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EX-ANTE PREDICTABILITY OF STOCK RETURNS IN A FRONTIER MARKET

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Abstract

This study reports results on the ex-ante predictability of stock returns using real-time stock market data in Vietnam, a frontier market, from June 2008 to June 2022. Countries classified as a frontier market are often known for currency manipulation, financial market illiquidity, and political instability. Despite the enormous risk usually posed by these inefficiencies, potential profits are large and achievable for many investors. This study provides evidence of an existing strategy to form out-of-sample long portfolios that generate statistically significant and positive mean monthly returns even in the presence of transaction costs. I also justify the magnitude of these returns by showing that they exceed those of VnIndex and MSCI Vietnam Index. The results reject the hypothesis that the stock prices in Vietnamese market follow random walks, thus opposing the stock market efficiency hypothesis. Evidence found in this study provides a better understanding of informational efficiency in a frontier equity market setting. Specifically, there are several implications on portfolio selection strategies, stock price patterns, and trading behaviour bias related to the Vietnamese stock market can be drawn from this study.

JEL classification: G11, G12, G14, G15, G17

Keywords: Ex Ante Predictability, Frontier Markets, Investment Portfolio, Market Efficiency, Return Forecasting, Vietnamese Stock Market

1. Introduction

While ex-post predictability of returns is studied by using full-period information, ex-ante predictability of returns is studied by using only information that is available to investors in real time. On the one hand, there is abundant evidence that stock returns are predictable ex post facto. Basu (1977), Banz (1981), Jegadeesh (1990), Fama and French (1992), Jegadeesh and Titman (1993), and Carhart (1997) demonstrate the predictive power of firm-level predictors such as firm size, book-to-market, and prior returns. On the other hand, the literature remains inconclusive on the ex-ante predictability of stock returns, especially for cases of a frontier market. A frontier market is a term given to countries that are in their earliest stage of economic development. These countries are more established than the least developed countries but still have not met the standards of being called an emerging market. Despite risks often involved in such markets, including currency risk, liquidity risk, and political risk, an investor can exploit great potential profits from a frontier market with appropriate analyses and well-diversified portfolios (Meziani, 2020).

In this study, I plan to enrich current investing literature by inspecting the ex-ante predictability of the cross-section of stock returns using Vietnamese stock market data. The focus of this study is on the context of a frontier market since it is widely expected that frontier stock markets are less efficient than

developed stock markets. Lower degree of the efficiency creates greater chance for an investor to be able to generate returns consistently above market averages as implied by the efficient market hypothesis (Fama, 1970). In a comparative analysis between active and passive investing within the context of a frontier market, Speidell (2016) expresses that some of the elements of market inefficiency, such as market capitalization, market liquidity, and bid-ask spread, which make the frontier market asset class more attractive to investors, pose significant challenges to passive managers who attempt to maintain an index-like portfolio. On the empirical evidence, Uludag and Ezzat (2016), documenting the evidence of long memory in major European frontier stock markets, imply that investors can exploit predictability and earn speculative returns by using past stock return information. de Groot et al. (2012) reveal that portfolios sorted on book-to-price ratio and past returns in frontier markets generate economically and statistically significant excess returns of about 5% to 15% annually. While currently known emerging markets are in the progress of being part of the developed world, frontier markets are perfect candidates to join the future emerging market list. Foreseeing this path, patient investors betting on frontier markets will now be rewarded in the future.

A secondary motivation for my study is the recent development of the Vietnamese stock market as it provides an interesting setting to investigate the ex-ante predictability of stock returns. Comprising two main stock exchanges, the Ho Chi Minh City Stock Exchange (HOSE) and the Ha Noi Stock Exchange (HNX), the Vietnamese stock market has been developed in terms of number of listed firms, market capitalization, and liquidity. Starting with only two listed companies in July 2000, as of May 2022 there are 752 listed companies on the two aforementioned stock exchanges with a total capitalization of 5,490 trillion Vietnamese dollar (≈ 234.44 billion U.S. dollar, using the exchange rate of June 2022).[1] This is of approximately 65.37% of Vietnam's 2021 GDP. As a stock market develops, investors gain confidence in seeking efficient allocation for their wealth (Demirgüç-Kunt and Maksimovic, 1996) and the question on whether stock returns are ex ante predictable is always the long-standing interest to both academics and practitioners.

