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Is Indonesia's stock market different when it comes to predictability?

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ABSTRACT

We construct a unique dataset consisting of 342 firms aimed at stock return predictability. Using seven predictors, we show that unlike in conventional markets, it is capital expenditure that is the most successful predictor of returns. However, the overall evidence of out-of-sample predictability when using other conventional return predictors is weak. Capital expenditure-based forecasting models do lead to profits also although these are small. This tends to imply that for markets that are at the nascent stages of development, such as Indonesia, capital expenditure might have a role to play in shaping the market. Our results are in sharp contrast to the literature on emerging markets.

1. Introduction

In this paper, we study Indonesia's stock market. Our inquiry begins with an examination of factors that predict Indonesia's stock returns and concludes with an analysis of the economic ramifications of any such evidence of stock return predictability. The question of 'why Indonesia' needs a special mention by way of motivation. To begin to understand 'why Indonesia', the first step is to acknowledge what work has been done on emerging markets in general on the issue of asset price predictability. Amongst emerging markets, at the stock-level there are studies on China and India. Narayan et al. (2015), Westerlund et al. (2015), Narayan and Sharma (2016) examine stock return predictability for China. These studies show that Chinese stock returns are predictability based on order imbalance, US futures returns, and financial ratios. On India evidence is equally supportive of stock return predictability. Studies by Narayan and Bannigidadmath (2015) and Bannigidadmath and Narayan (2016) show that financial ratios predict Indian stock returns. These studies document robust statistical and economic significance of stock return predictability.

Amongst emerging markets, China and India are different both in terms of institutional structures that regulate foreign investments and market structures. Both are considered more developed than Indonesia. Indonesia is unique because its market is at a nascent stage of development. Unlike China and India, Indonesia's financial system is not as competitive as China and India. The lessons on stock return predictability from a market so different from well-developed emerging markets may offer fresh insights that will aid our knowledge of asset return predictability more broadly.

Our approach is that we compile a new dataset on Indonesia's stocks. We have a total of 342 stocks for which daily time-series data are available for 10 years, from 2008 to 2018. We categorize these stocks into sectors and form panels of stocks Narayan and Sharma (2011) and Narayan et al. (2014). We match these panels of stocks' excess returns with a wide range of predictors. This dataset, like most panel datasets of this sort, offer statistical challenges. The first issue is predictors tend to be persistent. The second issue is predictors can potentially be endogenous. The third issue is that of cross-sectional dependence. These three issues need to be addressed to produce a robust test of the null hypothesis of no predictability. Our approach in dealing with these issues is to use the Westerlund and Narayan, 2015 (WN, 2015) panel predictive regression model that is devised purely to address these three statistical

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challenges. With our econometric framework, therefore, we are not exposed to the type of criticisms often labelled at panel data studies with similar research question to ours.

Our approaches offer three main results. First, we find strong evidence of in-sample predictability but relatively weak evidence of out-of-sample predictability. The overall message is that Indonesia's stock market behaves differently compared to developed markets (Westerlund and Narayan, 2014; Westerlund and Narayan, 2015) and emerging markets (Narayan and Bannigidadmath, 2015) in the sense that sectoral excess return predictability is not robust. The predictor, capital expenditure (*CAP*) out of a list of 7 predictors, stands out to some extent because it is a successful predictor. We, therefore, test the economic significance of sectoral excess return predictability by using *CAP*. We draw on a rich literature in asset pricing studies that evaluate economic significance using a mean-variance (MV) investor utility function. In this setup, an investor has a two-asset portfolio in which one is a risky asset (which is the sector-based investment) and a risk-free asset (which is a Treasury bill rate). The investor's portfolio allocation is dependent on expected returns, volatility of returns, and risk aversion. Assuming no short-selling and borrowing, we show that investors across sectors can potentially make profits of between 1.26% to 2.02% per annum. These profits are at least 4 times lower than those reported in the literature (see Narayan and Bannigidadmath, 2015). Moreover, we show that a simple buy-and-hold (B&H) strategy beats MV profits in 4 of the 8 sectors. B&H profits are in the 1.69% to 10.66% range.

Our statistical and economic outputs contribute to the literature on Indonesia. Very little is known about the stock pricing behaviour and trading performance of Indonesia's stocks. To the best of our knowledge, there is only one study which examines stock level trading of Indonesian stocks. Hart et al. (2003) use a sample of 34 stocks (1989–1999) and show that stocks sorted on multiple firm characteristics are profitable.[1] Our study builds on this on at least two fronts. First, the Hart et al. (2003) study is based on 34 stocks and covers an old-time period when the Indonesian stock market was underdeveloped. We consider 10 times more stocks (342 stocks) and analyse the recent decade—a time, as Section II details, when the Indonesia financial system has achieved remarkable growth. Second, moving average trading rules have their advantages but the cost of using these rule-based trading strategies is that such strategies are not based on a theoretical framework. We believe, in keeping with the recent literature on excess return forecasting, that by employing a mv utility function- based analysis of trading outcomes we have a more robust framework to address the economic significance of predictor information.

We also contribute to a growing literature that examines statistical and economic significance of sectoral stock returns; see, inter alia, Westerlund and Narayan (2015), Narayan and Bannigidadmath (2015), and Bannigidadmath and Narayan (2016). These studies show that sectoral stock returns are both in-sample and out-of-sample predictable and that using these predictability models' investors can devise meaningful trading strategies. Our results, from a completely different market—a market which is at a nascent stage of development, is unable to replicate the evidence provided from other emerging markets. The experience of Indonesia is in sharp contrast to how the Chinese and Indian markets function for instance and opens up the prospect of a role for capital expenditures as a predictor of returns. This calls for more research on Indonesia's stock market.

