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Predictability in sovereign bond returns using technical trading rule: do developed and emerging markets differer?[1]

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[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

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Abstract

The study examines the predictability of 48 sovereign bond markets based on a strategy of 27,000 technical trading rules. These rules represent four popular trading rule classes, they are: moving average, filtering, support and resistance, and channel breakout rules, with numerous variants in each class. Empirical results show that (i) investing in sovereign bond markets is predictable, based on the buy-sell signals generated by trading rules, with the predictability of the emerging Asian markets being significantly higher than those of the advanced markets; (ii) the predictability is generally higher when the US tightens its monetary policies or undergoes recession; (iii) two-thirds of sovereign bond markets have a higher predictability when we use a machine learning algorithm to determine the best trading rule strategy; and (iv) the predictability of a sovereign bond market is higher when the economy has a less effective government, lower regulatory quality, narrower financial openness, higher political risk, lower income and faster real money growth. Our results suggest that shocks originating from US monetary policy or economic conditions could have a considerable spillover effect on sovereign bond markets, particularly the emerging Asian markets.

Keywords: trading rule, return predictability, monetary cycle, machine learning, business cycle, spillover, market efficiency

JEL classification: C58, D83, E32, E50, G12, G14, G17

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I. Introduction

There are extensive studies on the existence of memory in 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 possibly result from an inefficient price discovery process in sovereign bonds, a substantial risk premium priced in the market prices, or a combination of both.[2] The resulting impact may have important implications for government and corporate borrowing costs and access to financing and, therefore, can weigh on economy-wide financial conditions. Therefore, predictability of sovereign bond markets merits closer scrutiny.

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 that predictability is affected by US monetary and business cycles, given that global markets are managing the transition towards US monetary policy normalisation. We examine these issues in three steps. First, we apply numerous trading rules to sovereign bond markets to assess predictability using the trading-rule strategy and predictability during different US monetary and business cycles. Second, we apply a machine learning algorithm to the trading rule strategy to determine ways to improve the return predictability. Finally, a regression analysis is conducted to uncover the relationship between return predictability and various social and economic factors. 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 and US recessions? (iii) If no, can machine learning techniques increase predictability? (iv) What social and economic factors could explain predictability in sovereign bond markets?

There are four major findings in this study. First, investing in sovereign bond markets is predictable based on the buy-sell signals generated by trading rules. In particular, the predictability of emerging Asian markets is significantly higher than those of advanced markets. Second, the predictability is generally higher when the US tightens its policy or undergoes economic recession. Third, two-thirds of the sovereign bond markets have a higher predictability when we use a machine learning algorithm to determine the best trading rule strategy. Finally, the predictability of a sovereign bond market is higher when the economy has a less

[2] 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 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).

effective government, lower regulatory quality, narrower financial openness, higher political risk, lower income and faster real money growth.

Taken together, our results contribute to the research field in two respects. First, while trading rule analysis is commonly applied to evaluate predictability of equity and exchange rate markets, this paper is one of a few to offer a comprehensive study of predictability of sovereign bond markets worldwide and of their potential responses to spillovers of US economic conditions and monetary policies. Second, to our best knowledge, this is the first paper using machine learning techniques together with popular trading rules to evaluate the predictability of sovereign bond markets.

The remainder of the paper is organised as follows. The next section reviews several major studies on technical trading rules. Section 3 discusses the methodologies, which include applications of technical trading rules, machine learning analysis and identification of determinants. Section 4 describes the data on sovereign bond returns and potential determinants of the predictability. Section 5 presents the empirical results. The last section concludes our findings and discusses its implications.

II. Major studies on sovereign bond market predictability and technical trading rules

Studies on sovereign bond market predictability and its potential determinants have grown quickly in literature of sovereign risk surveillance.[3] Focusing on the US Treasury market, Shynkevich (2016) investigates the predictability of bond returns across different market segments and varying market conditions and finds that the predictability is inversely related to interest rate risk, but positively related to default risk. Fakhry and Richter (2015) and Fakhry et al. (2017) find evidence of inefficiency in the sovereign bond markets of the US, Germany, Greece, Italy, Portugal and Spain before and during crisis, which arises from the fact that these markets are too volatile as measured by a new volatility test.[4] Zunino et al. (2012) ranked sovereign bond market efficiency for 30 sovereign bond markets estimated by the complexity-

[3] Early studies include Hall and Miles (1992), who find evidence of predictability in excess returns in the sovereign bond markets of US, Canada, UK, France, Germany and Japan. They found the slope of the yield curve helped predict subsequent bond excess return for US and Canada, while there was evidence of positive serial correlation in excess returns for four other markets.

[4] The basic argument of the test is that, in an ideal world, future cash flows should determine the behaviour of prices today; therefore, as Shiller (1992) argues, any excess volatility is evidence of inefficient markets.

entropy causality plane,[5] and found that the stage of economic development and market size of the sovereign bond market could affect efficiency levels. Charfeddine et al. (2018) study the time variation in sovereign bond market efficiency for US, UK, India and South Africa, which was found to depend on prevailing economic, political and market conditions.

Another strand of study on possible explanations for association between the predictability in international bond market returns and the monetary policies and/or economic conditions emerges as a major issue amid concerns over monetary policy normalisations in major economies. From the perspective of monetary policies, one possible explanation is that interventions by US monetary authorities may create predictable moves in international currency markets that technical traders would be able to exploit. They would subsequently create predictable changes in prices of interest rate-sensitive assets, such as sovereign bonds (Shynkevich, 2016). The associated uncertainties on monetary conditions could also contribute to varying bond risk premia, which subsequently increases return predictability (Ireland, 2015, and Jiang and Tong, 2017). Another possible explanation is that international bond markets are increasingly integrated over time, which facilitate a stronger spillover effect of the US bond risk premia on international bond markets (Dahlquist and Hasseltoft, 2013).

From the perspective of economic conditions, the predictability can be explained by the link performance of bonds and bond portfolio to business cycles, for instance the cyclical variation in bond risk premia (Ludvigson and Ng, 2009). Gargano et al. (2017) find that countercyclical bond risk premia, as driven by heightened uncertainty, contribute to higher predictability of bond market returns during recessions. They also find that disagreement spikes in bad times generate the time series momentum, leading to predictability in returns. These findings are consistent with Cujean and Hasler (2017), who attribute the higher stock market predictability during recession to the situation when economic conditions deteriorate, uncertainty rises and investors' opinions polarise, based on an equilibrium model.[6]

To evaluate market predictability, technical trading rules are regarded as one of the simplest techniques, given its objectiveness and readiness in computation. It is primarily based on the premise that past price trends predict future price movements without rigorous economic or financial theories.[7] Many financial practitioners view technical analysis as an important forecasting tool in making

[5] It measures the presence of temporal patterns in deviations from the ideal position associated to a totally random process. The distance to this random ideal location can be used to define a ranking of efficiency.

[6] For empirical studies on stock returns, Rapach et al. (2010), Henkel et al. (2011) and Dangl and Halling (2012) also found that predictability was concentrated in economic recessions and was largely absent during expansions.

[7] Depending on the class of trading rules used; some trading rules attempt to look for imminent market correction after a rapid movement in certain direction, similar to the oscillator trading rules; while some rules are trend-chasing, expecting that the current trend will continue, such as support and resistance rules.

short-term trading decisions (Menkhoff, 2010),[8] while academics mostly focus on technical trading rules[9] in investigating forecasting power of technical analysis. Sweeney (1986) and Brock et al. (1992) are pioneers in this area who find technical trading rules can generate excess returns in foreign exchange and equity markets respectively. Tian et al. (2002) expanded the set of trading rules used by Brock et al. (1992) and examined the predictability of stock price movements in markets with different efficiency level, in particular US and Chinese equity markets[10]. Hsu et al. (2016) studied the 41 currencies and the time series and cross-sectional variation in return predictability across sub-periods and geographic group. They found that emerging market currencies were more predictable with technical analysis than developed country currencies.

In literature, there are four types of theoretical models on why technical indicators could have predictive ability (Neely et al., 2014). These models include: (i) differences in the time for investors to receive information; (ii) different responses to information by heterogeneous investors; (iii) under-reaction and over-reaction to information; and (iv) effects of investors' sentiment. Among these models, the second one is useful to explain why technical indicators display enhanced predictive ability during recessions, during which the different responses are led by consumption smoothing asset sales by households that experience job losses and liquidation sales of margined assets by some investors.

III. Methodology

The section details several components that support our analysis. We first discuss several popular trading rules that are commonly used to evaluate predictability of equity and exchange rate markets. We also discuss two empirical advanced methods that are commonly employed in big-data analysis: the bootstrapping simulation and the Naive Bayes Classifier (NBC). The former tests significance of excess returns of trading rule strategy using a simulated distribution of the excess returns, while the latter determines ways to improve the predictability by learning from the historical performance of different trading rules.

[8] The study surveyed 692 fund managers in five countries, including those in the US. 87% of the respondents put at least some importance in technical analysis when making trading decisions.

[9] In a comprehensive survey by Park and Irwin (2007), 58 out of 76 modern technical analysis studies surveyed applied technical trading rules.

[10] They found that while there was no evidence to support the forecasting power of technical trading rules on US equity market after 1975, they could generate excess return in the Chinese stock markets.

3.1 Popular trading rules

In this assessment, we explore four popular classes of technical trading rules: moving average (MA), filtering (FL), support and resistance (SR), and channel breakout (CB) rules. These rules are "return-chasing" in nature and have proved useful in the literature to predict returns in equity and foreign exchange markets. Their usefulness can be explained by the existence of positive feedback traders, who buy (sell) after asset prices rise (fall), as a result of overreaction to information (Hong and Stein, 1999).

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 1 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, so prices become predictable.

The other three trading rules could generate trading signals in a similar logic, which are illustrated in Figures 2-4. 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.

By considering several variants of each trading rule and a range of different plausible parameterisations of each variant (e.g. Sullivan et al., 1999, and White, 2000), we obtain a large number of possible trading rules. Intuitively, choosing few rules may cause bias in statistical inference due to data mining. However, choosing too many rules may reduce the power of the test due to the inclusion of many underperforming rules. We therefore find a balance and select a fairly large variety of reasonable parameters that lie in the ranges considered by Shynkevich (2016), who applies the same universe of 27,000 technical trading rules to study predictability of US Treasury markets. The detailed logic for each class of trading rule, including the specifications, is provided in the Appendix. As can be seen, the variation on holding a position of a fixed minimum of days in all four classes allows the possibility of a neutral position[11]; whereas, in the basic form, the trader would keep an open buy (sell) position until the opposite trading signal emerged. Meanwhile, the two filters of fixed percentage band and time delay applied to MA and SR rules are meant to mitigate the influence of volatility and present stronger

[11] The neutral position is triggered when the buy or sell signal is not triggered at the end of the fixed holding period.

evidence that a new trend has formed. Only one of the two filters is applied in a certain specification of trading rule.

3.2 Performance measure

For evaluation of the predictability of each sovereign bond market, we use the excess return from trading rule strategy over the buy-and-hold return, or, in short, excess return, in this study.[12] 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).

Apart from this setting, we impose a "double-or-out" trading strategy in calculating the excess return, as in Brock et al. (1992), Bessembinder and Chan (1998), and Shynkevich (2016).[13] Specifically, we suggest that 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 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.

To be specific to sovereign bond markets, the measure is slightly modified by introducing a one-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 in returns on bond portfolios can have a spurious nature due to nonsynchronous trading of the bonds.[14] Subsequently, the presence of synchronous bias inflates autocorrelations in the return series and overestimates the true predictability in returns and exaggerates the profitability of trend-chasing strategies designed to exploit the time series momentum.

[12] 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.

[13] The "double-or-out" strategy 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 signals 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.

[14] More specifically, the nonsynchronicity arises from the fact that components of the underlying indexes can cause spurious serial correlation in quoted index values.

Taking into account all the considerations, 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: [15]

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

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

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.[16]

In the empirical results, we express this excess return in a Sharpe ratio (i.e., normalising the excess returns by its standard deviation and presenting it in annualised form), so as to facilitate comparison across sovereign bond markets given that all the excess returns are expressed in standardised form.

3.3 Test for significance of trading rule returns with bootstrapping

The test aims to check whether the trading rule strategy performs no better than the benchmark buy-and-hold strategy. Specifically, the testing procedure is based on the following test statistic:

$$\overline{V_l} = \frac{1}{K}\sum_{k=1}^{K}\left(\sqrt{N} * \overline{ER_k}\right)/\ \sigma_k \tag{2}$$

where $\overline{ER_k} = \sum_{t=201}^{T} ER_{k,t} / N$ is the average excess return for the k-th trading rule out of K trading rules and N=*T-200*[17] is the sample size, and σ_k is a consistent estimator[18] for the standard deviation of $\sqrt{N} * \overline{ER_k}$.

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

16 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 a 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.

17 We follow Shynkevich (2016) and standardize all trading rules to start generating signals only from the 201th observation because some rules require 200 days of previous data to provide a trading signal. Meanwhile, T would vary depending on sample size of individual sovereign bond index.