Following Cooper et al. (2005), I seek to understand whether considering *book-to- market*, *size*, *momentum*, and *beta* predictors benefits a real time investor who must allocate funds across stocks listed on HOSE and HNX over the period of June 2008 and June 2022. Distinguishing feature of my study is that an investor is given a chance to decide ex ante how to employ these real time (pre-determined) predictor variables to form trading portfolios for the next period, and then the portfolios' performance is reported, with and without the passive indexes as benchmarks. While my goal is to mitigate hindsight bias as much as possible, I note here that the investor in my analysis has some benefits of hindsight. In reality, the investor faces a much larger set of forecasting variables and has no strong prior beliefs in any predictor, thereby he or she may not form trading strategies using only *book-to- market*, *size*, *momentum*, and *beta* predictors. This hindsight bias is also discussed and acknowledged in Cooper et al. (2005).

To the best of my knowledge, this is the first paper studying ex ante predictability of stock returns in Vietnamese stock market. The results of this study provide a better understanding of informational efficiency in a frontier equity market setting. Specifically, there are several implications on portfolio selection strategies, stock price patterns, and trading behavior bias related to Vietnamese stock market can be drawn from these results.

[1] The data can be retrieved from State Security Commission of Vietnam through this link: http://www.ssc.gov.vn/ubck/faces/vi/vimenu/vipages_vithongtinthitruong/thongkettck/quymothitruong?_adf.ctrl-state=1b8c8774a0_4&_afrLoop=544109307541000

2. Data and Methodology

I utilize all common stocks that are listed on the Ho Chi Minh City Stock Exchange (HOSE) and the Ha Noi Stock Exchange (HNX) during the period of June 2008 to June 2022. Data including monthly stock prices, index prices, and financials are obtained from S&P Global Market Intelligence's Capital IQ platform. Table 1 provides the sample distribution and descriptive statistics of monthly returns. According to the table, numbers of listed stocks increased more than threefold to 732 stocks in 2021 before decreasing to 693 in mid-2022, with 11 out of 15 years spotting a year-over-year increase in numbers of total listed stocks. These statistics confirm the expansion in Vietnamese stock market over the study period. Although the signs of mean monthly returns reported in the last three columns are nearly consistent (with a few exceptions), the degree of mean monthly return dispersion of studied sample stocks is higher than that of VNIndex and of MSCI Vietnam Index. This is rational since the sample is covering the complete Vietnamese equity universe rather than a particular elite group of stocks.[2]

Table 1: Sample distribution and mean monthly returns.

Year	Number of Stocks in the Sample	Mean Monthly Equally-Weighted Return of Stocks in the Sample (%)	Mean Monthly Return on VNIndex (%)	Mean Monthly Return on MSCI Vietnam Index (%)
2008	240	-10.16	-2.65	-1.19
2009	346	6.44	4.62	2.95
2010	500	-1.33	-0.07	0.74
2011	545	-5.59	-2.45	-3.85
2012	556	2.05	1.55	1.47
2013	541	3.18	1.84	0.55
2014	550	3.34	0.77	0.39
2015	564	0.76	0.63	-0.34
2016	577	0.88	1.21	-0.67
2017	621	2.00	3.38	4.16
2018	639	-0.80	-0.61	-1.02
2019	623	1.82	0.65	0.58
2020	680	3.70	1.77	1.62
2021	732	6.16	2.69	1.87
2022	693	-4.30	-3.60	-4.89

Note: Full sample period ranges from June 2008 to June 2022. The mean monthly return for year 2008 (2022) are calculated using only data of July, August, September, October, November, and December (January, February, March, April, May, and June) of the year.

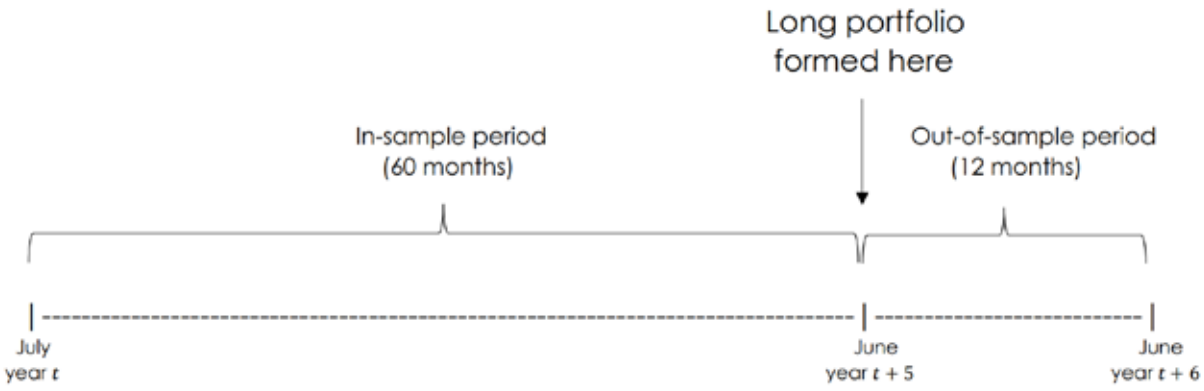
At the end of June of every year in the study period, I form 4 predictor variables for stocks in the sample following Cooper et al. (2005). The *book-to-market* (BM) predictor variable for June of year t is formed by dividing the book value of equity at fiscal year-end $t-1$ by the market value of equity at the end of December of year $t-1$. The *size* (SIZE) predictor variable for June of year t is defined as the market value of equity at the end of June of year t. The *momentum* (MOM) predictor variable for June of year t is the 1-year-lagged holding-period returns that is calculated from July of year $t-1$ to May of year t. The *beta* (BETA) predictor variable for June of year t is defined as the sum of the coefficients in

