-0,25	-0,51	-0,28	-0,28	-0,26
2021M10	0,05	-5,86	-0,31	0,10	-0,12	-0,20	0,15	-0,49	-0,32	0,23	-0,33
2021M11	0,19	-5,92	0,02	0,07	-0,11	0,00	-0,12	-0,73	-0,22	-0,23	-0,26
2021M12	0,13	-6,07	-0,15	-0,25	-0,07	0,01	0,11	-0,74	-0,38	-0,51	-0,31
2022M01	0,23	-6,08	-0,26	-0,11	-0,69	-0,33	-0,43	-0,70	-0,26	0,16	-0,45
2022M02	0,09	-9,62	-0,08	-0,13	0,25	0,07	-0,18	-0,34	0,09	-0,41	0,23
2022M03	0,08	-9,71	0,08	0,35	0,01	0,18	-0,06	-0,10	0,77	0,57	-0,05
2022M04	-0,08	-9,77	4,19	-0,33	-0,10	-0,02	-0,26	-0,87	-0,20	-0,37	0,07
2022M05	-0,24	-9,77	-0,03	-0,08	0,01	0,18	0,01	-0,60	0,12	0,22	0,28
2022M06	0,00	-9,82	0,07	-0,21	0,01	-0,22	-0,02	-0,33	1,02	0,23	-0,18
2022M07	-0,03	-9,85	-0,07	0,04	0,00	0,01	0,07	-0,66	-0,16	-0,54	-0,32
2022M08	0,04	-9,89	0,10	0,06	0,00	0,36	-0,09	-0,59	-0,33	0,39	0,24
2022M09	0,10	-9,91	-0,20	-0,03	0,04	-0,01	-0,25	-0,60	-0,50	-0,22	-0,26
2022M10	0,05	-9,95	-0,31	0,10	-0,30	-0,20	-0,07	-0,58	-0,31	0,18	-0,33
2022M11	0,19	-10,01	0,02	0,07	0,16	0,00	-0,21	-0,82	0,00	0,06	-0,26
2022M12	0,13	-10,16	-0,15	-0,25	-0,39	0,01	0,04	-0,83	-0,03	-0,77	-0,31

Continuation of Table 6

DATE	SAHOL	OTKAR	VESBE	AKSA	AKGRT	CCOLA	ENKAI	TOASO	FROTO	EREGL	AEFES
21M01	-0,03	-0,21	-0,55	-0,82	-0,64	0,80	0,33	-0,20	-0,55	-0,27	-0,21
21M02	0,55	-0,01	-0,33	-0,08	-0,16	1,81	0,22	0,54	-0,30	-0,08	0,74
21M03	0,41	0,41	0,17	0,02	-0,47	2,53	0,40	1,18	0,45	0,03	0,27
21M04	-0,49	-0,03	-0,76	-0,02	-0,57	3,45	0,89	0,94	-0,31	-0,06	-0,21
21M05	-0,27	0,35	0,02	0,08	-0,48	-2,81	-0,13	2,03	0,27	0,07	-0,17
21M06	-0,24	-0,13	-0,34	-0,25	-0,85	-2,11	-0,12	-1,05	0,01	-0,16	-0,37
21M07	0,55	-0,17	-0,19	0,06	-0,65	-0,80	0,11	-0,23	0,06	-0,09	0,45
21M08	0,67	0,23	-0,02	0,21	-0,65	0,23	-0,09	0,24	0,13	0,08	0,14
21M09	-0,18	-0,02	0,03	0,03	-0,88	1,13	0,27	0,30	0,05	0,09	0,24
21M10	-0,37	-0,15	-0,59	-0,26	-0,73	2,36	0,16	0,72	-0,31	0,01	-0,11
21M11	-0,35	-0,49	0,11	-0,12	-0,84	2,99	0,27	1,23	0,22	-0,13	-0,37
21M12	-0,01	-0,50	-0,19	-0,27	-1,08	4,20	0,41	1,33	-0,15	-0,19	-0,07
22M01	0,06	-0,21	-0,31	-0,61	-1,11	5,31	0,31	1,67	-0,31	-0,27	-0,08
22M02	0,48	-0,01	-0,46	-0,02	-0,63	6,15	0,53	2,28	-0,14	-0,08	0,65
22M03	0,22	0,41	0,29	0,02	-0,94	6,70	0,78	2,81	0,52	0,03	0,13
22M04	-0,58	-0,03	-0,19	-0,07	-1,04	7,46	0,76	2,47	-0,33	-0,06	-0,32
22M05	-0,18	0,35	0,28	0,07	-0,94	1,03	0,24	3,46	0,19	0,07	-0,10
22M06	-0,05	-0,13	-0,35	-0,21	-1,31	1,59	0,03	0,30	-0,10	-0,16	-0,25
22M07	0,62	-0,17	-0,05	0,07	-1,12	2,75	-0,01	1,03	-0,05	-0,09	0,51
22M08	0,55	0,23	0,20	0,20	-1,11	3,65	0,29	1,42	0,05	0,08	0,05
22M09	-0,35	-0,02	0,10	0,02	-1,35	4,41	0,22	1,40	0,00	0,09	0,11
22M10	-0,41	-0,15	-0,57	-0,25	-1,19	5,52	0,13	1,75	-0,33	0,01	-0,15
22M11	-0,21	-0,49	0,19	-0,11	-1,30	6,02	0,59	2,20	0,23	-0,13	-0,28
22M12	0,15	-0,50	-0,11	-0,28	-1,54	7,11	0,24	2,24	-0,11	-0,19	0,04