Since the distribution of $\overline{V_l}$ is not known, we employ the stationary bootstrap method of Politis and Romano (1994) to simulate the empirical distribution.[19] First, for each trading rule k, we resample the realised excess return series $ER_{k,t}$, one block of observations at a time with replacement, and denote the resulting series by $ER^*_{k,i}$. This process is repeated B times and for each replication i, we compute the sample average of the bootstrapped returns denoted by $\overline{ER^*_{k,i}}$. Finally, we construct the following bootstrap test statistics to form the distribution for $\overline{V_l}$;

$$\overline{V_{l,i}} \;=\; \frac{1}{K}\sum_{k=1}^{K}\left(\sqrt{N} * (\overline{ER^*_{k,i}} - \overline{ER_k} * I_{((\sqrt{N}*\overline{ER_k})/\,\sigma_k > -A)})\right) / \,\sigma_k, \qquad (3)$$

where i = 1,2,....B and I is an indicator function which equals one when the condition is satisfied and zero otherwise and A = $\sqrt{2\ln\ln N}$. The test's p-value is subsequently obtained by comparing $\overline{\mathrm{V_l}}$ with the quantiles of $\overline{\mathrm{V_{l,i}}}$.

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. 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. In an extreme case, if there is only one trading rule that extremely outperforms, but all the remaining rules suffer a loss, the strategy will likely be rejected, given that the average value is biased downward in magnitude (i.e., given that it takes into account those poorly performing rules as well).

3.4 Supervised machine learning algorithm using NBC

We use a machine learning technique to evaluate whether or not the returns from the trading rule strategy can be optimised through learning from the past performance of trading rules. The predictability of a sovereign bond market is higher if our machine learning algorithm can increase the returns from investing in the market with the trading rule strategy.

[18] The estimate σ_k is computed using the stationary bootstrap procedure;

$$\sigma_k^2 = \widehat{\gamma_{0,k}} + 2 * \sum_{i=1}^{N-1} k(N,i)\,\widehat{\gamma_{i,k}} * \sum_{i=1}^{N-1} k(N,i)\,\widehat{\gamma_{i,k}},$$

where $\widehat{\gamma_{i,k}} = \sum_{i=1}^{N-1}(ER_{k,t} - \overline{ER_k})(ER_{k,t+i} - \overline{ER_k})/N$, i = 0,1...N-1, are the empirical covariances

and kernel weights are given by

$$k(N,i) = \frac{N-i}{N}(1-q)^i + \frac{i}{N}(1-q)^{N-i},$$

with q being the smoothing parameter. We follow Shynkevich (2016) and set q = 0.1

[19] Politis and Romano's method resamples blocks of varying length of the original trading rule return series $ER_{k,t}$ to form a simulated return series. The block length follows a geometric distribution with expected block length equal to the inverse of a smoothing parameter.

The algorithm involves three stages. The first two stages use the data from 2000 to 2016 for in-sample estimations gauged by the NBC and model calibrations by adjusting to different market conditions respectively, while the last stage uses the 2017 data for an out-of-sample prediction. The framework is outlined in Figure 5.[20]

In the training stage, the algorithm learns the pattern of historical performances of trading rules under different market conditions using NBC. 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. 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 to maximise 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 considered useful.

IV. Data

4.1 Sovereign bond market indices

This study employs 48 sovereign bond indices covering AEs and EMEs compiled by Bank of America (BofA) and Merrill Lynch (see Table 1 and Figure 6). The indices' constituents are fixed rate nominal sovereign debt with maturity over one year, weighted by market capitalisation. The indices are calculated in the form of total return price series, including those of capital gain, accrued interest and cash flow received during the month. The original data is denominated in local currency, but we convert them into US dollars so as to facilitate cross-country comparison.[21] The bond indices obtained from Bloomberg are in daily frequency with the sample period spanning from 3 January 2000, to 30 September 2017. Given this period, most of the countries (29 out of 48) have complete data for the whole sample period.

20 The framework is primarily based on Hastie et al. (2009).

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

Table 2 shows the average daily return of each sovereign bond index, its standard deviation (SD), the Sharpe ratio (i.e., the mean-SD ratio) and the sample period. Averages are reported for groups of AEs and EMEs classified according to the MSCI classification of developed and emerging markets.[22] As can be seen, there are notable differences in characteristics of sovereign bond markets among different economy groups. For example, emerging Asian sovereign bond markets have the largest daily returns on average (i.e., 5.9%) with the smallest SD (i.e., 6.9%), while other EMEs have the smallest return on average (i.e., 4.5%) with the largest SD (i.e., 14.7%). After adjusting for the risk, emerging Asian markets are found to have a higher return than other markets, with the Sharpe ratio of emerging Asian markets being the highest (i.e., 0.99 in standard score), followed by AEs (i.e., 0.56) and other EMEs (i.e., 0.34).

4.2 Relevant market characteristics to the predictability

We consider a wide range of market characteristics that are considered relevant to the predictability of sovereign bond markets. Puy (2016) considers that governance and accountability, political instability, strength of money and economic risk are potentially important for fund flows in bond markets, given that these variables can identify countries which are more sensitive to global contagion. Zunino et al. (2012) and Charfeddine et al. (2018) also indicated that the prevailing economic, political and market conditions could strongly affect the degree of return predictability of sovereign bond markets.

Table 3 describes these variables. Specifically, the variables of "government effectiveness" and "regulatory quality" measured by the World Bank reflect perceptions of public services quality and governments' ability to formulate sound policies to promote private sector development respectively. Political instability is proxied by the index of political stability and absence of violence and terrorism constructed by the World Bank, which measures perceptions of the likelihood of political instability and politically motivated violence. The financial openness is measured by Chinn and Ito (2006), which codifies the tabulation of restrictions on cross-border financial transactions reported by the IMF. The strength of money is measured by real money growth. The market depth of public bonds is measured by the size of public debt as a percentage of GDP.[23] Finally, we consider the standard deviations of GDP growth and inflation between 2000 and 2016 and the GDP per capita at Purchasing Power Parity as important economic conditions of the sovereign bond markets.

[22] Details of these groupings can be seen on the website https://www.msci.com/market-classification.

[23] Public debt refers to the cumulative total of all government borrowings less repayments that are denominated in a country's home currency. Details of the definition can be seen on the website of CIA World Factbook at https://www.cia.gov/library/publications/the-world-factbook/rankorder/2186rank. html.

Table 4 presents averages of these variables by economic group. As can be seen, there are noticeable differences in fundamental structures of economy groups that may give rise to difference in the predictability of their sovereign bond markets. For example, AEs are characterised with a deeper market for public bonds (i.e., 77.7%), a more effective government (i.e. 1.58) and a higher degree of financial openness (i.e. 0.95)[24]; emerging Asia displays stronger growth of money in real terms (i.e., 7.5%) among EMEs, while other EMEs show a stronger volatility in inflation (i.e., 2.7%) and output (i.e., 3.2%).

Tables 5 and 6 present the correlation matrix of the variables and the results of principal component analysis in descending order of proportion of total variation explained endogenously. Some highly correlated variables (such as government effectiveness, regulatory quality, political risk, real GDP per capita and financial openness) are grouped together in the first principal component, which explains 57.4% of total variation. This component can be regarded as the stage of social and economic development of a sovereign bond market given that the factor loading of these variables is notably larger than other variables with a similar magnitude (ranging from 0.36 to 0.42). The second principal component (explaining 14.3%) is economic uncertainty, given that it is composed of volatilities of output growth (0.75) and inflation (0.50). The third component (explaining 12.6%) represents the market depth of public bonds provided that the component weighs largely on the size of government debt (-0.80). The fourth component is relevant to the strength of money since it weighs heavily on real money growth (0.61). The remaining factors are considered to be unclassified since there are more contrasts between variables, which make interpretations of principal components less straight forward. That said, these components explain only 9.7% in total variations among all variables.

V. Empirical results

5.1 Are sovereign bond markets predictable?

We assess the predictability from three perspectives in this section. We first provide an overview of potential excess returns acquired from investing in each of the 48 sovereign bond indices using the 27,000 trading rules. Robustness of the predictability is tested using our bootstrapping method. Next, we examine whether the predictability of international sovereign bond markets differs during US monetary policies or business cycles. Phases of US monetary cycle (easing and tightening) are determined by whether the US Federal Fund target rate is on an increasing or decreasing trend (Figure 7), while the US business cycles (expansion and recession) are determined based on the turning points as identified by OECD

[24] Government effectiveness spans from a scale of -2.5 (least effective) to 2.5 (most effective), while financial openness measure spans from a scale of 0 (least open) to 1 (most open).

based on US real GDP (Figure 8).[25] Finally, we explore the room for improved predictability of trading rule strategy using a machine learning algorithm, attempting to provide evidence on the robustness of the trading rule strategy's predictability.

5.1.1 Which markets are more predictable?

Table 7 summarises the daily average returns from trading-rule-based investment in sovereign bond markets. As mentioned in section III, all the returns are risk adjusted, annualised and scaled up by the average annualised SD of the daily returns from applying trading rules to the 48 sovereign markets during the sample period from 2000 Q1 to 2017 Q3.[26] Markets are ranked in order of the size of the returns (column 2).

As shown in the column, most of these returns are positive, meaning that these sovereign bond markets are mostly profitable from using trading rules. The overall average is 1.1%, with the most profitable market being China (5.2%), followed by most of the EMEs, such as Philippines (4.7%), Peru (4.5%) and Greece (3.5%). In comparison, most of the AEs have much smaller returns with some being unprofitable from the trading rule strategies, including Luxembourg (-0.6%), UK (-0.7%) and Switzerland (-1.0%). Furthermore, some trading rules are unprofitable, with the percentage of unprofitable trading rules (column 4) ranging from 5.8% for China to 83.5% for Chile. When excluding these unprofitable trading rules, ranking of market returns remains largely the same (i.e., column 3), except that Philippines becomes the most profitable market (i.e., 6.2%), followed by Peru (5.7%) and China (5.6%).

Significance of these returns is reported in Table 7 and Figure 9. Column 5 of Table 7 reports the bootstrapped p-value, which checks each economy for whether or not the hypothesis of no outperformance for the overall trading strategy is rejected. Figure 9 also depicts the returns and the test of significance in one chart. The number of bootstrap resamples (i.e., B) is set to 1000 to run the test, which is considered sufficiently large to reduce the additional layer of randomness introduced by the resampling scheme.[27] As can be seen, 13 out of 48 market returns (i.e., 27%) have a smaller bootstrapped p-value than the 10% level, meaning that

[25] The OECD uses the real Gross Domestic Product (GDP) as the reference for identification of turning points in the growth cycle for the US. The turning point detection algorithm is a simplified version of the original Bry and Boschan routine, which does not include the correction for outlier, as such a correction is implanted at an earlier stage of the filtering process.

[26] The annualised daily average returns are divided by annualised standard deviation of daily returns. The average annualised SD is 8.4% based on the daily returns from applying trading rules on the 48 sovereign bond market indices. Returns are scaled up to facilitate easier comparisons with the raw returns of sovereign bond market indices.

[27] The smoothing parameter for the stationary bootstrap is set to be 0.1. Hsu and Kuan (2005) find that the smoothing parameters of 0.01, 0.1, and 0.5 in the stationary bootstrap yield similar results.

these market returns are statistically significant. Significant returns are mostly from investing in emerging Asia and other EMEs (see Figure 9 or column 6 of Table 7). Most of the AEs, however, are not significantly profitable from the investment.[28]

5.1.2 Is the predictability higher during the tightening phase of US monetary cycles and US economic recession?

Figure 10 is a scatter plot of the risk-adjusted excess returns from the trading rule strategy, conditional on US monetary regimes. Comparing returns between the US monetary tightening and easing phases, almost two-thirds of sovereign bond markets (i.e., 64.5%) scatter above the 45-degree line (i.e., the dotted line), suggesting that the trading-rule strategy could acquire a higher predictability during the tightening phase than those acquired during the easing phase. Among these markets, most of the AEs scatter closely to the 45-degree line, compared with emerging markets, which scatter widely. In particular, Philippines and Indonesia scatter noticeably above the line while China and Egypt are well below the line.[29]

Figure 11 shows a similar plot to Figure 10, but it is conditional on US business cycles. Comparing returns between the US economic recession and expansion phases, 60% of sovereign bond markets scatter above the 45-degree line, reflecting that the predictability of the trading rule strategy could be higher during the US economic recession phase than the expansion phase, particularly for China, whose return is substantially higher during US economic recessions.[30,31]

5.1.3 Can the predictability of the trading rule strategy be increased by a machine learning algorithm?

Our empirical results show that the machine learning algorithm generally improves the performance of the trading rule strategy. In particular, Emerging Asia benefits the most from the machine learning algorithm, while the additional return of AEs is, on average, lower. These can be seen in (i) Table 8, which summarises the number of sovereign bond markets that have an additional return using our algorithm and

28 The results remain robust for the average return per transaction. Details can be available upon request.

29 We check whether there exists any market that has a substantial deviation between different policies/cycles in predictability. Specifically, for each market, we first calculate the deviation in excess returns and then calculate the two influence statistics. A market's excess return is regarded as an outlier compared to other markets when the influence statistic is significantly large in magnitude. Three influence statistics are used, including the scaled difference, and covariance ratio. Based on two influence statistics, China and Egypt are considered outliers, while the other two are marginal.

30 Based on the two influence statistics, China, Indonesia, Egypt and Morocco are considered outliers.

31 This finding is also in line with the theory on different responses to information by heterogeneous investors discussed in section II.

(ii) Figure 12, which depicts the distribution of these additional returns. These additional returns are all risk adjusted, annualised and scaled up by the average SD of the excess returns.

As shown in Table 8, 31 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%).

As depicted in Figure 12, emerging Asian markets have 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.