[2] VNIndex is a capitalization-weighted index of all publicly listed companies on HOSE. The MSCI Vietnam Index captures the performance of the large and mid-cap segments of the Vietnamese stock market.

the regression of stock returns on lagged and contemporaneous market returns. This regression is estimated using no more than 60 months and no less than 24 months of prior returns. These predictor variables are constructed and utilized frequently in capital asset pricing literature.

A simple recursive modelling approach is developed to simulate an investor's real-time decision-making process. In this approach, a real time investor uses knowledge from analyzing stocks in in-sample periods to form long portfolios that are evaluated in out-of-sample periods. In-sample periods are rolling 5-year windows with the first one extending from July 2008 to June 2013. This first in-sample period will be rolled forward 1 year to become the second in-sample period, which covers from July 2009 to June 2014. I keep rolling forward until I reach the last in-sample period in this study, July 2017 - June 2022 period. Out-of-sample periods are identified as the 12-month (July to June) periods following the corresponding in-sample periods. For example, the first out-of-sample period of July 2013 - June 2014 is corresponded to the first in-sample period of July 2008 - June 2013. To help readers visualize this recursive modelling approach, Figure 1 illustrates the timeline of an in-sample period and its corresponding out-of-sample period. There are 9 pairs of in-sample and out-of-sample periods in total.

Figure 1: Timeline of an in-sample period and it's corresponding out-sample period



Note: The first in-sample period ranges from July 2008 to June 2013. The next in-sample period is determined by rolling the current in-sample period forward 1 year. Out-of-sample periods are identified as the 12-month (July to June) periods following the corresponding in-sample periods.

The following steps are used to form long portfolios for out-of-sample periods. First, at the end of June of each year t of the in-sample period 1, stocks are sorted into terciles (three equal groups) based on each predictor variable (BM, SIZE, MOM, and BETA). Second, a real time investor constructs 66 rules using all possible one-way and two-way independent sorts of the four predictor variables' terciles. There is a total of 66 rules including 12 one-way rules (for example, one-way rule BM1 is the BM tercile containing stocks with smallest BM values) and 54 two-way rules (for example, two-way rule SIZE3BETA2 is the intersection of two terciles: SIZE3 and BETA2). I exclude two-way rules that identify more than one tercile of a particular variable (for example, MOM1MOM2 does not exist in this study's rules set since there are no such stocks concurrently belonging to MOM1 and MOM2 terciles). Third, the monthly equally weighted returns are calculated for each of the 66 rules from July of year t to June of year $t + 1$ of the in-sample period 1. I move to next June-to-July cycle in the same in-sample period and repeat the above procedures until I reach the last cycle completing the in-sample period 1. Fourth, I then rank the 66 rules based on the mean of 60 (12 months of June-to-July cycle × 5 cycles) monthly equally weighted returns. The 7 top rules (≈ 10% of 66 rules) that generate the highest mean monthly returns for the entire 5-year in-sample period 1 will define stocks for my long portfolio in the out-of-sample period 1. I then examine the performance, monthly returns, of this long portfolio for 12-month period as ruled by the out-of-sample period 1. After completing the evaluation of the long portfolio in the out-of-sample period 1, I move to the in-sample period 2 by rolling the in-sample period 1's window

forward 1 year, and the process is repeated. These procedures produce a time series of monthly out-of-sample long portfolio returns from July 2013 to June 2022. It is worth noting here that Cooper et al. (2005) also perform examinations of short portfolios and zero-cost combined portfolios. Replicating these procedures is irrelevant in Vietnamese stock market because short selling remains illegal over there.[3] I also justify the magnitude of the ex-ante predictability by examining whether simulated real-time long portfolios outperform benchmark indexes, VnIndex or MSCI Vietnam Index. Empirical results are reported in the next section.

