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Time-series Predictability of Mutual Fund Investing in Indonesia

The Effects of Macroeconomic Indicators on Time-series Predictability

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ABSTRACT

This paper identifies the macroeconomic indicators of time-series predictability at an investment style level for mutual funds in Indonesia. At the time of writing, the Indonesian emerging economy is recovering from the impact of the COVID-19 pandemic, and is well into its election cycle. Investments into mutual funds has grown significantly within the past decade in Indonesia. Furthermore, mutual funds in Indonesia have been found to outperform market benchmarks, which incentivize retail investors to buy mutual fund shares as opposed to alternative assets. This paper is written mainly through the perspective of a retail investor in Indonesia, to examine the accuracy of simple time-series forecasting methods and how it is affected by macroeconomic indicators. The results find that only the time-series predictability of money market mutual fund returns is affected by macroeconomic indicators. Mutual fund investors in Indonesia can expect higher time-series predictability in money market mutual funds when inflation rates are low, short-term policy rates and business confidence are high, and when the economy is exhibiting stable growth through increases in real GDP.

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1. INTRODUCTION

Retail investors are often overlooked in the financial market and its existing literature. This may be due to how institutional investors make up the majority of the volumes traded across most financial markets (Salvucci, 2023). On the other hand, institutional, or commonly referred to as "smart money" investors, are usually the first to receive news, can execute trades at a moment's notice, and can restructure their portfolios with minimal transaction costs.

Retail investors who trade individually and with their own limited capital also seek to benefit from financial markets. In 2021, retail investors made up over 22% of the daily volume traded globally, and the individual investor market reached over $7.2 trillion in size by 2023 (Salvucci, 2023). Additionally, mutual funds have become increasingly popular in emerging markets. An example highlighted in one of the largest global emerging economies is Indonesia, where mutual funds have seen stable growth in net market capitalization over the past decade (*Capital Market Assessment February,* 2022).

Despite differences in market knowledge and trading volumes, both retail and institutional investors benefit from diversification, predictability, and analysis of certain market indicators. However, it is often costly for retail investors in both time and capital to consider which sectors and firms are appropriate for their portfolio. Instead, it is common for them to entrust their investments with mutual funds, thus delegating the diversification of their investments.

Diversification aside, timing of purchase and choice of assets are key considerations for both institutional and retail investors. For retail investors purchasing shares of a mutual fund, previous work has found that there is persistence in past "winner" funds, which have consistently outperformed the market benchmark (Avramov & Wermers, 2006; Droms, 2006), and that timing purchases according to the business cycle increases returns (Avramov & Wermers, 2006). Therefore, retail investors could attempt to forecast mutual fund returns in order to maximize their returns according to the business cycle and macroeconomic conditions. These indicators are especially more volatile in emerging economies, which might benefit retail investors in emerging economies more than developed economies. However, we question the accuracy of these simple forecasting models typically implemented by retail traders.

Indonesia is an interesting geographical setting for this research because of its status as an emerging market and its policies declaring that mutual fund returns are untaxed (*Mutual Funds,* 2022). Furthermore, this paper examines this question with respect to the time setting of the COVID-19 pandemic, up to the year 2024; the economic recovery succeeding the recession. Therefore, we are able to examine the strength of various forecasting models during an economic downturn and its recovery in an emerging market. Additionally, Indonesian mutual funds significantly outperform the market by delivering positive alphas after adjustment with respect to risk factors based on the Carhart four factor model (Vidal & Vidal-Garcia, 2023), which provide further reason to investigate the viability of attempts at out-of-sample forecasting by retail investors. Thus, the primary research question is as follows:

"*How do macroeconomic indicators affect time-series predictability in forecasting mutual fund returns in Indonesia?"*

In addition to untaxed returns, mutual funds allow retail investors in Indonesia access to various asset mixes, including equity, fixed income, a balance of both equity and fixed income, and even money market assets. This intermediary access allows retail investors to purchase shares of mutual fund investment styles that matches their investment horizon and risk appetite. Limited research has been conducted on time-series predictability of mutual funds in general, especially for the spatial and temporal context discussed by this paper. Furthermore, as we know of there have been no attempts at explaining time-series predictability across the four formally recognized mutual fund investment styles in Indonesia. Therefore, we also investigate the secondary research question:

"*How does time-series predictability differ between various investment styles of mutual fund returns in Indonesia?"*

This paper aims to investigate the relationship between time-series predictability and macroeconomic indicators for the four main mutual fund investment styles in Indonesia. We apply three different time-series models that we expect are replicable by retail investors, and generate both single and combined forecasts, which are then evaluated using a rolling window approach to assess time-series predictability. We then apply a general dynamic fixed effects model and four subgroup dynamic fixed effects models to investigate the relationship between time-series predictability and various macroeconomic variables. This paper contributes to previous work on time-series predictability of asset returns by examining the four types of mutual funds in Indonesia. As of the time of writing, time-series predictability of asset returns has only been investigated with respect to sector indices (Park & Newaz, 2023). We find that short-term policy rates, changes in real GDP, and business confidence positively affect time-series predictability of money market mutual fund returns, while changes in CPI negatively affect it. The effects of macroeconomic variables are not significant in other mutual fund types.

