HONG KONG MONETARY AUTHORITY

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PREDICTABILITY IN SOVEREIGN BOND RETURNS USING TECHNICAL TRADING RULES WITH MACHINE LEARNING

Key points:

- *This study examines the predictability of returns on 48 sovereign bond markets in emerging markets and advanced economies based on a trading-rule strategy that includes 27,000 technical trading rules. These rules represent four popular trading rule classes (including moving average, filtering, support and resistance, and channel breakout rules) with numerous variants in each class. A market that profits more from the trading-rule strategy is considered more predictable.*

- *In addition, we use a machine learning (ML) algorithm, which is based on the Naïve Bayesian classifier, to check the robustness of the predictability. Taking a supervised learning approach, our ML algorithm learns which trading rule performs better under different market conditions and decides the most appropriate one for an out-of-sample prediction.*

- *Empirical results show that (i) most sovereign bond markets of the emerging market economies, particularly in emerging Asia, are more predictable from the trading-rule strategy; and (ii) the predictability of these economies is even higher when the US tightens its monetary policies; but (iii) the predictability for advanced economies is notably lower, in comparison to emerging market economies.*

- *When using the ML algorithm for testing the out-of-sample performance, 65% of sovereign bond markets have a higher predictability than when it's not used. However, the lower predictability for advanced economies remains robust.*

- *Our results imply that shocks originating from monetary policies of the US could have more impact on some sovereign bond markets in emerging Asia. The higher predictability may reflect a less efficient price discovery, a higher risk premium, or a combination of the two, in these sovereign bond prices.*

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I. INTRODUCTION

There are extensive studies on the existence of memory in the financial time series of equity and foreign exchange markets worldwide, highlighting the importance of monitoring predictability of these markets. However, only a few studies discuss sovereign bond market predictability. In fact, a predictable sovereign bond market can be possibly resulted from a less efficient price discovery, a higher risk premium, or a combination of the two, in the sovereign bond price.[1] The resulting impact may have important implications for government and corporate borrowing costs and access to financing and, therefore, can affect economy-wide financial conditions. Thus, predictability of sovereign bond markets merits closer scrutiny.[2]

This paper analyses the predictability of numerous sovereign bond markets based on technical trading rule analysis. While providing an overview of market predictability, we especially assess the extent to which predictability is affected by US monetary policies, given that global markets are managing the transition towards US monetary policy normalisation.

We examine these issues in two main steps. First, we apply numerous trading rules to sovereign bond markets to assess the predictability of trading-rule strategy and the predictability during different US monetary policy cycles. Secondly, we apply a machine learning algorithm to the trading-rule strategy to check the robustness of the return predictability. The results can shed light on several issues that are not well discussed in literature: (i) Are sovereign bond markets predictable? (ii) If yes, which markets are more predictable? Is the predictability higher during tightening of US monetary policy? (iii) If no, can a machine learning technique increase predictability?

The remainder of this memorandum is organised as follows. The next section discusses data and methodology. Section 3 presents the empirical results. The last section concludes our findings and discusses their implications.

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[1] The profitability of technical analysis indicates market inefficiency under a strict interpretation of weak-form efficiency which rules out return predictability based on historical information. However, such predictability may actually be a reflection of time-varying bond risk premia, which violates the expectation hypothesis that assumes a constant bond risk premium. In equity and currency markets, some studies find that the risk premia may not be strongly associated with returns from trading rule strategy (see Park and Irwin, 2007 and Ivanova et al., 2016).

[2] Details can be seen in the speech by Lucas Papademos, at the time the Vice President of the ECB, at the Third conference of the Monetary Stability Foundation on "Challenges to the financial system – ageing and low growth" on 7 July 2006.

II. DATA AND METHODOLOGY

2.1 *Sovereign bond indices*

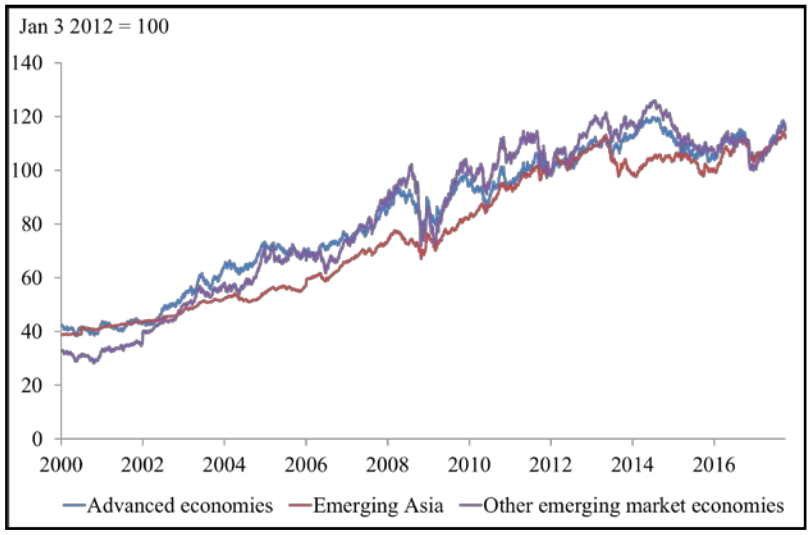
This study employs 48 sovereign bond indices covering both advanced economies (AEs) and emerging market economies (EMEs) compiled by Bank of America (BofA) Merrill Lynch (see Table 1 and Figure 1). The indices' constituents are fixed rate nominal sovereign debt with maturity over 1 year, weighted by market capitalisation. The indices are calculated in the form of the total return price series, including those of capital gain, accrued interest and cash flow received during the month. The original data are denominated in local currency, but we convert them into US dollars to facilitate cross-country comparison.[3] The bond indices obtained from Bloomberg are in daily frequency with the sample period spanning 3 Jan 2000 to 30 Sep 2017. Over this period, the majority of countries (30 out of 48) had complete data for the whole sample period.

