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A STUDY OF INDONESIA'S STOCK MARKET: HOW PREDICTABLE IS IT?

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ABSTRACT

Using monthly data from January 1995 to December 2017, this paper tests whether Indonesian stock index returns are predictable. In particular, we use eight macro variables to predict the Indonesian composite and six sectoral index returns using the feasible generalized least squares estimator. Our results suggest that the Indonesian stock index returns are predictable. However, the predictability depends not only on the macro predictor used but also on the indexes examined. Second, we find that the most popular predictor is the exchange rate, followed by the interest rate. Finally, our main findings hold for a number of robustness tests.

Keywords: *Stock returns; Predictability; Macro predictors; Investor utility.*
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I. INTRODUCTION

This paper tests whether the Indonesian stock index returns are predictable. The empirical evidence from the stock return predictability literature is extensive but far from provides a consensus conclusion on stock return predictability. The literature has evidenced that financial ratios—that is, the Book-to-Market ratio (BM), Dividend Yield (DY), Dividend Payout (DP), the ratio of dividend to price, and the ratio of Price to Earnings (PE)—and macro variables—such as the inflation rate, crude oil prices, interest rates, and aggregate output—are able to predict stock returns (e.g., Fama, 1981; Campbell, 1987; Campbell and Shiller, 1988; Fama and French 1989; Kothari and Shanken, 1997; Lamont, 1998; Pontiff and Schall, 1998; Rapach et al., 2005; Driesprong et al., 2008). However, the evidence on out-of-sample predictability is limited and not robust (Bossaerts and Hillion, 1999; Goyal and Welch, 2003; Butler et al., 2005; Welch and Goyal, 2008).

Most related papers use samples from the US market or other developed markets and the stock return predictability literature is scarce in emerging markets. Although recent studies investigate emerging markets such as China (Narayan et al., 2015; Westerlund and Narayan, 2015; Narayan et al., 2016a), South Africa (Gupta and Modise, 2012, 2013), and India (Narayan and Bannigidadmath, 2015), none considers the Indonesian market. We contribute to this literature by offering new evidence on the Indonesian stock market.

Our approach is as follows. In the first step, we collect all stock indexes and macro predictors that are widely used in the stock return predictability literature for the Indonesian market. Based on data availability, we obtain one composite index, six sector indexes, and eight macro predictors. We use monthly data from January 1995 to December 2017. In the second step, we apply the Feasible Generalized Least Squares (FGLS) estimator of Westerlund and Narayan (2015), which accounts for persistency, endogeneity, and heteroskedasticity for in-sample predictability as well as out-of-sample forecasting. Finally, we complement our analysis with a number of robustness tests.

Our paper offers the following findings. First, we provide new evidence of stock return predictability in the Indonesian market. However, the predictability depends not only on the macro predictor used but also on the indexes examined. Not all eight macro predictors are able to predict stock returns, but some (e.g., Exchange Rate (*EX*) and Interest Rate (*IR*)) are more powerful than others. In-sample predictability is found in all indexes and predictors except Industrial Production Growth (*IPG*), Import Growth (*IP*), and Export Growth (*EP*). Out-of-sample predictability is found in the composite, basic materials, consumer goods, and financials indexes, but not in the healthcare, industrials, and telecommunications indexes. Second, the most popular predictor test involves the Exchange Rate (*EX*). It predicts returns for the composite index and all sector indexes for the in-sample test and three of seven indexes for the out-of-sample test. The next most popular predictor is the Interest Rate (*IR*), which predicts six (three) indexes in the in-sample (out-of-sample) test. Finally, we apply robustness tests using different sets of in-sample and out-of-sample proportions and find consistent results.

We structure the remainder of the paper as follows. Section II describes the data collection procedure and empirical models. Section III discusses the main findings and robustness tests. Section IV concludes the paper.