2. THEORETICAL FRAMEWORK

Park and Newaz (2023) find time-series predictability in the returns of various sector indices based on various indicators. The methodology and motivations in their paper is the main inspiration for this research. They first create a weighted forecast using three models; a naïve model in which past returns forecast future returns, a simple exponential smoothing model, and an ARMA model. They then observe if the predictability in these models can be represented through a fixed effects panel and a dynamic common correlated effects panel with various fund-level and macroeconomic indicators as explanatory variables. We instead apply their methods in investigating the effects of various indicators on time-series predictability on mutual funds rather than sector indices. However, the main commonality is that this paper is mainly written to investigate the issue through an individual retail investor perspective. The findings of their paper also pertain to a mutual fund setting, because both sector indices and mutual funds allow retail investors to diversify their investment and lower idiosyncratic risk. They find that their time-series methodology generates higher return predictability in cyclical, sensitive, and defensive sector indices when controlling for fund-level and macroeconomic variables. However, their time-series predictability investing strategy only outperforms classic buy-and-hold strategies and momentum strategies when controlling for market cap in cyclical sectors, illiquidity in both cyclical and sensitive sectors, dividend yield in defensive sectors, and term spreads in cyclical sectors.

Furthermore, Bandono et al (2020) find that some macroeconomic indicators and the performance of general mutual funds affect the performance of RDPT; a classification of mutual funds tailored specifically to fund infrastructure development in Indonesia. Like Park and Newaz (2023), they implement time-series in their methodology. However, Bandono et al (2020) do not focus on the effects of macro or fund-level variables on the time-series predictability of mutual fund returns, but rather on predicting the performance of these RDPT funds using time-series methodology. Despite the different focal points, Bandono et al (2020) find that some macroeconomic indicators including policy rates and real GDP positively and significantly affect returns of these RDPT mutual funds, while CPI negatively and significantly affects returns. Other macroeconomic variables besides the aforementioned do not significantly affect returns. We can thus reasonably infer that some macroeconomic variables may affect time-series predictability, as they have been shown to affect mutual fund returns, although we cannot yet say anything about the sign and magnitude of their effects. This is because macroeconomic indicators have previously been shown to be strong predictors of returns, but not significant predictors of time-series predictability (Park & Newaz, 2023).

Additionally, Avramov and Wermers (2006) form investment strategies in US domestic equity mutual funds by incorporating predictability in manager skills, fund risk loadings, and benchmark returns. Their unique method of out-of-sample forecasting and mutual fund investing strategy generates economically significant results when tested against Fama-French and momentum benchmark strategies. They find that predictability in manager skills is the main driver of investment profitability, and that portfolios constructed based on the predictability of their time-series model outperform the Fama-French and momentum benchmarks by 2 to 4% yearly and an additional 3 to 6% by choosing funds that outperform their industry benchmarks. Our study aims to contribute to these findings by laying the foundation for a predictability-based strategy based on time-series methodology, but it does not attempt to construct optimal portfolios as in Avramov and Wermers (2006).

As an added, Rakowski and Wang (2009) also find robust time-series predictability on short-term mutual fund returns based on capital flows. They find that past fund flows have a positive effect on future fund returns, and that daily flows are subject to end-of-day and end-of-month seasonality. Although we are not investigating the effects of capital fund flows and instead investigating the effects of macroeconomic variables on time-series predictability, we can now assume that both fund-level and macroeconomic variables affect the time-series predictability of mutual funds. Therefore, we expect that different mutual fund investment styles exhibit different degrees of time-series predictability due to the different volumes of fund flows across the four investment styles of mutual funds in Indonesia.

We can thus synthesize our first hypothesis based on the discussed literature. Based on Avramov and Wermers (2006), we know that fund-level indicator predictability affects profitability when investing in mutual funds. Their out-of-sample forecasting methods using these indicators outperform Fama-French and momentum benchmarks, thus indicating that out-of-sample forecasting methods may provide value to investors. In combination with the findings of Park and Newaz (2023), which confirm that mutual fund investing strategies based on time-series predictability outperform momentum and buy-and-hold strategies under certain macroeconomic and sector level conditions, we have reason to believe that time-series predictability may benefit mutual fund investors in Indonesia. In terms of a context-specific study, Bandono et al (2020) provides evidence of macroeconomic effects on mutual fund performance in Indonesia, yet we cannot say anything of their effects on time-series predictability. However, following Park and Newaz (2023) that find business cycles as a significant predictor of time-series predictability for all sampled sectors including in emerging markets. Therefore, in terms of Indonesian mutual funds in general we hypothesize the following:

Ha) Macroeconomic variables affect the time-series predictability of mutual funds in Indonesia.