Table 1. Sovereign bond market indices

Region	Country
Advanced economies	Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Iceland, Ireland, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, UK, US
Emerging Asia	China, India, Indonesia, Korea, Malaysia, Philippines, Taiwan, Thailand
Other emerging market economies	Brazil, Chile, Czech Republic, Egypt, Greece, Hungary, Mexico, Morocco, Nigeria, Peru, Poland, Russia, Slovakia, Slovenia, South Africa, Turkey

[3] Another rationale for this choice is that we can assume all trading rules are measured from a US investor's point of view.

Figure 1: Time series plot of sovereign bond indices



Notes:

1. The time series plots refer to the average bond index values for sovereign bond markets under each economic group.

2. All bond indices are rebased with value at 3 Jan 2012 equals 100.

3. Greece is excluded from the calculation for other emerging market economies due to a much more volatile index series when compared to its peers.

Source : Bloomberg

2.2 *Four selected classes of trading rules*

In this assessment, we explore four popular classes of technical trading rules, including moving average (MA), filtering (FL), support and resistance (SR), and channel breakout (CB) rules. These rules have been proved useful in the literature on predicting returns in equity and foreign exchange markets. [4]

According to the MA rule, buy and sell signals are generated by two moving averages of the level of the index – a long-period average and a short-period average. Figure 2 provides a graphical illustration of how the rule generates trading signals. In its simplest form, this strategy is expressed as buying (or selling) when the short-period moving average rises above (or falls below) the long-period moving average. The rationale is that when the short-period moving average penetrates the long-period moving average, a trend is considered initiated, and so prices become predictable.

[4] Technical trading rules are a forecasting technique commonly applied by market practitioners. Other popular forecasting techniques include chart analysis, pattern recognition analysis, and seasonality and cycle analysis (Park and Irwin, 2007)

