



New technical indicators and stock returns predictability

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ABSTRACT

We find that combining de-noising stock returns by wavelet transform with new proposed technical indicators can significantly improve the accuracy of stock returns forecasts, in which the new technical indicators can directly reflect the trend of stock returns series. Empirical results indicate the stock returns forecasts generated by new technical indicators are statistically and economically significant both in-sample and out-of-sample prediction performance. And when multivariate information is used to predict stock returns, its predictability is also significant. In addition, it is robust for the prediction performance of new indicators using some extension and robustness analysis.

1. Introduction

Stock returns forecasting is a wonderful topic and is significant for asset pricing, asset allocation and risk management. An influential work by Goyal and Welch (2008) demonstrates that a few basic variables have a better in-sample predictability, but a worse out-of-sample prediction ability compared with the historical average. So far, a large body of literatures of forecasting stock returns employ different macroeconomic variables.¹ However, most of the macroeconomic indicators fail to obtain good out-of-sample prediction performance, and the main reason for weak prediction ability is structural instability.

In fact, it is well known that stock returns forecasting is really difficult. Among the existing literatures, the out-of-sample $R^2(R^2_{OOS})$ of predictor exceeding 3% is rare over benchmark of historical average. However, the prediction ability of the historical averages benchmark is weak. Hence, the distance between the prediction of stock returns and financial practice is still long. The existing researches which present insufficient consistent out-of-sample evidence indicate that new predictors need to be constructed to better establish the empirical reliability in forecasting stock returns. Therefore, the main objective of this paper is to construct some new effective predictors to obtain better prediction performance of stock returns.

A noteworthy literature proposed by Neely et al. (2014) demonstrates how to forecast the equity risk premium using technical indicators including moving-average rule, momentum rule and volume-based indicators. Technical analysis, which dates back at least to Cowles (1933), employs past prices, trading volumes and other available data to determine price trends that are believed to persist into the future. The out-of-sample $R^2(R^2_{OOS})$ obtained by 14 technical indicators is positive for the out-of-sample period from Jan.1966 to Dec.

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¹ Variables include dividend ratios (Fama & French, 1988; Goyal & Welch, 2003; Lewellen, 2004), short interest index (Rapach et al., 2016), stock variances (Guo, 2006; Ludvigson & Ng, 2007), inflation (Campbell & Vuolteenaho, 2004), economic policy uncertainty (Chen et al., 2017), news-implied volatility (Manela & Moreira, 2017), manager sentiment (Jiang et al., 2019), and among others.

2011, but the best predictor of $VOL(1,12)$ only reaches R^2_{OoS} of 0.80%. Moreover, we find that the ability of above predictors is instable due to the selection of out-of-sample periods. If the out-of-sample period is selected from 1947.01 to 2018.12, the R^2_{OoS} of some predictive indicators is negative. The reason is that most of these technical indicators based on past prices or volume, which fails to directly reflect the trend of stock returns.

Unlike Neely et al. (2014), we propose some new technical indicators to obtain superior out-of-sample prediction performance for stock returns where these indicators are constructed by the trend of stock returns. To more effectively construct new technical indicators, the construction is divided into two steps. Firstly, forced wavelet de-noising is used to de-noise stock returns series. Wavelet transform (WT) is a transform analysis method, which results in a time-frequency window representing discontinuities and sharp peaks. After reducing noise in the time series of stock returns, new moving-average (NMA) rule, new moving-median (NMM) rule and new simple momentum (NM) rule are suggested to construct the new technical indicators. We make contributions to the literatures in three aspects. Firstly, new technical indicators are constructed based on stock returns rather than stock prices, which can directly reflect the trend of stock returns. Secondly, investors can use new technical indicators to obtain more precise stock returns forecasts and allocate assets in real time. Thirdly, the forecasting ability of new technology indicators is stable, independent of the out-of-sample period and business cycle.

When we make an empirical analysis for full sample, a more significant in-sample prediction ability is found in new technical indicators. Using univariate regression model with each predictor, we obtain the forecasts for out-of-sample stock returns from January 1947 to December 2018. Following the relative literatures, we use the out-of-sample $R^2(R^2_{OoS})$ to evaluate the statistical performance of individual forecasts. We also employ the CW statistic proposed by Clark and West (2007) to inspect the statistical significance of stock returns predictability. The results demonstrate that the predictability of new technical indicators is improved. In detail, all new technical indicators can generate larger R^2_{OoS} , with an average R^2_{OoS} of 5.976%. The R^2_{OoS} values of NMA (1,9), NMA (1,12), NMA (2,6), NMM (1,12) remarkably improve to 8.151%, 7.076%, 7.368%, 7.286%, respectively. Notably, all new technical indicators obtain the significance of predictability at the 1% level.

Certainty equivalent returns (CER), Sharpe ratio and average turnover are employed to evaluate economic value of stock returns forecasts. A mean-variance investor allocates his/her own assets between stocks and riskless assets. The empirical results show that the three evaluation indicators have been remarkably improved when we use new technical indicators to forecast stock returns. All the stock returns forecasts are significant economically. Notably, all new technical indicators generate larger CER gains than macroeconomic variables and technical indicators considered in this paper which obtain a maximum of 17.913%, with an average of 13.701%.

Through a series of extension and robustness analysis, we test how the new technical indicators can produce better out-of-sample prediction performance, including combining information from individual forecasts, linking to business cycles, prediction performance over time, and alternative out-of-sample periods. Fortunately, the improvement of prediction ability is presented in a slice of integrated information methods as well, namely, principal component analysis (PCA), and five popular combination methods from Pettenuzzo et al. (2014) and Rapach et al. (2010). After implementing integrated information from individual forecasts, more accurate forecasts are obtained in new technical indicators, reaching a maximum of 10.453%, with an average of 9.782%.

Extension analysis linking to business cycle exhibits the source of improvement for predictability. Taking new technical indicators as predictors obtains superior prediction performance in both recession and expansion. Particularly, when these indicators, namely, NMA(1,6), NMA(1,12), NMM(1,12) and NM (12), employed to forecast stock returns during recession period, the R^2_{OoS} values can be improved to 11.650%, 12.156%, 12.199% and 15.273%, respectively.

How does predictability develop over time? The recursive R^2_{OoS} is calculated from January 1958, taking four new technical indicators, NMA (1,9), NMA (1,12), NMA (2,6) and NMM (1,12), for example. It is noteworthy that from 1978 to 2018, the R^2_{OoS} value increased steadily, about 8%. Furthermore, in different out-of-sample periods, the new technical indicators are still stable. All R^2_{OoS} values generated by the technical indicators are positive, the maximum value exceeding 9.043%. In addition, the portfolio exercise of new technology indicators is also robust when considering transaction costs.