These results have several implications. First, it suggests that sovereign bond markets, particularly emerging Asian economies, are significantly predictable by applying a trading rule strategy. Second, sovereign bond markets are more predictable during US monetary tightening cycles and economic recessions than during other episodes. Returns for AEs do not differ substantially during different US monetary cycles, while there is a larger dispersion among emerging Asia and other EMEs. Finally, the predictability of advanced markets remains immaterial, while the predictability of emerging markets can be improved by optimising the strategy with a machine learning algorithm. These results can be explained by the fact that US monetary shocks create predictable changes in prices of interest rate sensitive assets (Shynkevich, 2016; Ireland, 2015; and Jiang and Tong, 2017) while the spillover effect of the US bond risk premia on international bond markets have increased given heightened uncertainty in the US monetary policies (Dahlquist and Hasseltoft, 2013) and the economic conditions (Cujean and Hasler, 2017), and that emerging markets tend to have a stronger response to global liquidity conditions after the global financial crisis (Fong et al., 2018).

5.2 What are the determinants of predictability of sovereign bond markets?

In this section, we identify major factors attributed to predictability from sovereign bond markets. As discussed in earlier sections, these factors are mainly associated with four main principal components, which represent (i) the stage of social and economic development, (ii) economic uncertainty, (iii) market depth of public debt and (iv) strength of money. On the technical front, we use the conventional least square regression to link the predictability with all the principal components, in which significant components can be considered important for affecting the predictability in general. We also use a logistic regression model to relate the predictability with principal components given that returns can be categorised as statistically significant against insignificant. In addition to the common features of linear regressions, the logistic regression offers an estimate of the odds ratio,[32] which helps identify the relative importance of different factors in the regression.

Table 9 presents the empirical results of the two specifications. Focusing on the full model of the least square regression, we find that two of the nine principal components are statistically significant at the 5% level (i.e., column 2). The first (fourth) principal component has a negative (positive) coefficient, meaning that an increase in the principal component's level will decrease (increase) the returns. These empirical findings remain consistent when insignificant variables are removed one by one based on a stepwise regression approach (i.e., column 3). Comparing the two components, the first one has a larger coefficient in magnitude than the fourth one. This suggests that, other things being equal, the predictability has a stronger association with the first component than the fourth one on average, given that all the independent variables (i.e., the principal components) are normalised to be zero mean and unity variance.

Focusing on the results of the logistic regression (i.e., columns 4 and 5), we find that results are consistent with those of the least square regression, with the first and fourth components being significant at the 10% level. After removing insignificant components, the odds ratios of the components suggest that the odds of the predictability would increase by 75.5% (127.2%) respectively when the first (fourth) components increase (decrease) by one SD.

Based on magnitude of the estimated coefficients, the empirical findings suggest that the predictability of sovereign bond markets is affected largely by i) the stage of social and economic development (i.e., the first principal component) and the strength of money (i.e., the fourth principal component). An economy with a more effective government, better regulatory quality, wider financial openness, less political risk and higher income would have a lower predictability of its sovereign bond market, while the predictability is higher when sovereign bond markets face a faster real money growth. The quality of governance and regulatory authorities, level of political risk and income level are likely to reflect the stage of social and economic development, while level of financial openness could reflect the level of openness in the sovereign bond market, which could affect the speed for the incorporation of new information on bond prices. A stronger strength of money indicates a higher likelihood of inflation booms affecting asset values (Puy, 2016). Faster real money growth may also result in higher uncertainty of expected inflation, which could increase economic value from predicting bond returns (Sarno et al., 2016).

[32] The odds of an event occurring is the probability that the event will occur divided by the probability that the event will not occur. In epidemiology, the odds ratio is a relative measure of risk, telling us how much more likely it is that someone who is exposed to a certain risk factor will develop a disease as compared to someone who is not exposed.

VI. Conclusion

By analysing the predictability of 48 sovereign bond markets 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, particularly emerging Asian ones, could be predictable. The predictability is also higher when the US tightens its monetary policies or undergoes a recession. In comparison, the predictability for AEs remains lower despite using a machine learning algorithm in adjusting our trading rule strategy. Finally, social and economic development and real money growth can significantly affect predictability, in which the effect of government effectiveness is the largest among other factors.

Our results suggest that some sovereign bond markets could have a higher predictability during tightening of 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 US, which are likely to lead to higher government bond interest rates and bouts of volatility. In particular, the informational efficiency of the sovereign bond markets could be a crucial factor that merits policymakers' closer attention.

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Sovereign bond market indices and grouping

Table 1

Group	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

Summary statistics on sovereign bond indices

Table 2

Region	Country	Mean	SD	Sharpe ratio	Series start
Advanced economies	Iceland	9.14	9.10	1.00	Jan-2003
	New Zealand	7.92	13.43	0.59	Jan-2000
	Australia	6.60	12.83	0.51	Jan-2000
	Portugal	6.51	13.62	0.48	Jan-2000
	Ireland	6.47	12.48	0.52	Jan-2000
	Switzerland	6.14	11.98	0.51	Jan-2000
	Spain	5.99	12.01	0.50	Jan-2000
	Belgium	5.97	11.20	0.53	Jan-2000
	Italy	5.97	11.98	0.50	Jan-2000
	Austria	5.82	10.87	0.54	Jan-2000
	Denmark	5.74	10.52	0.55	Jan-2000
	France	5.64	10.87	0.52	Jan-2000
	Netherlands	5.54	10.63	0.52	Jan-2000
	Canada	5.53	9.44	0.59	Jan-2000
	Finland	5.39	10.45	0.52	Jan-2000
	Germany	5.36	10.56	0.51	Jan-2000
	Sweden	4.76	12.01	0.40	Jan-2000
	Norway	4.71	12.16	0.39	Jan-2000
	Singapore	4.71	6.61	0.71	Jul-2000
	US	4.59	4.59	1.00	Jan-2000
	UK	4.36	10.71	0.41	Jan-2000
	Hong Kong	3.81	2.83	1.35	Jul-2000
	Luxembourg	2.13	9.71	0.22	Jan-2009
	Japan	1.35	10.73	0.13	Jan-2000
	Group average	**5.42**	**10.47**	**0.56**	

Summary statistics on sovereign bond indices

Table 2 (Cont')

Region	Country	Mean	SD	Sharpe ratio	Series start
Emerging Asia	Philippines	10.23	8.29	1.23	Jan-2005
	Indonesia	7.72	13.65	0.57	Jan-2005
	India	6.55	7.59	0.86	Jan-2000
	Thailand	5.99	7.06	0.85	Jan-2003
	China	5.61	3.36	1.67	Jan-2005
	Taiwan	4.11	4.81	0.85	Jul-2000
	Korea	4.08	2.72	1.49	Nov-2011
	Malaysia	2.97	7.47	0.40	Jan-2006
	Group average	**5.91**	**6.87**	**0.99**	
Other emerging market economies	Brazil	10.49	18.50	0.57	Jan-2006
	Poland	7.89	14.91	0.53	Jan-2000
	Hungary	7.82	16.78	0.47	Jan-2000
	Czech Republic	7.71	12.40	0.62	Jan-2000
	Slovakia	7.07	10.56	0.67	Jan-2004
	South Africa	5.51	20.98	0.26	Jan-2000
	Greece	5.38	25.49	0.21	Jan-2000
	Mexico	4.14	13.69	0.30	Jan-2002
	Peru	3.92	7.57	0.52	Jan-2012
	Turkey	3.49	16.45	0.21	Jan-2005
	Russia	3.47	10.01	0.35	Jan-2012
	Slovenia	3.45	11.61	0.30	Jan-2008
	Chile	3.02	9.93	0.30	Jan-2010
	Morocco	2.83	7.06	0.40	Jan-2011
	Nigeria	-1.86	17.88	-0.10	Jan-2012
	Egypt	-2.92	21.04	-0.14	Jan-2011
	Group average	**4.46**	**14.68**	**0.34**	

Notes:

1. "Mean" denotes annualized percentage return on respective sovereign bond index, while "SD" denotes annualized standard deviation of index's daily return.
2. Sharpe ratio is calculated as mean return divided by the standard deviation of returns.

Source: Bloomberg and author estimates.

Data source and definition of macro-economic and governance indicators

Table 3

Variable	Definition	Unit of measurement / scale	Reference time point	Source
Public debt as % of GDP	Cumulative total of all government borrowings less repayments that are denominated in a country's home currency	%	latest available (2016 or 2017)	CIA World Factbook
Real GDP per capita	GDP per capita at PPP	log US$	2016	World Bank
Government effectiveness	Perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies	-2.5 (least favorable) to 2.5 (most favorable)	2016	World Bank
Regulatory quality	Perceptions of the ability of the government to formulate and implement sound policies and regulations which permit and promote private sector development.	-2.5 (least favorable) to 2.5 (most favorable)	2016	World Bank
Financial openness	Chinn & Ito financial openness index which codifies the tabulation of restriction on cross-border financial transactions reported in the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER).	0 (least open) to 1 (most open)	2015 (latest available)	Chinn & Ito (2006)
Political risk	Political stability and absence of violence/terrorism measures perceptions of the likelihood of political stability and/or politically-motivated violence, including terrorism.	-2.5 (least favorable) to 2.5 (most favorable)	2016	World Bank
Real money growth	Year-on-year growth rate of broad money minus inflation rate	%	2016	World Bank
Inflation volatility	Standard deviation of annual inflation rate	%	2000 - 2016	World Bank
Output volatility	Standard deviation of annual real GDP growth rate	%	2000 - 2016	World Bank

Summary statistics on macro variable and governance variables

Table 4

Indicator	Advanced economies	Emerging Asia	Other emerging market economies	All
Public debt as % of GDP (%)	**77.74**	**40.51**	58.87	65.92
Real GDP per capita (In US$)	**10.77**	**9.60**	9.80	10.28
Government effectiveness	**1.58**	0.39	**0.17**	0.94
Regulatory quality	**1.57**	**0.19**	0.21	0.92
Financial Openness	**0.95**	**0.36**	0.58	0.74
Political risk	**0.86**	**-0.54**	-0.29	0.27
Real money growth (%)	**3.33**	**7.45**	6.15	4.87
Inflation volatility (%)	**1.42**	1.95	**2.68**	1.91
Output volatility (%)	2.38	**1.99**	**3.18**	2.58

Notes:

1. Financial openness refers to the Chinn & Ito (2002) Index, which codifies the tabulation of restrictions on cross-border financial transactions reported in the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER). It is constructed as the first principal component of four binary variables, which indicate i) presence of multiple exchange rates, ii) restrictions on current account transactions, iii) restrictions on capital account transactions; and iv) requirement of the surrender of export proceeds, respectively. Higher value indicates higher degree of openness for the capital account. The measure spans from 0 (least open) to 1 (most open).
2. Political risk, government effectiveness and regulatory quality come from World Bank Development Indicators. It spans from a scale of -2.5 (least favourable) to 2.5 (most favourable) for each measurement. A higher value indicates a more favourable condition.
3. Figures for each indicator refer to the simple average in each economic grouping. Numbers highlighted in green (red) indicate the group with highest (lowest) value for each indicator.

Correlation matrix of the nine selected macro-economic and financial factors — Table 5

	Public debt as % of GDP	Real GDP per capita	Financial Openness	Government effectiveness	Regulatory quality	Political risk	Real money growth	Inflation volatility	Output volatility
Public debt as % of GDP	1.00								
Real GDP per capita	0.23	1.00							
Financial Openness	0.26	0.76	1.00						
Government effectiveness	0.18	0.89	0.71	1.00					
Regulatory quality	0.11	0.88	0.77	0.96	1.00				
Political risk	0.22	0.80	0.68	0.87	0.85	1.00			
Real money growth	-0.49	-0.56	-0.41	-0.55	-0.49	-0.56	1.00		
Inflation volatility	-0.24	-0.39	-0.50	-0.59	-0.58	-0.53	0.27	1.00	
Output volatility	-0.05	-0.05	-0.13	-0.28	-0.21	-0.23	0.08	0.56	1.00

Principal component analysis of the nine selected macro-economic and financial factors — Table 6

	P1	P2	P3	P4	P5	P6	P7	P8	P9
Public debt as % of GDP	0.15	0.21	<u>**-0.80**</u>	0.35	0.06	0.39	-0.04	0.12	-0.06
Real GDP per capita	<u>**0.40**</u>	0.23	0.17	0.00	0.17	0.20	-0.43	-0.70	-0.12
Financial Openness	<u>**0.42**</u>	-0.01	0.15	-0.12	-0.10	0.25	-0.26	0.35	0.72
Government effectiveness	<u>**0.41**</u>	0.01	0.25	0.00	-0.07	0.08	-0.20	0.53	-0.66
Regulatory quality	<u>**0.36**</u>	0.08	0.10	0.53	0.49	-0.51	0.22	0.08	0.14
Political risk	<u>**0.40**</u>	0.03	0.10	-0.17	-0.13	0.32	0.81	-0.17	-0.03
Real money growth	-0.29	-0.29	0.41	<u>**0.61**</u>	0.05	0.54	0.03	-0.01	0.01
Inflation volatility	-0.29	<u>**0.50**</u>	0.16	-0.30	0.64	0.28	0.08	0.22	0.00
Output volatility	-0.14	<u>**0.75**</u>	0.21	0.29	-0.53	-0.10	0.03	0.03	0.06
Proportion of total variation explained endogenously (%)	**57.42**	**14.33**	**12.63**	**5.88**	3.49	3.06	2.01	0.86	0.32

Note: The figures bonded and underlined for the first 4 principal components (P1 to P4) refer to the variables that are most relevant for each of these components.