Figure 2: Graphical illustration of moving average (MA) rule

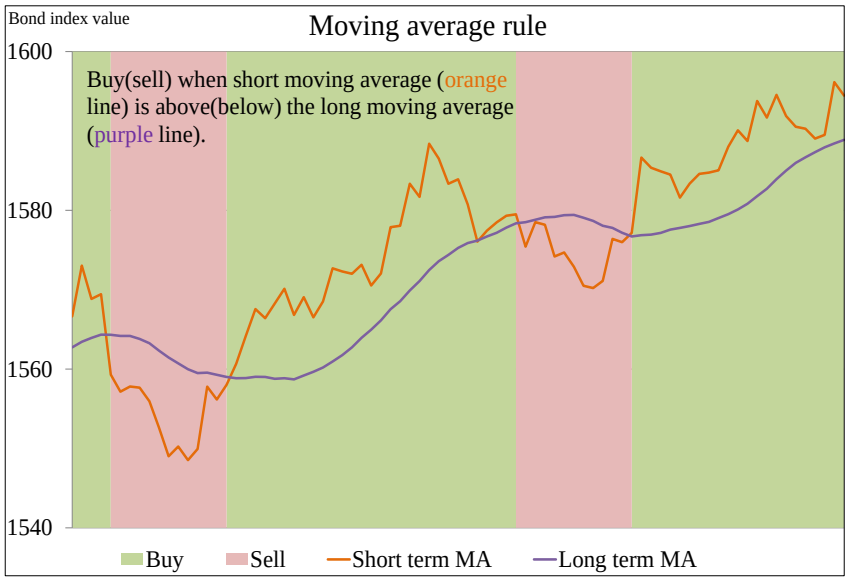
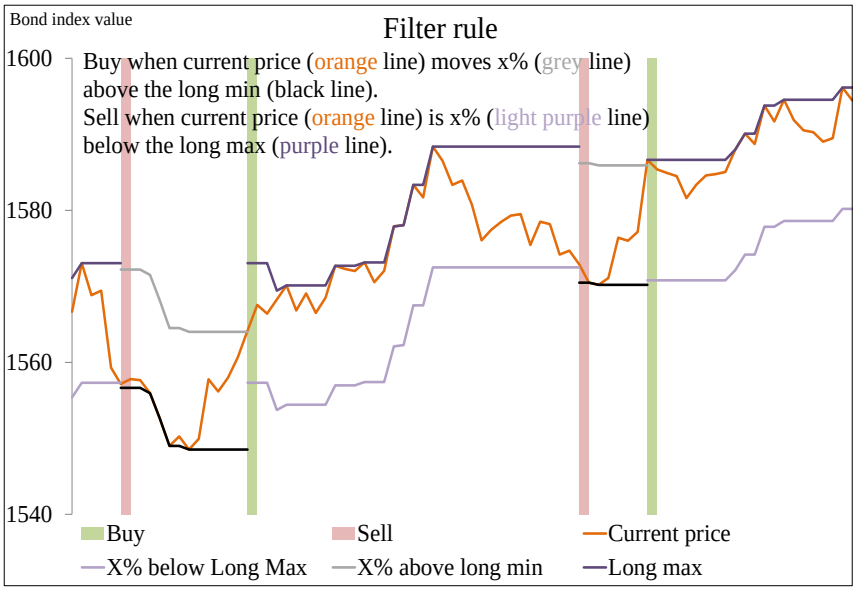
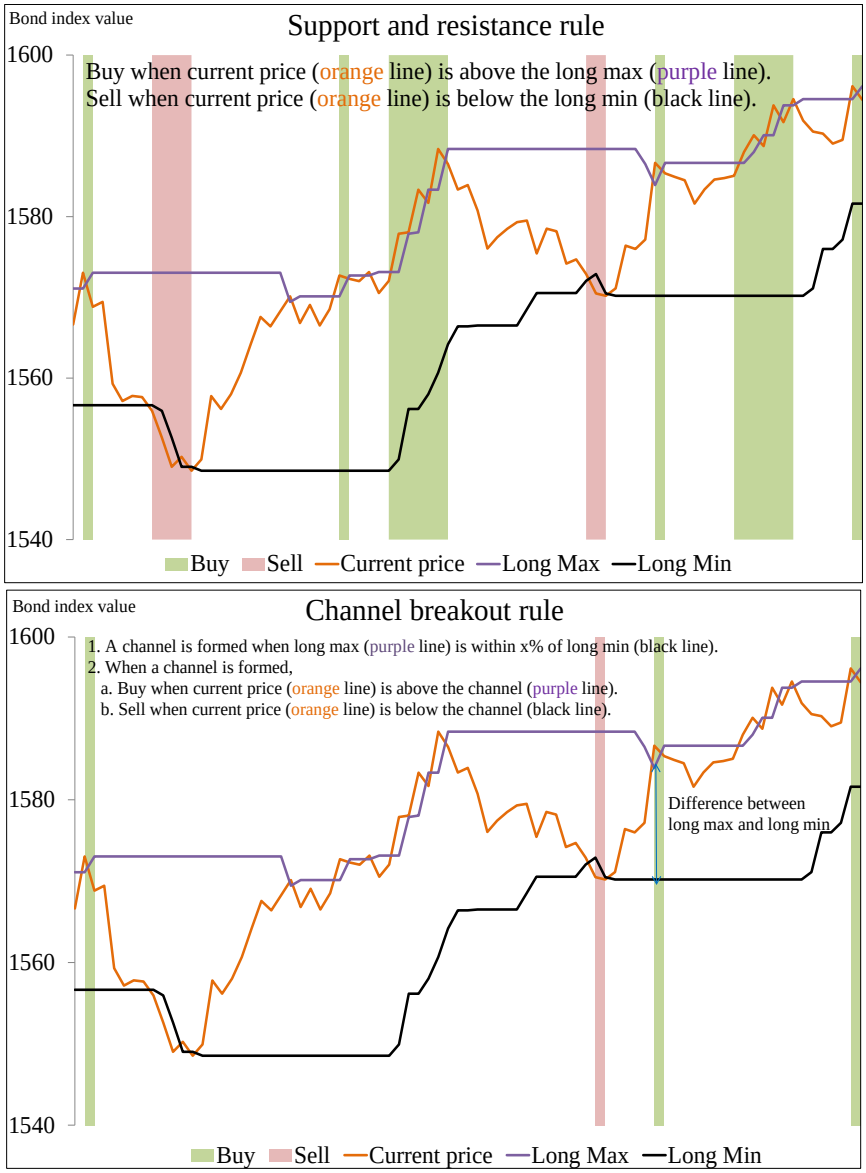


Figure 3 illustrates how the other three trading rules could generate trading signals in a similar logic. Specifically, FL rules attempt to follow trends by buying (selling) an asset whenever its price has risen (fallen) by a given percentage; SR trading rules are based on the premise that a breach of a support or resistance level (lower and upper bounds through which the price appears to have difficulty in penetrating) will trigger further rapid price movement in the same direction; and CB trading rules seek to identify time-varying support and resistance levels, or a 'channel of fluctuation' on the presumption that, once breached, further rapid price movement in the same direction will ensue.

Figure 3. Graphical illustrations of FL, SR, and CB trading rules





2.3 *Performance measure*

A total of 27,000 technical trading rules are selected in our strategy to study the predictability of sovereign bond markets, taking into consideration a number of variants of each class of trading rules and a range of different plausible parameterisations of each variant.[5] A large number of selected rules ensures an extensive variety of reasonable parameters for testing return predictability. Intuitively, choosing just a few rules might cause bias in statistical inference due to

[5] Some examples of variants include number of days in short- or long-moving averages (for MA rules); number of days to define a local high/low (for FL rules); number of days in support and resistance range (for SR rules); and number of days for a channel (CB). Details of these variants are summarised in the Appendix.

data mining, on the one hand, while on the other, choosing too many rules might reduce the power of the test due to the inclusion of many under-performing rules (Shynkevich, 2016).