We are also able to synthesize a second hypothesis to address our question of time-series predictability across different investment styles of mutual funds in Indonesia. Following the findings in Avramov and Wermers (2006), we know that incorporating risk loadings increases return predictability from equity mutual funds. Although they do not investigate non-equity mutual funds, we interpret their findings on the effects of risk loadings to be suggestive of differences in time-series predictability across the four different formally recognized mutual fund investment styles in Indonesia. Additionally, Rakowski and Wang (2009) find that fund flows affect time-series predictability of mutual fund returns. It is reasonable to assume that fund flows differ across the investment styles, based on the differences in the underlying asset classes. For example, equity mutual funds purchase stocks to fit a certain portfolio, in the process accumulating dividends and unrealized returns overtime, whereas fixed income mutual funds mainly invest in long-term government obligations, which liquidate at maturity, and money market funds exhibiting the most frequent fund flow activity. Therefore, we hypothesize the following regarding the time-series predictability of mutual funds in Indonesia based on their investment styles:

Hb) The time-series predictability of the four different investment styles of mutual funds in Indonesia are affected differently by our macroeconomic indicators.

3. DATA AND METHODOLOGY

3.1 Sample mutual funds and macroeconomic indicators

We first select five of the domestic mutual funds for each of the four investment styles. Acknowledging that this paper is mainly written to assess the accuracy of time-series forecasting by retail investors, we select the five most popular funds for each style based on assets under management. We select a time period beginning from the 25th of April, 2019 that spans until the end of 2024, which encompasses time periods before, during, and after the COVID-19 pandemic. Daily returns and their corresponding dates are extracted from the Bloomberg database, whereas macroeconomic variables are extracted from the OECD statistics database. The selection of macroeconomic indicators in this paper includes long-term policy rates, short-term policy rates, real GDP growth, CPI, and an indicator for the business cycle are inspired by the findings in Bandono et al (2020) and Park and Newaz (2023). Long term policy rates refer to the rates on government bonds that mature in 10 years, whereas short term policy rates refer to rates on the money market (i.e., short term government issued papers). Real GDP growth is expressed as a percentage, and measured quarterly along with CPI and business confidence as an indicator of the business cycle.

3.2 Measuring time series predictability

To measure time-series predictability that emulates the forecasting performance of less rational investors, we apply a rolling window method as seen in Park and Newaz (2023). We choose to apply this method instead of popular alternatives such as subperiod analysis or time-varying parameter models because the rolling window does not assume the return generation process or forecasting model to be always correct (Ping & Brooks, 2011, as cited in Park & Newaz, 2023). In our method, investors observe daily mutual fund returns in the previous 200 trading days, which we call the training window, and estimate a forecast of daily return for the next day. After a window of 25 days which we call the evaluation period, the investor then evaluates the forecasting accuracy of their predictions with respect to the observed daily returns. Lastly, the investor calculates the predictability in the rolling window based on the evaluation period. The lengths of these windows are inspired by Moskowitz, Ooi, and Pedersen (2011, as cited in Park & Newaz, 2023).

The retail investors in our model are assumed to forecast returns using three models similarly to Park and Newaz (2023): exponential smoothing, autoregressive moving average (ARMA), and a naïve model. Firstly, the exponential smoothing model predicts future returns as the weighted average of the current return and the immediate-past forecast. Secondly, the ARMA models use lagged returns and past errors to predict future returns. After testing up to three lags for each autoregressive and moving average term on a random mutual fund from our sample, we find that ARMA(2,2) model is appropriate because it minimizes both the Akaike information criterion (AIC) and Bayesian information criterion (BIC). This means that this ARMA model is the best forecasting model based on AIC, and is the "correct" time-series model based on BIC (Chakrabarti & Ghosh, 2011b). However, this is a strong assumption, because the ARMA parameters vary per forecast, hence the appropriate lags may vary as well. Despite this, it is reasonable to assume that retail investors may not have the knowledge or tools necessary to assess the information criteria per every daily forecast, and hence they apply a simple ARMA(2,2) model (see Appendix B). Lastly, the naïve model takes the historical average return of the training window to forecast returns on the next day. The naïve model serves as the benchmark model to determine time-series predictability. The rolling ARMA(2,2) model is generated using STATA MP 17.0, while the naïve model and exponential model are generated using Microsoft Excel. We compile the processed data on Excel.