It was observed that some stocks have positive and negative predictive values in Table 6. The estimation charts for each stock are presented in Figure 1.

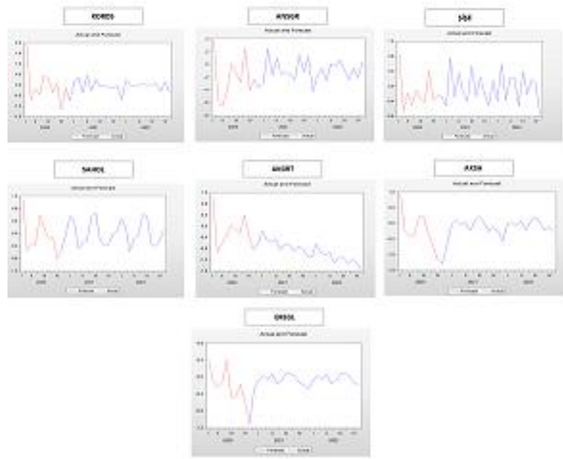

Figure 1. Forecasting values charts for stocks in the BIST Dividend (XTM25)

The blue line depicts the forecasting values for the range January 2021 - December 2022. We interpret the ARMA results for stocks that have a positive SIM effect.

The forecasting values for KORDSA surged from the lowest value of -0.74 to the highest value of 0.37 in the first quarter of 2021. KORDSA fluctuated in the second quarter, slightly fell in the third quarter and finally plummeted in the last quarter of 2021 till the early days of the following year’s January. The forecasting values for KORDSA almost followed the same pattern in 2022. We recommend the investors to buy KORDSA in the early days of January and sell it in the second quarter.

The forecasting values for ANSGR fell in January and February and soared from the lowest value of -0.36 to the highest value of 0.24 in the first quarter of 2021. ANSGR forecasting value fluctuated in the second quarter, slightly fell in the third quarter, and fluctuated in the last quarter of 2021. ANSGR forecasting values plunged in January and February and slipped back till the end of the last quarter of 2022. We recommend the investors to buy ANSGR in February and sell it in March 2021 and stay in cash in 2022.

The forecasting values for SISE fell in January, plunged in February, and soared from the lowest value of -0.53 to the highest value of 0.75 in the first quarter of 2021. SISE forecasting values fluctuated in the second and third quarter, finally slipped back in the last quarter of 2021. SISE forecasting value fell sharply in February and surged in March in the first quarter of 2022, fluctuating the rest of the year. We recommend the investors to buy SISE in February and sell it in March.

The forecasting values for SAHOL surged from the lowest value of -0.03 to the highest value of 0.55 in the first quarter, slipped back in the second quarter, increased in the third quarter and finally dropped in the last quarter of 2021. The forecasting values for SAHOL almost followed the same pattern in 2022.

The forecasting values for AKGRT decreased gradually with ups and downs in 2021 and 2022.

The forecasting values for EREGL increased from the lowest value of -0.27 to the highest value of 0.03 in the first quarter, fluctuated in the second quarter, increased slightly in the third quarter and finally dropped in the last quarter of 2021. The forecasting values for EREGL almost followed the same pattern in 2022.