The rest of the paper proceeds in the following way. Section II contains a brief overview of the literature relating to Indonesia's stock market in general. This accounting is followed by an overview of Indonesia's stock market. This overview provides the motivation as to why we study the Indonesian market. Section III is about the data and results. The final section contains key concluding remarks. A feature of this section is that it identifies an agenda for future research on a market about which very little is known.

2. Motivation for studying Indonesia

Indonesia is a unique market to study for several reasons. To begin to understand how the Indonesian stock market and indeed the financial system is so different from other emerging and regional markets it is important to start by comparing Indonesia with these markets on stock market indicators. Table 1 paves the way for understanding this difference. In terms of market size, Indonesia fares comparably with some of the well-established emerging markets, such as Russia and Brazil, but lags its neighbours, such as Malaysia, the Philippines, Singapore, and Thailand. This tends to reflect the fact that Indonesia is in a growth phase with much catching-up to do. This point is reflected in market returns. Indonesia, over the 2008–2017 period, enjoyed an annual average market growth of 7.9% which beats all major emerging markets (India, China, Russia, Brazil, and South Africa). Indonesia's market growth has also outperformed Singapore (4.6%) and Malaysia (3.9%), and is only surpassed by the Philippines (8.5%) and Thailand (10.5%). The growth phase of the market is also reflected in data on turnover volume where Indonesia is ranked ahead of Brazil and South Africa amongst major emerging markets and well ahead of regional markets of Malaysia, the Philippines, Singapore, Vietnam, and India. Amongst regional markets, only Thailand and China have higher turnover volume.

Aside from data, an institutional feature of the Indonesian stock market is that it has Islamic financial connotations. Indonesia with a population of over 260 million has the largest Muslim population. There is growing demand for Islamic investments and Islamic goods and services. The Islamic nature of Indonesia's stock market is different from other emerging markets because investments are guided by the principles of Islam, and thus the market conducts itself differently compared to conventional (or non-Islamic) stock markets (Kuran, 1995). The following 5 principles guide investment and trading activities: excessive uncertainty is banned (*gharar*), interest rate type behaviour is not allowed (*riba*), 'unethical' investments are prohibited (*haram*), speculation is not encouraged (*maysir*), and risk–return sharing is key (Hearn et al., 2011; Abbes and Trichilli, 2015).

These investing principles have implications on the balance sheet of Islamic firms. Several studies point out that to qualify and

[1] There is a time-series (index-based and not stock based) predictability paper on Indonesia by Phan et al. (2019). Though on time-series index data, the paper does not explore any trading outcomes, so the economic story is lacking.

Table 1
Selected stock market indicators, summary table, average 2008–2017.

Country	Total return (%)	Turnover volume	Turnover value	Market value	Cap % of GDP
Indonesia	7.9	238,564,220	62,555,759.6	265,991.2	42.062
Malaysia	3.9	61,427,691	79,252,403.9	316,420.2	135.243
Philippines	8.5	63,765,889	25,411,059.4	160,098.2	75.008
Singapore	4.6	113,012,336	1,85,585,987.4	457,772.2	228.813
Thailand	10.5	250,056,660	1,51,056,282.4	243,150.8	85.265
Vietnam	NA	10,442,287	11,783,792.1	38,665.9	20.986
India	0.9	73,577,824	360,405,938	1,111,648.3	74.461
China	2.3	557,125,190	555,593,120	569,930.5	57.188
Russia	−4.9	10,696,842,500	274,658,692	587,834.8	41.016
Brazil	−1.7	66,352,292	536,045,280	853,447.7	47.344
South Africa	3.9	30,459,638	244,211,608	394,377.1	253.047

The table shows the averages of the variables per country for the period 2008–2017. Total return (%), turnover volume, turnover value, market value, and market capitalization (Cap) as a percentage of GDP denote, respectively, the growth in the total return index (i.e. log of total return index minus log of total return index (−1), where the second part is the lag of total return index), turnover by volume (i.e. the number of shares traded per year), turnover by value (in millions of US dollars), and market value of assets (in millions of US dollars), market capitalization of listed companies as a percentage of GDP. The data on these variables are taken from Datastream.

maintain the Islamic status a firm's total debt to market capitalization, cash and interest-bearing securities to market capitalization, and accounts receivables to market capitalization, should be less than 33% of the 24-month average trailing market capitalization (see Narayan et al., 2017). On the basis of these financial criterion, Narayan, Phan, Sharma, and Westerlund (2016: p.211) argue that: "Given the screening criteria applicable to business activities and, in particular, the financial health of individual stocks, the discriminatory ability of Islamic stocks could offer a different story regarding stock return predictability compared to what we already know with respect to non-Islamic stocks".

A final point is about the global demand for Islamic products, which has risen over the last decade. Ibrahim (2015) argues that the Islamic assets are no longer an investment option for faith-based (Muslim) investors only and that it is catering for the needs and demands of new customers which are non-Muslims (see also Umar, 2017). Islamic investment, therefore, has little to do with religious beliefs but more to do with the value added it brings and offers to both consumers and investors. It is this feature of Islamic finance which has made it more attractive outside of Islamic countries. Indonesia with the largest Muslim faith-based consumer and producer market is at an early stage of development. Its market, as shown in Table 1, has grown rapidly. With this type of growth, it is attracting investors. The Indonesia market, therefore, is different; thus, how well its prices can be predicted may offer fresh lessons.

3. Approach and methods

The aim of this section is threefold. First, we present and discuss the WN (2015) empirical framework for modelling excess return predictability. Second, we conduct an out-of-sample forecasting exercise, aimed at testing the robustness of the in-sample estimates. This exercise is implemented such that it compares the performance of excess return forecasts emanating from predictor variables against those from a constant returns model. The metric of evaluation is the out-of-sample $\boldsymbol{R^2}$ test. We conclude this section by discussing the MV investor utility framework employed to judge economic significance of our predictor-based forecasting models.