Returns from technical trading rules

Table 7

Country/ region	Average Sharpe ratio (annualized and scaled[4])		Share of unprofitable rules, %	Bootstrapped p-value	Region
	All rules	Positive rules only			
China	5.21	5.64	5.80	***0.00***	Emerging Asia
Philippines	4.73	6.21	16.70	***0.00***	Emerging Asia
Peru	4.46	5.65	14.72	***0.04***	Other EMEs
Greece	3.52	3.88	6.66	***0.01***	Other EMEs
Nigeria	3.01	5.05	24.35	**0.08**	Other EMEs
India	2.89	4.04	19.46	***0.01***	Emerging Asia
Indonesia	2.62	3.76	20.17	***0.04***	Emerging Asia
Brazil	2.37	3.11	15.48	***0.02***	Other EMEs
Hong Kong	1.97	2.79	19.72	**0.05**	AEs
Thailand	1.86	3.82	35.48	**0.08**	Emerging Asia
Taiwan	1.76	2.85	26.16	**0.08**	Emerging Asia
Slovenia	1.41	2.45	24.53	0.13	Other EMEs
Portugal	1.37	2.54	25.64	**0.09**	AEs
Malaysia	1.32	3.02	35.58	0.20	Emerging Asia
Czech Republic	1.30	1.96	20.43	0.12	Other EMEs
Canada	1.00	1.92	29.53	0.16	AEs
Russia	0.90	2.38	32.39	0.28	Other EMEs
Iceland	0.89	2.01	30.28	0.20	AEs
Ireland	0.86	1.95	28.66	0.17	AEs
New Zealand	0.81	1.64	28.33	0.21	AEs
Italy	0.80	1.77	32.06	0.20	AEs
Australia	0.72	1.54	29.37	0.23	AEs
Sweden	0.71	1.68	33.08	0.23	AEs
Finland	0.71	1.60	29.84	0.24	AEs
Morocco	0.70	2.55	39.80	0.31	Other EMEs
US	0.66	1.47	29.88	0.25	AEs
Slovakia	0.66	2.71	38.77	0.29	Other EMEs
Poland	0.65	1.58	32.06	0.25	Other EMEs
Norway	0.60	1.48	32.76	0.28	AEs
Singapore	0.60	2.01	38.63	0.26	AEs
Austria	0.57	1.59	33.54	0.28	AEs
Turkey	0.56	2.10	40.72	0.32	Other EMEs
Spain	0.55	1.61	33.71	0.27	AEs
Netherlands	0.51	1.48	33.25	0.29	AEs
Denmark	0.50	1.48	32.17	0.30	AEs
France	0.47	1.52	35.15	0.30	AEs
Germany	0.41	1.42	34.99	0.33	AEs
Korea	0.39	0.46	11.13	0.06	Emerging Asia
Belgium	0.39	1.59	38.04	0.31	AEs
Egypt	0.35	3.10	48.23	0.35	Other EMEs
Japan	0.19	1.30	42.61	0.40	AEs

Returns from technical trading rules

Table 7 (Cont')

Country/ region	Average Sharpe ratio (annualized and scaled[4]) All rules	Positive rules only	Share of unprofitable rules, %	Bootstrapped p-value	Region
Hungary	-0.10	1.18	52.01	0.53	Other EMEs
South Africa	-0.30	1.04	55.89	0.61	Other EMEs
Luxembourg	-0.55	1.56	58.86	0.62	AEs
Mexico	-0.60	1.11	65.63	0.72	Other EMEs
UK	-0.71	0.70	69.09	0.76	AEs
Switzerland	-1.04	1.01	75.69	0.81	AEs
Chile	-2.30	1.69	83.50	0.89	Other EMEs
Average	***1.06***	***2.34***	***34.17***		

Notes:

1. Positive rules refer those trading rules that could generate positive excess return over benchmark measure (buy-and-hold strategy)
2. Share of unprofitable rules refers to the ratio of the number of rules with negative returns to the total number of effective trading rules. Effective rules are those that generate at least 1 buy or sell signal in the sample period.
3. Bootstrapped p-value refers to the p-value from the SPA test applied on average return from all effective rules, as outlined in the methodology section.
4. The Sharpe ratio is scaled up by the average annualized SD of the returns from applying trading rules on the 48 sovereign bond market indices.

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

Table 8

Region	Improved by machine learning? 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: "Improved by machine learning" refers to higher average excess returns from a machine learning algorithm, compared with the benchmark strategy where all 27,000 trading rules are included and equally weighted.

Regression results of profitability on principal components derived from nine potential macro-economic and financial factors

Table 9

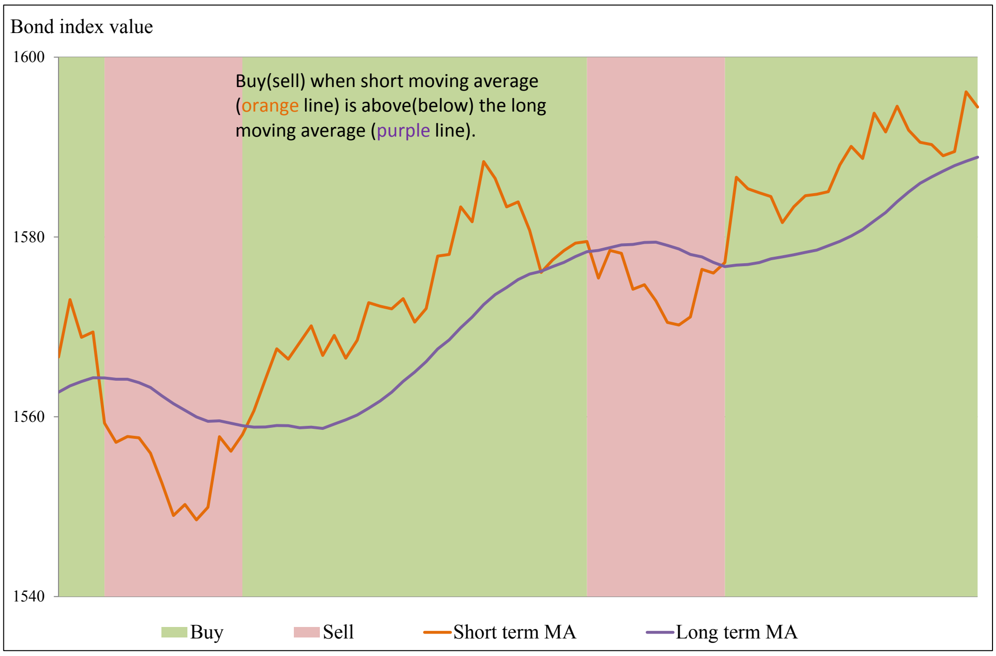
Explanatory Variable	Least square regression		Logistic regression		
	Full model	Selected model	Full model	Selected model	Odds ratio
P1	-0.69*	-0.69*	-1.9*	-1.41*	-75.50%
P2	-0.15		-0.11		
P3	0.05		0.01		
P4	0.46*	0.46*	1.01*	0.82*	127.23%
P5	-0.22		-0.4		
P6	0.21		0.51		
P7	0.17		0.51		
P8	0.01		0.86		
P9	0.24		0.35		
Constant	1.07*	1.07*	-1.92*	-1.61*	
Adjusted R-squared / McFadden R-squared	0.31	0.37	0.45	0.32	
Akaike info criterion	3.38	3.25	1.04	0.88	
Schwarz criterion	3.78	3.41	1.44	1	
Hannan-Quinn criteria	3.53	3.31	1.19	0.93	
F-statistic / LR statistic	3.21	8.24	22.83	15.99	
Prob (F-statistic / LR statistic)	0.01	0	0.01	0	

Notes:

1. Selected model is chosen by using a "stepwise" method based on F-statistic.
2. "*" denotes significant at a 5% level.

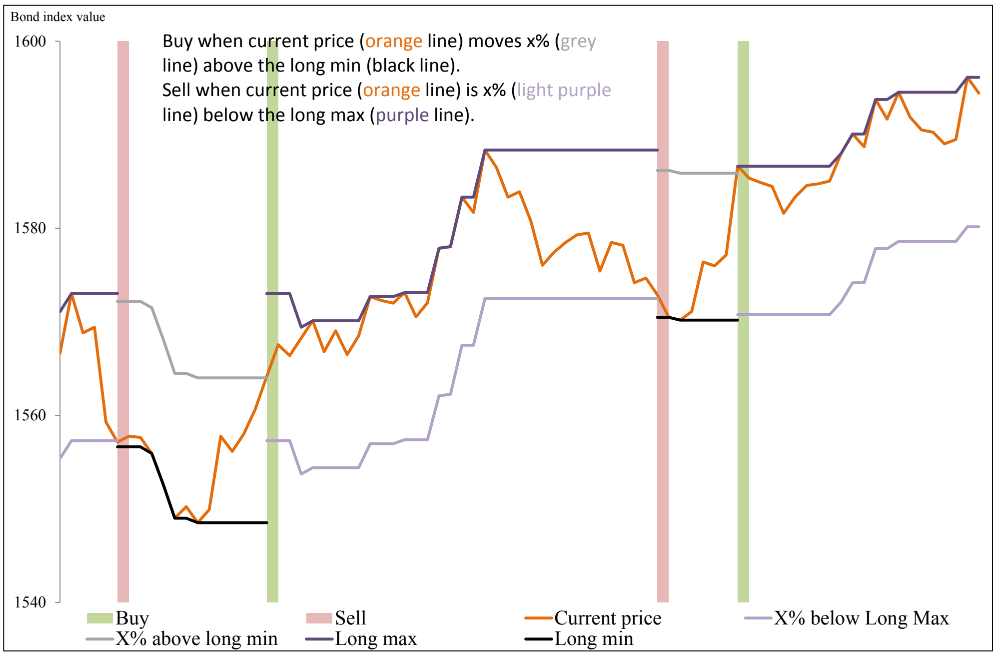
Graphical illustration of MA rule

Figure 1



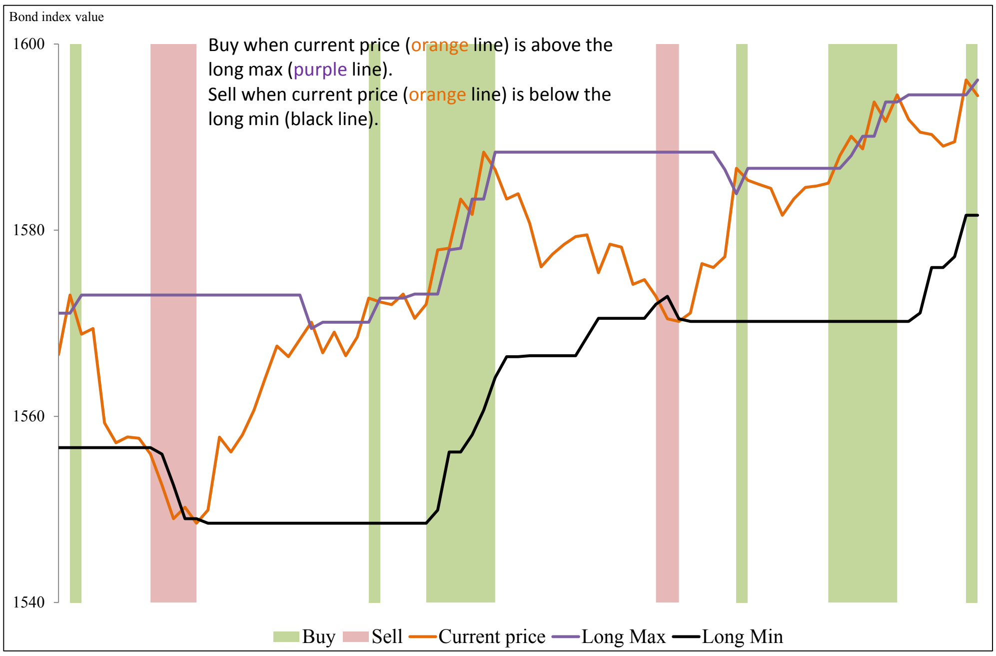
Graphical illustration of FL rule

Figure 2

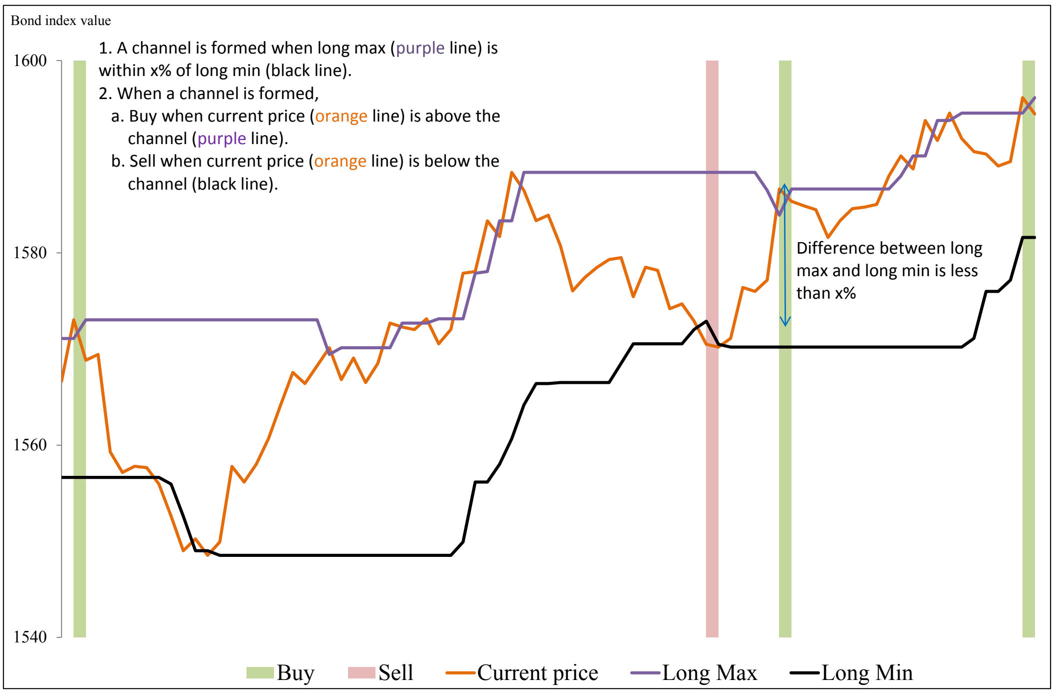


Graphical illustration of SR rule

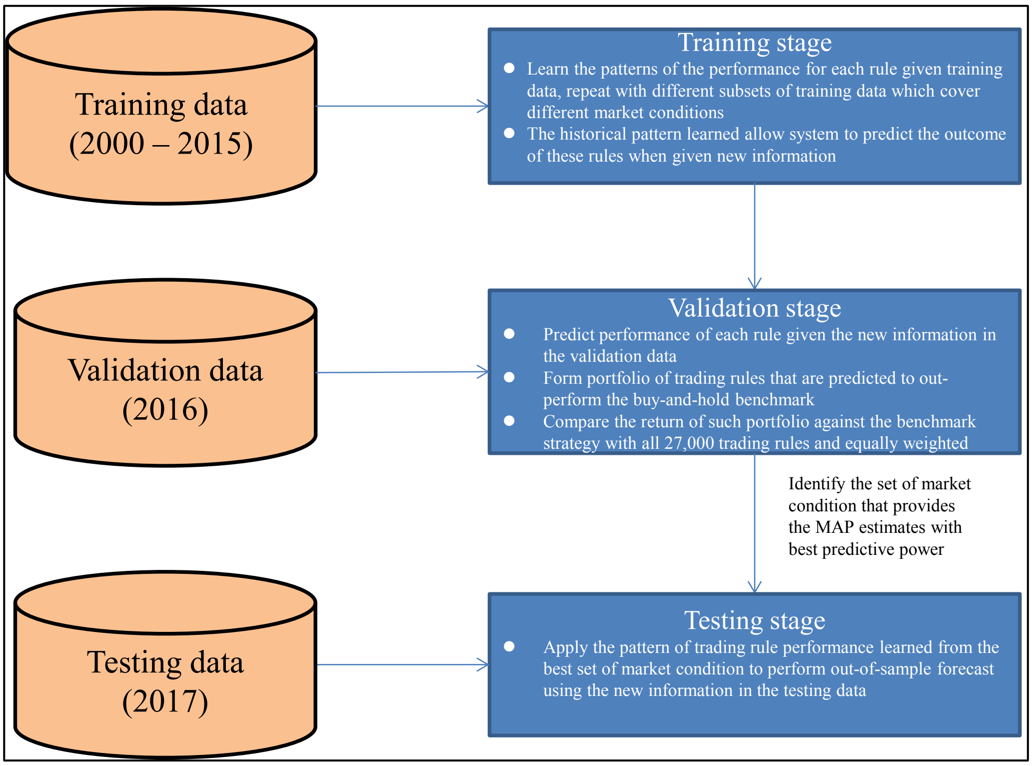
Figure 3



Graphical illustration of CB rule Figure 4

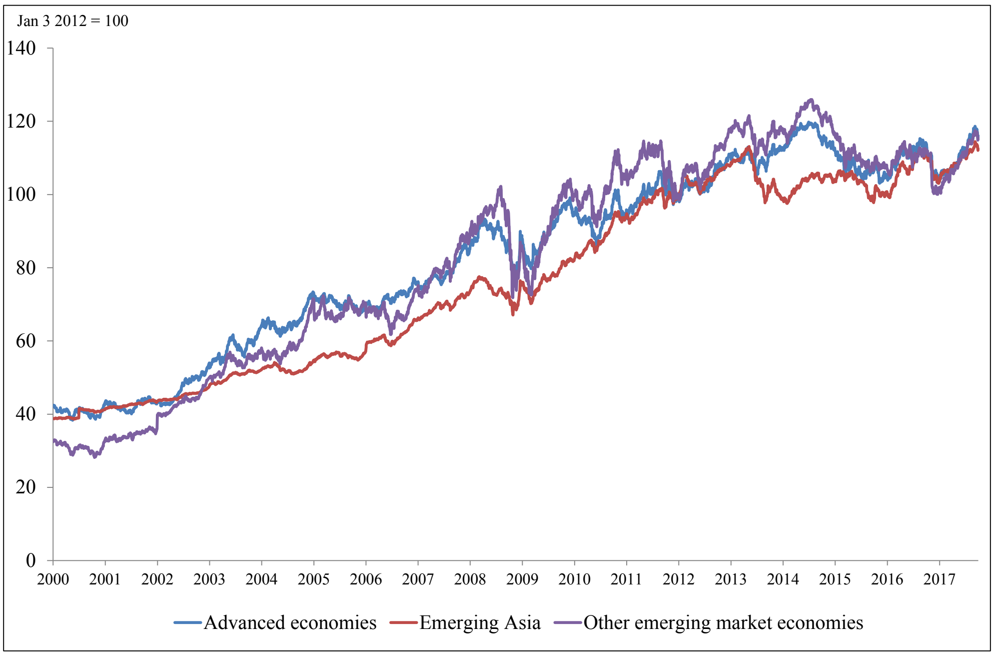


Machine learning system for each sovereign bond market Figure 5



Time series plot of sovereign bond indices

Figure 6



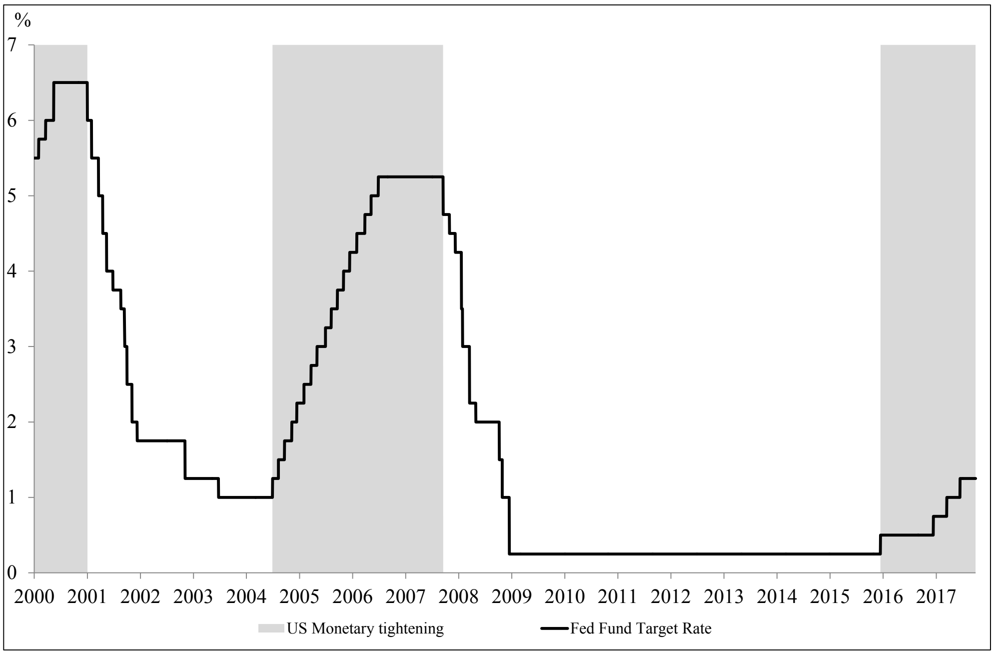
Notes:

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 Jan 3 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

US monetary cycle

Figure 7

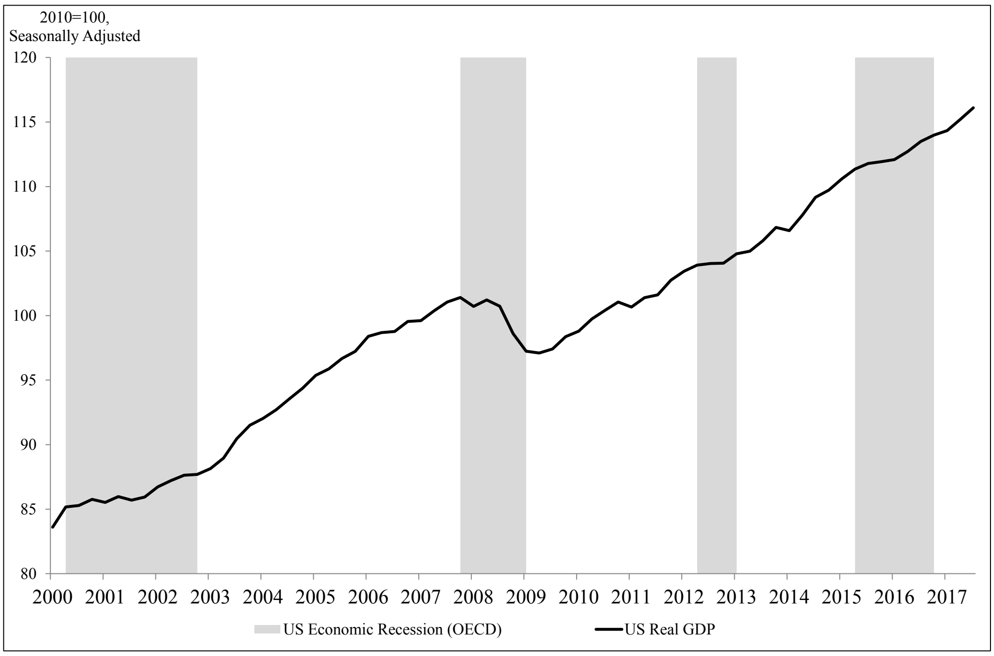


Note: Areas not shaded denote US monetary easing phase.

Sources: Federal Reserve Bank of St. Louis and author estimates.

US business cycle based on OECD definition

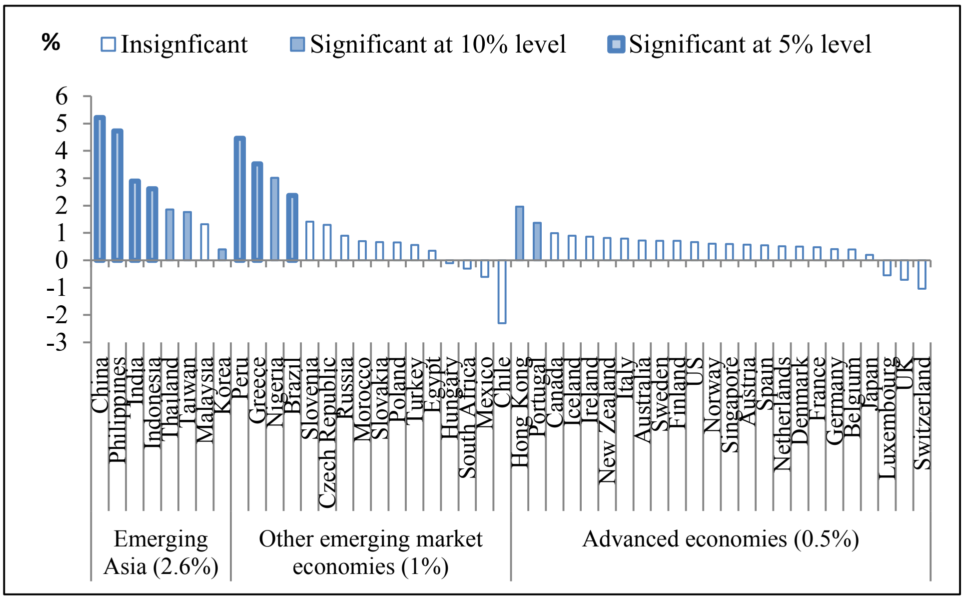
Figure 8



Note: Areas not shaded denote US economic expansion phase.
Sources: Federal Reserve Bank of St. Louis and OECD.