The remaining of this paper is as follows: Section 2 shows our research data, including macroeconomic variables, technical indicators and new technical indicators. Section 3 presents the econometric methodology including in-sample regression model, out-of-sample forecasting approach and evaluation method. Section 4 reports empirical analysis through in-sample predictive ability, out-of-sample prediction performance and portfolio exercise. Section 5 investigates five kinds of extensions and robustness analysis, containing combining information from individual forecasts, linking to business cycle, prediction performance over time, and alternative out-of-sample period. The conclusion is given in the last Section.

2. Data

2.1. Existing predictors

In this paper, we take two types of common predictors as its competing strategies, namely macroeconomic indicators proposed by Welch and Goyal (2008) and technical indicators² suggested by Neely et al. (2014). These existing predictors are described as follows.

² Numerous literatures have proposed a variety of technical indicators to test profitability of trading strategies, including filter rules (Fama & Blume, 1966), moving-average strategy (Brock et al., 1992; Lo et al., 2000), momentum (Conrad & Kaul, 1998), automated pattern recognition (Lo et al., 2000), and volume-based indicators (Sullivan et al., 1999)).

2.1.1. Macroeconomic indicators

Following relative literatures (see, e.g., Rapach et al., 2010; Neely et al., 2014; Wang et al., 2018), 14 prevailing macroeconomic variables³ are employed as predictor to predict monthly excess returns, which are originate from Welch and Goyal (2008). The excess stock returns is the difference between the returns of the S&P 500 including dividends and the log returns of a risk-free bill. For brevity, we provide short descriptions of macroeconomic variables as:

- Dividend yield (log), DY: difference between the log of dividends and the log of lagged prices.
- Dividend-price ratio (log), DP: the log of dividends on the S&P 500 index minus the log of stock prices.
- Earnings-price ratio (log), EP: the log of earnings on the S&P 500 index minus the log of stock prices.
- Dividend-payout ratio (log), DE: difference between the log of dividends and the log of earnings on the S&P 500 index.
- Stock returns variance, SVAR: sum of squared daily returns on the S&P 500 index.
- Net equity expansion, NTIS: ratio of 12-month moving sums of net issues by NYSE-listed stocks to total end-of-year market capitalization of NYSE stocks.
- Book-to-market ratio, BM: ratio of book value to market value for the Dow Jones Industrial Average.
- Long-term yield, LTY: long-term government bond yield.
- Treasury bill rate, TBL: interest rate on a 3-month Treasury bill (secondary market).
- Term spread, TMS: difference between the long-term yield and the Treasury bill rate.
- Long-term returns, LTR: returns on long-term government bonds.
- Default returns spread, DFR: difference between the long-term corporate bond returns and the long-term government bond returns.
- Default yield spread, DFY: difference between BAA- and AAA-rated corporate bond yields.
- Inflation, INFL: calculated from the Consumer Price Index (CPI) (all urban consumers) and used lagged for one month to account for the delay in the release of the CPI.

Table 1 reports descriptive statistics of 14 macroeconomic variables and excess stock returns from 1927:01 to 2018:12. The excess stock returns averages 0.005, generating a monthly Sharpe ratio of 0.094 and a standard deviation of 0.0054. Additionally, although the first-order autocorrelation of the excess stock returns is only 0.0086, most of macroeconomic variables show high persistence.

2.1.2. Technical indicators

We also employ 14 technical indicators as competing strategy to our proposed index. These technical indicators are proposed by Neely et al. (2014)⁴ and based on two popular technical strategies. Firstly, they suggested a moving-average (MA) rule which yields a buy or sell signal ($S_{i,t} = 1$ or $S_{i,t} = 0$, respectively). And this strategy as follows:

$$S_{i,t} = \begin{cases} 1 & \text{if } MA_{s,t} \geq MA_{l,t} \\ 0 & \text{if } MA_{s,t} < MA_{l,t} \end{cases}, \quad (1)$$

where

$$MA_{j,t} = (1/j) \sum_{i=0}^{j-1} P_{t-i} \text{ for } j = s, l; \quad (2)$$

P_t denotes the stock price of S&P 500 index; and l denotes the length of the short (long) MA ($s < l$). They define the MA indicator with MA lengths s and l by $MA(s, l)$. Obviously, the MA strategy reflects the changing trend of stock price, and the short MA is more susceptible to recent price changes than the long MA. In this paper, we employ the MA rule to forecast stock returns with $s = 1, 2, 3$ and $l = 6, 9, 12$.

Secondly, a simple momentum (MoM) rule is also proposed to forecast stock returns. This rule is given by

$$S_{i,t} = \begin{cases} 1 & \text{if } P_t \geq P_{t-m} \\ 0 & \text{if } P_t < P_{t-m} \end{cases}. \quad (3)$$

From an intuitive point of view, the current stock price is higher than the previous M period, emerging a "positive" momentum and relatively high expected excess returns, thus yielding a signal for buy. They define the MoM indicator with P_t and P_{t-m} by $MoM(m)$. Following Wang et al. (2018), we consider $m = 1, 3, 6, 9, 12$ in this paper.

2.2. Construction of new technical index

Although these above technical indicators improve prediction accuracy, they still fail to obtain the desired results. One possible reason is that they do not directly reflect the trend of stock returns. However, the trend in stock returns plays an important in predictability. Given this, new technical indicators based on stock returns are necessarily constructed. The construction of new technical

³ Those 14 economic variables are available at homepage of Amit Goyal at <http://www.hec.unil.ch/agoyal/>.

⁴ Besides the moving-average rule and momentum rule, Neely et al. (2014) also suppose volume-based indicators. Because the length of sample period is different, it is difficult to obtain volume of stock from 1927 to 1949, we do not consider this technical indicator in this paper.

Table 1
Summary statistics.

	Mean	Std.Dev.	Min.	Median	Max.	Skewness	Kurtosis	$\rho(1)$
Ret	0.005	0.054	−0.339	0.009	0.346	−0.432	10.929	0.085
DP	−3.380	0.463	−4.524	−3.352	−1.873	−0.195	2.609	0.992
DY	−3.375	0.461	−4.531	−3.347	−1.913	−0.222	2.586	0.992
EP	−2.742	0.416	−4.836	−2.793	−1.775	−0.578	5.577	0.987
DE	−0.638	0.328	−1.244	−0.630	1.380	1.530	9.071	0.991
SVAR	0.003	0.006	0.000	0.001	0.071	5.815	47.038	0.632
BM	0.565	0.266	0.121	0.540	2.028	0.784	4.432	0.985
NTIS	0.017	0.026	−0.058	0.017	0.177	1.619	11.016	0.980
TBL	0.034	0.031	0.000	0.029	0.163	1.094	4.330	0.993
LTY	0.051	0.028	0.018	0.042	0.148	1.101	3.637	0.996
LTR	0.005	0.024	−0.112	0.003	0.152	0.578	7.567	0.044
TMS	0.017	0.013	−0.037	0.018	0.046	−0.273	3.176	0.960
DFY	0.011	0.007	0.003	0.009	0.056	2.499	11.998	0.975
DFR	0.000	0.014	−0.098	0.001	0.074	−0.373	10.561	−0.118
INFL	0.002	0.005	−0.021	0.002	0.059	1.083	16.929	0.480

This table provides the summary statistics for the excess stock returns of the S&P 500 index (Ret) and 14 macroeconomic variables from January 1927 to December 2018. All data can be downloaded free from homepage of Amit Goyal. $\rho(1)$ is the first-order autocorrelation.

indicators is divided into two steps.