3.1. Panel data predictive regression model (in-sample test)

The econometric model has the following representation:

$$ESR_{it}^{s} = \alpha_i + \beta_i PREDICTOR_{it-1}^{s} + \epsilon_{it} \tag{1}$$

The dependent variable in this regression is $ESR_{it}{}^{s}$, which denotes excess returns of stocks (i) in each sector (s), where $i = 1, \ldots, N$ and $t = 1, \ldots, T$ represent, respectively, the cross-sectional and time-series dimensions of our panel setup. $PREDICTOR_{it}$ represents one of the seven predictors that we use to test for excess return predictability. It has a first-order autoregressive representation:

$$PREDICTOR_{it}^{s} = \rho_i PREDICTOR_{it-1}^{s} + \varepsilon_{it} \tag{2}$$

If the predictor is endogenous—an issue often associated with such empirical questions—then the errors terms from Eqs. (1) and (2) will be significantly correlated, as:

$$\epsilon_{it} = \delta_i \varepsilon_{it} + \vartheta_{it}$$

where ε_{it} and $\vartheta_{it}$are mean zero and finite fourth order moments, and ϵ_{it}, ε_{it}, and ϑ_{it} have the following variance $\sigma_{\epsilon i}{}^{2}$, $\sigma_{\varepsilon i}{}^{2}$, and $\sigma_{\vartheta i}{}^{2}$, respectively. Then, the null hypothesis of no predictability is simply tested as:

$$\beta_i = \beta + \frac{\sigma_{\vartheta i}}{\sigma_{\varepsilon i}} \frac{b_i}{N^p T^q} \tag{3}$$

where $b_i$is the random drift parameter that is iid with mean $\mu_b$and variance $\sigma_b{}^2$, N and T are the cross-sectional and time series dimensions with $p \geq 0$ and $q \geq 0$. The powers p and q determine the rate at which b_i shrinks towards its hypothesized value under the null hypothesis.

To test for predictability, Westerlund and Narayan (2015) suggest setting $\beta = 0$ and using b_i as a measure of the extent of predictability. We can examine the no predictability null as $H_0: \mu_b = \sigma_b{}^2 = 0$ (M1), $H_0: \mu_b = 0$,given $\sigma_b{}^2 = 0$ (M2), or $H_0: \sigma_b{}^2 = 0$,given $\mu_b = 0$ (M3). while the alternative hypothesis can be tested as $H_1: \mu_b \neq 0$ or $\sigma_b{}^2 > 0$, or both. WN (2015) propose a Lagrange Multiplier (LM) test to examine the null hypothesis of no predictability.

3.2. Out-of-sample forecasting evaluation

This section is about out-of-sample forecasting evaluation. To achieve this objective, we simply follow the time-series return forecasting literature (see Campbell and Thompson, 2008; Westerlund and Narayan, 2012), where typically the out-of-sample forecasting performance of the (unrestricted) predictive regression model using a constant and $PREDICTOR_{it-1}$ as a predictor is compared to that of the (restricted) constant-only model. The constant-only model is obtained by simply setting $\beta_1 = \ldots = \beta_N = 0$. Once we generate return forecasts from the unrestricted and restricted models, we are able to compute the relative out-of-sample R^2 (OOS_R^2).Therefore, following Fama and French (1989), who propose a time-series version of the out-of-sample R^2, we can construct the average OOS_R^2, which is defined as $OOS\_R^2 = \Sigma_{i=1}{}^N OOS\_R_i{}^2/N$, where $OOS\_R_i{}^2 = 1 - MSE_{i,U}/MSE_{i,R}$. Here, $MSE_{i,U}$ and $MSE_{i,R}$ are the mean squared error from the unrestricted and restricted predictive regression models for stock i, respectively. By construction, therefore, if $OOS\_R^2 > 0$ it implies that the stock return predictor-based predictive regression model outperforms the constant returns model.

3.3. Economic significance

The economic significance of forecasts generated using the predictors follows, amongst others, Marquering and Verbeek (2004). It can be demonstrated using the MV utility function on the assumption that the investor holds two assets—one risky (r_{t+1}, the sectoral stock as in our story) and one risk free ($r_{f,t+1}$, the short-rate). The allocation of investment funds in this two asset portfolio is $E((r_{it+1}{}^*|I_t))/\delta[var_t(r_{it+1}{}^*)]$, where $r_{it+1}{}^*$ denotes sectoral excess returns (which is obtained from our forecasts), $\delta >$ measures the extent of relative risk aversion (which we set to 6 to denote a medium risk averse investor, *var* is the variance (which is the variance of forecasted excess returns). The portfolio weight (w) is constrained to be between 0 and 100% such that there is no short-selling or borrowing. With weights obtained, investor profit becomes:

$$Profit_t = (1 - w_{t+1}^*)r_{f,t+1} + w_{t+1}^*(r_{t+1} - r_{f,t+1}) \tag{4}$$

Profits, as represented by Eq. (4), are averaged over time and across stocks to obtain what we refer to as average sectoral profits.

4. Empirical results

4.1. Data

We compile a unique firm level data for Indonesia's stock market (the Jakarta Stock Exchange). The dataset covers all major sectors of the Indonesia market and includes all such sectoral firms. Filtering of data based on a search for consistent time-series data for which all variables, as listed in Table 2 are available leads to a final dataset consisting of 342 stocks. We have daily data. All data are obtained from the Bloomberg system. These stocks belong to eight different sectors, namely, basic materials, communications, consumer cyclical, consumer non-cyclical, energy, finance, technology, and utility. All data are available for the most recent decade from 1/2/2008 to 4/30/2018.