For evaluating the predictability of each sovereign bond market in this study, we use the excess return from trading rule strategy over the buy-and-hold return, in short, the excess return.[6] Thus, a market is considered predictable when the trading rule strategy outperforms the buy-and-hold one (i.e., the excess return of the market is greater than zero).

In addition to this setting, we impose a "double-or-out" trading strategy in calculating the excess return[7]. Specifically, we prescribe the investor has a long position at each single trading day by default. On a certain day, if a buy signal emerges from a trading rule, the long position of the investment will be doubled at a borrowing cost for that day. In contrast, if the rule emits a sell signal, the default long position will be liquidated and the proceedings will be invested at a risk-free rate. No action will be taken otherwise if there is no signal from the trading rule. The investment will return to the default long position the next day where the above process will be repeated.

In keeping with sovereign bond markets, the measure is slightly modified by introducing a 1 day delay between the generation of trading signals (i.e., at time t) and the time when the respective trading position is taken (at time t+1) in the calculation of the excess return. The rationale behind this modification is that bonds are not as heavily traded as many of the equities or currencies so the predictability of returns on bond portfolios can have a spurious nature due to nonsynchronous trading of the bonds.[8] Subsequently, the presence of synchronous bias inflates autocorrelations in the return series thus overestimating the true predictability of returns and exaggerating the profitability of trend-chasing strategies designed to exploit the time series momentum.

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[6] Another common benchmark employed in literature is the risk-free return through the "long-or-short" strategy (Sullivan et al., 1999). We do not consider this benchmark in this study as it requires taking a short position which could be costly in the case of bond trading.

[7] This strategy is employed by Brock et al. (1992), Bessembinder and Chan (1998), and Shynkevich (2016), It is a symmetric strategy where a trader will increase (decrease) the default long position by the same percentage (specifically 100%) upon a buy (sell) signal. Alternative to this strategy would be an asymmetric strategy where different reactions to buy and sell signal are assumed. However, as Bessembinder and Chan (1998) suggested, in the absence of compelling reasons, searching through the different combination of such asymmetric strategy could potentially increase the problem of data snooping bias.

[8] More specifically, the nonsynchronicity arises from the fact that components of the underlying indexes since bid-ask bounce, and stale quotes can cause spurious serial correlation in quoted index values.

Taking account of all the considerations above, the net form of the excess return given a trading signal at day *t* over the buy-and-hold strategy, denoted by ER_t, can be expressed as: [9]

$$ER_t = [(lnS_{t+2} - lnS_{t+1}) - i_{t+1}] * \mathrm{I}_t, \quad (1)$$

where

$$\mathrm{I}_t = \begin{cases} 1 & \text{if buy} \\ 0 & \text{if neutral} \\ -1 & \text{if sell} \end{cases} \quad \text{and} \quad i_t = \begin{cases} rk_t & \text{if buy} \\ 0 & \text{if neutral} \\ rf_t & \text{if sell} \end{cases}$$

and S_t is the closing price of the bond index at time *t*, rk_t is the risky rate at time *t*, and rf_t is the risk-free rate at time *t*.[10] Therefore, a positive excess return suggests that the trading rule strategy outperforms the buy-and-hold benchmark. The significance of the excess return is tested by a bootstrapping procedure since the distribution of the excess returns is not known.[11]

2.4 *Supervised machine learning algorithm*

The algorithm basically involves three stages. The first two stages use data from 2000 to 2016 for in-sample estimations gauged by the Naïve Bayes Classifier (NBC) and model calibrations by adjusting to different market conditions respectively, while the last stage uses 2017 data for an out-of-sample prediction. The framework is outlined in Figure 4.[12]

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[9] The excess return is derived as follows. Consider an investor with capital \$A. In the case of buy signal, at time t the one-day benchmark return (in amount) is $A * (lnS_{t+1} - lnS_t)$. When buy signal emerges, investor would borrow another \$A at risky rate at time t+1 (due to 1 day delay imposed), which would earn him a total of $A * [(lnS_{t+1} - lnS_t)] + A * [(lnS_{t+2} - lnS_{t+1}) - rk_{t+1}]$. The excess return, w.r.t. initial capital \$A, is then $[(lnS_{t+2} - lnS_{t+1}) - rk_{t+1}]$. In the case of sell signal, the investor would sell at time t+1 and reinvest at risk-free rate, that would earn him $A * rf_{t+1}$. However, at the same time the investor would forgo $A * [(lnS_{t+2} - lnS_{t+1})]$ that would be earned if he maintained the asset at time t+1. The excess return in this case would equal $-[(lnS_{t+2} - lnS_{t+1}) - rf_{t+1}]$.