II. DATA AND METHODOLOGY

We download data on Indonesian stock index returns and macro predictors for our sample from Datastream and Global Financial Database. First, we collect monthly price data for the Indonesia Stock Exchange Composite and Indonesian Datastream sector indexes. The start dates of the composite and sector indexes are varied. Our sample starts in January 1995, when the data for the composite index and six sector indexes were available, and ends in December 2017. The oil and gas sector is excluded because it has been inactive since 2011 and three other sectors (consumer services, technology, and utilities) are excluded because their data are only available for short periods.[4] Our second data set consists of common macro predictors in the stock return prediction literature. Based on the availability of macro predictors in the Indonesian market, we end up with eight variables: inflation (*INF*), change in the interest rate (*IR*), industrial production growth (*IPG*), change in the money supply M1 (*M1*), the Indonesian rupiah exchange rate return (*EX*), import growth (*IP*), export growth (*EP*), and crude oil price growth (*OIL*).

As suggested by the stock return predictability literature, our predictive regression can be written as:

$$ER_t = \alpha + \beta X_{t-1} + \epsilon_t \tag{1}$$

where ER_t is the stock index excess return and X_{t-1} is the macro predictor. Westerlund and Narayan (2012, 2015) argue that this model potentially faces issues of persistency, endogeneity, and heteroskedasticity.[5] Consider the predictors of stock returns, as follows:

$$X_t = \mu\,(1 - \rho) + \rho X_{t-1} + \varepsilon_t \tag{2}$$

$$\epsilon_t = \gamma\varepsilon_t + \eta_t \tag{3}$$

where $|\rho| \leq 1$ and ϵ_t and ε_t are independent and identically distributed, have a zero mean, and are uncorrelated with each other. This assumption can be violated in the case of endogenous predictors and will lead to a biased β estimate using the OLS estimator. Moreover, persistent predictors and heteroskedastic stock returns create an efficiency problem. We use the generalized least squares model of Westerlund and Narayan (2012, 2015)[6] to remove all those issues from our predictive regression models.

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[4] Data for the consumer services, technology, and utilities indexes are available from June 2007, July 2009, and December 2003 onward, respectively.

[5] Stambaugh (1999) and Lewellen (2004) also make the same argument.

[6] This model has been used widely in the predicting literature (Narayan et al., 2014; Bannigidadmath and Narayan, 2015; Narayan et al., 2015; Narayan and Bannigidadmath, 2015; Narayan and Gupta, 2015, Narayan and Sharma, 2015; Phan et al., 2015; Narayan et al., 2016b; Sharma, 2016; Devpura et al., 2017; Han et al., 2017; Narayan et al., 2017a, 2017b; Kuo, 2018, Narayan et al, 2018; Phan et al., 2018; Salisu et al., 2018; Salisu and Isah, 2018).

III. EMPIRICAL RESULTS

A. Preliminary Results

We report selected descriptive statistics of returns for the Indonesia stock composite index and sector indexes (Panel A) and our macro predictor variables (Panel B) in Table 1. Indonesia index excess returns have a monthly average composite index of -0.061% and the monthly mean of the sectoral indexes varies from -0.705% (financials sector) to 0.706% (industrials sector). The basic materials sector has the most volatile returns and the industrials sector experiences the least volatility. Consider the second to last column in Table 1, where we report the AR(1) coefficient: note that the persistency of index excess returns is low, at less than 30%, in all cases. The last column reports the *p*-values for a Lagrange multiplier test for an autoregressive conditional heteroskedasticity (ARCH) effect. The index excess returns of the composite index and basic materials and telecommunications sectors are found to have strong ARCH effects. The descriptive statistics of the macro predictors are reported in Panel B. We find that the AR(1) coefficient is less than 50% for most predictors, which suggests low persistence in these variables.

Table 1.
Descriptive Statistics

This table reports the selective descriptive statistics for excess returns for stock market composite and sectoral indexes (Panel A) and eight macro predictors (Panel B): inflation (*INF*), change of interest rate (*IR*), industrial production growth (*IPG*), change of money supply M1 (*M1*), Indonesian Rupiah exchange rate return (*EX*), import growth (*IP*), export growth (*EP*), and crude oil price growth (*OIL*). The statistics include the mean value, standard deviation, AR(1), and ARCH(1). AR(1) refers to the autoregressive coefficient of order 1, while ARCH (1) refers to a Lagrange multiplier test of the zero slope restriction in an ARCH regression of order 1 and the p-value of the test is reported.