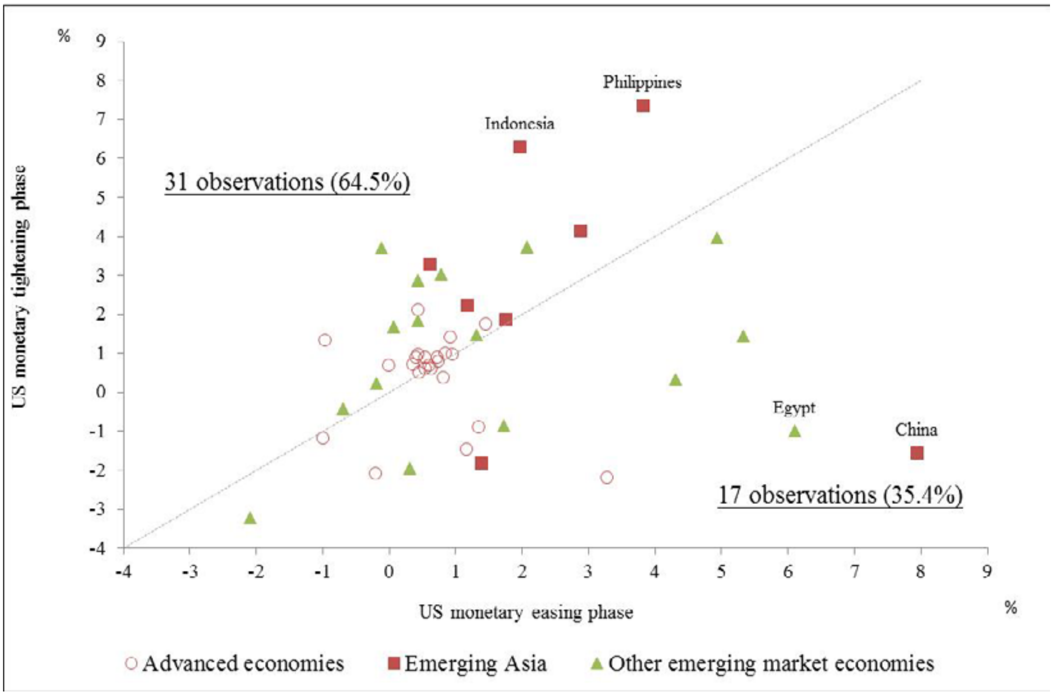
Annualised risk-adjusted average returns from trading-rule-based investment in sovereign bond markets during the sample period from 2000 Q1 to 2017 Q3

Figure 9



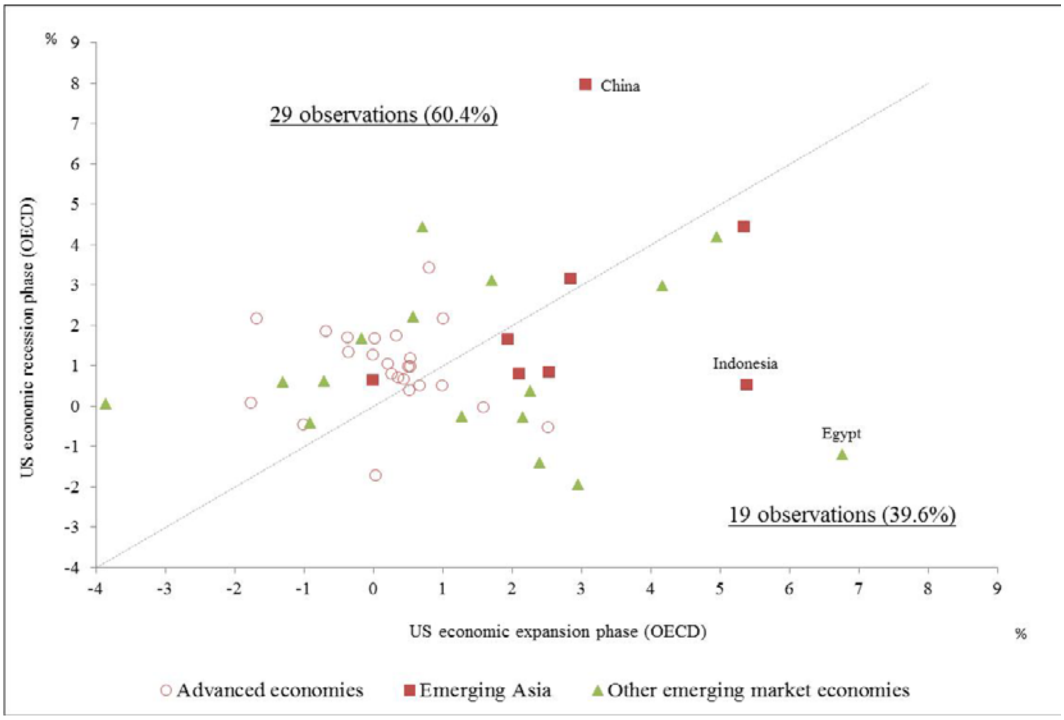
Note: All the returns are risk adjusted, annualized, and scaled up by the average annualized SD of the daily returns from apply trading rules on the 48 sovereign markets.

Scatter plot of conditional returns on the US monetary conditions Figure 10



Note: It 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.

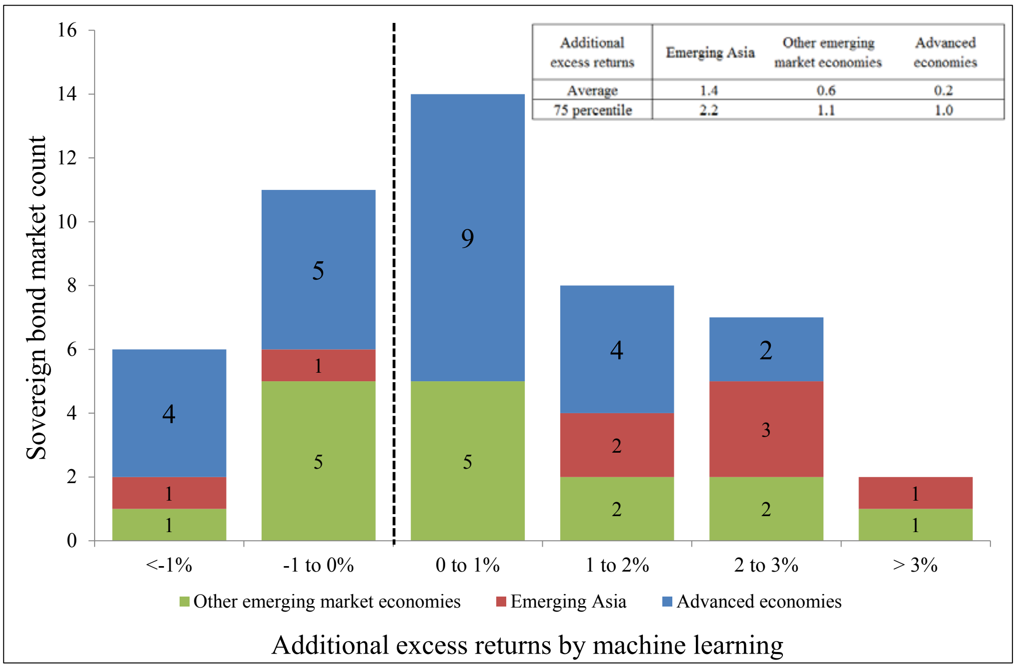
Scatter plot of conditional returns on the US economic conditions Figure 11



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

Additional returns earned from trading rule strategy formulated by a machine learning algorithm

Figure 12



Notes: It 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.

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).

<u>Moving average (MA)</u>
A moving average rule is implemented by first constructing two moving averages: a short term moving average (SMA, average of recent x days' closing prices including current closing price) and long term moving average (LMA, average of recent y days' closing prices including current closing price) where x must be strictly less than y. Buy and sell signals are generated when the SMA crosses the long term LMA. An investor should buy when the SMA is greater than the LMA, and sell when the SMA is less than the LMA.

Three variations on the basic MA rule are also considered:

1. Fixed holding period: all changes in positions are held for a minimum of c days irrespective of the trading signals generated during that time.
2. Fixed percentage band filter: a trading signal is generated only when the difference between the current closing price and the maximum or minimum exceeds a predefined percentage (b),
3. Time delay filter: the trading signal is only generated when it is maintained for d days.

The specifications for different parameters are described as below;

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

<u>Filter rules (FL)</u>
A standard filter rules generates a buy (sell) signal when current closing price increases (decreases) by at least x percent above (below) subsequent minimum (maximum). In basic form, subsequent maximum (minimum) is defined as the highest (lowest) price while holding a buy (sell) position (not including current closing price).

Three variations on the standard FL rule are also considered:

1. Allow for neutral positions to be held if the increase or decrease in the price

is more than another predefined threshold (y, where y<x).

2. Redefine high (low) prices to be highest (lowest) closing price for the previous e days (not including current closing price), where e is a predefined number.
3. Fixed holding period: all changes in positions are held for a minimum of c days irrespective of the trading signals generated during that time.

The specifications for different parameters are described as below;

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) = 6504

Support and resistance (SR)

Rules based on support and resistance level involve buying the asset when the current closing price exceeds a local maximum (resistance) and selling when the closing price is less than a local minimum (support). The local maximum (minimum) is defined as the highest (lowest) closing price over the previous n days (excluding current closing price).

Three variations on the basic SR rule are also considered:

1. Fixed holding period: all changes in positions are held for a minimum of c days irrespective of the trading signals generated during that time.
2. Fixed percentage band filter: a trading signal is generated only when the difference between the current closing price and the maximum or minimum exceeds a predefined percentage (b),
3. Time delay filter: the trading signal is only generated when it is maintained for d days.

The specifications for different parameters are described as below;

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) = 2520

Channel breakout (CB)

Channel breakout can be considered as a variation of support and resistance with additional "channel" criteria on local maximum and minimum. A buy (sell) signal is triggered when the current closing price moves above (below) a channel, where a channel is defined as the occasion where the local maximum is within x percent of the local minimum. The local maximum and minimum are defined in the same way as that under the support and resistance rule.

The following variation on the basic CB rule is also considered:

1. Fixed holding period: all changes in positions are held for a minimum of c days irrespective of the trading signals generated during that time.

The specifications for different parameters are described as below;

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 = 3696

Total number of rules = 6,504 (24.1%) + 14,280 (52.9%) + 2,520 (9.3%) + 3,696 (13.7%) = **27,000**

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Predictability in sovereign bond returns using technical trading rule: do developed and emerging markets differ?[1]

Tom Fong and Gabriel Wu,

Hong Kong Monetary Authority

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Predictability in sovereign bond returns using technical trading rules: do developed and emerging markets differ?

Presented by *Tom Fong*
Hong Kong Monetary Authority

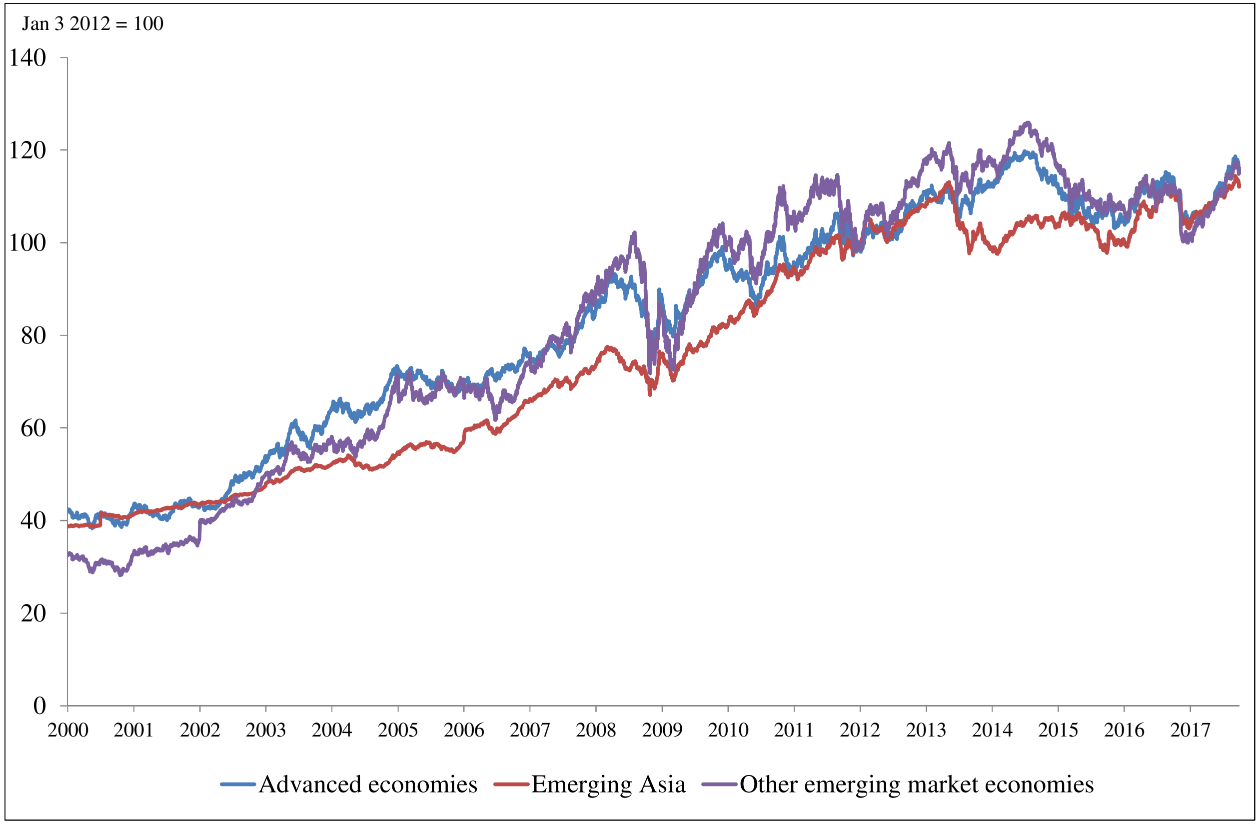
(collaborated with Gabriel Wu)

Bank Indonesia / IFC
"International Workshop on Big Data for Central Bank Policies"
Bali, 25 July 2018

Agenda

- Objective of the study
- Major findings
- Analytical framework
- Empirical results
- Conclusion

Sovereign bonds appear to be more responsive since major AEs begin their monetary policy normalization



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 Jan 3 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.