The variables are excess returns which is the predictive variable. We have firm level predictor variables, namely: *CAP* is the firm level capital expenditure, *DY* is the dividend yield for individual firms, *EVBV* is the enterprise value to book value at the firm level, *PE* captures the price earnings ratio for individual firms, *PRI* is the price to sales ratio, *PB* is the price to book value and, *PRICF* is the price to cash flow ratio.

These 342 stocks are divided into 8 sectors based on the Global Industry Classification Standard (GICS); see Table 2. The number of stocks in each of the sectors varies and is in the range of 2 (utility) to 54 (basic material).

4.2. Preliminary evidence and motivation

We begin with the persistency (Table 3) and endogeneity (Table 4) of our data series. The first-order autoregressive (AR(1)) coefficient of the predictor variables and panel unit root test results are presented in Table 3. From the AR(1) estimates it is clear that excess returns have a coefficient close to zero while all predictors have a coefficient close to one. By comparison, the panel unit root test of Im et al. (2003) reported in Table 5 implies that all variables are panel stationary. Yet the fact that the AR(1) coefficient closes on zero implies that while stationary there is persistency which can potentially distort tests for the null hypothesis of no predictability. The implication is that persistency of predictors is an issue that needs to be modelled. From Table 3 it is clear that the null hypothesis that the slope coefficient on the error term in Eq. (3) is zero is rejected mostly at the 1% level for all predictors except *CAP*. This suggests that all predictors are endogenous except *CAP*. The implication is that predictor endogeneity is an issue which we need

Table 2
Summary of the dataset.

Sector	Total Observations	List of predictors
Communication	45,798	1. EVBV 2. PB 5. CAP
Consumer Noncyclical	140,088	1. EVBV 2. PB 3. PE 4. PRI 5. CAP 6. PRICF 7. DY
Consumer cyclical	175,110	1. EVBV 3. PE 5. CAP 6. PRICF 7. DY
Energy	61,962	1. EVBV 2. PB 3. PE 4. PRI 5. CAP
Financial	261,318	1. EVBV 2. PB 3. PE 4. PRI 5. CAP 6. PRICF
Material	105,066	1. EVBV 2. PB 3. PE 4. PRI 5. CAP 6. PRICF
Technology	16,164	1. EVBV 2. PB 3. PE 4. PRI 5. CAP 7. DY
Utility	5388	1. EVBV 2. PB 3. PE 4. PRI 5. CAP 6. PRICF

This table summarizes our dataset. Column 1 names the sector. The total number of observations in each sectoral panel appears in Column 2. The final Column notes the list of predictors used to test excess sectoral return predictability. The predictors are: (a) *CAP* is the firm level capital expenditure, (b) *DY* is the dividend yield for individual firms, (c) *EVBV* is the enterprise value to book value at the firm level, (d) *PE* captures the price earnings ratio for individual firms, (e) *PRI* is the price to sales ratio, (f) *PB* is the price to book value and (g) *PRICF* is the price to cash flow ratio.

to deal with.

The final issue we deal with is cross-sectional dependence (CD). We test for it using the Pesaran et al. (2008) CD test. The results occupy Table 6. We see that the null hypothesis of no CD is comfortably rejected (at the 1%) in all sectors, suggesting that CD is an issue with our panel data and it needs to be dealt with in tests for predictability.

The presence of predictor persistency and endogeneity together with CD motivates the use of the WN (2015) panel unit root test which this test accounts for all these three issues.

4.3. In-sample predictability

Three sets of predictability results are reported in Table 7. Panel A has results for the null hypothesis of no predictability against the alternative of predictability but not on average. Panel B tests the null hypothesis of no predictability by setting mean and variance of beta equal to zero against the alternative that beta = 0 and/or variance > 0. Panel C contains results when the null hypothesis of no predictability is tested against the alternative of a homogenous predictive slope different from zero. Reading results in Panel A, we

Table 3
Autoregressive results.

Variable	Basic mat	Communications	Consumer cyclical	Consumer Non-cyclical	Energy	Finance	Technology	Utility
Excess returns	−0.041	−0.042	−0.022	−0.034	0.013	−0.056	−0.069	−0.023
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CAP	0.988	0.991	0.991	0.992	0.989	0.985	0.702	0.984
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DY	0.997	0.996	0.996	0.996	0.997	0.996	0.996	NA
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	NA
EVBV	0.985	0.999	0.993	0.998	0.999	0.953	0.956	0.984
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PE	0.997	0.995	0.994	0.995	0.992	0.993	0.982	0.916
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PRI	1.001	1.001	0.998	0.996	0.995	0.995	0.998	0.997
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PRICF	0.995	0.993	0.988	0.986	0.998	0.992	0.996	0.987
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PB	0.998	0.998	0.993	0.997	0.999	0.993	0.994	0.995
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

In this table, we report the first-order autoregressive (AR(1)) coefficient for the predictive variable and predictor variables. We specifically test the persistency of the predictive variable and predictor variables. Column 1 reports the abbreviation for each of the firm level variables and from columns 2 to 9 are the eight sectors. Excess returns is the predictive variable followed by the AR(1) coefficients for the firm level predictor variables: *CAP* is the firm level capital expenditure, *DY* is the dividend yield for individual firms, *EVBV* is the enterprise value to book value at the firm level, *PE* captures the price earnings ratio for individual firms, *PRI* is the price to sales ratio, *PB* is the price to book value, and *PRICF* is the price to cash flow ratio. A *p*-value of less than or equal to 0.05 suggests statistical significance at the 5% level.

Table 4
Endogeneity results.