Panel A: Stock Index Excess Returns							
	Mean	**SD**	**Skewness**	**Kurtosis**	**JB**	**AR(1)**	**ARCH**
Composite	-0.061	8.006	-1.653	10.178	0.000	0.195	0.035
Basic Materials	-0.630	11.496	-0.765	5.456	0.000	0.260	0.000
Consumer Goods	0.190	9.856	-1.162	8.817	0.000	0.172	0.694
Financials	-0.705	10.335	-0.680	7.753	0.000	0.159	0.988
Health Care	0.242	10.277	-0.508	8.240	0.000	0.111	0.296
Industrials	0.706	9.703	0.808	17.437	0.000	0.111	0.325
Telecommunications	-0.020	10.642	-1.351	11.506	0.000	-0.020	0.000
Panel B: Predictors							
	Mean	**SD**	**Skewness**	**Kurtosis**	**JB**	**AR(1)**	**ARCH**
INF	0.757	1.343	4.413	29.044	0.000	0.634	0.000
IR	-0.032	6.864	2.214	39.894	0.000	-0.421	0.000
IPG	0.233	0.592	-1.524	7.803	0.000	0.604	0.000
M1	1.240	3.432	0.390	5.849	0.000	-0.125	0.000
EX	0.659	7.006	3.344	35.511	0.000	0.215	0.000
IP	0.544	10.332	-0.067	4.081	0.000	-0.322	0.000
EP	0.497	8.517	-0.339	4.117	0.000	-0.382	0.000
OIL	0.441	8.470	-0.701	4.403	0.000	0.260	0.000

However, the coefficient is higher than 60% in the case of *INF* and *IPG*, which suggests these predictors are persistent. Finally, the null hypothesis of no ARCH is comfortably rejected for all predictors, which indicates the predictors are heteroskedastic.

Next, we turn to Table 2, which reports the results of the endogeneity test of the predictor variables. The results are reported for 56 predictive regressions based on seven stock market index excess returns and eight macro predictors. We find endogeneity in 15 predictive regressions. The predictors with the highest number of endogeneity cases are *EX* (five cases) and *IR* (four cases). Considering the indexes, we find that the industrials sector has a high number of cases of endogeneity.

Table 2.
Endogeneity Test

This table reports the results for the endogeneity test in the predictive regression model. The endogeneity test is based on a regression of residuals from the predictive regression model on residuals from the first-order autoregressive predictor regression model. The equation is as below:

$\epsilon_t = \gamma\varepsilon_t + \eta_t$

where ϵ_t is the residual from the predictive regression model $ER_t = \alpha + \beta X_{t-1} + \epsilon_t$ and ε_t is the residual from the AR(1) regression of the predictor $X_t = \mu(1-\rho) + \rho X_{t-1} + \varepsilon_t$. We report the p-value of the test that coefficient γ in the equation is zero. Rejecting the null that $\gamma = 0$ suggests the endogeneity exists in the predictive regression model. ***, **, and * denote the statistical significance at the 1%, 5%, and 10% levels, respectively.