Our objective

- Evaluate the predictability of sovereign bond markets using technical trading rules
- Evaluate the robustness of the predictability using both a statistical test and machine learning technique
- Assesses whether the predictability is affected or not by changes in the monetary policy and economic business cycle in the US.
- Identify potential factors driving the predictability

Major findings

- Investing in sovereign bond markets of EMEs, particularly of emerging Asian economies, are significantly profitable

- Profits from investing in advanced economies' remains very thin even though we use an advanced (machine-learning) technique in profit optimization

- The profit is notably higher when the US tightens its monetary policies or undergoes an economic recession

- Several domestic factors, including government effectiveness, regulatory quality, political risk, financial openness, income level and real money growth, can significantly affect the predictability

Analytical framework

- 4 classes of trading rules considered
    1. Moving average (MA)
    2. Filter (FL)
    3. Support and resistance (SR)
    4. Channel breakout (CB)

        - A total of **27,000** trading rules considered

- Performance measured by excess return over “buy-and-hold” strategy

- Robustness of the return is tested by two advanced methods
    1. Superior Predictive Ability (SPA) test
    2. Naïve Bayes Classifier (NBC) technique

Data

- 48 Bond index data
  - Bank of America (BofA) Merrill Lynch sovereign bond index
  - Local currency, fixed rate nominal sovereign debt with maturity over 1 year
  - Weighted by market capitalization
  - Total return index
  - Covering both AEs and EMEs
  - With sample period from Jan 2000 to Sep 2017

Notable differences in the returns of sovereign bond markets among different economic groups

Economic group	Mean	SD	Sharpe ratio
AE	5.42	10.47	0.56
Emerging Asia	6.22	8.13	0.87
Other EMEs	4.46	14.68	0.34

Notes:

1. AEs and EMEs (including emerging Asia and other EMEs) classified according to the MSCI classification of developed and emerging markets
2. Mean" denotes annualized average daily return on respective sovereign bond index, while "SD" denotes annualized standard deviation of index's daily return.
3. Sharpe ratio is calculated as mean return divided by the standard deviation of returns.

- Emerging Asian markets have the highest return than other markets, after adjusting for risk (i.e. Sharpe ratio)

These economic groups also display vastly different economic, social and financial conditions

Variable	AE	Emerging Asia	Other EMEs
Public debt as % of GDP (%)	**77.74**	**40.51**	58.87
Real GDP per capita (ln US$)	**10.77**	**9.60**	9.80
Government effectiveness	**1.58**	0.39	**0.17**
Regulatory quality	**1.57**	**0.19**	0.21
Financial Openness	**0.95**	**0.36**	0.58
Political risk	**0.86**	**-0.54**	-0.29
Real money growth (%)	**3.33**	**7.45**	6.15
Inflation volatility (%)	**1.42**	1.95	**2.68**
Output volatility (%)	2.38	**1.99**	**3.18**

Note: Figures for each indicator refer to the simple average in the each economic grouping. Numbers highlighted in **green** (**red**) indicate the group with highest (lowest) value for each indicator.

- AEs are characterised with a deeper market for public bonds, a more effective government and a higher degree of financial openness
- Emerging Asia displays stronger growth of money in real terms
- While other EMEs show a larger volatility in both inflation and output

Principal component analysis is applied to group similar factors together

Variable	1st PC	2nd PC	3rd PC	4th PC
Public debt as % of GDP (%)	0.15	0.21	**-0.80**	0.35
Real GDP per capita (ln US$)	**0.40**	0.23	0.17	0.00
Government effectiveness	**0.42**	-0.01	0.15	-0.12
Regulatory quality	**0.41**	0.01	0.25	0.00
Financial Openness	**0.36**	0.08	0.10	0.53
Political risk	**0.40**	0.03	0.10	-0.17
Real money growth (%)	-0.29	-0.29	0.41	**0.61**
Inflation volatility (%)	-0.29	**0.50**	0.16	-0.30
Output volatility (%)	-0.14	**0.75**	0.21	0.29
Proportion of total variation explained endogenously (%)	**57.42**	**14.33**	**12.63**	**5.88**

Note: For brevity, only the first 4 principal components (which in total explain 90% of the variations) are shown.

- Based on principal component analysis, we can classify the first 4 components as below
  - 1st component: Stage of social and economic development
  - 2nd component: Economic uncertainty
  - 3rd component: Market depth of sovereign bond market
  - 4th component: Strength of money

Superior Predictive Ability test

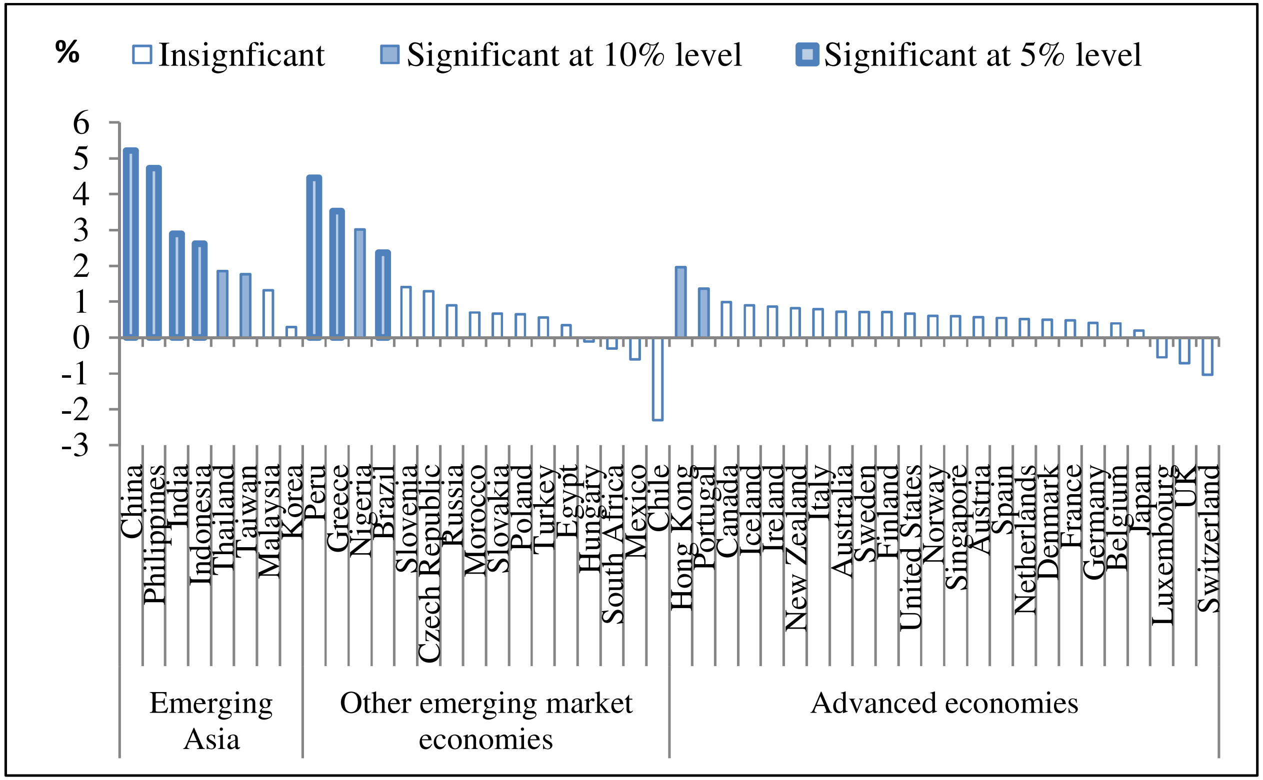
- Applying a large number of trading rules on predicting returns are susceptible to unintentional data mining or data snooping problem

- Hansen (2005)'s Superior Predictive Ability (SPA) test address such problem, as it takes into account the joint distribution of all trading rules.

- To obtain the distribution, the test involves a large scale bootstrapping simulation on the trading rule returns:
    - 27,000 trading rules
    - 1,000 bootstrapping simulations
    - 48 sovereign bond indices in daily frequency
    - Thousands of observations for each index

- The output of the SPA test is the p-value, which indicates the level of significance that trading rule returns are greater than 0

SPA test indicates significant trading rule returns for most of the emerging Asian markets



Notes

1. All the returns are risk adjusted, annualized, and scaled up by the average annualized SD of the daily returns from apply trading rules on the 48 sovereign markets.
2. Statistically significance of average trading rule returns is determined by the p-value of SPA test.

- 12 out of 48 markets record significant trading rule returns at 10% level
- Among them, half of them are from emerging Asia

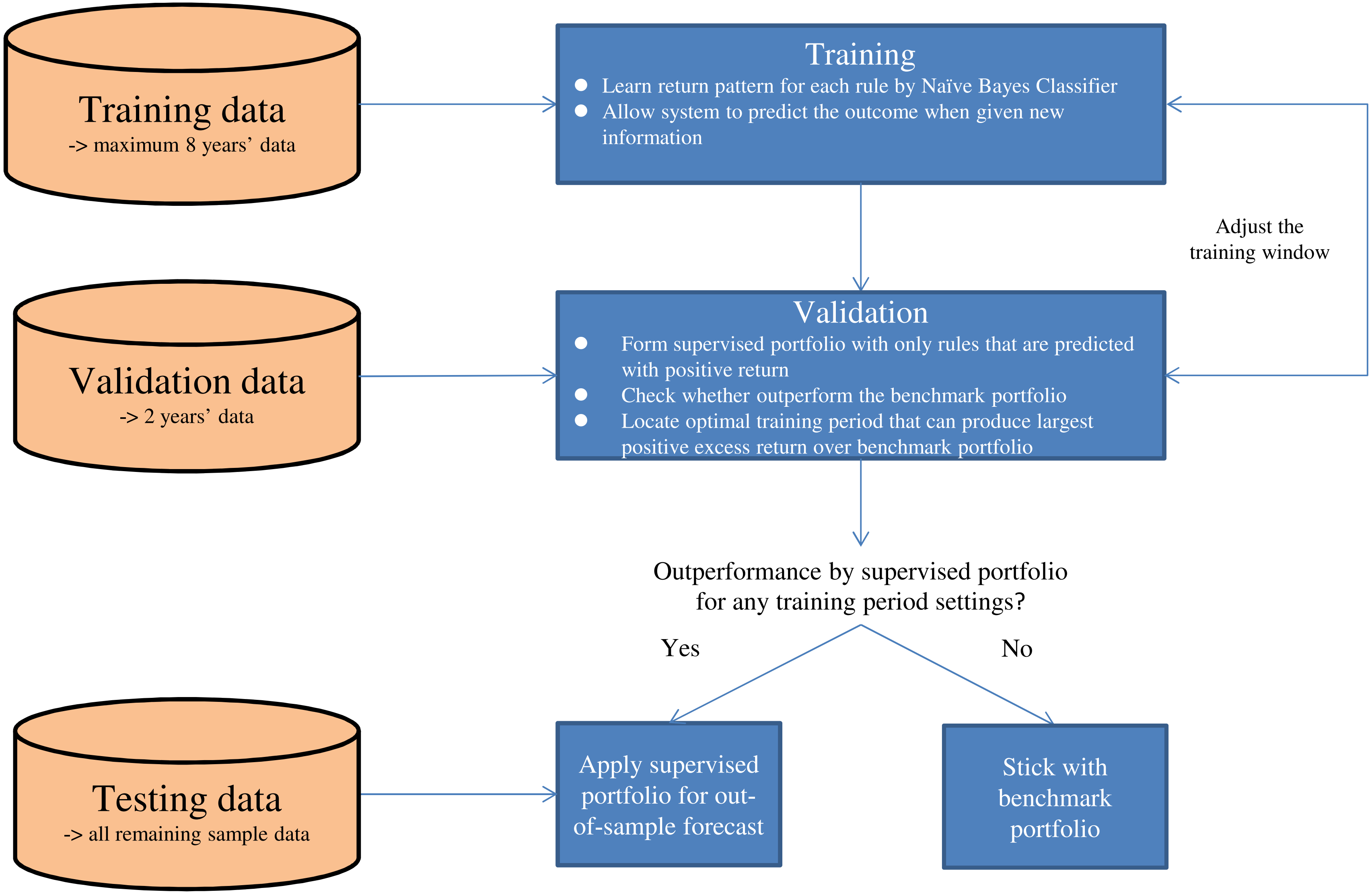
Machine learning – Naïve Bayes Classifier

- Robustness of the profitability of each sovereign bond market is also tested by a simple machine learning system, which determines rooms for increasing the average returns acquired from the trading-rule investment.

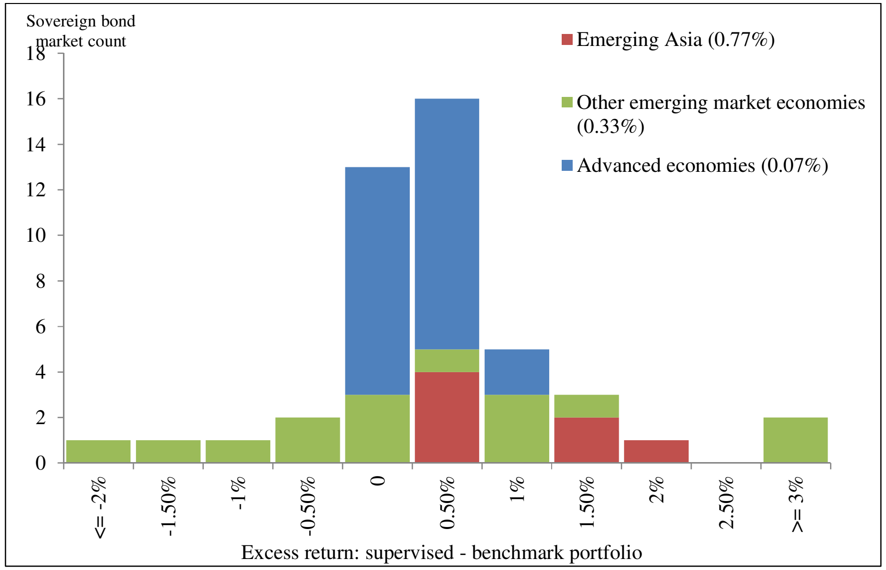
- The training system involves 2 parts; training and validation stage.
  - In the training stage, Naïve Bayes Classifier technique is adopted for system to "learn" the pattern of each trading rule's return given its historical investment performance.
  - The knowledge learned is then applied in the validation stage in forming a "supervised" portfolio, where only trading rules predicted with good performance are included, with higher weights assigned to those that are more likely to be profitable. The supervised portfolio is then evaluated to see whether it outperforms a benchmark portfolio which uses all 27,000 trading rules with equal weighting.