Additionally, single forecasts from the aforementioned three models are merged into combined forecasts, as previous literature has found combined forecasts to perform better than single forecasts (Hibon & Evgeniou, 2005, as cited in Park & Newaz, 2023). We use two simple combination methods. The first method takes the average of the predictions, while the second method takes the median of the predictions. We thus arrive at five potential predictions for daily returns on the next day. For each evaluation period τ, we measure time-series predictability PD_τ as the largest reduction in forecasting errors relative to the naive model. This is our main dependent variable. This definition of time-series predictability is inspired directly by Park & Newaz (2023).

$$PD_\tau = max_m(1 - M_{m,\tau}/M_{v,\tau}) \tag{1}$$

where M_m is the root mean squared error (RMSE) of a single or combined forecast except for the naive forecast, and M_v is the root mean squared error of the naive forecast. This method is similar to finding the model with the lowest out-of-sample R^2 (Henkel, Martin, & Nardari, 2011).

3.3 Dynamic Fixed Effects Model

To examine how macroeconomic variables affect PD_τ, we apply a dynamic fixed effects model with an autoregressive term expressed in $PD_{s,\tau-i}$. The dynamic fixed effects estimator is as follows:

$$PD_{s,\tau} = \alpha_s + \beta x_{s,\tau} + \gamma PD_{s,\tau-i} + e_{s,t} \tag{2}$$

Where a is a cross section fixed effect, $x_{s,\tau}$ are the various macroeconomic indicators at the end of the evaluation period, $PD_{s,\tau-i}$ is a lagged value of PD, and e is the error term. We add eight lagged values of PD to account for the serial correlation that may be caused by overlaps in evaluation periods as seen in Park and Newaz (2023). Therefore, there are eight iterations of $\gamma PD_{s,\tau-i}$, where i has a range

i: [0,8]. We remove the first eight days of observations due to the missing values of lagged observations. After processing, we are left with a highly balanced panel with 899 observations for each of the 20 mutual funds, except for one fund that as previously mentioned had an omitted outlier at 888 observations. This brings the pooled observations to a total of 17,979.

3.4 Robustness Checks

We have reason to believe that a dynamic fixed effects model is the most simple and appropriate fit for our panel due to past literature (Park & Newaz, 2023; Bandono et al, 2020). However, we will still perform a robustness check on the main model using the Hausman test to ascertain that the fixed effects model is a better fit than the random effects model.

We perform three additional robustness checks on the general model to confirm the asymptotic assumptions of a fixed effects model. Firstly, we compute an adjusted Wald test for groupwise heteroscedasticity. We correct for robust standard errors after finding that groupwise heteroscedasticity exists in our sample. Additionally, we formally test for serial correlation in our panel using the Wooldridge test. We also test for slope heterogeneity using a standardized Swamy's test as written in Pesaran & Yamagata (2008). Furthermore, we also test our fixed effects model against a dynamic common correlated effects (DCCE) model, which assumes heterogeneity in coefficients that are randomly distributed around an average coefficient. This model is one of the two models used in Park and Newaz (2023) to investigate time-series predictability of sector index returns. The DCCE estimator is as follows:

$$PD_{s,\tau} = \alpha_s + \beta x_{s,\tau} + \gamma PD_{s,\tau-i} + \delta_s f_\tau + e_{s,t} \qquad (3)$$

Where f is a vector of unobserved common factors, and δ is a vector of heterogeneous factor-loading (Chudik & Pesaran, 2015, as cited in Park & Newaz, 2023).

We first generate a fixed effects model for our general sample comprising 20 mutual funds with equal number of investment styles, and then we generate four fixed effects models to conduct a subgroup analysis on the effects of macroeconomic variables on each respective mutual fund investment style. Additionally, we remove one outlier that returns a PD value less than -20. We investigate these fixed effects models and the corresponding robustness checks using STATA MP 18.0.

Table 1.

Descriptive statistics for time-series predictability, returns, and macroeconomic indicators

Variable	N	Mean	SD	Min	Max	Skew	Kurt
PD	17,980	0.02	0.10	-3.36	0.98	-1.67	14.85
RE	17,980	-0.00	0.01	-0.06	0.13	0.82	30.64
BC	17,980	5.58	13.47	-35.75	18.98	-1.89	6.31
SR	17,980	4.89	1.29	3.75	6.95	0.61	1.58
LR	17,980	6.67	0.39	5.93	7.82	0.41	2.76
CPI	17,980	121.97	4.50	116.34	129.40	0.23	1.45
ΔRGDP	17,980	0.95	2.01	-6.89	3.27	4.05	-2.59

Note: This table shows summary statistics for the dependent variable, returns, and macroeconomic indicators. PD is time-series predictability, RE is daily returns expressed as a percentage change, BC is business cycle measured by the Bank Indonesia business confidence survey, SR are short-term rates on three month maturity money market papers, LR is long-term rates on ten year maturity treasury bills, CPI is the consumer price index, and ΔRGDP is the quarterly percentage growth in real GDP.