Generally speaking, the signal contains noise, especially in the process of signal acquisition, the receiver will introduce noise in addition to acquiring the target signal. Therefore, before further analyzing the signal, we need to extract the effective signal.

This true is also used in stock returns series. Hence, before constructing the new indicators, the wavelet transform is used to achieve the result of de-noising in stock returns.

2.2.1. Wavelet decomposition

Wavelet transform⁵ (WT) is a kind of transform analysis method. It not only inherits and develops the idea of short-term fourier transform location, but also overcomes the defect that the window size does not change with the frequency, resulting in the discontinuity and peak of time-frequency window representation. Through the operation of stretching and translation, the signal (function) is gradually multi-scale refined, and finally the high-frequency time subdivision and low-frequency frequency subdivision are obtained. That is to say, any square integrable function $y(t)$ can be decomposed into two parts, some scaling functions $\varphi_{M,n}(t)$ and wavelet functions $\psi_{m,n}(t)$, with their corresponding approximation coefficients $S_{M,n}$ and detail coefficients $T_{m,n}$ (see Daubechies, 1992; Jaffard et al., 2001)

$$y(t) = \sum_{n=-\infty}^{\infty} S_{M,n} \varphi_{M,n}(t) + \sum_{m=-\infty}^M \sum_{n=-\infty}^{\infty} T_{m,n} \psi_{m,n}(t), \quad (4)$$

where

$$\varphi_{M,n}(t) = 2^{-M/2} \varphi(2^{-M}t - n), \quad (5)$$

$$\psi_{m,n}(t) = 2^{-m/2} \psi(2^{-m}t - n). \quad (6)$$

Those two functions are the representation of the approximation part and the high frequency information in $y(t)$. M and m are scale parameters that control the dilation (stretching or squeezing) of the scaling and wavelet functions; n is a translation parameter that controls the translation (horizontal movement) of the scaling and wavelet functions. And the approximation coefficients and detail coefficients can be obtained by

$$S_{m,n} = \int_{-\infty}^{\infty} y(t) \varphi_{m,n}(t) dt, \quad (7)$$

$$T_{m,n} = \int_{-\infty}^{\infty} y(t) \psi_{m,n}(t) dt. \quad (8)$$

From the above integration, we can see that expansion formula will be effective for the infinite continuous signal $y(t)$. In the real worlds, the signals are usually discrete and its length is limited. For the discrete signal $y(t)$ with length $N = 2^M$, the wavelet transform is defined as following

⁵ This transform approach has cited in a large body of literatures as in Haven et al., 2012; Tan et al., 2012; Rua & Nunes, 2009; Wang et al., 2017; Faria & Verona, 2018.

$$y(t) = \sum_{n=0}^{2^{M-m-1}} S_{M,n} \varphi_{M,n}(t) + \sum_{m=1}^M \sum_{n=0}^{2^{M-m-1}} T_{m,n} \psi_{m,n}(t). \quad (9)$$

Following relative literatures as in Gençay et al., 2002; Daubechies, 1992; Addison, 2002; Haven et al., 2012, when processing a signal that is not an integer power of 2, the signal is usually filled with zeros to increase its length to the next integer power of 2. In Fig. 1, we show wavelet transform process from level 1 to level 4 as an example.

2.2.2. Wavelet de-noising

Based on the wavelet transform, wavelet de-noising can be performed in time series. In the decomposition process, the approximation coefficient vector $S_{M,n}$ and the detail coefficient vector $T_{m,n}$ present information at low frequency and at high frequency (noisy) of the time series, respectively. Hence, in the process of de-noising, $S_{M,n}$ vector will remain unchanged, while $T_{m,n}$ vector will be employed for the goal of de-noising. And we implement the forcing de-noising approach among the wavelet de-noising method.⁶ In this approach, all the high frequency coefficients $T_{m,n}$ in the wavelet decomposition structure are set to 0, that is, all the high frequency parts are filtered out, and then the signal is reconstructed by wavelet, because it is relatively simple, and the de-noised signal is relatively smooth.

From the above mentioned, the process of wavelet de-noising is manipulated by following three steps:

Step1: Decomposition. The discrete wavelet transform at a certain level M , for a given time series $y(t)$, is performed, with the db5 wavelet function, then the scaling coefficient vector $S_{M,n}$ and wavelet coefficient vectors $\{T_{M,n}, T_{M-1,n}, \dots, T_{1,n}\}$ are obtained.

Step2: Forced de-noising. Although forced de-noising method is simple and effective, useful components of signals are easily lost. To address this problem, we set part of high frequency coefficients to 0. In this paper, we decompose time series of stock returns at level 4, resulting in wavelet coefficient vectors $\{T_{4,n}, T_{3,n}, T_{2,n}, T_{1,n}\}$, and coefficient vectors $\{T_{2,n}, T_{1,n}\}$ are set to 0.

Step3: reconstruction. Reconstruct the $y(t)$ after wavelet de-noising by thresholding wavelet coefficients $\{\hat{T}_{M,n}, \hat{T}_{M-1,n}, \dots, \hat{T}_{1,n}\}$ rather than detail coefficient vectors $\{T_{M,n}, T_{M-1,n}, \dots, T_{1,n}\}$.

All the wavelet de-noising steps are performed by the wavelet toolbox in Matlab 2018. Fig. 2 shows original data of stock returns and de-noising data by wavelet transform. It obviously that after forced de-noising, the curve of excess stock returns is smoother, but the overall trend characteristics of the excess stock returns are still retained.

2.2.3. Construction methodology

Combining de-noising stock returns by wavelet transform, we will construct new technical indicators according to relative strategies being similar to Neely et al. (2014). Firstly, we propose a new moving-average (NMA) rule based on the de-nosed excess stock returns rather than stock price. This rule is defined by

$$S_{i,t} = \begin{cases} 1 & \text{if } NMA_{s,t} \geq NMA_{l,t} \\ 0 & \text{if } NMA_{s,t} < NMA_{l,t} \end{cases}, \quad (10)$$

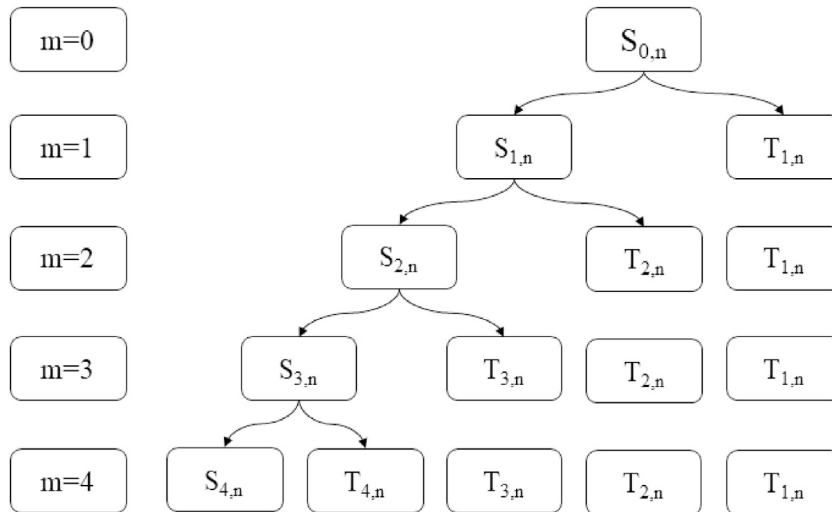


Fig. 1. Wavelet transform process from level 1 to level 4. The $S_{M,n}$ and $T_{m,n}$ denote corresponding approximation coefficients and detail coefficients, respectively.