3. Empirical Results

Table 2 provides the description of the best rules sorted from each in-sample period. These rules will be used to form long portfolios that are evaluated in out-of-sample periods. According to the table, the first in-sample period, ranging from July 2008 to June 2013, produces the following 7 best rules: BM1BETA1, BM1SIZE1, SIZE1BETA1, BM3BETA3, BM2SIZE1, SIZE3MOM1, BM3SIZE1. These rules help identify stocks to be included in the long portfolio for the corresponding out-of-sample period, ranging from July 2013 to June 2014. For example, BM1BETA1 is one of the best rules suggested from the in-sample period 1. Then, a fragment of to-be-formed long portfolio for the out-of-sample period 1 is to buy all stocks concomitantly found in the smallest BM tercile and the smallest BETA tercile, sorted at the end of June 2013. This long portfolio also includes other stocks defined by the rest of the 6 best rules. Investors following this method of portfolio construction might notice that the best rules do not change remarkably from year to year. For example, looking at best rules sets of two of the last in-sample periods, we can see the difference between them is that BM3MOM1 and SIZE1MOM1 replace BM3MOM3 and SIZE1BETA1. This is because these two in-sample periods are still sharing the same 4 years of information. Table 2 also reports the decomposition of all best rules generated throughout this study. Stocks in the lowest tercile of SIZE have a relatively higher chance to be selected for long portfolios as the SIZE1 tercile makes most appearances (48 appearances) in all best rule sets. It is interesting to note here that stocks that belong to medium SIZE tercile (SIZE2) or medium MOM tercile (MOM2) have never been included in any long portfolio during the period of study.

Figure 2 illustrates the main results of this study. While Figure 2 (a) plots mean monthly returns of long portfolios for both in-sample and out-of-sample periods, Graph (b) and (c) of the figure plot the spreads between the mean monthly returns of long portfolios and the mean monthly returns of a passive index for both in-sample and out-of-sample periods. According to Figure 2 (a), the time series of the in-sample mean monthly returns is quite smooth since the rule sets do not change intensively from this to the next in-sample period. This happens because moving to the next in-sample period, small weight is given to the latest year's returns as only one year of new information is added to the previous 4 years. With no surprise, in-sample mean monthly returns are consistently positive since these are ex post returns generated from best rules. My interests lie in the time series of out-of-sample mean monthly returns, which are revealed to be positive throughout the years except for 1 occasion, the period of July 2017 to June 2018, where a slightly below zero return is shown. On the comparison between in-sample and out-of-sample performances, there are 5 occasions (out of nine) where mean monthly returns of are observed to be better for out-of-sample periods over their corresponding in-sample periods. The important implication of these results is that a real time investor can be able to profit from utilizing four predictor variables, book-to- market, size, momentum, and beta, to help him or her develop winning strategies.

[3] Since August 2020, the Vietnam Ministry of Finance has been looking for comments to implement some notable changes regarding intraday stock trading and short selling. However, the discussion is still ongoing, and these practices are still publicly prohibited at the point of writing this paper, July 2022.