There are four formally recognized mutual fund investment styles in Indonesia: Equity (EQ), fixed income (FI), balanced (BA), and money market (MM). We use the Bank Indonesia survey of business confidence as a proxy of the business cycle. Business confidence, CPI, and real GDP growth are measured quarterly. Short-term rates, long-term rates are measured monthly (see Appendix A). Note that we do not include daily returns in our model following the methodology in previous literature (Park & Newaz, 2023).

The average time-series predictability in our sample takes on a positive value. This indicates that in our sample, the single and combined forecasts from the ARMA model and exponential smoothing model tends to outperform the naïve model in forecasting one step ahead daily returns.

4. RESULTS AND DISCUSSION

Table 2.

Correlation matrix

	PD	Day	RE	EQ	FI	BA	MM	BC	SR	LR	CPI	ΔRGDP
PD	1.00											
Day	0.02***	1.00										
RE	-0.00	0.04***	1.00									
EQ	-0.16*	0.00	-0.01	1.00								
FI	0.07***	0.00	0.00	-0.33***	1.00							
BA	-0.10***	0.00	0.00	-0.33***	-0.33***	1.00						
MM	0.19***	0.00	0.01	-0.33***	-0.33***	-0.33***	1.00					
BC	0.00	0.72***	0.02**	-0.01	-0.01***	0.02**	-0.01	1.00				
SR	-0.02	0.75***	0.02*	-0.01	-0.01	0.02**	-0.01	0.30***	1.00			
LR	-0.05***	0.07***	0.03***	0.02*	0.02***	-0.04***	0.01	-0.07***	0.10***	1.00		
CPI	-0.03***	0.98***	0.04***	-0.01*	-0.02***	0.04***	-0.01	0.63***	0.82***	0.19***	1.00	
ΔRGDP	0.04***	0.15***	0.01	-0.02**	-0.02***	0.06***	-0.02*	-0.12***	-0.06***	-0.35***	0.08***	1.00

Note: In addition to the variables listed in table 1, this correlation matrix includes Day which is the time variable, represented by trading days (with gaps), EQ, FI, BA, and MM which are dummy variables for equity, fixed income, balanced, and money market mutual funds respectively. *, **, and *** refer to significance at the 5%, 1%, and 0.1% respectively.

4.1 Correlations between PD and our indicators

We first observe the correlation matrix for our variables in Table 2. We find that PD has a positive and significant correlation with the time variable, confirming our assumption that serial correlation may exist, possibly due to overlaps in evaluation periods. We cannot say for certain that this suspicion is true, as we will formally test for serial correlation using a robustness test later.

Additionally, we find PD does not have any significant correlation with our proxy for business confidence. This finding contradicts that of Park and Newaz (2023), which suggests that time-series predictability is stronger in economic downturn. We speculate that the reason for this may be the different allocations of underlying assets between mutual funds and sector indices across different phases of the business cycle. To elaborate, during times of economic distress, fund managers may choose to shift the fund portfolio to more defensive sectors, which immediately affects the overall return predictability of the portfolio. In contrast, the composition of sector indices retains their compositions through both economic downturn and growth. As a result, the behavior of the sector index does not change throughout time.

Furthermore, we find significant correlations between PD and the four investment styles. We find that the fixed income funds tend to exhibit the highest time-series predictability, followed by balanced funds, money market funds, and lastly, full equity funds. We expect that fixed income mutual funds would exhibit relatively high time-series predictability, while full equity funds would exhibit the least time-series predictability due to the nature of the underlying assets.

We also find that our selected macroeconomic indicators have significant correlations with PD. We find that long-term rates and CPI negatively correlate with time-series predictability, while short-term rates, and real GDP growth positively and significantly correlate with time-series predictability. Furthermore, there is no perfect collinearity between any of the variables.

4.2 General dynamic fixed effects model for sampled Indonesian mutual funds

Table 3.

General dynamic fixed effect model for time-series predictability

PD	Coefficient	Robust SE	t	[95% C.I.]	
Constant	0.2622	0.1843	1.42	-0.1236	0.6481
SR	0.0051	0.0040	1.28	-0.0032	0.0135
LR	0.0025	0.0053	0.47	-0.0086	0.0136
CPI	-0.0025	0.0018	-1.34	-0.0063	0.0014
*Δ*RGDP	0.0018	0.0017	1.07	-0.0018	0.0054
BC	0.0004	0.0003	1.41	-0.0002	0.0011
σ_u	0.0116				
σ_e	0.0661				
ρ	0.0298				
Overall R^2	0.5439				
Between R^2	0.9612				
Within R^2	0.5183				

Note: This table presents the results for the general fixed effects model with time-series predictability PD as the dependent variable. We exclude the coefficients of the eight lagged values of PD for conciseness and focus on macroeconomic variables. σ_u is the time-invariant fund-specific term, σ_e is the standard deviation of the error term, and ρ is the proportion of variance explained by the fund-specific term. *, **, and *** refer to significance at the 5%, 1%, and 0.1% respectively.