⁶ The main wavelet de-noising methods include forced de-noising, soft threshold, hard threshold, and default threshold de-noising.

where

$$NMA_{j,t} = (1/j) \sum_{i=0}^{j-1} R_{t-i} \text{ for } j = s, l; \quad (11)$$

R_t denotes the de-noised excess returns of S&P 500 index; s (l) denotes the length of the short (long) NMA ($s < l$). We denote the NMA indicator with $NMA(s, l)$. Intuitively, as Neely et al. (2014), this rule can yield a buy or sell signal ($S_{i,t} = 1$ or $S_{i,t} = 0$, respectively). Specifically, if stock returns begin to decline, short-term NMA declines faster than long-term NMA, eventually lower than long-term NMA, and produces a sell signal. We consider $s = 1, 2$ and $l = 6, 9, 12$ in this paper.

Secondly, following Yi et al. (2019), the median is considered as an alternative criterion to construct technical indicators, which is to avoid relying on the average subjectively. We call this construction as new moving-median (NMM) rule, which consists of

$$S_{i,t} = \begin{cases} 1 & \text{if } NMM_{s,t} \geq NMM_{l,t} \\ 0 & \text{if } NMM_{s,t} < NMM_{l,t} \end{cases}, \quad (12)$$

where

$$NMM_{j,t} = \text{Median} \left\{ \{R_t\}_{t-j+1}^t \right\} \text{ for } j = s, l; \quad (13)$$

We denote the NMM indicator with $NMM(s, l)$. Similarly, when stock returns has been falling recently, the short NMM tend to be lower than long NMM, eventually yields a sell signal. We consider $s = 1, 2$ and $l = 9, 12$ in this paper.

Thirdly, a new simple momentum (NM) rule is also constructed based on stock returns. This rule is given by

$$S_{i,t} = \begin{cases} 1 & \text{if } R_t \geq R_{t-m} \\ 0 & \text{if } R_t < R_{t-m} \end{cases}. \quad (14)$$

Intuitively, current stock returns are lower than the level before m periods, showing a "negative" momentum and a lower expected excess returns, leading to a sell signal. We denote the NM indicator by $NM(m)$. Following Wang et al. (2018), we consider $m = 1, 3, 6, 12$ in this paper.

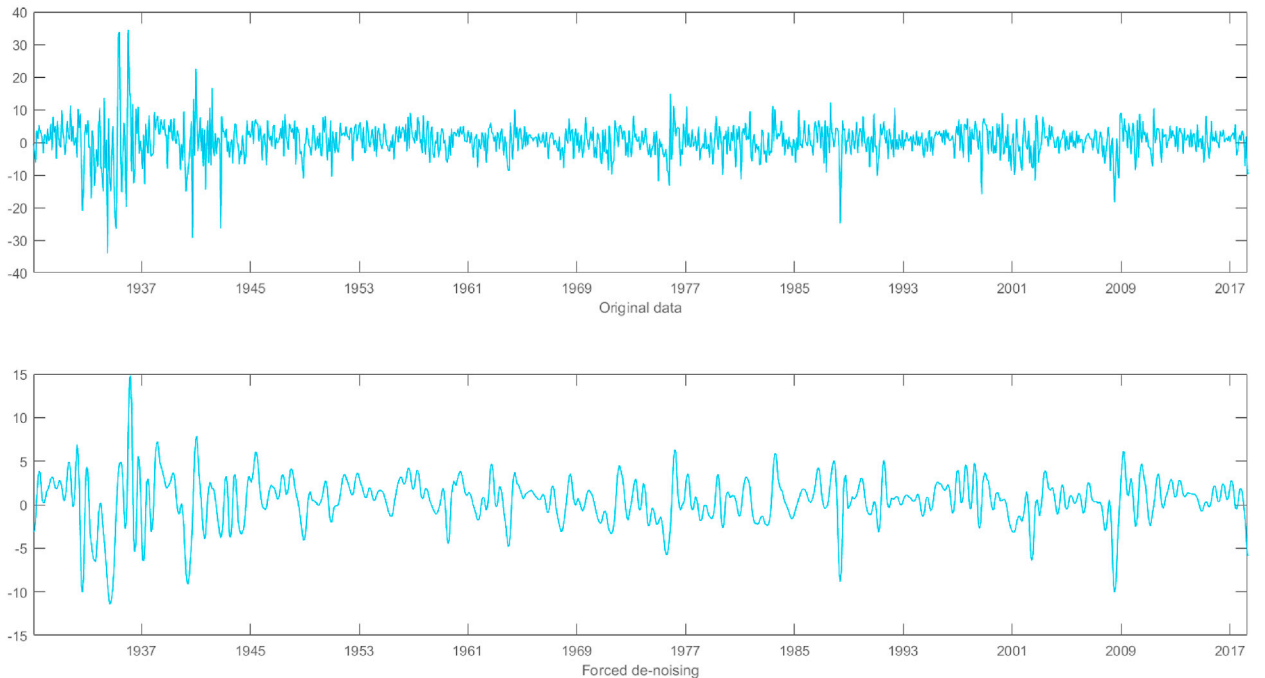


Fig. 2. Original data of stock returns and de-noising data by wavelet transform.

3. Methodology

3.1. Conventional regression model

Following relative literatures as in [Pettenuzzo et al., 2014](#); [Rapach et al., 2016](#), a conventional regression is employed as follow:

$$r_{t+1} = \alpha_i + \beta_i x_{i,t} + \varepsilon_{i,t+1}, \quad (15)$$

where r_{t+1} denotes the excess stock returns at month $t+1$; $x_{i,t}$ denotes the i -th predictor of all indicators including existing predictors and new technical index at month t ; and $\varepsilon_{i,t+1}$ indicates that the error term follows a mutually independent and identical normal distribution. α_i and β_i denote the estimated parameter according to the ordinary least squares (OLS). Traditionally, the null hypothesis, $\beta = 0$, meaning the predictor in interested model has no predictive ability, can be tested by standard t statistics. To enhance test ability of in-sample, we employ a one-side alternative hypothesis proposed by [Inoue and Kilian \(2004\)](#) in which the null of $\beta = 0$ against the alternative of $\beta > 0$ by computing heteroskedasticity-consistent- t -statistic.