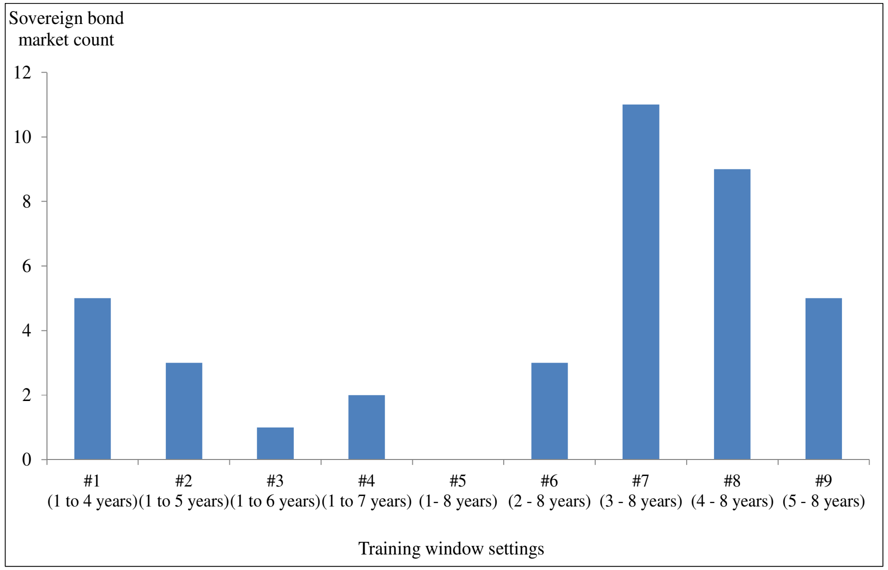
- Once the system is validated to be successful in improving returns for certain sovereign bond market, it will be applied to a set of testing data as out-of-sample forecasting (testing stage).

Machine learning set-up



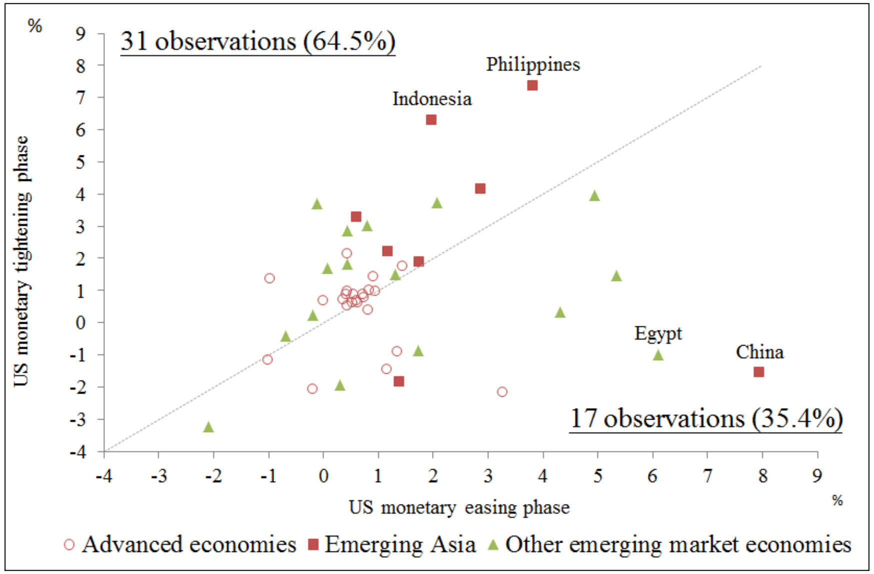
Improvements in returns for EMEs with machine learning technique, but not really for AEs

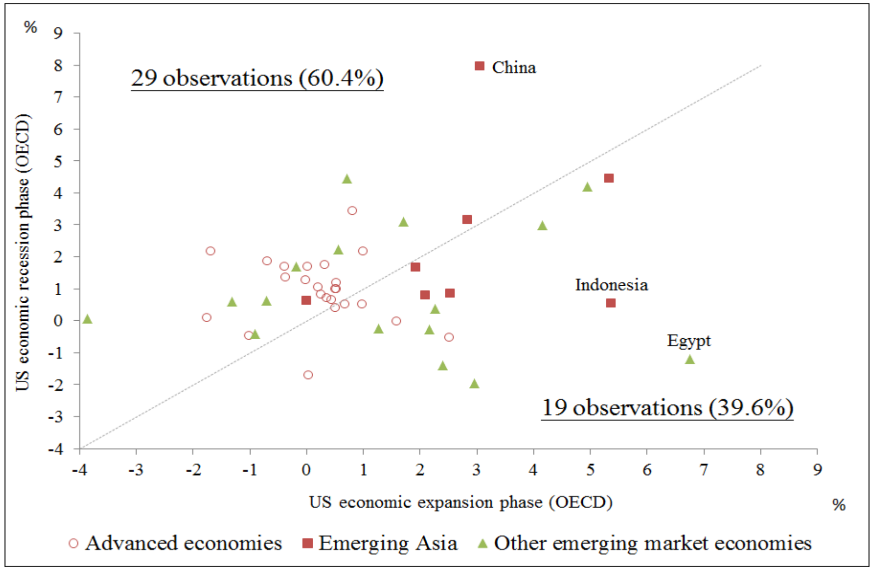




- Returns of emerging markets can substantially increase when applying machine-learning technique in profit optimization.
- However, returns of advanced markets cannot be increased further despite applications of the advanced technique.
- Optimal learning period usually fall at the later part of the training data

Trading rules usually attain higher returns when US tightens its monetary policy or undergoes economic recession





- Returns for AEs do not differ substantially during different US monetary cycles, while there are a larger dispersion among both emerging Asia and other EMEs.
- Chine earns a substantially higher returns during US economies recession than expansion.

Return predictability is associated with level of social and economic development, and rate of real money growth

Explanatory Variable	Least square regression		Logistic regression		
	Full model	Selected model	Full model	Selected model	Odds ratio (selected model)
P1	-0.69*	-0.69*	-1.9*	-1.41*	-75.50%
P2	-0.15		-0.11		
P3	0.05		0.01		
P4	0.46*	0.46*	1.01*	0.82*	127.23%
P5	-0.22		-0.4		
P6	0.21		0.51		
P7	0.17		0.51		
P8	0.01		0.86		
P9	0.24		0.35		
Constant	1.07*	1.07*	-1.92*	-1.61*	
Adjusted R-squared / McFadden R-squared	0.31	0.37	0.45	0.32	
Akaike info criterion	3.38	3.25	1.04	0.88	
Schwarz criterion	3.78	3.41	1.44	1	
Hannan-Quinn criteria	3.53	3.31	1.19	0.93	
F-statistic / LR statistic	3.21	8.24	22.83	15.99	
Prob (F-statistic / LR statistic)	0.01	0	0.01	0	

Notes:
1. Dependent variable used in each model: trading rule returns (least square regression); binary variable which equals 1 when trading rule is statistically significant at 10% level (logistic regression).
2. Selected model is chosen by using a “stepwise” method based on F-statistic. “*” denotes significant at a 5% level.

- Both ordinary least square regression and logistic regression are estimated.
- Principal components extracted from the observable factors as explanatory variables
- The 1st PC (stage of social and economic development) and 4th PC (strength of money) are found to be significant under both specifications

Conclusion

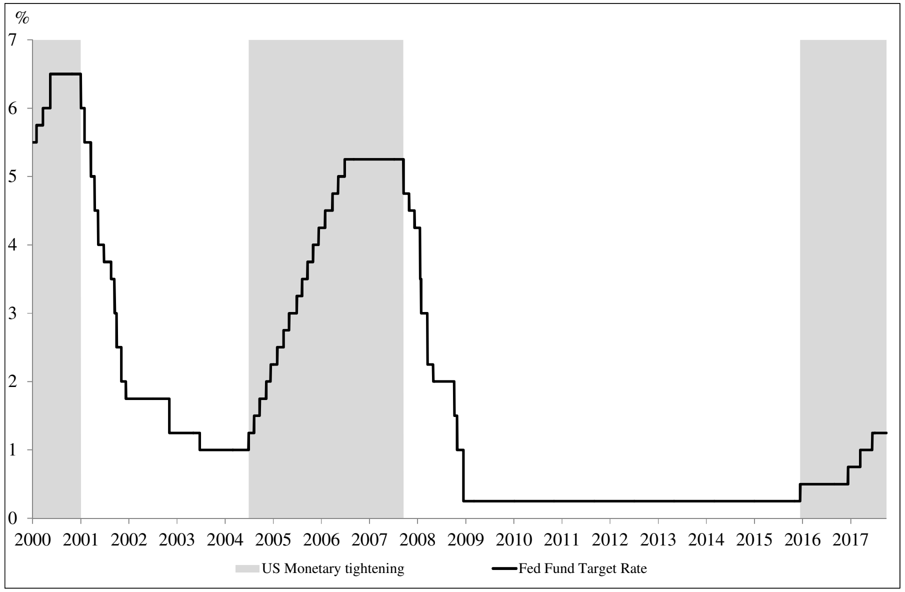
- Sovereign bond markets could be predictable with trading rule strategies
- Robustness of the predictability is tested by advanced data mining and machine learning technique
- Policy implications:
    - Considerable spillover impact from the US to inefficient markets such as emerging Asian ones
    - Promoting not only the financial development but also the social and economic development

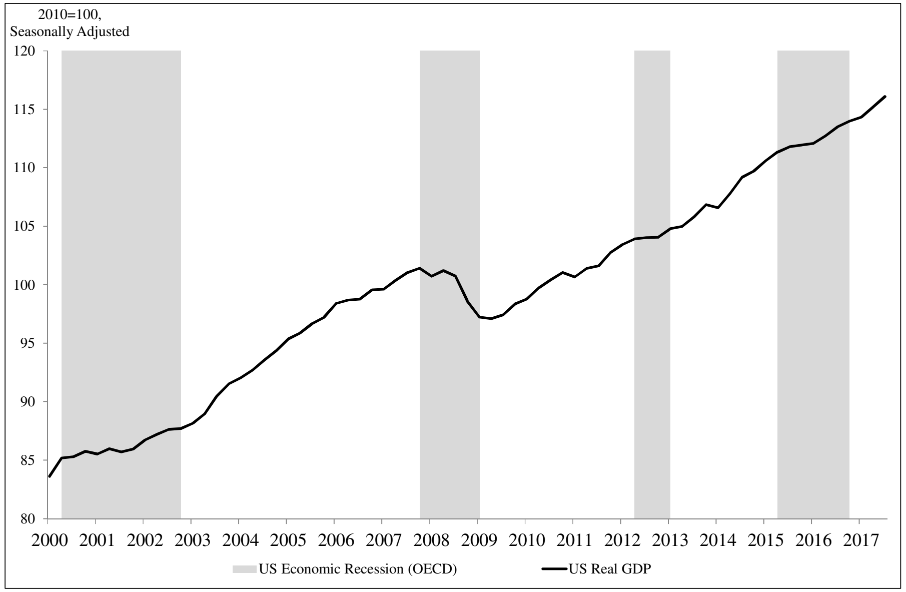
Appendix: Classification of countries/regions by economic grouping

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

Note: Classification according to the MSCI classification of developed and emerging markets, see https://www.msci.com/market-classification for details.

Appendix: US monetary and business cycles





Note: Areas not shaded denote US monetary easing phase.
Sources: Federal Reserve Bank of St. Louis and author estimates.

Note: Areas not shaded denote US economic expansion phase.
Sources: Federal Reserve Bank of St. Louis and OECD.

Appendix: Technical details of the SPA test

- The SPA test in this study is based on the following test statistics

$$\overline{V_l} = \frac{1}{K}\sum_{k=1}^{K}\left(\sqrt{N} * \overline{ER_k}\right)/\ \sigma_k \qquad (1)$$

where $\overline{ER_k} = \sum_{t=201}^{T} ER_{k,t}\ /\ N$ is the average excess return for the *k*-th trading rule out of *K* trading rules and *N*=*T*-200 is the sample size, and σ_k is a consistent estimator for the standard deviation of $\sqrt{N} * \overline{ER_k}$

- The joint distribution of all trading rules is empirically drawn by applying stationary bootstrap method of Politis and Romano (1994) to the observed values of $ER_{k,t}$

- In each bootstrapping simulation, we compute the sample average of the bootstrapped returns denoted by $\overline{ER_{k,i}^{*}}$ The process is repeated B times and we construct the following bootstrap test statistics to form the distribution for $\overline{V_l}$;

$$\overline{V_{l,i}} = \frac{1}{K}\sum_{k=1}^{K}\left(\sqrt{N} * \left(\overline{ER_{k,i}^{*}} - \overline{ER_k} * I_{\left(\left(\sqrt{N}*\overline{ER_k}\right)/\ \sigma_k > -A\right)}\right)\right)/\ \sigma_k \qquad (2)$$

where i = 1,2,….B and I is an indicator function which equals one when the condition is satisfied and zero otherwise, and A = $\sqrt{2 \ln \ln \mathrm{N}}$

- The test's p-value is subsequently obtained by comparing $\overline{\mathrm{V}_l}$ with the quantiles of $\overline{\mathrm{V}_{l,i}}$.