We find that none of our chosen macroeconomic variables are significant in explaining time-series predictability PD in the general fixed effects model that includes all 20 mutual funds in our sample. The general fixed effects model explains 54.39% of the variance in our sample, 96.12% of the between fund variance, and 51.83% of the within fund variance. We obtain a test-statistic for the joint significance of the model to be $F(13, 19) = 723.06$, resulting in $p = 0.000$. This indicates that our model has a jointly significant explanatory effect on PD.

Before we speculate about the findings from our general models, we conduct robustness checks as mentioned in the methodology section. Using the Hausman test to test the suitability of our fixed effects model compared to a random effects model, we find a resulting $\chi^2(13) = 616.73$, with $p = 0.000$. Therefore, we reject the null hypothesis that the random effects model is more appropriate for our study. We also test for groupwise heteroskedasticity, and find significant evidence of heteroskedasticity in our sample ($\chi^2(20) = 68231.67$, $p = 0.000$). Therefore, we correct for robust standard errors. Furthermore, although we have reason to believe that serial autocorrelation exists in our sample, we formally test for it using the Wooldridge test (Wooldridge, 2002) which tests for first-order autocorrelation. Although this test is not widely used, its reliability has been tested to a satisfactory degree (Drukker, 2003). We obtain a test statistic $F(1,19) = 3.072$, with $p = 0.0958$. Although insignificant at the 5% significance level, it is significant at the 10% level. This indicates that there is still a high probability that serial correlation exists in our panel data, thus justifying our inclusion of eight lagged values of PD as regressors. Furthermore, we test for slope heterogeneity using the adjusted Swamy test, obtaining an adjusted test statistic $\delta = 227.586$, with $p = 0.000$. We therefore infer that the slopes between funds in our general dynamic fixed effects model are heterogeneous.

We can now entertain possible reasons as to how the results of our general model came into fruition. One main reason is that the slope heterogeneity in our sample may be severe. Fixed effects models return biased results when this asymptotic assumption of slope homogeneity is not met (Rüttenauer & Ludwig, 2020) and also affects its predictive power. In our context, it may be that the time-series predictability in our sampled mutual funds respond differently to changes in macroeconomic indicators. We will explore this claim further in the subgroup analysis. Furthermore, although we tested for serial correlation and concluded that panel wise serial correlation exists in our model, we cannot formally test the number of lags that are serially correlated. This is because our sample does not fulfill the requirements of either of the two tests that are able to check for serial correlations up to the n-th lag (Born & Breitung, 2016; Inoue & Solo, 2006). Therefore, we cannot reject the null from our first hypothesis that states that our selection of macroeconomic indicators affects time-series predictability of mutual funds in Indonesia.

4.3 Subgroup dynamic fixed effects models

Table 4.

Subgroup analysis for each mutual fund investment style in Indonesia

PD	EQ	FI	BA	MM
Constant	0.0325	0.8056	0.0119	0.0448*
	(0.0141)	(0.5474)	(0.0570)	(0.0139)
SR	0.0004	0.0178	0.0001	0.0013*
	(0.0003)	(0.0148)	(0.0002)	(0.0003)
LR	0.0007	0.0081	-0.0043	0.0029
	(0.0011)	(0.0094)	(0.0028)	(0.0011)
CPI	-0.0003	-0.0077	0.0002	-0.0006**
	(0.0002)	(0.0054)	(0.0005)	(0.0001)
*Δ*RGDP	0.0000	0.0065	-0.0010	0.0007*
	(0.0001)	(0.0045)	(0.0006)	(0.0002)
BC	0.0000	0.0014	-0.0000	0.0001*
	(0.0000)	(0.0009)	(0.0001)	(0.0000)
σ_u	0.0006	0.0124	0.0020	0.0007
σ_e	0.0150	0.0898	0.0638	0.0223
ρ	0.0015	0.0186	0.0009	0.0009
Overall R^2	0.9144	0.3918	0.6787	0.9413
Between R^2	1.0000	0.6598	0.9998	1.0000
Within R^2	0.9111	0.3892	0.6707	0.9401

Note: This table presents the results for four subgroup fixed effects models with time-series predictability PD as the dependent variable, categorized on the basis of mutual fund investment styles in Indonesia. The figures in brackets below each coefficient indicate the robust standard errors clustered for five clusters. *, **, and *** refer to significance at the 5%, 1%, and 0.1% respectively.