3.2. Out-of-sample forecasting evaluation

Following relative literatures as in [Neely et al., 2014](#); [Wang et al., 2018](#), we obtain out-of-sample forecasts by employing the recursive estimation window method. In detail, the full sample of excess stock returns, including T observations, and all predictors are divided into two parts, namely in-sample portion consisting of the first V observations and out-of-sample containing the last P observations (i.e., $V + P = T$).

In this paper, the historical average of excess returns can be taken as a natural benchmark. And the historical average benchmark can be also obtained by

$$\bar{r}_{t+1} = \frac{1}{t} \sum_{i=1}^t r_i, \quad (18)$$

where r_t denotes the actual value of stock returns at month t .

Following relative literatures (see, e.g., [Ferreira & Santa-Clara, 2011](#); [Wang et al., 2018](#); [Lin, 2018](#); [Jiang et al., 2019](#); [Dai & Zhu, 2020](#); [Z. Dai, Zhou, Wen, & He, 2020a](#); [Z.F. Dai, Dong, Kang, & Hong, 2020b](#)), in order to evaluate predictor's prediction performance, we take a widespread out-of-sample R^2 statistic to test whether the out-of-sample forecasts yielded by the given model outperform the historical average benchmark. The R^2_{OoS} is computed by

$$R^2_{OoS} = 1 - \frac{MSPE_{model}}{MSPE_{bench}}, \quad (19)$$

where $MSPE_{model} = \frac{1}{T-V} \sum_{t=V+1}^T (r_t - \hat{r}_t)^2$ and $MSPE_{bench} = \frac{1}{T-V} \sum_{t=V+1}^T (r_t - \bar{r}_t)^2$. $MSPE_{bench}$ and $MSPE_{model}$ are the mean squared predictive errors (MSPE) of the historical average benchmark and the given model, respectively. Intuitively, a positive R^2_{OoS} manifests that the interested model can obtain more accurate predictability of stock returns than the historical average benchmark.

Furthermore, to evaluate significance of predictability, we use [Clark and West \(2007\)](#) statistic (CW hereafter) to measure forecasting models. Mathematically, [Clark and West \(2007\)](#) statistic is defined as following.

$$f_{i,t} = (r_t - \bar{r}_t)^2 - (r_t - \hat{r}_t)^2 + (\bar{r}_t - \hat{r}_t)^2. \quad (20)$$

We can obtain the CW statistic through regression $\{f_t\}_{V+1}^T$ on a constant, that just is t -statistics for the constant.

4. Empirical results

In this section, we will present the empirical analysis of in-sample test and the out-of-sample prediction performance for traditional predictors and new technical indicators.

4.1. In-sample results

[Inoue and Kilian \(2004\)](#) hold that in-sample predictability is a necessary condition for out-of-sample predictability. It is unreasonable to study out of sample predictability when the whole sample is not predictable enough. In view of this, this section uses the samples from 1927.01 to 2018.12 to conduct in-sample tests on the prediction performance of new technical indicators.

[Table 2](#) shows the in-sample results of different predictors, including the estimation of β_i for the economic model in (1), the standard t -statistics, the heteroskedasticity-consistent t -statistics and R^2 statistics. And the predictors contain macroeconomic variables, technical variables and new technical indicators. For all existing predictors, 12 out of 14 macroeconomic variables generate positive coefficient, and all the technical indicators have results with positive slope coefficient. At first glance, it seems that all value of R^2 are small. However, [Campbell and Thompson \(2008\)](#) suggested monthly R^2 statistics of close to 0.005, which is economically enough to represent

Table 2

In-sample results.

Panel A: Macroeconomic variables					Panel B: Technical indicators					Panel C: New technical indicators				
Predictor	β	t_std	t_hc	R^2	Predictor	β	t_std	t_hc	R^2	Predictor	β	t_std	t_hc	R^2
DP	0.502	1.427	0.936	0.002	MA(1,6)	0.788**	2.304	2.043	0.005	NMA(1,6)	2.578***	8.121	7.853	0.057
DY	0.616	1.744	1.119	0.003	MA(1,9)	0.838**	2.410	1.969	0.005	NMA(1,9)	2.687***	8.480	8.397	0.061
EP	0.814*	2.080	1.887	0.004	MA(1,12)	0.902**	2.565	2.070	0.006	NMA(1,12)	2.934***	9.314	9.119	0.073
DE	−0.309	−0.621	−0.345	0.000	MA(2,6)	0.583	1.690	1.431	0.003	NMA(2,6)	2.575***	8.113	7.941	0.056
SVAR	−0.397	−1.393	−0.541	0.002	MA(2,9)	0.816*	2.343	1.918	0.005	NMA(2,9)	2.399***	7.523	7.455	0.049
BM	1.292	2.113	1.031	0.004	MA(2,12)	0.967**	2.760	2.248	0.007	NMA(2,12)	2.636***	8.297	8.507	0.059
NTIS	12.886	2.042	1.298	0.004	MA(3,6)	0.298	0.868	0.712	0.001	NMM(1,9)	2.620***	8.270	8.208	0.058
TBL	0.085	1.604	1.587	0.002	MA(3,9)	0.626	1.797	1.442	0.003	NMM(1,12)	2.745***	8.669	8.532	0.064
LTY	0.069	1.176	1.237	0.001	MA(3,12)	0.580	1.653	1.347	0.002	NMM(2,9)	2.515***	7.910	7.914	0.054
LTR	0.097	1.448	1.500	0.002	MOM(1)	0.348	1.048	0.983	0.001	NMM(2,12)	2.664***	8.410	8.526	0.060
TMS	0.162	1.290	1.273	0.002	MOM(3)	0.182	0.537	0.489	0.000	NM (1)	2.035***	6.340	6.214	0.035
DFY	0.082	0.347	0.117	0.000	MOM(6)	0.676	1.954	1.618	0.003	NM (3)	2.634***	8.310	8.220	0.059
DFR	0.179	1.505	0.948	0.002	MOM(9)	0.894**	2.563	2.133	0.006	NM (6)	2.384***	7.479	7.326	0.048
INFL	0.211	0.685	0.370	0.000	MOM(12)	0.700	1.986	1.594	0.004	NM (12)	2.689***	8.500	8.321	0.062

This table reports the in-sample results of different predictors for full sample from 1927.01 to 2018.12. And the predictors contain macroeconomic variables and technical variables assumed by [Neely et al. \(2014\)](#) and new technical indicators. The slope coefficients, namely, β , are estimated by the ordinary least squares (OLS) regression model in (1). *, ** and *** denoted significance at 10%, 5% and 1% levels, respectively. The t_std denotes the standard t-statistic, which is computed from the two-sided hypothesis test. And the t_hc denotes the heteroskedasticity-consistent t-statistics calculated from the one-sided (upper-tail) hypothesis test. R^2 statistics are shown in the last column of each panel.

the predictive ability. Therefore, all predictors have predictive ability. Moreover, the prediction performance of technical indicators is superior to macroeconomic variables, with larger R^2 value in most case, which is consistent with Neely et al. (2014).