Variables	Basic material	Communications	Consumer cyclical	Consumer non-cyclical	Energy	Finance	Technology	Utility
PE	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(2.339)	(16.931)	(17.695)	(0.713)	(19.057)	(2.197)	(11.130)	(2.811)
PRI	0.000	0.053	0.001	0.002	0.002	0.000	0.000	0.229
	(5.086)	(74.817)	(30.091)	(58.568)	(26.871)	(5.141)	(3.601)	(80.831)
CAP	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(−0.666)	(0.598)	(0.021)	(0.612)	(−0.796)	(0.791)	(−0.959)	(0.046)
PRICF	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(8.544)	(8.842)	(3.109)	(8.084)	(2.703)	(6.705)	(3.066)	(2.473)
DY	−0.025	−0.058	−0.021	−0.047	−0.056	−0.066	−0.063	NA
	(−56.806)	(−56.152)	(−67.058)	(−101.688)	(−58.897)	(−160.973)	(−40.698)	NA
PB	0.009	0.114	0.003	0.007	0.000	0.014	0.005	0.091
	(48.252)	(99.990)	(26.279)	(63.009)	(7.731)	(76.623)	(18.539)	(56.277)
EVBV	0.001	0.019	0.000	0.001	0.000	0.001	0.000	0.008
	(20.455)	(35.216)	(8.313)	(27.777)	(7.936)	(15.948)	(9.586)	(17.440)

This table reports the endogeneity results. We specifically test whether in the returns predictive regression model, each predictor is endogenous or not. The test is based on running a regression of the residuals from the predictive regression model on the residuals from each predictor model of the first-order regression model. The coefficient on the predictor residual is reported together with the *t*-test which examines the zero-slope condition. The predictor variables covered include 7 firm level variables as follows: *PE* captures the price earnings ratio for individual firms, *PRI* is the price to sales ratio, *CAP* is the firm level capital expenditure, *PRICF* is the price to cash flow ratio, *DY* is the dividend yield for individual firms, *PB* is the price to book value and *EVBV* is the enterprise value to book value at the firm level.

see that consumer non-cyclical and utility are the two sectors where most (6) predictors predict returns. *PRICF* and DY predict returns of utility and consumer non-cyclical, respectively. For the financial sector, only *PB*, *PRI* and *CAP* predict returns while for technology (*PRI* and *CAP*), communications (*EVBV* and *PB*) and basic materials (*PE* and *CAP*) predict returns. No evidence of predictability is found for the consumer cyclical sector. The joint null hypothesis test model (Panel B) provides much stronger evidence of sectoral predictability. For basic materials, *PE*, *PRI*, *CAP* and *PRICF*, for consumer non-cyclical *EVBV*, *PB*, *PE*, *PRI*, *CAP*, and *DY*; for utility, *EVBV*, *PB*, *PE*, *PRI*, *CAP* and *PRICF*, for energy, *EVBV*, *PB*, *PE*, *CAP*, and *PRICF*; for technology, *PB*, *PE*, *PRI*, *CAP*, and *PRICF*; for communications, *EVBV*, *PB*, and *CAP*; and for communications, *EVBV*, *PB* and *CAP* predict returns. The most successful predictor is *CAP*—it predicts returns of all sectors. *PB* is the second most popular predictor, predicting returns of 6/8 sectors, followed by *EVBV*, *PE* and *PRI* (5/8 sectors). *DY*, by comparison, is the least common predictor, predicting returns of only 2/8 sectors.

4.4. Out-of-sample predictability

The results from out-sample tests are presented in Table 8. When $OOS\_R^2 > 0$ and DM > 0 then our predictor-based model is

Table 5
Panel unit root test.

Variables	Basic mat	Communications	Consumer cyclical	Consumer Non-cyclical	Energy	Finance	Technology	Utility
Excess returns	−112.617	−73.530	−143.975	−131.450	−82.914	−177.621	−44.256	−27.304
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PE	−9.641	−6.273	−11.545	−10.687	−8.330	−13.702	−4.828	−8.880
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PRI	−8.970	−2.247	−4.221	−7.223	−5.839	−10.161	−3.799	−0.500
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.309)
CAP	−15.568	−10.299	−20.513	−16.881	−14.253	−29.542	−6.354	−4.006
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PRICF	−9.525	−4.670	−11.011	−11.617	−8.151	−9.793	−1.944	−2.289
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.026)	(0.011)
DY	−7.846	−3.470	−3.552	−8.204	−3.186	−7.300	−0.723	NA
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.235)	NA
PB	−8.596	−3.843	−7.065	−7.213	−4.419	−12.593	−4.625	−2.072
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.019)
EVBV	−10.293	−3.901	−5.597	−6.767	−7.120	−11.801	−5.402	−3.514
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

This table report the IPS (2003) panel unit root test which examines the null hypothesis of a panel unit root. The *p*-values are stated in the parenthesis. A *p*-value of less than or equal to 0.05 suggests statistical significance at the 5% level. The excess return is the predictive variable calculated as the log price returns minus the log returns of the EMLCTRUU Index. The predictor variables covered include 7 firm level variables as follows: *PE* captures the price earnings ratio for individual firms, *PRI* is the price to sales ratio, *CAP* is the firm level capital expenditure, *PRICF* is the price to cash flow ratio, *DY* is the dividend yield for individual firms, *PB* is the price to book value and *EVBV* is the enterprise value to book value at the firm level.

Table 6
Cross-sectional dependence of stock returns.