The forecast values for AKSA increased from the lowest value of -0.82 to the highest value with 0.02 in the first quarter, fluctuated in the second quarter, and increased in the third quarter. It started to decline in the last quarter of 2021.

We presented the stock forecasting values in IDX High Dividend (IDXHIDIV20) between January 2021 and December 2022 in Table 7.

It was observed that some stocks had positive and negative predictive values in Table 7. There was no significant positive SIM effect for stocks in IDX High Dividend (IDXHIDIV20) index. For this reason, we did not interpret the forecast value charts for stocks in IDX High Dividend (IDXHIDIV20) index.

Table 7. Forecasting values for stocks in IDX High Dividend (IDXHIDIV20)

DATE	BBRI	TLKM	BMRI	BBCA	ASII	BBNI	INTP	INDF	PTBA	UNTR
2021M01	-0,13	-0,09	-0,07	-0,06	-0,31	0,17	0,19	-0,20	0,07	-0,01
2021M02	-0,18	-0,18	0,04	0,01	0,30	0,15	0,12	0,08	1507,08	0,09
2021M03	0,52	0,06	0,30	0,03	0,36	-0,04	0,34	0,26	-0,11	0,17
2021M04	0,04	-0,03	0,25	0,03	0,15	0,63	0,14	-0,03	0,18	-0,14
2021M05	-0,22	0,09	-0,08	-0,05	-0,10	0,11	-0,15	0,06	0,15	-0,26
2021M06	0,34	-0,12	0,06	-0,02	0,04	-0,28	0,46	0,13	-0,10	0,33
2021M07	-0,38	-0,09	-0,17	-0,25	0,10	0,22	-0,10	-0,05	0,04	0,37
2021M08	0,10	0,06	0,93	-0,02	0,10	0,19	-0,03	-0,05	0,23	-0,13
2021M09	0,22	0,02	0,21	0,08	0,20	-0,08	0,25	-0,02	0,26	-0,06
2021M10	-0,39	0,20	-0,27	-0,12	-0,39	-0,19	-0,23	0,09	-0,39	0,50
2021M11	-0,09	-0,10	-0,10	-0,10	0,07	-0,02	-0,16	0,15	3,13	-0,30
2021M12	-0,32	-0,14	851,76	-0,22	-0,09	-0,37	0,01	888,22	-0,99	-0,03
2022M01	-0,11	0,03	-0,07	-0,06	-0,08	-0,17	0,20	-0,20	0,07	0,30
2022M02	0,19	-0,01	0,04	0,01	0,19	0,11	0,12	0,08	1507,08	0,00
2022M03	0,03	0,12	0,30	0,03	0,32	0,49	0,34	0,26	-0,11	-0,22
2022M04	0,36	-0,10	0,25	0,03	0,23	0,14	0,14	-0,03	0,18	0,11
2022M05	-0,19	-0,01	-0,08	-0,05	-0,25	-0,02	-0,15	0,06	0,15	0,00
2022M06	0,01	-0,16	0,06	-0,02	0,17	0,28	0,46	0,13	-0,10	-0,05
2022M07	0,02	-0,06	-0,17	-0,25	-0,04	-0,02	-0,10	-0,05	0,04	0,29
2022M08	-0,13	0,11	0,93	-0,02	0,21	-0,13	-0,03	-0,05	0,23	0,28
2022M09	0,15	0,04	0,21	0,08	0,10	0,30	0,25	-0,02	0,26	-0,19
2022M10	-0,11	0,18	-0,27	-0,12	-0,33	-0,14	-0,23	0,09	-0,39	0,15
2022M11	-0,41	-0,13	-0,10	-0,10	0,02	-0,33	-0,16	0,15	3,13	0,00
2022M12	-0,16	-0,15	851,76	-0,22	-0,07	-0,26	0,01	888,22	-0,99	0,17

The stock forecasting values in MSCI France High Dividend Yield (MSCIFRDIV) between January 2021 and December 2022 are presented in Table 8.