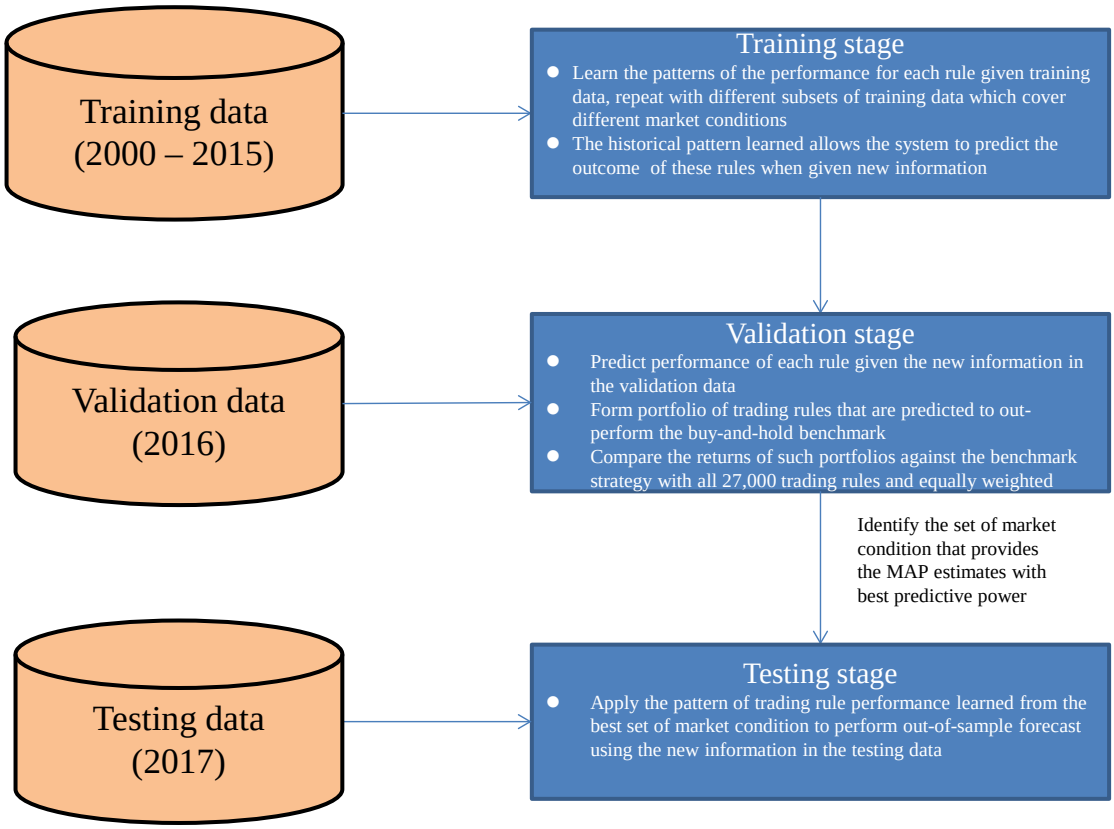
[10] As illustrated, a risky (borrowing) and risk-free (lending) rate are required for the calculation of excess return. Following Shynkevich (2016), we set the yield on the 3-month US Treasury bill as the lending rate and the 3-month US dollar LIBOR as the borrowing rate. Historical data on both interest rates are retrieved from the Federal Reserve Bank of St. Louis.

[11] This testing procedure follows the spirit of the superior predictive ability (SPA) test introduced by Hansen (2005) to address potential simulation bias, except that the SPA test compares the maximum return while our method compares the average return in the test. Such difference is considered because we primarily want to assess the overall performance of the trading rule strategy, rather than to identify whether a few trading rules outperform.

[12] The framework is primarily based on Hastie et al. (2009).

In the training stage, the algorithm learns the pattern of historical performances of trading rules under different market conditions. Three sample periods, including: (i) from 2000 to 2007; (ii) from 2008 to 2013; and (iii) from 2014 to 2015 are considered as reflections of tranquil, stressful, and post-crisis market conditions respectively. For each of these market conditions, the algorithm is able to make a prediction for the most likely outcome (positive or negative excess return) of the rules, namely the maximum *a posteriori* (MAP) estimate. When new information is given, these MAP estimates are then used to formulate a strategy that is built by the portfolio of 27,000 trading rules, where a higher weight is assigned to a rule that is predicted to attain a positive excess return, but zero weight to a rule that is predicted to attain a negative excess return (i.e., such rules are excluded from the strategy). In the validation stage, the algorithm determines the best strategy that maximises the excess return based on the 2016 data. In the testing stage, the algorithm uses this best strategy to predict the potential excess returns in the out-of-sample period. If the excess return of the strategy suggested by our algorithm is higher than a benchmark excess return from using all 27,000 trading rules with equal weights (i.e., without weights adjusted by our machine learning algorithm), then the algorithm is regarded as useful.