Sectors	Correlation	CD	*p*-value
Basic materials	0.052	73.553	0.000
Communications	0.059	35.592	0.000
Consumer cyclical	0.041	97.438	0.000
Consumer non-cyclical	0.063	119.955	0.000
Energy	0.059	48.535	0.000
Finance	0.050	177.122	0.000
Technology	0.035	7.109	0.000
Utility	0.019	0.966	0.334
All firms	0.048	615.692	0.000

In this table, we report the average pair-wise cross-sectional correlation coefficients of returns in column 2. The correlations are computed for stocks in each of the 8 sectors plus “all firms” taken together (last row). Each sector represents a panel. The CD test, reported in column 3, is proposed by Pesaran et al. (2008) and, essentially, examines the null hypothesis of no cross-section correlation. The *p*-values used to decide on the null hypothesis are reported in the last column.

superior to a constant-only model of excess returns. We read evidence from OOS_R^2. $OOS\_R^2 = 0$ in 4 sectors (with *EVBV*, *PE* and *PB* predictors), 3 sectors (with *PRI* predictor), 2 sectors (with *DY* and *PRCF* predictors), and in all 8 sectors when using the *CAP* predictor. This implies that both these predictor models and their competitor (constant-only) model have equal predictive power. The $OOS\_R^2 > 0$ in 4 cases only and it is less than 0 in 14 cases. Overall, therefore, the evidence from OOS_R^2 suggests that the predictor-based models are weaker compared to the constant returns model. This evidence is corroborated by the DM test statistic. Our main conclusion is that while we do find strong evidence of in-sample predictability out-of-sample predictability is weak. The exception to a large extent is the *CAP* predictor—the most successful in-sample predictor, for which in out-of-sample tests OOS_R^2 suggests that it is equally powerful. The main takeaway from this analysis is that the variable *CAP* stands out as an important and robust predictor of Indonesian sectoral excess returns.[2]

4.5. Trading outcomes of predictability—what are the implications?

This section documents the economic importance of predictability. Profits are estimated based on forecasted returns within a MV utility function as described in Section 4.3. The results occupy Table 9. Given that we only find robust evidence of predictability when using *CAP* as a predictor, we only test for economic significance of *CAP*.

This table reports economic significance of sectoral return forecasts. Column 2 presents mean-variance (MV) utility-based profits where portfolio weight is maximized based on forecasted excess returns scaled by risk aversion factor (which takes a value 6

[2] Sharma (2019) undertakes an in-sample and out-of-sample test of inflation predictability for Indonesia and also finds strong in-sample evidence.

Table 7
Panel predictability test results.

Panel A: variance = 0 given mean = 0

	Basic materials	Communications	Consumer cyclical	Consumer non-cyclical	Utility	Energy	Finance	Technology
EVBV	0.00 (0.99)	36.33*** (0.00)	0.00 (0.99)	7.79*** (0.00)	13.23*** (0.00)	0.10 (0.75)	12.23 (0.40)	1.19 (0.21)
PB	0.00 (0.99)	46.48*** (0.00)	NA	12.61*** (0.00)	17.67*** (0.00)	1.76 (0.68)	16.12*** (0.00)	21.12 (0.15)
PE	0.23*** (0.00)	NA	0.00 (0.99)	39.15*** (0.00)	14.11*** (0.00)	2.89* (0.09)	0.00 (0.99)	0.00 (0.99)
PRI	0.03 (0.85)	NA	NA	36.82*** (0.00)	27.39*** (0.00)	NA	0.73*** (0.00)	5.31** (0.02)
CAP	5.22** (0.02)	0.17 (0.68)	0.08 (0.55)	2.08*** (0.00)	13.41*** (0.00)	0.007 (0.93)	12.00*** (0.00)	13.27*** (0.00)
PRICF	0.001 (0.99)	NA	0.09 (0.54)	0.09 (0.76)	47.14*** (0.00)	5.02 (0.11)	0.00 (0.99)	1.34 (0.25)
DY	NA	NA	0.00 (0.98)	> 100*** (0.00)	NA	NA	NA	NA

Panel B: mean = variance = 0

	Basic materials	Communications	Consumer cyclical	Consumer non-cyclical	Utility	Energy	Finance	Technology
EVBV	0.006 (0.99)	37.38*** (0.00)	3.18 (0.20)	49.86*** (0.00)	13.23*** (0.00)	> 100*** (0.00)	0.69*** (0.00)	2.89 (0.24)
PB	0.96 (0.62)	46.90*** (0.00)	NA	44.69*** (0.00)	17.68*** (0.00)	0.17*** (0.00)	30.34*** (0.00)	> 100*** (0.00)
PE	> 100*** (0.00)	NA	4.19 (0.12)	43.57*** (0.00)	14.12*** (0.00)	9.66*** (0.00)	2.10 (0.35)	90.83*** (0.00)
PRI	> 100*** (0.00)	NA	NA	51.21*** (0.00)	27.77*** (0.00)	NA	> 100*** (0.00)	> 100*** (0.00)
CAP	> 100*** (0.00)	1.83*** (0.00)	0.37*** (0.00)	18.50*** (0.00)	21.43*** (0.00)	92.84*** (0.00)	58.29*** (0.00)	> 100*** (0.00)
PRICF	> 100*** (0.00)	NA	15.97*** (0.00)	2.34 (0.31)	47.18*** (0.00)	2.62*** (0.00)	1.13 (0.56)	> 100*** (0.00)
DY	NA	NA	14.65*** (0.00)	> 100*** ((0.00)	NA	NA	NA	NA

Panel C: mean = 0 given variance = 0

	Basic Materials	Communications	Consumer Cyclical	Consumer Non-cyclical	Utility	Energy	Finance	Technology
EVBV	0.006 (0.94)	1.41 (0.34)	3.17* (0.08)	42.07*** (0.00)	0.002 (0.97)	> 100*** (0.00)	> 100*** (0.00)	1.70 (0.19)
PB	0.96 (0.33)	0.41 (0.52)	NA	32.09*** (0.00)	0.011 (0.92)	> 100*** (0.00)	13.62*** (0.00)	> 100*** (0.00)
PE	> 100*** (0.00)	NA	4.19** (0.04)	4.42** (0.04)	0.013 (0.91)	6.78*** (0.00)	2.10 (0.15)	90.83*** (0.00)
PRI	> 100*** (0.00)	NA	NA	14.40*** (0.00)	0.013 (0.91)	NA	> 100*** (0.00)	> 100*** (0.00)
CAP	> 100*** (0.00)	1.88*** (0.00)	> 100*** (0.00)	> 100*** (0.00)	8.02*** (0.00)	92.86*** (0.00)	46.29*** (0.00)	> 100*** (0.00)
PRICF	> 100*** (0.00)	NA	15.90*** (0.00)	2.25 (0.13)	0.041 (0.84)	> 100*** (0.00)	1.13 (0.29)	> 100*** (0.00)
DY	NA	NA	14.69*** (0.00)	> 100*** (0.00)	NA	NA	NA	NA