Table 8. Forecasting values for stocks in MSCI France High Dividend Yield (MSCIFRDIV)

DATE	SCHN	DANO	SASY	BOUY	EXHO	AKE
2021M01	-0.09	-0.11	0.01	0.01	-0.37	0.00
2021M02	-0.03	0.05	0.03	-0.12	0.10	-0.14
2021M03	0.08	0.10	-0.01	0.34	0.22	0.11
2021M04	-0.18	-0.17	-0.13	0.07	-0.08	-0.26
2021M05	-0.01	-0.02	0.04	0.10	0.20	0.14
2021M06	0.03	0.07	-0.05	0.10	0.05	-0.01
2021M07	-0.08	-0.08	-0.08	-0.01	0.35	-0.24
2021M08	0.11	0.10	0.20	-0.15	-0.22	0.17
2021M09	-0.01	-0.01	-0.09	0.03	0.04	-0.09
2021M10	-0.10	0.16	0.02	-0.02	-0.23	-0.11
2021M11	-0.08	-0.07	0.05	-0.20	-0.37	0.01
2021M12	0.08	0.08	0.08	-0.04	0.24	0.17
2022M01	-0.17	-0.11	0.01	0.01	0.01	0.00
2022M02	-0.11	0.05	0.03	-0.12	0.35	-0.14
2022M03	0.17	0.10	-0.01	0.34	0.26	0.11
2022M04	-0.16	-0.17	-0.13	0.07	-0.09	-0.26
2022M05	-0.09	-0.02	0.04	0.10	-0.22	0.14
2022M06	0.06	0.07	-0.05	0.10	-0.04	-0.01
2022M07	-0.04	-0.08	-0.08	-0.01	0.16	-0.24
2022M08	0.06	0.10	0.20	-0.15	0.01	0.17
2022M09	-0.01	-0.01	-0.09	0.03	0.30	-0.09
2022M10	-0.06	0.16	0.02	-0.02	-0.08	-0.11
2022M11	-0.11	-0.07	0.05	-0.20	-0.24	0.01
2022M12	0.06	0.08	0.08	-0.04	-0.06	0.17

It was observed that some stocks had positive and negative predictive values in Table 8. The forecasting value charts for each stock are presented in Figure 3.

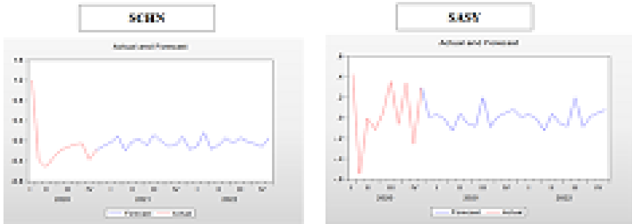

Figure 2. Forecasting values charts for stocks in MSCI France High Dividend Yield (MSCIFRDIV)

The forecasting values for SCHN slipped back in January and February and increased slightly from the lowest value of -0.09 to the highest value of 0.08 in the first quarter of 2021. SCHN forecasting values fell in April and May and increased slightly in June, fluctuated in the third quarter and finally dipped slightly for two months and increased in December in the last quarter of 2021. The forecasting values for SCHN almost followed the same pattern in 2022.

The forecasting values for SASY slightly increased in the first quarter of 2021. SASY forecasting values fluctuated in the second and third quarters with a jump in August and finally slightly climbed in the last quarter of 2021. The forecasting values for SASY almost followed the same pattern in 2022.

The stock's forecasting values in DivDAX between January 2021 and December 2022 are presented in Table 9.