However, after the implementing the new technical indicators to forecast stock returns, not only the slope coefficients are positive, but also above 2 at 1% level. This manifests that stock returns can be significantly forecasted by new technical indicators, because the absolute value of the standard t-statistics is more than 6. In theory, the well-known Stambaugh (1999) bias may exaggerate the importance of t-statistics. Hence, to test the stock returns predictability, we employ the one-side (upper-tail) test supposed by Inoue and Kilian (2004) to eliminate this deviation. The null hypothesis is $\beta = 0$ against $\beta > 0$ and the heteroskedasticity-consistent t-statistics is presented in the third column of each panel. We find that the absolute values of all heteroskedasticity-consistent t-statistics are above 6, which further ensures the significance of predictability. Moreover, the R^2 value of the new technical indicators is at least 8 times higher than that of the technical indicators in Neely et al. (2014).

Overall, all the new technical indicators have significant in-sample prediction ability compared with the existing prediction indicators considered in this paper, which provides the basis for out-of-sample prediction.

4.2. Out-of-sample forecasting results

We use univariate regression model to forecast stock returns from January 1947 to December 2018. Table 3 reports the out-of-sample statistical performance of different predictors by MSPE, R^2_{Oos} and CW statistical evaluation. We find that it is difficult to exceed the historical average when using macroeconomic variables to forecast stock returns. Specifically, 11 out of 14 macroeconomic variables produce negative R^2_{Oos} , which is consistent with previous literature, indicating that they fail to obtain accurate stock returns forecasts (see, e.g., Campbell & Thompson, 2008; Wang et al., 2018; Neely et al., 2014). When utilizing technical indicators to forecast stock returns, we find that it is consistent with Neely et al. (2014) and shows that technical indicators can obtain forecasts of stock returns. Unfortunately, 10 out of all technical indicators in Neely et al. (2014) generate negative R^2_{Oos} and larger MSPE if the out-of-sample period is selected from 1947.01 to 2018.12.

After implementing new technical indicators, the prediction performance of each predictor is significantly improved. All new technical indicators can generate larger R^2_{Oos} and smaller MSPE than macroeconomic variables and technical indicators, with an average R^2_{Oos} of 5.976%. In particular, the R^2_{Oos} values of NMA (1,9), NMA (1,12), NMA (2,6), NMM (1,12) remarkably improve to 8.151%, 7.076%, 7.368%, 7.286%, respectively. And relative MSPE values are reduce to 15.738, 15.922, 15.872, 15.886, respectively. It is noteworthy that the statistical results of CW show that all the new technical indicators have significant predictability at the level of 1%.

Finally, comparing to the out-of-sample results obtained by technical indicators in Neely et al. (2014), we find there exist opposite signs of R^2_{Oos} between the both if the out-of-sample period is selected from 1947.01 to 2018.12. The main reasons are as followings. The technical indicators in Neely et al. (2014) are constructed by use of the stock price which do not directly reflect the trend of stock returns. If the out-of-sample period is selected from 1947.01 to 2018.12, 10 out of all technical indicators in Neely et al. (2014) generate negative R^2_{Oos} which indicates these 10 technical indicators obtain less accurate predictability of stock returns than the historical average benchmark. However, the new technical indicators are constructed by use of the de-noising stock returns which can directly reflect the trend of stock returns series. And, all of R^2_{Oos} for the new technical indicators are significantly positive, which means the new technical indicators significantly outperform the historical average benchmark.

Table 3
Out-of-sample results.

Macroeconomic variables			Technical indicators			New technical indicators		
Predictor	MSPE	R^2_{Oos}	Predictor	MSPE	R^2_{Oos}	Predictor	MSPE	R^2_{Oos}
DP	17.147	−0.074*	MA(1,6)	17.297	−0.947	NMA(1,6)	16.030	6.445***
DY	17.201	−0.389**	MA(1,9)	17.142	−0.043*	NMA(1,9)	15.738	8.151***
EP	17.385	−1.463*	MA(1,12)	17.058	0.449**	NMA(1,12)	15.922	7.076***
DE	17.385	−1.458	MA(2,6)	17.140	−0.034	NMA(2,6)	15.872	7.368***
SVAR	17.108	0.154	MA(2,9)	17.086	0.284**	NMA(2,9)	16.072	6.204***
BM	17.386	−1.467	MA(2,12)	16.992	0.833***	NMA(2,12)	16.467	3.898***
NTIS	17.243	−0.633	MA(3,6)	17.145	−0.061	NMM(1,9)	15.946	6.937***
TBL	17.123	0.067*	MA(3,9)	17.081	0.312*	NMM(1,12)	15.886	7.286***
LTY	17.251	−0.677*	MA(3,12)	17.151	−0.093	NMM(2,9)	15.949	6.920***
LTR	17.265	−0.761	MOM(1)	17.210	−0.439	NMM(2,12)	16.372	4.452***
TMS	17.117	0.103	MOM(3)	17.159	−0.140	NM (1)	16.650	2.830***
DFY	17.164	−0.169	MOM(6)	17.153	−0.105	NM (3)	16.309	4.818***
DFR	17.170	−0.205	MOM(9)	17.301	−0.970	NM (6)	15.998	6.635***
INFL	17.145	−0.060	MOM(12)	17.148	−0.075	NM (12)	16.340	4.639***

This table reports the out-of-sample results of macroeconomic variables, technical indicators and new technical indicators. The prediction performance is evaluated by out-of-sample R^2 (R^2_{Oos}) multiplied by 100 to denote the percent value. Univariate predictive regression model is used to yield stock returns forecasts with each predictor. MSPE are the mean squared predictive errors by $MSPE = \frac{1}{T-M} \sum_{t=M+1}^T (r_t - \hat{r}_t)^2$. Statistical significance for positive R^2_{Oos} is measured using Clark and West (2007) statistic. *, ** and *** denotes significance at 10%, 5% and 1% levels, respectively. The in-sample period is 1927:01–1947:12, and the out-of-sample period is 1947:01–2018:12.

In conclusion, all the new technical indicators can significantly improve the stock returns predictability. That is to say, the new technical indicators have better out-of-sample prediction ability.