Table 2: Description of best rules

Panel A: Best rules

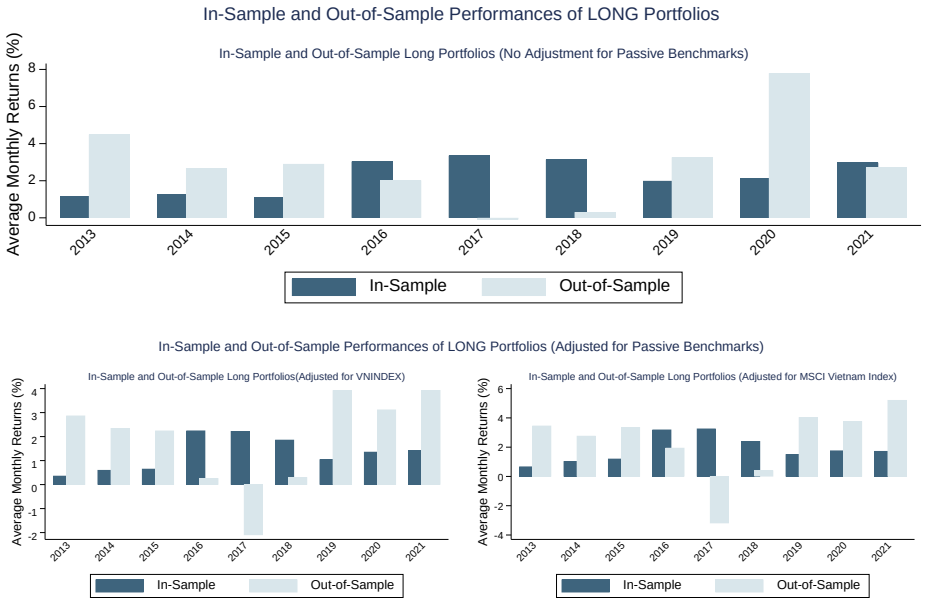
In-sample Period	Out-of-Sample Period	Best Rules
July 2008-June 2013	July 2013-June 2014	BM1BETA1; BM1SIZE1; SIZE1BETA1; BM3BETA3; BM2SIZE1; SIZE3MOM1; BM3SIZE1
July 2009-June 2014	July 2014-June 2015	BM1SIZE1; BM3SIZE1; SIZE1BETA2; BM2SIZE1; BM3BETA2; BM1BETA1; SIZE1BETA1
July 2010-June 2015	July 2015-June 2016	SIZE1MOM3; BM3SIZE1; SIZE1BETA2; BM3BETA2; SIZE1BETA1; BM1BETA1; BM3BETA1
July 2011-June 2016	July 2016-June 2017	SIZE1MOM3; BM3SIZE1; SIZE1BETA2; BM3MOM3; SIZE1; SIZE1BETA1; SIZE1MOM1
July 2012-June 2017	July 2017-June 2018	SIZE1MOM3; BM3SIZE1; SIZE1BETA2; SIZE1; SIZE1BETA3; SIZE1BETA1; BM3MOM3
July 2013-June 2018	July 2018-June 2019	BM3SIZE1; SIZE1MOM3; SIZE1BETA2; SIZE1MOM1; SIZE1; SIZE1BETA1; SIZE1BETA3
July 2014-June 2019	July 2019-June 2020	BM3SIZE1; SIZE1MOM3; SIZE1BETA1; SIZE1BETA2; SIZE1; BM3MOM3; SIZE1MOM1
July 2015-June 2020	July 2020-June 2021	SIZE1BETA3; BM3SIZE1; BM3BETA3; SIZE1; SIZE1BETA2; BM3MOM3; SIZE1BETA1
July 2016-June 2021	July 2021-June 2022	SIZE1BETA3; BM3SIZE1; BM3BETA3; BM3MOM1; SIZE1BETA2; SIZE1; SIZE1MOM1

Panel B: Decomposition of best rules

In-sample Period	Out-of-Sample Period	Decomposition of Best Rules											
		BM 1	BM 2	BM 3	SIZE 1	SIZE 2	SIZE 3	BETA 1	BETA 2	BETA 3	MOM1	MOM2	MOM3
July 2008-June 2013	July 2013-June 2014	2	1	2	4	0	1	2	0	1	1	0	0
July 2009-June 2014	July 2014-June 2015	2	1	2	5	0	0	2	2	0	0	0	0
July 2010-June 2015	July 2015-June 2016	1	0	3	4	0	0	3	2	0	0	0	1
July 2011-June 2016	July 2016-June 2017	0	0	2	6	0	0	1	1	0	1	0	2
July 2012-June 2017	July 2017-June 2018	0	0	2	6	0	0	1	1	1	0	0	2
July 2013-June 2018	July 2018-June 2019	0	0	1	7	0	0	1	1	1	1	0	1
July 2014-June 2019	July 2019-June 2020	0	0	2	6	0	0	1	1	0	1	0	2
July 2015-June 2020	July 2020-June 2021	0	0	3	5	0	0	1	1	2	0	0	1
July 2016-June 2021	July 2021-June 2022	0	0	3	5	0	0	0	1	2	2	0	0
Total		**5**	**2**	**20**	**48**	**0**	**1**	**12**	**10**	**7**	**6**	**0**	**9**

Note: The book-to-market (BM) predictor variable for June of year t is formed by dividing the book value of equity at fiscal year-end $t-1$ by the market value of equity at the end of December of year $t-1$. The size (SIZE) predictor variable for June of year t is defined as the market value of equity at the end of June of year t. The momentum (MOM) predictor variable for June of year t is the 1-year-lagged holding-period returns that is calculated from July of year $t-1$ to May of year t. The beta (BETA) predictor variable for June of year t is defined as the sum of the coefficients in the regression of stock returns on lagged and contemporaneous market returns. This regression is estimated using no more than 60 months and no less than 24 months of prior returns. At the end of June of each year t of an in-sample period, stocks are sorted into terciles (three equal groups) based on each predictor variable (BM, SIZE, MOM, and BETA). A real time investor then constructs 66 rules using all possible one-way and two-way independent sorts of the four predictor variables' terciles. The 66 rules include 12 one-way rules (for example, BM1 is the BM tercile containing stocks with smallest BM values) and 54 two-way rules (for example, SIZE3BETA2 is the intersection of two terciles: SIZE3 and BETA2). 7 best rules are those generating the highest mean monthly returns for an entire 5-year in-sample period. These rules will define stocks for my long portfolio in the corresponding out-of-sample period.