Table 9. Forecasting values for stocks in DivDAX

DATE	ALVG	BASF	BAYER	BMW	DAIGN	DPWGN	DTEGN	EON	LHAG	PSMGN	SIEGN	VNAN
2021M01	0.14	0.33	-0.03	0.21	0.15	0.12	0.21	0.03	0.12	0.46	0.21	-0.01
2021M02	0.23	0.33	0.45	0.06	0.19	-0.06	0.06	-0.14	0.22	0.05	0.40	0.01
2021M03	-0.35	-0.34	0.09	0.34	0.41	0.03	0.22	0.08	0.41	0.59	0.00	0.05
2021M04	-0.19	-0.07	0.17	-0.20	0.03	-0.15	-0.16	0.10	-0.03	-0.37	-0.15	0.11
2021M05	0.52	0.49	-0.16	0.37	0.22	0.25	-0.02	-0.09	0.13	0.04	0.03	-0.22
2021M06	-0.29	-0.24	0.03	0.13	0.23	-0.04	0.09	-0.05	0.37	0.35	-0.04	0.16
2021M07	-0.25	0.05	-0.01	0.01	0.01	-0.26	-0.05	0.04	0.08	0.31	-0.10	-0.22
2021M08	0.39	0.36	0.16	0.13	0.19	-0.06	0.15	0.33	-0.03	0.17	0.33	-0.06
2021M09	-0.14	-0.25	0.32	-0.03	-0.10	0.04	-0.03	0.37	0.06	-0.19	0.03	0.07
2021M10	-0.38	-0.19	-0.06	-0.18	-0.24	-0.08	-0.01	-0.20	-0.33	0.09	-0.20	0.01
2021M11	-0.04	0.09	0.13	-0.17	-0.04	-0.15	-0.04	0.08	-0.41	0.17	0.00	0.04
2021M12	0.12	0.02	0.05	0.06	0.17	0.10	0.08	0.04	0.01	-0.05	0.06	-0.07
2022M01	-0.29	-0.09	-0.07	0.13	0.05	0.18	0.01	-0.15	0.12	-0.02	-0.08	-0.12
2022M02	0.20	0.25	0.17	0.03	0.11	0.09	-0.02	-0.01	0.22	-0.04	0.27	-0.06
2022M03	0.20	0.10	0.27	0.30	0.34	0.03	0.20	0.13	0.41	0.74	0.22	0.00
2022M04	-0.39	-0.28	-0.08	-0.21	-0.02	-0.28	-0.17	0.00	-0.03	-0.36	-0.28	0.08
2022M05	0.26	0.29	0.03	0.35	0.18	0.21	-0.02	-0.01	0.13	-0.01	-0.16	-0.24
2022M06	0.13	0.09	-0.03	0.12	0.20	0.06	0.09	-0.06	0.37	0.35	0.15	0.15
2022M07	-0.22	0.00	0.06	-0.01	-0.02	-0.19	-0.05	-0.01	0.08	0.32	-0.11	-0.23
2022M08	0.06	0.14	0.22	0.13	0.17	-0.12	0.15	0.38	-0.03	0.16	0.13	-0.07
2022M09	0.10	-0.04	0.27	-0.03	-0.12	-0.05	-0.03	0.35	0.06	-0.19	0.15	0.07
2022M10	-0.20	-0.13	0.00	-0.19	-0.26	-0.05	-0.01	-0.22	-0.33	0.09	-0.12	0.01
2021M11	-0.32	-0.11	0.06	-0.17	-0.05	-0.06	-0.04	0.11	-0.41	0.17	-0.18	0.04
2022M12	0.18	0.12	0.08	0.06	0.15	0.10	0.08	0.02	0.01	-0.05	0.09	-0.07

Table 9 shows that some stocks have positive and negative predictive values. Figure 3 presents the point estimation charts for each stock.

Figure 3. Forecasting values charts for stocks in DivDAX

The forecasting values for SIEGN surge in the first quarter of 2021 and slightly fall and fluctuate in the second quarter and jump in the third quarter and finally fall in the last quarter of 2021. The forecasting values for SIEGN increase from the lowest value of -0.08 to the highest value of 0.27 in the first quarter of 2022 and drop in the second quarter and increase in the third quarter and finally fall in the last quarter of 2022.

5. Conclusion

The SIM effect was analyzed for dividend indices in addition to broad-based indices for markets under review. Stocks investors are eager to collect cash dividends and benefit from principal appreciation to maximize their returns. Stocks in dividend indices distribute cash dividends regularly every year. Therefore, we expect dividend-paying stocks have higher returns between November and May than other stocks because a corporation’s management team or stock analysts can foresee the year-end profit and the dividend amount in November. Besides, stockholders determine the actual dividend amount and the payment date in April. In other words, the traditional SIM period and dividend payout period coincide. For this reason, the dividend index is a valuable variable that previous researchers did not consider. In our opinion, dividend index and individual stock level of SIM inquiry for markets under review is new in the SIM research and leads to new knowledge discovery. Another original point of the article is that it reveals stocks with positive SIM effects and their forecasted values. Forecasting values charts for stocks in each market shed light on stock investors about the price fluctuations of the stock in the years ahead. Thus, stock investors can directly use the findings of the article.