4.3. Portfolio performance

In the process of asset allocation between risk-free assets and stocks of interest, we calculate certainty equivalent returns (CER) with a mean variance investor to evaluate the economic value of the stock returns prediction considering risk aversion (see, e.g. [Campbell & Thompson, 2008](#); [Avramov, 2002](#); [Neely et al., 2014](#)). In other words, we try to find that whether the stock returns forecasts generated by new technical indicators are significant economically. In portfolio exercise, investors can allocate his or her asset with relative weights, and the optimal weights are determined by

$$w_{i,t} = \frac{1}{\gamma} \frac{\hat{r}_{i,t+1}}{\hat{\sigma}_{i,t+1}^2}, \quad (21a)$$

where $\hat{\sigma}_{i,t+1}^2$ denotes the variance of stock returns, which is estimated by past five-year moving window of monthly stock returns, γ is investor's risk aversion with 3 as in [Rapach et al. \(2010\)](#). Following relative literatures (see, e.g., [Rapach et al., 2010](#) and [Neely et al., 2014](#)), we limit stock weight to lie in an interval at $[0, 1.5]$.

Then, the portfolio returns for month $t+1$ can be given by

$$R_{p,t+1} = w_{i,t} r_{i,t+1} + R_{f,t+1}, \quad (21b)$$

In a portfolio constructed by Eqs. (20) and (21a,b), an average CER is

$$\text{CER}_i = \hat{\mu}_i - 0.5\gamma\hat{\sigma}_i^2, \quad (22)$$

where $\hat{\mu}_i$ and $\hat{\sigma}_i$ are the mean and variance of portfolio, respectively.

[Table 4](#) shows the portfolio performance of predictor including macroeconomic variables, technical indicators and new technical indicators. Columns 2, 6 and 10 of [Table 3](#) show CER gains, which are the differences between CERs from given model and CERs generated by historical average. Then multiply the difference by 1200 to get the annualized percentage value. The third, seventh and eleventh columns in [Table 3](#) show the monthly Sharpe ratio, which is the standard deviation of the average portfolio returns over the risk-free rate divided by the excess portfolio returns. The average monthly turnover in fourthly, eighth, and twelfth columns is determined by the percentage of wealth traded monthly following [DeMiguel et al. \(2009\)](#).

Comparing with the macroeconomic variables, we find that 12 out of 14 technical indicators have positive CER gains, generating larger CER gains, while 6 out of 14 macroeconomic variables generate positive CER gains. Furthermore, the monthly Sharpe ratio and the average monthly turnover generated by technical indicators are higher than macroeconomic variables. These results are basically consistent with [Neely et al. \(2014\)](#). Fortunately, all the univariate regression applied to new technical indicators generate larger CER gains than existing indicators, reaching a maximum of 17.913%, with an average of 13.701%. In addition, compared with

Table 4
Portfolio performance.

Macroeconomic variable				Technical indicator				New technical indicator			
Predictor	CER gains	Sharpe ratio	Relative average turnover	Predictor	CER gains	Sharpe ratio	Relative average turnover	Predictor	CER gains	Sharpe ratio	Relative average turnover
DP	2.054	0.140	0.023	MA(1,6)	0.886	0.154	0.050	NMA(1,6)	13.455	0.300	0.088
DY	2.132	0.141	0.019	MA(1,9)	2.039	0.159	0.048	NMA(1,9)	17.913	0.328	0.167
EP	0.039	0.141	0.043	MA(1,12)	2.906	0.169	0.050	NMA(1,12)	15.154	0.324	0.054
DE	-2.208	0.129	0.061	MA(2,6)	1.133	0.145	0.050	NMA(2,6)	15.646	0.311	0.082
SVAR	-1.957	0.107	0.050	MA(2,9)	2.593	0.163	0.050	NMA(2,9)	14.745	0.303	0.078
BM	-3.453	0.095	0.035	MA(2,12)	3.922	0.179	0.051	NMA(2,12)	12.349	0.299	0.134
NTIS	-11.346	0.102	0.072	MA(3,6)	-0.174	0.129	0.052	NMM(1,9)	14.573	0.306	0.078
TBL	1.446	0.139	0.038	MA(3,9)	1.574	0.150	0.051	NMM(1,12)	17.790	0.327	-0.110
LTY	2.058	0.143	0.032	MA(3,12)	1.024	0.146	0.052	NMM(2,9)	14.758	0.308	0.087
LTR	-1.801	0.125	0.055	MOM(1)	0.238	0.133	0.046	NMM(2,12)	13.170	0.304	0.096
TMS	0.287	0.144	0.057	MOM(3)	-0.449	0.126	0.052	NM (1)	3.318	0.229	0.080
DFY	-2.160	0.096	0.044	MOM(6)	1.694	0.153	0.050	NM (3)	10.005	0.287	0.104
DFR	-0.045	0.130	0.051	MOM(9)	0.317	0.153	0.053	NM (6)	14.818	0.300	0.070
INFL	-0.263	0.129	0.050	MOM(12)	1.345	0.152	0.052	NM (12)	14.121	0.305	0.102

This table reports certainty equivalent returns (CER) of univariate regression models based on different predictors, including macroeconomic variables, technical indicators and new technical indicators. We report CER differences between assets of interest and natural benchmarks multiplied by 1200 to show annual percentages. The stock weight is restricted within a range of 0 and 1. The monthly Sharpe ratio is the mean portfolio returns in excess of the risk-free rate divided by the standard deviation of the excess portfolio returns. And the average monthly turnover is defined by the percentage of wealth traded each month. The out-of-sample period is 1947:01–2018:12.

macroeconomic variables and technical indicators, the monthly Sharpe ratio and the average monthly turnover from new technical indicators are remarkably improved. A mean-variance investor is willing to employ new technical indicators to allocate his or her portfolio.

Overall, portfolio results manifest that the predictive power of new technical indicators has economic significance.

5. Extension and robustness analysis

In this Section, we provide a series of extension and robustness analysis to further test the performance of new technical indicators in improving the predictability of stock returns. Firstly, to research the contribution of multivariate information, we employ five combination approaches presented in subsection 5.1. The business cycle is then seen as a predictable source of new technology indicators, as shown in subsection 5.2. Moreover, we calculate recursive R^2_{OoS} values to analysis how the predictability of new technical indicators evolves over time in section 5.3. Finally, we also consider the transaction cost of stock trading to test the robustness of the forecasts.

5.1. Multivariate results

In this subsection, we provide extension analysis combined multivariate information to further research the predictive ability of new technical indicators. Numerous literatures have employed the multivariate information to forecast stock returns (see, e.g., Rapach et al., 2010; Ludvigson & Ng, 2007; Rapach et al., 2016; Neely et al., 2014; Zhu & Zhu, 2013; Dangel & Halling, 2012; Wang et al., 2019; Z. Dai, Zhou, Wen, & He, 2020a; Z.F. Dai, Dong, Kang, & Hong, 2020b).