Figure 2: In-sample and out-of-sample performances of long portfolios



Note: The figure illustrates performance of long portfolios in out-of-sample periods. While graph (a) plots mean monthly returns of long portfolios for both in-sample and out-of-sample periods, graph (b) and (c) plot the spreads between the mean monthly returns of long portfolios and the mean monthly returns of a passive index for both in-sample and out-of-sample periods. For in-sample performance bars, the date indicates the last year in the 5-year in-sample period. The out-of-sample performance bars are plotted next to their corresponding in-sample performance bars.

The next question naturally being asked is whether it is worth to reconstruct long portfolios every year while there always exists an option of investing in a passive index. The answer lies in graph (b) and (c) of Figure 2. Even with passive indexes adjustment, the overall results remain unchanged. It is implied from these graphs that the real time investor employing the methodology to select investment strategies outperforms both passive indexes 8 out of 9 occasions during the period of study. In Table 3 Panel A, I also perform simple *t*-tests to see whether the time series of benchmark indexes and mean monthly returns for out-of-sample periods are statistically different from zero. Results of the tests confirm evidence observed in Figure 2. On average, long portfolios not only earn an out-of-sample mean monthly return of 2.85%, statistically greater than zero at the 1% significance level, but also outperform VNIndex and MSCI Vietnam Index by 1.84%, statistically greater than zero at the 1% significance level, and 2.39%, statistically greater than zero at the 1% significance level, respectively. The results of this study contradict those of Cooper et al. (2005) who indicate the ability of an investor to outperform the passive index in real time is dubious when using the same set of predictors on all NYSE, AMEX, and NASDAQ nonfinancial firms. Our results are valuable since ex ante cross-sectioning of stock returns seems to produce above-market returns on exactly the same factors employed in Cooper et al. (2005).

I also adjust the out-of-sample mean monthly returns of long portfolios for transaction costs, which are set at 0.15% annually according to Vo and Truong (2018). These transaction costs account for fees and tax in the Vietnamese market. Reporting results in the presence of transaction costs, Table 3 Panel B concludes that profits shown in Figure 2 still persist. After taking into account the transaction costs, long portfolios earn an out-of-sample mean monthly return of 2.44%, statistically greater than zero at the 1% significance level. Panel B of the table also confirms that after accounting for transactions costs, long portfolios still outperform benchmark indexes during the period of study.

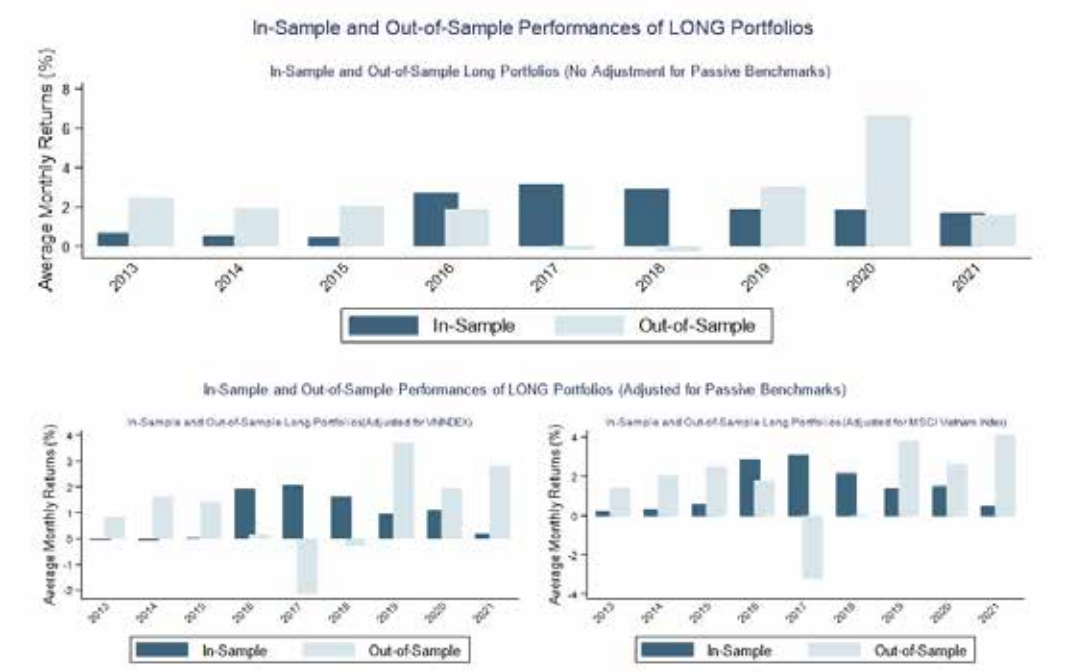
Table 3: Out-of-sample test results by portfolios