	INF	*IR*	*IPG*	*M1*	*EX*	*IP*	*EP*	*OIL*
Composite	-0.239	-0.293***	0.986	0.178	-0.219***	0.071	0.091	0.083
	[0.595]	[0.000]	[0.335]	[0.210]	[0.002]	[0.151]	[0.140]	[0.157]
Basic Materials	0.550	-0.175	0.076	0.315	-0.162	0.063	0.138	0.197**
	[0.408]	[0.115]	[0.959]	[0.122]	[0.108]	[0.376]	[0.119]	[0.018]
Consumer Goods	-0.733	-0.392***	2.440**	0.094	-0.271***	0.037	0.073	0.071
	[0.176]	[0.000]	[0.049]	[0.589]	[0.002]	[0.551]	[0.338]	[0.324]
Financials	-0.330	-0.417***	0.475	0.015	-0.502***	0.058	0.068	0.081
	[0.581]	[0.000]	[0.721]	[0.935]	[0.000]	[0.371]	[0.396]	[0.289]
Health Care	0.312	-0.203**	0.897	0.025	-0.221**	0.049	0.059	0.041
	[0.594]	[0.041]	[0.497]	[0.890]	[0.014]	[0.442]	[0.455]	[0.590]
Industrials	1.428**	-0.193**	0.436	-0.041	-0.377***	0.007	0.019	0.130*
	[0.011]	[0.038]	[0.728]	[0.810]	[0.000]	[0.907]	[0.798]	[0.069]
Telecommunications	-0.456	-0.161	-0.212	0.461**	0.151	0.010	0.000	0.020
	[0.448]	[0.118]	[0.876]	[0.014]	[0.106]	[0.879]	[0.998]	[0.803]

The preliminary analysis provides evidence of persistency, endogeneity, and heteroskedasticity. Therefore, it is essential to apply the FGLS estimator of Westerlund and Narayan (2015) to test stock return predictability in the Indonesian market.

B. In-sample Predictability

We report the results for in-sample predictability in Table 3. The results can be summarized in three main points. First, *EX* is the strongest predictor, since its coefficients are statistically significant in the composite index and all sectors' predictive regression models. Second, *IR* is the second most popular predictor, since it is unable to predict only the industrials sector returns. Third, *IP* and *EP* are the weakest predictors and are unable to predict any of the indexes. Next are *OIL* and *M1*, which only predict returns for the basic materials and industrials indexes. The *INF* predictor predicts the returns of the composite index and three of six sector indexes. In conclusion, the predictive power of stock returns differs among the eight macro predictors, with some (e.g., *EX* and *IR*) being more powerful than others. In addition, with eight predictors and seven composite and sector indexes, there are 56 time series predictive regression models in total and significant predictability is found in 19 (34%) of them.

Table 3.
In-Sample Test

This table reports results on composite and sectoral index excess return predictability using eight macro predictors. The predictive regression model is the bias-adjusted FGLS estimator proposed by Westerlund and Narayan (2015). The coefficient of the predictors is reported. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	INF	*IR*	*IPG*	*M1*	*EX*	*IP*	*EP*	*OIL*
Composite	-1.447***	-0.621***	1.021	0.030	-1.112**	0.030	-0.068	0.081
	[0.002]	[0.000]	[0.395]	[0.906]	[0.000]	[0.740]	[0.562]	[0.316]
Basic Materials	-0.704	-0.636***	-0.449	0.304	-1.004***	0.034	0.142	0.310***
	[0.248]	[0.000]	[0.703]	[0.338]	[0.000]	[0.775]	[0.364]	[0.006]
Consumer Goods	-2.572***	-0.688***	1.348	-0.049	-1.149***	-0.012	-0.001	0.045
	[0.000]	[0.000]	[0.276]	[0.823]	[0.000]	[0.894]	[0.991]	[0.510]
Financials	-1.597**	-0.777***	0.714	-0.032	-1.062***	0.075	-0.011	0.083
	[0.019]	[0.000]	[0.637]	[0.911]	[0.000]	[0.454]	[0.927]	[0.186]
Health Care	-0.262	-0.528***	1.460	0.162	-0.590***	0.089	0.087	0.064
	[0.648]	[0.000]	[0.187]	[0.475]	[0.000]	[0.367]	[0.521]	[0.530]
Industrials	-0.378	0.032	1.065	0.644***	0.251***	0.017	0.032	0.104
	[0.587]	[0.739]	[0.426]	[0.000]	[0.000]	[0.849]	[0.783]	[0.144]
Telecommunications	-1.064**	-0.388***	-0.428	0.407	-0.539***	-0.021	-0.123	0.059
	[0.027]	[0.000]	[0.790]	[0.104]	[0.000]	[0.818]	[0.153]	[0.391]

C. Out-of-sample Forecasting

This section investigates out-of-sample forecasting. We compare the forecasting accuracy of two models: the macro predictor–based model (competition) and the historical average model (benchmark). This is important because Welch and Goyal (2008) argue that investors only consider predictors that can provide good out-of-sample performance. We use 50% of the sample as the in-sample period to predict the other 50% of the sample. We apply the recursive forecasting approach and use the out-of-sample *R*-squared ($00R^2$) measure to evaluate forecasting accuracy.