Figure 4: Machine learning system for each sovereign bond market



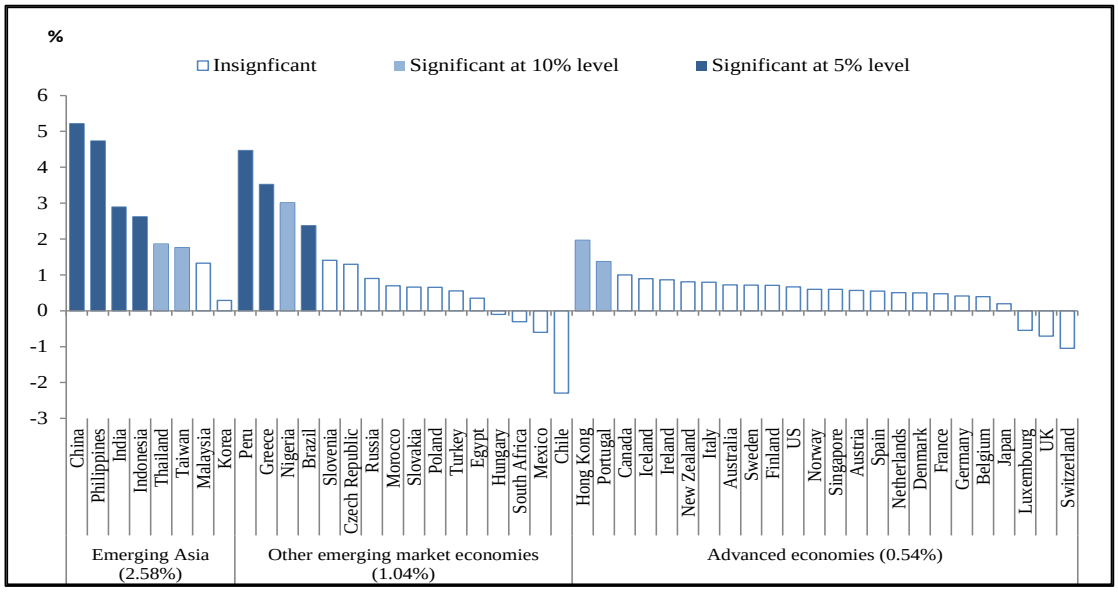
III. EMPIRICAL RESULTS

Are sovereign bond markets predictable? Which markets are more predictable?

Our results show that most sovereign bond markets, particularly, emerging Asian markets, are predictable by trading rules. These can be seen in Figure 5, which presents the average excess returns from 27,000 trading-rule strategies in each sovereign bond market in the full sample period. All excess returns are risk adjusted, annualised, and scaled up by the average SD of the excess returns to facilitate a fair comparison across markets.

As shown in the figure, the majority of excess returns are positive, meaning that the trading-rule-based investments mostly outperform the buy-and-hold benchmark in these sovereign bond markets. The average excess returns of emerging Asian and other EMEs are 2.6% and 1.0% respectively, with the most predictable markets being China and Peru in the two respective regions. In comparison, most of the AEs are less predictable given a much smaller excess return (0.5%). Among these markets, Hong Kong is the most predictable market based on our trading rule strategies, while Luxembourg, the UK, and Switzerland are less predictable given their negative excess returns from trading-rule strategies. Overall, the excess return is 1.1% on average[13].

Figure 5: Annualised and risk-adjusted average excess returns from trading-rule-based investment in sovereign bond markets during the sample period from 2000 Q1 to 2017 Q3



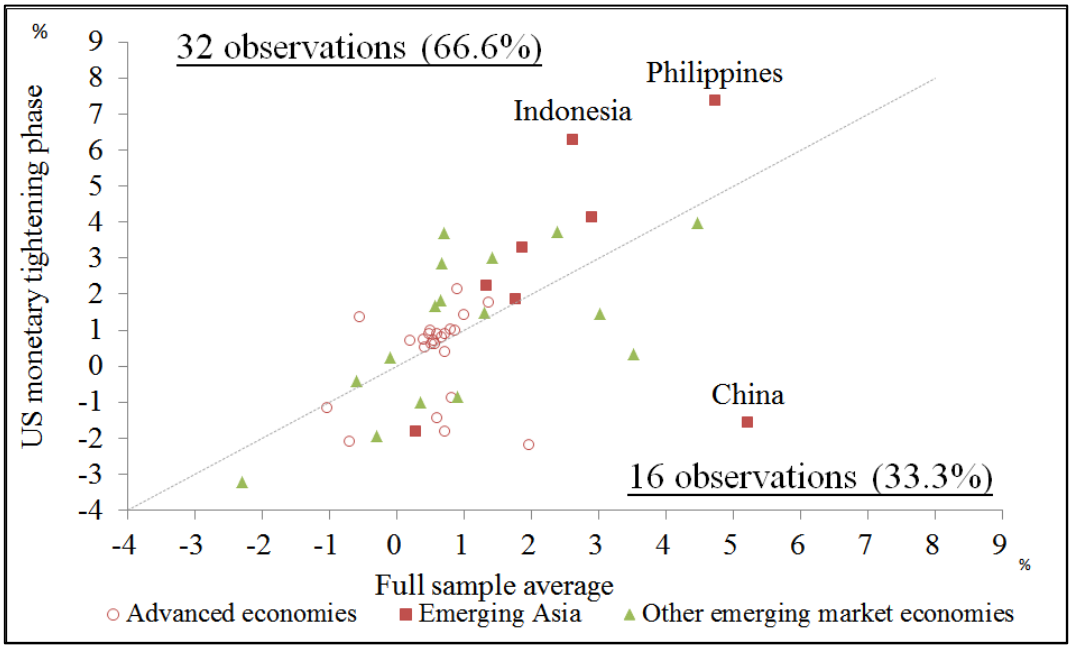
Notes: (a) All the excess returns are risk adjusted, annualised, and scaled up by the average annualised SD of the daily excess returns from the applied trading rules on the 48 sovereign markets; (b) Statistical significance of the excess returns from trading-rule strategy is based on the bootstrapping procedure.