This table reports results from panel predictability tests. Results are organised into three panels. Panel A contains results when the null is tested as variance of the slope coefficient = 0 given that the mean of the slope coefficient = 0. Panel B results test the null that both the mean and variance of the slope coefficient = 0. Panel C results are based on testing that null that the mean of the slope coefficient = 0 given its variance = 0. * (**) *** denote statistical significance at the 10% (5%) 1% levels. The parenthesis contains *p*-values. Finally, NA stands for not available due to either small sample size or lack of data.

Table 8
Out-of-sample evaluation.

Sectors	*EVBV*		*PB*		*PE*		*PRI*		*CAP*		*PRICF*		*DY*	
	OOS_R^2	DM (*p*-value)	OOS_R^2	DM (*p*-value)	OOS_R^2	DM (*p*-value)	OOS_R^2	DM (*p*-value)	OOS_R^2	DM (*p*-value)	OOS_R^2	DM (*p*-value)	OOS_R^2	DM (*p*-value)
Utility	0.000	0.847 (0.397)	−0.001	−2.113 (0.035)	0.000	−0.251 (0.802)	−0.006	−3.324 (0.001)	0.000	1.496 (0.135)	−0.004	−2.267 (0.023)	−0.004	−2.267 (0.023)
Materials	0.013	−2.491 (0.013)	0.016	−7.119 (0.000)	0.000	0.000 (1.000)	0.000	−2.993 (0.003)	0.000	1.106 (0.269)	0.000	2.727 (0.006)		
Financial	0.000	0.581 (0.561)	0.000	0.666 (0.505)	−0.010	−6.347 (0.000)	−0.002	−9.159 (0.000)	0.000	0.333 (0.739)	−0.009	−0.155 (0.877)		
Energy	−0.043	−17.541 (0.000)	−0.079	−21.89 (0.000)	0.000	−0.235 (0.814)	0.000	1.146 (0.252)	0.000	−1.434 (0.152)				
Consumer noncyclical	0.000	−3.157 (0.002)	0.000	−0.363 (0.716)	−0.002	−11.596 (0.000)	0.000	−3.284 (0.001)	0.000	0.122 (0.903)	0.000	0.590 (0.555)	0.000	−0.325 (0.745)
Consumer cyclical	0.007	−0.010 (0.992)			−0.016	−3.113 (0.002)			0.000	−1.612 (0.107)	−0.015	0.305 (0.760)	0.040	−0.325 (0.745)
Technology	−0.008	−1.753 (0.080)	0.000	−0.154 (0.877)	0.000	−1.349 (0.177)	−11.693	−24.99 (0.000)	0.000	−1.507 (0.132)			0.000	−1.523 (0.128)
Comm.	0.000	−7.552 (0.000)	0.000	−1.015 (0.310)					0.000	−1.863 (0.063)				

We report three test statistics; namely, the out-of-sample (OOS_R^2), which examines the difference in the mean squared errors from the predictive regression model and the constant returns model. The Clark and West MSFE-adjusted test statistic, denoted with an asterisk, examines the null hypothesis that the $OOS\_R^2 = 0$ against the alternative that $OOR^2 > 0$; The final test statistic is the Diebold-Mariano (DM) statistic, which examines the null hypothesis that the difference in MSFE between the two models is equal. The test has a nonstandard distribution and *p*-values used to take a decision on the null are reported in parentheses. The sample period is 02/01/2008 to 30/04/2018. The in-sample period is 50% of this sample, and out-of-sample forecasts are generated using the recursive approach as in Narayan and Bannigidadmath (2015).

Table 9
Economic significance.

	MV profits	MV-SD	B&H profits	B&H-SD
Utility	1.259	1.825	−12.045	3.193
Materials	1.457	1.888	1.694	3.893
Financial	1.575	1.887	6.972	3.302
Energy	1.819	14.19	−8.432	3.805
Consumer noncyclical	2.021	13.11	10.658	3.039
Consumer cyclical	1.698	3.176	8.658	3.533
Technology	1.692	3.222	−3.019	3.396
Comm.	1.773	3.441	−7.629	3.612

This table reports economic significance of sectoral return forecasts. Column 2 presents mean-variance (MV) utility-based profits where portfolio weight is maximized based on forecasted excess returns scaled by risk aversion factor and return variance (which is proxied by 30-day rolling moving average of sectoral returns). MV profit standard deviation (MV-SD) is noted in column 3. Column 4 computes the buy and hold (B&H) profits and its standard deviation (B&H-SD) is reported in the final column.

reflecting an investor who takes a medium level of risk) and return variance (which is proxied by 30-day rolling moving average of sectoral returns). MV profits and standard deviation (MV-SD) are noted in columns 2 and 3 respectively. Column 4 computes the buy and hold (B&H) profits and its standard deviation (B&H-SD) is reported in the final column. We observe small MV sectoral profits, in the 1.26% (utility) to 2.02% (consumer non-cyclical) range. These annualized profits are much lower than sectoral MV profits reported for other markets such as the US (see Westerlund and Narayan, 2015) and India (see Narayan and Bannigidadmath (2015).[3] We see that a simple B&H strategy beats the MV strategy in 4 of the 8 sectors. The main implication is that unlike the more developed markets, Indonesia's stock market is less predictable from both statistical and economic points of view.[4]