Portfolio	Observation	Mean	Std. dev.	*t*-test (H_0: mean = 0)			
				t-statistic	*p*-value (H_a: mean > 0)	*p*-value (H_a: mean > 0)	*p*-value (H_a: mean > 0)
Panel A: Unadjusted							
VNIndex	108	1.01	5.67	1.85	0.967	**0.066**	**0.033**
MSCI Vietnam Index	108	0.46	5.99	0.80	0.787	0.426	0.213
Long Portfolio	108	2.85	8.01	3.70	0.999	**0.000**	**0.000**
Long Portfolio – VNIndex	108	1.84	7.28	2.63	0.995	**0.009**	**0.005**
Long Portfolio – MSCI Vietnam Index	108	2.39	7.86	3.16	0.999	**0.002**	**0.001**
Panel B: Adjusted for Trading Costs							
VNIndex	108	1.01	5.67	1.85	0.967	**0.066**	**0.033**
MSCI Vietnam Index	108	0.46	5.99	0.80	0.787	0.426	0.213
Long Portfolio	108	2.44	7.99	3.18	0.999	**0.002**	**0.001**
Long Portfolio – VNIndex	108	1.43	7.27	2.05	0.979	**0.043**	**0.022**
Long Portfolio – MSCI Vietnam Index	108	1.98	7.84	2.63	0.995	**0.009**	**0.005**

Note: The table reports descriptive statistics and results of t-tests for long portfolios and benchmark indexes. Panel A (Panel B) reports mean monthly returns unadjusted (adjusted) for transaction costs. Figures in Mean and Std. dev. columns are reported in percentage. For readers' convenience, p-values are made bold if they indicate statistical significance levels.

4. Robustness Checks

Figure 3: In-sample and out-of-sample performances of long portfolios



Note: The figure illustrates performance of long portfolios in out-of-sample periods under Sharpe ratio criterion. While graph (a) plots mean monthly returns of long portfolios for both in-sample and out-of-sample periods, graph (b) and (c) plot the spreads between the mean monthly returns of long portfolios and the mean monthly returns of a passive index for both in-sample and

out-of-sample periods. For in-sample performance bars, the date indicates the last year in the 5-year in-sample period. The out-of-sample performance bars are plotted next to their corresponding in-sample performance bars.

Table 4: Robustness check for out-of-sample test results by portfolios under Sharpe ratio and terminal wealth criteria

Portfolio	Observation	Mean	Std. dev.	*t*-test (H_0: mean = 0)			
				t-statistic	*p*-value (H_a: mean < 0)	*p*-value (H_a: mean # 0)	*p*-value (H_a: mean > 0)
Under Sharpe ratio criterion							
Panel A: Unadjusted							
VNIndex	108	1.01	5.67	1.85	0.967	**0.066**	**0.033**
MSCI Vietnam Index	108	0.46	5.99	0.80	0.787	0.426	0.213
Long Portfolio	108	2.13	6.58	3.37	0.999	**0.001**	**0.000**
Long Portfolio – VNIndex	108	1.12	5.57	2.09	0.981	**0.039**	**0.019**
Long Portfolio – MSCI Vietnam Index	108	1.67	6.33	2.74	0.996	**0.007**	**0.004**
Panel B: Adjusted for Trading Costs							
VNIndex	108	1.01	5.67	1.85	0.967	**0.066**	**0.033**
MSCI Vietnam Index	108	0.46	5.99	0.80	0.787	0.426	0.213
Long Portfolio	108	1.68	6.56	2.66	0.996	**0.009**	**0.005**
Long Portfolio – VNIndex	108	0.67	5.55	1.25	0.894	0.213	0.106
Long Portfolio – MSCI Vietnam Index	108	1.22	6.31	2.01	0.977	**0.047**	**0.023**
Under terminal wealth criterion							
Panel C: Unadjusted							
VNIndex	108	1.01	5.67	1.85	0.967	**0.066**	**0.033**
MSCI Vietnam Index	108	0.46	5.99	0.80	0.787	0.426	0.213
Long Portfolio	108	2.54	7.80	3.38	0.999	**0.001**	**0.000**
Long Portfolio – VNIndex	108	1.53	6.76	2.34	0.990	**0.021**	**0.010**
Long Portfolio – MSCI Vietnam Index	108	2.08	7.45	2.72	0.996	**0.007**	**0.003**
Panel D: Adjusted for Trading Costs							
VNIndex	108	1.01	5.67	1.85	0.967	**0.066**	**0.033**
MSCI Vietnam Index	108	0.46	5.99	0.80	0.787	0.426	0.213
Long Portfolio	108	2.07	7.77	2.78	0.997	**0.007**	**0.003**
Long Portfolio – VNIndex	108	1.06	6.73	1.71	0.948	**0.090**	**0.045**
Long Portfolio – MSCI Vietnam Index	108	1.52	6.91	2.07	0.987	**0.041**	**0.020**