In the study, we aimed to provide empirical insight into the “Sell in May” (SIM) effect in Turkey, Indonesia, France, and Germany stock exchange markets, analyzing Turkey’s BIST All, BIST Dividend (XTM25), Indonesia’s IDX Composite, France’s CAC All (PAX), MSCI France High Dividend Yield (MSCIFRDIV), and Germany’s CDAX, DivDAX price indices, and individual stocks in dividend indices. We used Linear, Quantile regression, and Autoregressive moving average (ARMA) models.

The Linear regression results revealed a positive SIM effect only for CAC All (PAX) index. The quantile regression results revealed a positive SIM effect for BIST Dividend (XTM25) and CAC All (PAX) indices. According to the Linear regression, one out of seven and the Quantile regression, two out of seven indices revealed a positive SIM effect. The Linear and Quantile regression results revealed no SIM effect for BIST All, MSCI France High Dividend Yield (MSCIFRDIV), CDAX, and DivDAX indices. Besides, regression results revealed no SIM effect for BIST Dividend (XTM25) and Indonesia IDX Composite indices. The index level analysis showed that anomalies in the markets diminished by the time passed. Thus, an investor would not earn a return above the market average under these circumstances.

We also analyzed the SIM effect for each stock in dividend indices. Individual stock level analysis of the SIM effect is also unique for the markets under review. The Linear regression model for individual stocks in the BIST Dividend (XTM25) index revealed significant negative SIM effects only for ENKAI. The Quantile regression model for individual stocks in the BIST Dividend (XTM25) index revealed significant positive SIM effects for KORDS, ANSGR, SISE, SAHOL, AKSA, AKGRT, and EREGL and negative SIM effects for YGGYO, CCOLA, ENKAI, and TOASO. Seven out of twenty-five stocks had a positive SIM effect in the dividend index on individual stock level. The Quantile regression results revealed a negative SIM effect for ASII in IDX High Dividend (IDXHIDIV20) index on individual stock level. The Linear regression results revealed a negative SIM effect for EXHO stock of MSCI France High Dividend Yield (MSCIFRDIV) index. The Quantile regression results reveal a positive SIM effect for the SCHN and SASY stocks of the MSCI France High Dividend Yield (MSCIFRDIV) index on individual stock level. The Quantile regression results reveal a positive SIM effect for SIEGN of DivDAX index on individual stock level. One out of twelve stocks have a positive SIM effect in the dividend index on individual stock level.

We recommend investment managers to closely follow KORDS, ANSGR, SISE, SAHOL, AKSA, AKGRT, and EREGL stocks of Turkey, SCHN and SASY stocks of France, and SIEGN stock of Germany if they want to take advantage of the SIM effect.

Furthermore, we calculated forecasting values for stocks with a positive SIM effect for 2021 and 2022 with the ARMA model and interpreted charts. However, forecasting values should be approached with caution because of the Covid-19 pandemic. The forecasting values for KORDSA surged from the lowest to the highest in the first quarter of 2021. KORDSA fluctuated in the second quarter, slightly fell in the third quarter and finally plummeted in the last quarter of 2021 till the early days of the following year’s January. The forecasting values for ANSGR fell in January and February and soared from the lowest value to the highest value in the first quarter of 2021. ANSGR forecasting value fluctuated in the second quarter, slightly fell in the third quarter, and fluctuated in the last quarter of 2021. The forecasting values for SISE fell in January, plunged in February and soared from the lowest to the highest in the first quarter of 2021. SISE forecasting values fluctuated in the second and third quarters, and finally slipped back in the last quarter of 2021. The forecasting values for SAHOL surged from the lowest value to the highest value in the first quarter, slipped back in the second quarter, increased in the third quarter and finally dropped in the last quarter of 2021. The forecasting values for AKGRT decreased gradually with ups and downs in 2021. The forecasting values for EREGL increased from the lowest to the highest in the first quarter, fluctuated in the second quarter, increased slightly in the third quarter, and finally dropped in the last quarter of 2021. The forecasting values for SCHN slipped back in January and February and increased slightly from the lowest value to the highest value in the first quarter of 2021. SCHN forecasting values fell in April and May, increased slightly in June, fluctuated in the third quarter, finally dipped slightly for two months, and increased in December in the last quarter of 2021. The forecasting values for SASY slightly increased in the first quarter of 2021. SASY forecasting values fluctuated in the second and third quarters with a jump in August and finally slightly climbed in the last quarter of 2021.

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