4.6. Robustness tests

In the asset pricing literature where the subject of investigation is forecasting returns, studies have employed a range of robustness tests to confirm their findings. Before we proceed, it is important to acknowledge that up to this point of our analysis we had simultaneously addressed robustness along two lines. First, we—like all panel data studies on the type of question we ask—are aware that data are persistent, endogenous and cross-sectional dependent. To obtain robust results, we employed a panel predictive regression framework that addresses these issues. Second, we used more than one out-of-sample metrics to arrive at the same conclusion that out-of-sample predictability is supported with the cap predictor. What is left is to examine (a) whether using a different in-sample period (in years) would lead to same conclusions about the out-of-sample; and (b) whether assuming that less risky or a riskier investor changes the profits. We perform both (a) and (b)—these results are available upon request. For brevity, we summarize the key results here. We find that using a shorter in-sample period has a trivial change to the results but using a longer in-sample period makes our results somewhat weak. This is expected given that we only have 10 years of data and when we increase the in-sample period to 70%, we end up with a very small out-of-sample period for an out-of-sample forecasting evaluation. So, the point is that the sensitivity of our results has nothing to do with predictability (or otherwise) rather it merely reflects too small a sample period for out-of-sample evaluations.

Finally, when we assume a low risk and high-risk investor by changing the risk aversion parameter we find that profits do change. For low risk takers, profits are on average lower while for high risky takes profits are on average higher. The main feature of these results is that out-of-sample predictability does translate to meaningful economic profits regardless of the investor risk taking behaviour, keeping in the mind the nascent stage of development in the Indonesian stock market.

4.7. An explanation of the results

We find strong evidence that, unlike in other markets, capital expenditure predicts Indonesia's stock returns. We argue that a market which is at a nascent stage of development, like Indonesia, will have firms that will use capital expenditure to boost their market position and performance. This is because firms with more capital expenditure are more likely to go public (see Chemmanur et al., 2018). The motivation for going public is to raise money (which otherwise would be difficult to secure). These funds are then used to finance further capital expenditure, including research and development (R&D) (see Giudici and Bonaventura, 2018). The R&D intensity is important for firm development and growth. When the market is at a nascent stage, information is evolving and is relatively more imperfect. Therefore, as information becomes available, which is used to forecast demand for firm's goods and services, firms adjust their capital expenditure to meet the demand for their products (see Kim and Lee, 2018). Therefore, the main

[3] We are not strictly comparing Indonesia with these more developed markets because those results are based on different dataset and methods. The idea of highlighting the difference here is to give context to our findings. In interpreting our results, therefore, the usual caveats (when it comes to comparisons) should be kept in mind.

[4] We have not accounted for transaction costs because this is unknown in the Indonesian market. Indeed, accounting for transactions costs will lower profits. This will not change our main conclusion and indeed the story of the paper will remain unaffected.

message here is that capital expenditure is positively related to performance.

In addition, firms tend to increase capital expenditure during periods of high inflation. Indonesia has experienced periods of high inflation. Inflation in 2001, 2005, and 2008 was recorded at 6.55%, 11.11%, and 6.06%, respectively. These rates were considered to be beyond the target rate. This line of argument is supported by empirical evidence showing that firms do increase capital expenditure when faced with inflation pressures, as, for instance, documented in the work of Kemper et al. (2018).

5. Concluding remarks

This paper takes a fresh guard on predictability by considering a unique market, Indonesia, which is at a nascent stage of development. This uniqueness is accentuated by the fact that Indonesia is the largest Muslim country where demand for Islamic goods and services is on the rise given the importance and prominence of Islamic finance. The Islamic nature of the market is leading to greater attention of the market to both local and foreign investors. That the market is unique and offers an interesting platform to test stock return predictability motivated this study. The first upshot, and therefore contribution, is that we compile a unique stock-level data set for Indonesia. Our dataset consists of 342 firms, all having daily data for a decade. To the best of our knowledge there is no analysis of Indonesia's stock market as in-depth as we propose and conduct, certainly not from an asset pricing point of view. Doing so led to other contributions aside from dataset. We show that what is commonly regarded as a predictor of conventional stock prices (dividend yield) turns out to be the weakest predictor for Indonesia's stock returns. Surprisingly, it is capital expenditure that is the most successful predictor, predicting returns of all eight sectors followed by book-to-price ratio. Other financial ratios follow. However, capital expenditure turns out to be the only robust predictor. It is capital expenditure-based models that offer the most profits when trading strategy outcomes are evaluated in out-of-sample tests. However, these annualized profits fall in the 1.26% to 2.02% range, which are, compared to other developed country markets, economically small. Indeed, we find that in 50% of the sectors a simple buy-and-hold strategy outputs the mean-variance strategy.

The story of our paper is, therefore, different from popular belief (evidence-based) formed from conventional markets that financial ratios are leading predictors. For Indonesia, yes, financial ratios are important too, but the evidence is not as robust as what we have come to know; and, is it capital expenditure that is the leading predictor. However, we are unable to confirm that predictability of returns on Indonesia's stock market has economic relevance given that profits are relatively low. This tends to imply that for markets that are at the nascent stages of development, such as Indonesia, capital expenditure has a greater role to play. However, whether investors can benefit from such predictors is unclear from our analysis. Given this, more studies are needed on understanding asset pricing behaviour on the Indonesian stock exchange. An additional avenue of research will be to model structural breaks in the data in a predictability setting such as those proposed by Devpura, Sharma and Narayan (2019). This is relevant because a recent study by Sharma et al. (2018) shows that most time-series Indonesian data has undergone structural changes.

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