We now examine the dynamic fixed effects model for each subgroup based on the four different formally recognized mutual fund investment styles in Indonesia. We find that increases in real GDP, business confidence, and short-term rates positively and significantly affect time-series predictability of returns for money market mutual funds, while increases in CPI negatively and significantly affects it. We also find that the models account for most of the between variation across each of the five funds in their respective categories. We are unfortunately unable to calculate the test statistics for each model due to the clustering of standard errors to account for heteroskedasticity in our panel. We also check for slope heterogeneity in each model using the Swamy test. Similarly to our general model, we find significant evidence for slope heterogeneity in each of the four subgroups.

We now refer back to the claim made during the general fixed effects model section regarding slope heterogeneity. After testing for slope heterogeneity on each subgroup fixed effects model (see appendix C), we find significant evidence of slope heterogeneity four subgroups, despite already being categorized according to their respective investment styles. Therefore, the effects of macroeconomic indicators on time-series predictability of mutual funds not only differ based on investment style, but also between the largest funds in the same investment style. The failure of this fixed effects asymptotic assumption could therefore again indicate potential bias in our results. Regardless of this, we attempt to explain our findings on money market mutual funds in the following paragraphs.

The results for the money market mutual funds echo the findings in Bandono et al (2020). They found that CPI negatively affects RDPT mutual fund returns, while short-term policy rates and real GDP growth positively affects returns. Meanwhile, we find that CPI negatively affect time-series predictability of equity mutual fund returns, while real GDP growth, short-term policy rates, and business confidence positively affect time-series predictability. However, these findings contradict the findings in Park and Newaz (2023), that find higher time-series predictability in more volatile sectors. Although the money market sector is the least volatile out of the four investment styles, it exhibits the most significant time-series predictability in our sample with respect to our macroeconomic variables. This may be due to the specificity of the findings in Park and Newaz (2023), which are perhaps only applicable to equity asset classes.

Previous literature has found that term spreads are significant predictors for return predictability (Amisano & Savona, 2008), yet it has only been investigated with respect to equities. Although time-series predictability on money market returns have not been investigated in previous literature, increasing time-series predictability for money market funds due to short-term rates is expected. This may be due to the tendency of money market fund managers to quickly take advantage of arbitrage opportunities in response to changes in short-term interest rates (Kotomin, Smith, & Winters, 2011).

Furthermore, there has been limited work done on the effects of real GDP growth on time-series predictability of money market fund returns. Moreover, the causal relationships between real GDP growth and stock and bond markets are still ambiguous. However, we know that real GDP growth and the growth of financial markets are strongly positively correlated (Inc, 2010), hence this correlation could justify the positive effects of real GDP growth on the time-series predictability of money market mutual fund returns. To elaborate, when the growth of financial markets is stable, asset returns tend to stabilize as well (Inc, 2010). This makes it more likely for time-series predictability to become stronger during times of growth.

Additionally, limited work has also been done on the effects of CPI and business confidence on the time-series predictability of money market fund returns. However, we suggest one reason underlying the negative effect of CPI on money market fund return predictability. This may be due to losses being incurred in money market papers when inflation exceeds the short-term interest rate. Therefore, when CPI increases, which insinuates increasing inflation rates, returns from money market mutual funds may become less predictable, perhaps due to sudden losses. On the other hand, increasing business confidence has been shown to be associated with the investment growth of an economy (European Central Bank, 2019). However, similarly to real GDP growth, the causal effect of investment growth on financial market returns is still ambiguous. Regardless, we suggest that stable economic growth as implied by moderately increasing business confidence increasing the stability of returns from money market mutual funds, and thus increases time-series predictability.

4.4 Robustness check against dynamic common correlated effects model

Table 5.

DCCE models for mutual funds in general and subgroups

PD	GEN	EQ	FI	BA	MM
SR	0.0042	0.0006	0.0151	-0.0004	0.0015***
	(0.0036)	(0.0004)	(0.0144)	(0.0004)	(0.0005)
LR	0.0020	0.0004	0.0062	-0.0019	0.0032*
	(0.0016)	(0.0011)	(0.0058)	(0.0022)	(0.0013)
CPI	-0.0017	-0.0004*	-0.0055	-0.0002	-0.0006
	(0.0012)	(0.0002)	(0.0051)	(0.0005)	(0.0001)
ΔRGDP	0.0011	0.0000	0.0047	-0.0010*	0.0008***
	(0.0011)	(0.0001)	(0.0043)	(0.0005)	(0.0002)
BC	0.0003	0.0000	0.0009	0.0000	0.0001***
	(0.0002)	(0.0000)	(0.0008)	(0.0001)	(0.0000)
R^2	0.24	0.09	0.33	0.30	0.06
RMSE	0.75	0.01	0.07	0.06	0.02

Note: This table presents the results for four subgroup DCCE models with time-series predictability PD as the dependent variable, categorized on the basis of mutual fund investment styles in Indonesia, and a general (GEN) model including all funds in our sample. The figures in brackets below each coefficient indicate standard errors. *, **, and *** refer to significance at the 5%, 1%, and 0.1% respectively.