[13] The results remain robust for the average return per transaction.

Is the predictability higher when the US tightens its monetary policy?

Our results imply that some sovereign bond markets would have an increased predictability during the tightening phase of the US monetary cycle. This can be seen in Figure 6, which depicts a scatter plot of the sovereign bond markets' trading rule excess returns acquired during the US monetary tightening cycle against those over the full sample period. As can be seen, two-thirds of the sovereign bond markets scatter above the 45-degree line (i.e., the dotted line), suggesting these markets acquire higher excess returns than their overall excess returns from the trading rule strategy during the tightening phase. Among these markets, most of the AEs scatter closer to the 45-degree line, compared with emerging markets which scatter widely in the chart. In particular, the Philippines and Indonesia scatter noticeably above the line with the excess return being over 6%, while China is well below the line although its full sample excess return is the largest.

Figure 6: Scatter plot of excess returns conditional on the US monetary conditions



Note: All the excess returns are risk adjusted, annualised, and scaled up by the average annualised SD of the daily excess returns from the applied trading rules on the 48 sovereign markets.

Can the machine learning technique increase predictability?

Our empirical results show that the machine learning algorithm generally improves the performance of the trading rule strategy. In particular, Emerging Asia benefits most from the machine learning algorithm while the additional return of AEs is lower on average. These can be seen in (i) Table 3, which summarises the number of sovereign bond markets that have an additional return using our algorithm and, (ii) Figure 7, which depicts the distribution of these

additional returns. These returns are all risk adjusted, annualised, and scaled up by the average SD of the excess returns.

As shown in Table 3, 31 out of 48 sovereign bond markets (or 65%) have a better performance when using our algorithm. More emerging Asian markets (6 out of 8, or 75%) earn a higher return from using our algorithm, compared to AEs and other EMEs (both at 63%).

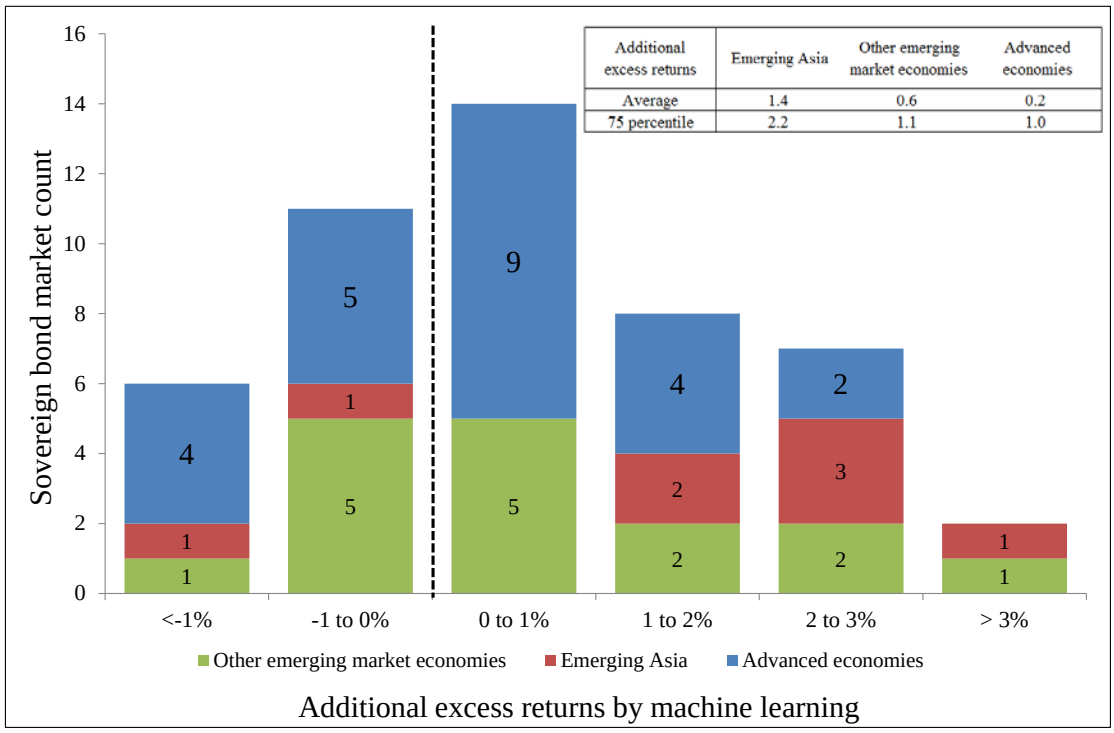
Table 3. Number of sovereign bond markets that have an additional return by incorporating the machine learning algorithm into the trading rule strategy

Region	Improved by machine learning? [(a)]		
	No	Yes (% of improved. markets)	All economies
All economies	17	31 (65%)	48
Emerging Asia	2	6 (75%)	8
Other EMEs	6	10 (63%)	16
AEs	9	15 (63%)	24

Note : (a) refers to higher average excess returns from the machine learning algorithm, compared with the benchmark strategy where all 27,000 trading rules are included and equally weighted.