Note: The table reports descriptive statistics and results of t-tests for long portfolios and benchmark indexes under Sharpe ratio (Panel A and B) and terminal wealth (Panel C and D) criteria. Panel A and C (Panel B and D) report mean monthly returns unadjusted (adjusted) for transaction costs. Figures in Mean and Std. dev. columns are reported in percentage. For readers' convenience, p-values are made bold if they indicate statistical significance levels.

In reality, investors face countless ways of forming portfolios. While it is obviously impossible to consider all variations in the portfolio forming methodology, I want to check for robustness of the above results using several alternative specifications. These variations are described in Table 5. Regardless of specification used, the results remain unchanged.

Table 5: Robustness checks

Type of model specification	Main model specification	Alternative specification for robustness checks
Ranking method	Mean return	-Sharpe ratio -Terminal Wealth
In-sample window length	5 years	-3 years -7 years -10 years
Number of best rules selected to form long portfolios	top 10% (top 7 rules)	-top 5% (top 4 rules) -top 15% (top 10 rules)
Passive benchmarks	VNIndex or MSCI Vietnam Index	-Equally-weighted return of all stocks in my sample -Value-weighted return of all stocks in my sample

5. Conclusion

While *book-to-market*, *size*, *momentum*, and *beta* predictors are widely known of explaining a substantial portion of return variations, ex ante predictability of stock returns remains inconclusive especially for frontier markets. This paper studies whether incorporating the aforementioned predictors benefits a real time optimizing investor who must allocate funds across 848 Vietnamese market's listed stocks over the June 2008 – June 2022 period. I find that stock returns of this frontier market are ex ante predictable. In general, out-of-sample long portfolios formed by in-sample-induced best rules do not only generate positive returns but also outperform the benchmark indexes even in the presence of transaction costs. The results are economically and statistically significant across several robustness checks. Aligned with Vo and Truong (2018), my results reliably reject the hypothesis that the stock prices in Vietnamese market follow random walks, thus oppose the stock market efficiency hypothesis by (Fama, 1970).

References

Banz, R.W., 1981. The relationship between return and market value of common stocks. Journal of financial economics 9, 3-18.

Basu, S., 1977. Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis. The journal of Finance 32, 663-682.

Carhart, M.M., 1997. On Persistence in Mutual Fund Performance. The Journal of Finance 52, 57-82.

Cooper, M., Gutierrez, J.Roberto C., Marcum, B., 2005. On the Predictability of Stock Returns in Real Time. The Journal of Business 78, 469-500.

de Groot, W., Pang, J., Swinkels, L., 2012. The cross-section of stock returns in frontier emerging markets. Journal of Empirical Finance 19, 796-818.

Demirgüç-Kunt, A., Maksimovic, V., 1996. Stock Market Development and Financing Choices of Firms. The World Bank Economic Review 10, 341-369.

Fama, E.F., 1970. Efficient Capital Markets: A Review of Theory and Empirical Work. The Journal of Finance 25, 383-417.

Fama, E.F., French, K.R., 1992. The Cross-Section of Expected Stock Returns. The Journal of Finance 47, 427-465.

Jegadeesh, N., 1990. Evidence of predictable behavior of security returns. The Journal of finance 45, 881-898.

Jegadeesh, N., Titman, S., 1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. The Journal of Finance 48, 65-91.

Meziani, A.S., 2020. Frontier Markets: Understanding the Risks. The Journal of Index Investing 11, 43-56.

Speidell, L., 2016. Frontier Market Investing: Active Versus Passive. The Journal of Investing 25, 20-26.

Uludag, B.K., Ezzat, H., 2016. Chapter 5 - Are Frontier Markets Worth the Risk?, in: Andrikopoulos, P., Gregoriou, G.N., Kallinterakis, V. (Eds.), Handbook of Frontier Markets. Academic Press, pp. 67-80.

Vo, X.V., Truong, Q.B., 2018. Does momentum work? Evidence from Vietnam stock market. Journal of Behavioral and Experimental Finance 17, 10-15.