Table 5 shows the results of our panel using the DCCE models used in Park and Newaz (2023). Compared to our fixed effects model, the DCCE model appears to provide more liberal estimates, as seen from the significant effects of CPI on equity mutual funds, change in real GDP on balanced funds, and long-term policy rates on money market funds. These effects were not significant in our fixed effects model. This may be due to the significant slope heterogeneity in our general and subgroup samples, which weakens the internal validity of our fixed effects model but does not violate any asymptotic assumptions for the DCCE model. However, the direction of the significant coefficients in our fixed effects model are identical to the DCCE model, and their magnitudes are not relatively different. Additionally, for both the general and subgroup models, our fixed effects models have marginally higher R-squared values compared to their DCCE counterparts. This indicates that the fixed effects models explain more variation in our panels compared to the DCCE models.

5. CONCLUSION

We have thoroughly described the results of our investigation on the relationship between time-series predictability of mutual funds in Indonesia and macroeconomic indicators. Inspired by the findings of Park and Newaz (2023), we put an emphasis on retail investors who are searching for predictability in their investments while not being as informed as institutional investors. We examined a total of 20 mutual funds across the four formally recognized investment styles of mutual fund in Indonesia based on the dynamic fixed effects model. The sampled time period covers periods before, during, and after the COVID-19 pandemic.

We infer some conclusions regarding the effects of macroeconomic variables on time-series predictability. Firstly, we find that macroeconomic indicators do not have a significant effect on mutual fund return time-series predictability in general in Indonesia. This is because we had suspected that different styles of mutual fund investment are affected differently by macroeconomic variables based on the significant slope heterogeneity in our general model. Secondly, we find that macroeconomic variables have varying degrees of effect on time-series predictability across the four investment styles. We find that only the time-series predictability of money market mutual funds is significantly affected by our selection of macroeconomic indicators. Therefore, investors who are seeking higher time-series predictability in their investments should seek out money market mutual funds, during periods of high business confidence, high short-term rates, and low inflation rates as measured by CPI. We find that our fixed effects model does not meet its assumption of slope homogeneity, but it still explains significantly more variation in our sample compared to a DCCE model.

There are some extensions to this research that could be addressed by future research. One major extension that warrants attention is a comparison between different strategies of mutual fund investing against a strategy of mutual fund investing that incorporates our measure of time-series predictability as a main indicator. For example, comparing the gains in returns in a portfolio that invests in mutual funds with high fund-specific and temporal time-series predictability against a typical buy and hold strategy, or a momentum strategy. Furthermore, the effects other non-macroeconomic indicators on mutual fund time-series predictability are worth examining, such as daily fund flows, assets under management, investor sentiment, or event studies incorporating election cycles as well.

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APPENDIX A

Variable descriptions

Variable Type	Variable Name	Symbol	Measurement Method
Explained Variable	Time-series predictability of mutual fund returns	PD	See equation 3.
Explanatory Variable	Short-term policy rates	SR	Interest rate on 3-month obligations taken at monthly intervals from OECD.
	Long-term policy rates	LR	Interest rate on 10-year obligations taken at monthly intervals from OECD.
	Consumer Price Index	CPI	Price for a common basket of goods in Indonesia. Measured quarterly from Bloomberg database.
	Percentage change in real GDP	ΔRGDP	Difference between most recent quarter real GDP and last quarter divided by last quarter. Measured quarterly from Bloomberg database.
	Business Confidence	BC	Bank Indonesia business confidence survey. Measured quarterly from Bloomberg database.
Grouping Variable	Equity mutual fund	EQ	Takes value 1 for equity mutual funds, and 0 all else.
	Fixed income mutual fund	FI	Takes value 1 for fixed income mutual fund, and 0 all else.

Balanced mutual fund	EQ	Takes value 1 for balanced mutual funds, and 0 all else.
Money market mutual fund	EQ	Takes value 1 for money market mutual funds, and 0 all else.

APPENDIX B

Akaike and Bayesian Information Criteria on randomly selected mutual fund from sample

ARMA model (p, q)	AIC	BIC
(1,1)	-7430.884	-7410.521
(2,1)	-7445.538	-7420.084
(3,1)	-7452.346	-7421.801
(1,2)	-7443.288	-7417.833
(2,2)	-7462.433	-7431.888
(3,2)	-7452.465	-7416.829
(1,3)	-7452.277	-7421.731
(2,3)	-7451.962	-7416.326
(3,3)	-7459.339	-7418.611

APPENDIX C

Adjusted Swamy tests for slope heterogeneity in subgroups

Investment Style	Adjusted Delta	p-value
Equity	5.837	0.000
Fixed income	186.312	0.000
Balanced	25.191	0.000
Money market	5.400	0.000