The $00R^2$ compares the accuracy of the forecasting mean squared errors from the competition (macro predictor–based) model and the benchmark model (historical average model). A positive $00R^2$ value implies that the forecasting of the competition model is more accurate than that of the benchmark model. In addition, we utilize Clark and West's (2007) mean squared forecasting error–adjusted statistic to test the null hypothesis $00R^2 \leq 0$, with the alternative hypothesis that $00R^2 > 0$. Finally, we also apply the mean, median, and trimmed median (T-mean) forecasting proposed by Rapach et al. (2010).

The main findings from out-of-sample tests are twofold. First, the null hypothesis $00R^2 \leq 0$ is rejected in at least one case for each predictor. The most popular forecasting models are those that use *EP* and *OIL*, since the null is rejected in four of seven indexes, followed by *INF*, *IR*, *IP*, and *EX*, for which the null is rejected in three of seven indexes. The mean forecasting combination approach also performs well because the null is rejected in four cases. Second, the composite, basic materials, and financial indexes provide solid evidence of out-of-sample predictability, since the null is rejected in most cases. On the other hand, we find no significant out-of-sample forecasting model for the health care, industrials, and telecommunications indexes.

Table 4.
Out-of-Sample Test

This table reports out-of-sample evaluations of forecasting excess returns using eight macro predictors vis-à-vis a constant returns model. We also apply three forecasting combination approaches of Rapach et al. (2010), namely the mean, median, and trimmed median (T-mean). A 50% in-sample period is used to generate recursive forecasts of excess returns for the remaining 50% of the sample. We report the out-of-sample ($00R^2$), which examines the difference in the mean squared errors from the competition model and the constant returns model. The Clark and West MSFE-adjusted test statistic, denoted with an asterisk, examines the null hypothesis that the $00R^2 = 0$ against the alternative that $00R^2 > 0$; *,**, and *** denote rejection of the null hypothesis at the 10%, 5%, and 1% levels of significance, respectively.

	INF	*IR*	*IP*	*M1*	*EX*	*IP*	*EP*	*OIL*	*MEAN*	*MEDIAN*	*TRIMMED*
Composite	3.779**	1.549*	1.289*	0.775	1.534*	1.012*	0.989*	3.388**	2.013*	1.519*	1.695*
	[0.011]	[0.076]	[0.077]	[0.129]	[0.074]	[0.098]	[0.094]	[0.017]	[0.055]	[0.075]	[0.067]
Basic Materials	-0.357	-0.564	-0.746	-1.051	0.797	-0.518	0.673*	4.694***	1.377*	0.008	0.543
	[0.322]	[0.464]	[0.499]	[0.598]	[0.134]	[0.334]	[0.068]	[0.003]	[0.084]	[0.312]	[0.204]
Consumer Goods	8.792***	2.077**	1.545**	0.040	4.427***	0.032	2.126**	2.135**	3.899**	4.175***	4.166**
	[0.000]	[0.036]	[0.018]	[0.183]	[0.010]	[0.135]	[0.035]	[0.027]	[0.014]	[0.010]	[0.011]
Financials	9.134***	5.556***	6.712***	4.444**	5.164***	0.388	3.423**	3.471**	5.622***	5.796***	5.747***
	[0.000]	[0.002]	[0.000]	[0.012]	[0.005]	[0.103]	[0.015]	[0.017]	[0.002]	[0.002]	[0.003]
Health Care	0.856	-0.890	-1.011	-3.303	-1.284	-5.312	-1.994	-1.254	-1.302	-0.635	-0.876
	[0.130]	[0.740]	[0.772]	[0.819]	[0.469]	[0.858]	[0.952]	[0.842]	[0.846]	[0.735]	[0.778]
Industrials	-3.718	-1.046	-1.146	-5.241	-1.762	-3.915	-1.719	-3.431	-2.043	-1.843	-1.870
	[1.000]	[0.983]	[0.992]	[0.830]	[0.914]	[0.969]	[0.473]	[0.677]	[0.937]	[0.989]	[0.975]
Telecommunications	-0.690	-1.288	-1.879	-3.807	-1.339	-9.201	-6.763	-3.241	-2.070	-1.735	-1.975
	[0.783]	[0.460]	[0.589]	[0.490]	[0.457]	[0.691]	[0.627]	[0.722]	[0.613]	[0.579]	[0.617]