As depicted in Figure 7, emerging Asian markets show the strongest improvement when using the algorithm, with an average additional return of 1.4% and a return of 2.2% at the 75th percentile. In comparison, the improvement for AEs is smaller, as reflected in the average additional return (i.e., 0.2%). For EMEs, the additional returns lie between the other two regions (i.e., 0.6%), but have a wider distribution. Overall, the additional return is 0.5% on average, against the average return of 0.4% in the benchmark case (i.e., an improvement of 125%).

Figure 7: Additional returns earned from the trading-rule strategy formulated by the machine learning algorithm



Note: The above refers to the additional excess returns of the trading-rule strategy formulated by the machine learning algorithm, over the benchmark strategy where all 27,000 trading rules are included and equally weighted.

IV. CONCLUSION

By analysing the predictability of 48 sovereign bond markets in AEs and EMEs using four popular classes of technical trading rules with a total of 27,000 variants and a machine learning algorithm in the sample period, we find that some sovereign bond markets of EMEs, particularly in emerging Asia, are predictable. The predictability of these economies is also higher when the US tightens its monetary policies. In comparison, the predictability for AEs remains lower despite using a machine learning algorithm in optimizing our trading-rule strategy.

Our results imply that some sovereign bond markets would have a higher predictability during tightening US monetary policies. This highlights the need for policymakers in these markets to contend with potential spillovers from shifts in monetary policy expectations in the U.S., which are likely to lead to higher government bond interest rates and bouts of volatility.

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Appendix: Universe of trading rules

This appendix describes in detail the logic for each class of trading rule, and lists out the parameters and combinations applied, which all follows Shynkevich (2016). In this study, the total number of rules is 27,000, covering 14,280 (or 52.9%) MA rules, 6,504 (or 24.1%) for FL rules, 2,520 (or 9.3%) for SR rules, and 3,696 (or 13.7%) for CB rules. Details of the variants for each rule are as follows:

Moving average (MA)

x: number of days in a short moving average
y: number of days in a long moving average
z: number of x–y combinations where y is strictly less than x
b: fixed band multiplicative value
d: number of days for the time delay filter
c: number of days a position is held, ignoring all other signals during that time
x = 1, 5, 10, 15, 20, 25, 30, 40, 50, 75, 100, 125, 150, 175 (14 values)
y = 5, 10, 15, 20, 25, 30, 40, 50, 75, 100, 125, 150, 175, 200 (14 values)
z = x + x * (y-1)/2 = 14 + 14 * 13 / 2 = 105
b = 0.005, 0.01, 0.015, 0.02, 0.025, 0.03, 0.035, 0.04, 0.045, 0.05 (10 values)
d = 2, 3, 4, 5 (4 values)
c = 3, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50 (11 values)

Number of rules in MA class = z ×(1 + b + d + c + b ×c) = 105 ×(1 + 10 + 4 + 11 + 10 ×11) = 14,280

Filtering rules (FL)

x: percentage change in price to initiate a position
y: percentage change in price to liquidate a position
z: number of x–y combinations where y is strictly less than x
e: number of days to define a local high (low)
c: number of days a position is held, ignoring all other signals during that time
x = 0.01, 0.015, 0.02, 0.025, 0.03, 0.035, 0.04, 0.045, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1, 0.12, 0.14, 0.16, 0.18, 0.2, 0.22, 0.24, 0.26, 0.28, 0.3 (24 values)
y = the same 24 values as
z = x * (y −1)/2 = 24 * 23/2 = 276
k = 3, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50 (11 values)
c = 3, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50 (11 values)

Number of rules in FL class = x ×(1 + k + k ×c) + z ×(1 + k) = 24 ×(1 + 11 + 11 ×11) + 253 ×(1 + 11) = 6,504

Support and resistance (SR)

n: number of days in the support and resistance range
b: fixed band multiplicative value
d: number of days for the time delay filter
c: number of days a position is held, ignoring all other signals during that time
n = 5, 10, 15, 20, 25, 30, 40, 50, 75, 100, 125, 150, 175, 200 (14 values)
b = 0.005, 0.01, 0.015, 0.02, 0.025, 0.03, 0.035, 0.04, 0.045, 0.05 (10 values)
d = 2, 3, 4, 5 (4 values) c = 3, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50 (11 values)

Number of rules in SR class = n ×(1 + b + d + c + b ×c + d ×c) = 14 ×(1 + 10 + 4 + 11 + 10 ×11 + 4 ×11) = 2,520

Channel breakout (CB)

n: number of days for a channel

x: difference between the high price and the low price as a percentage of the low price required to form a channel

c: number of days a position is held, ignoring all other signals during that time

n = 5, 10, 15, 20, 25, 30, 40, 50, 75, 100, 125, 150, 175, 200 (14 values)

x = 0.01, 0.015, 0.02, 0.025, 0.03, 0.035, 0.04, 0.045, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1, 0.12, 0.14, 0.16, 0.18, 0.2, 0.22, 0.24, 0.26, 0.28, 0.3 (24 values)

c = 3, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50 (11 values)

Number of rules in CB class = n ×x ×c = 14 ×24 ×11 = 3,696