D. Robustness Tests

We employ a number robustness tests for the baseline results. We employ different proportions for the in-sample and out-of-sample periods. Specifically, we use short periods (40%) and long periods (60%) to forecast the remaining 60% and 40% of the sample. Consider the 40% in-sample period in Panel A of Table 6. We observe that $00R^2$ is statistically positive for 29 predictive regression models. Each predictor provides a positive and statistically significant $00R^2$ in at least two cases. The most popular forecasting models are those that use *EX*, *EP*, and *OIL*, since the null is rejected in four of seven indexes, followed by *INF* and *IP*, for which the null is rejected in three out seven indexes. In addition, for the composite, basic materials, and financial indexes, the null is rejected in most forecasting models and there is no significant out-of-sample forecasting model for the health care, industrials, and telecommunications indexes. The results for the second choice of the in-sample proportion are reported in Panel B. In summary, the conclusion is consistent with those drawn from the baseline results.

Table 5.
Out-of-Sample Robustness Tests

This table reports the robustness tests of out-of-sample performance by using 40% (60%) in-sample period is used to generate recursive forecasts of excess returns for the remaining 60% (40%) of the sample.

Panel A: In-sample 40%											
	INF	*IR*	*IP*	*M1*	*EX*	*IP*	*EP*	*OIL*	MEAN	MEDIAN	TRIMMED
Composite	3.695***	3.065**	2.967**	2.386**	3.065**	2.629**	2.491**	4.055***	3.454**	3.110**	3.200**
	[0.004]	[0.019]	[0.018]	[0.040]	[0.018]	[0.026]	[0.027]	[0.007]	[0.013]	[0.018]	[0.017]
Basic Materials	0.401	-0.134	-0.191	-0.601	0.996*	-0.058	0.134*	3.651***	1.490*	0.488	0.803
	[0.147]	[0.325]	[0.349]	[0.473]	[0.097]	[0.233]	[0.087]	[0.004]	[0.056]	[0.188]	[0.135]
Consumer Goods	5.606***	-3.596**	2.263***	-0.460	4.159***	1.269*	2.088**	2.037**	4.121***	3.958***	4.219
	[0.000]	[0.049]	[0.004]	[0.168]	[0.008]	[0.064]	[0.028]	[0.029]	[0.005]	[0.007]	[0.005]
Financials	5.443***	-8.094	3.615***	0.825*	2.185**	-1.858	1.181**	1.458**	2.462**	2.883**	2.855
	[0.001]	[0.115]	[0.004]	[0.072]	[0.028]	[0.288]	[0.047]	[0.038]	[0.017]	[0.014]	[0.014]
Health Care	0.258	-4.056	-0.980	-2.995	-1.663	-5.085	-1.799	-1.379	-1.326	-0.667	-0.906
	[0.142]	[0.739]	[0.608]	[0.805]	[0.518]	[0.863]	[0.910]	[0.806]	[0.829]	[0.712]	[0.764]
Industrials	-5.075	-1.256	-1.181	-4.726	-1.972	-3.769	-2.592	-3.071	-2.059	-1.704	-1.857
	[1.000]	[0.994]	[0.998]	[0.820]	[0.954]	[0.976]	[0.425]	[0.692]	[0.960]	[0.993]	[0.988]
Telecommunications	-0.956	-0.238	-0.530	-1.473	-0.062	-8.053	-7.575	-1.885	-0.782	-0.317	-0.638
	[0.833]	[0.246]	[0.323]	[0.247]	[0.229]	[0.571]	[0.598]	[0.416]	[0.392]	[0.304]	[0.381]
Panel B: In-sample 60%											
	INF	*IR*	*IP*	*M1*	*EX*	*IP*	*EP*	*OIL*	MEAN	MEDIAN	TRIMMED
Composite	3.341**	1.295	1.303	0.473	1.324	1.052	0.632	3.639**	1.887*	1.306	1.501
	[0.024]	[0.119]	[0.106]	[0.192]	[0.115]	[0.129]	[0.146]	[0.028]	[0.087]	[0.116]	[0.105]
Basic Materials	-2.025	-1.913	-2.209	-2.184	0.390	-1.565	0.204	5.273***	0.997	-0.897	-0.138
	[0.576]	[0.699]	[0.745]	[0.749]	[0.194]	[0.468]	[0.105]	[0.007]	[0.173]	[0.487]	[0.347]
Consumer Goods	8.629***	4.092**	3.923***	-1.357	5.202**	0.953	2.908**	2.459**	4.469**	4.459**	4.512**
	[0.001]	[0.023]	[0.004]	[0.316]	[0.012]	[0.148]	[0.041]	[0.035]	[0.021]	[0.016]	[0.019]
Financials	9.368***	6.702***	6.900***	5.222**	6.408***	2.120*	4.402**	4.322**	6.425***	6.644***	6.402***
	[0.000]	[0.003]	[0.001]	[0.015]	[0.005]	[0.067]	[0.017]	[0.021]	[0.004]	[0.004]	[0.004]
Health Care	1.506*	-0.164	-0.371	-3.511	-0.523	-5.244	-1.226	-0.403	-0.803	0.053	-0.337
	[0.060]	[0.545]	[0.586]	[0.826]	[0.341]	[0.841]	[0.823]	[0.562]	[0.725]	[0.446]	[0.607]
Industrials	-3.279	-1.029	-1.099	-6.032	-1.478	-3.149	-2.546	-3.572	-2.244	-1.680	-1.754
	[0.998]	[0.965]	[0.980]	[0.858]	[0.834]	[0.931]	[0.779]	[0.624]	[0.927]	[0.962]	[0.941]
Telecommunications	-0.851	-0.711	-0.871	-0.711	-0.408	-6.838	-8.234	-2.210	-1.526	-0.739	-1.330
	[0.779]	[0.426]	[0.462]	[0.363]	[0.366]	[0.664]	[0.778]	[0.614]	[0.567]	[0.459]	[0.549]

IV. CONCLUDING REMARKS

This paper analyses how well macro predictors predict stock index returns in Indonesia. Our empirical analysis covers the Indonesian composite and sector indexes using monthly data from January 1995 to December 2017. We apply the newly developed FGLS estimator of Westerlund and Narayan (2012, 2015) for in-sample predictability and out-of-sample forecasting evaluation. First, we find that not all Indonesian macro predictors are able to predict Indonesian stock index returns. The most powerful predictor in the in-sample test is *EX*, which predicts returns for the composite index and all sectors, followed by *IR*, which is only unable to predict the returns of the industrials sector. The least powerful predictors are *IP* and *EP*, which have no predictive power for any of the indexes. Considering the out-of-sample tests, we find the most popular forecasting models are those that use *EP* and *OIL*, followed by those that use *INF*, *IR*, *IP*, and *EX*. In addition, the composite, basic materials, and financial indexes have solid evidence of out-of-sample predictability but we find no significant out-of-sample forecasting model for the healthcare, industrials, and telecommunications indexes. Finally, we conduct a robustness test in which, instead of using the 50% in-sample period, we use the 40% (60%) in-sample period to forecast the remaining 60% (40%) of the sample and evaluate the $00R^2$ statistics. The results from our robustness tests are similar to our baseline findings.

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