We use two strands of popular combination methods following Pettenuzzo et al. (2014). One is diffusion index method (diffusion index hereafter) where the common factor is taken as predictor to forecast stock returns:

$$r_{t+1} = \alpha + \beta_{DI} F_{DI,t} + \varepsilon_{t+1}, \quad (23)$$

$$x_{i,t} = \lambda'_i F_{DI,t} + \varepsilon_{i,t+1}, \quad (24)$$

where $F_{DI,t}$ denotes q-vector of latent factors ($q \ll N$), N denotes the total number of predictors, $N = 14$; $F_{DI,t}$ can be obtained by principal components; λ_t denotes a q-vector of factor loadings; $\varepsilon_{i,t+1}$ denotes error term assumed to follow an independent and identically normal distribution. Following Pettenuzzo et al. (2014), we employ the first principal component derived from 14 economic predictors, parsimoniously as predictor. Because it is difficult to improve the ability of out-of-sample prediction when using multiple principal components.

The second strand uses five different weighted averaging methods to combine forecasting information. The combination forecasts are computed by

$$\hat{r}_{c,t+1} = \sum_{i=1}^N \omega_{i,t} \hat{r}_{i,t+1}, \quad (25)$$

where $\omega_{i,t}$ is the combined weight of the i-th predictor; $\hat{r}_{i,t+1}$ is the forecast of i-th predictor; $\hat{r}_{c,t+1}$ is the combination forecast at t+1 month.

Following Rapach et al. (2010), the first weighted averaging methods is the mean of the predicted value (mean hereafter). In this approach, we take combination method with the same weight, that is, $\omega_{i,t}$ equals $1/N$. The second approach is median method (median hereafter). The third is trimmed mean method (trimmed mean hereafter). Unlike the mean method, we discard the smallest and largest forecast and take $\omega = 1/(N-2)$ to avoid the influence of maximum and minimum predictions in $\{\hat{r}_{i,t+1}\}_{i=1}^{14}$. In addition, discount mean squared prediction error combination approach is constructed with two value of θ , namely, 1 and 0.9 (DMSPE (1) and DMSPE (0.9) hereafter, respectively). The weight in DMSPE approach is calculated by

$$\omega_{i,t} = \varphi_{i,t}^{-1} \sum_{i=1}^N \varphi_{i,t}^{-1}, \quad (26)$$

where

$$\varphi_{i,t} = \sum_{s=m+1}^t \theta^{t-s} (r_s - \hat{r}_{i,s})^2, \quad (27)$$

θ is the discount factor, and m denotes the number of observations in-sample. DMSPE (1) and DMSPE (0.9) accord to 1 and 0.9 as discount factor to generate two discount MSPE combination approaches respectively.

Table 5 shows the multivariate prediction performance results based on macroeconomic variables, technical indicators and new technical indicators. Fortunately, all the R^2_{OoS} values of different predictors are positive, which shows that the multivariate forecasting models applied to relative predictors are significantly better than historical average. This important finding is consistent with existing literatures as in Ludvigson & Ng (2007) and Lin et al. (2018). Furthermore, after implementing new technical indicators to forecast stock returns, we find that the value of R^2_{OoS} can reach a maximum of 10.453%, with an average of 9.782%, which manifests that taking new technical indicator as predictor can significantly improve the prediction ability. Unfortunately, when combined with multivariate

Table 5
Multivariate results.

	Macroeconomic variables	Technical indicators	New technical indicators
Diffusion index	0.284**	0.095*	9.349***
Mean	0.515***	0.290*	10.453***
Median	0.396***	0.415**	8.182***
Trimmed mean	0.474***	0.336*	10.063***
DMSPE(1)	0.503***	0.287*	10.390***
DMSPE(0.9)	0.539***	0.290*	10.254***

This table reports the multivariate results of univariate regression model based on macroeconomic variables, technical indicators and new technical indicators. The forecast performance is evaluated by out-of-sample R^2 (R^2_{OoS}) multiplied by 100 to denote the percent value. In addition to diffusion index which is also called as principal component analysis (PCA), there are other popular combination methods including mean, median, trimmed mean, DMSPE (1) and DMSPE (0.9) employed to forecast stock returns. Statistical significance for positive R^2_{OoS} is measured using [Clark and West \(2007\)](#) statistic. *, ** and *** denotes significance at 10%, 5% and 1% levels, respectively. The out-of-sample period is 1947:01–2018:12.

information, the prediction performance of technical indicators is inferior to the macroeconomic variables in most case as combining approach shown above may be related to the over-fitting in forecasting stock returns.

In summary, after implementing integrated information from individual forecasts, the predictive ability of new technical indicators is more precise than existing predictors considered in this paper.

5.2. Business cycles

In this subsection, we will provide further analysis related to the business cycles to test the improved sources of expected stock returns, which have been studied in a massive amount of existing literatures (see, e.g., [Rapach et al., 2010](#); [Cochrane, 2007](#); [Neely et al., 2014](#); [Wang et al., 2018](#), [Wang et al., 2020](#)). Many studies have shown that stock returns predictability is associate with the alternation between recession and expansion periods. Following [Zhang et al. \(2019\)](#), we evaluate prediction performance linked to expansions and recessions by R^2_{OoS} for NBER-dated business cycles⁷:

$$R^2_{OoS,c} = 1 - \frac{\sum_{t=m+1}^T (r_t - \hat{r}_{t,t})^2 I_t^c}{\sum_{t=m+1}^T (r_t - \bar{r}_{t,t})^2 I_t^c}, \quad \text{for } c = \text{REC}, \text{EXP} \quad (28)$$

where c is the business cycles for recessions (REC) or expansions (EXP); I_t^c (I_t^{EXP}) is an indicator variable if month t falls into the NBER recessions (expansion) period, the value of the indicator variable is 1 and 0 otherwise.

[Table 6](#) gives the out-of-sample results considering business cycles based on macroeconomic variables, technical indicators and new technical indicators. Consistent with numerous literatures in forecasting stock returns (see, e.g., [Rapach et al., 2010](#); [Neely et al., 2014](#); [Wang et al., 2019](#)), the R^2_{OoS} values produced by any predictor during recession periods are greater than that in the expansion periods, which means that the predictability of stock returns is concentrated in the recession period. When using macroeconomic variables and technical indicators to forecast stock returns, we find that they fail to beat the historical average with negative R^2_{OoS} values in most case. However, all the new technical indicators yield positive and larger R^2_{OoS} values both in recession and expansion periods. In particular, when these four new technical indicators, NMA(1,6), NMA(1,12), NMM(1,12) and NM (12) are employed to forecast stock returns during recession periods, the R^2_{OoS} values can be improved to 11.650%, 12.156%, 12.199% and 15.273%, respectively.

Overall, combined with the business cycle, using new technical indicators can achieve better out-of-sample predictive performance both in recession and expansion.

5.3. Prediction performance over time

To test how predictability of new technical indicators over time, we begin to calculate recursive R^2_{OoS} values from January 1957, and take four new technical indicators of NMA(1,9), NMA(1,12), NMA(2,6) and NMM(1,12) for example. [Fig. 3](#) shows the trend of recursive R^2_{OoS} generated by these new predictors. Obviously, the observed predictability exhibits significant time-varying characteristics. During the 1957–1976 period, the prediction ability of new technical indicators is unstable due to the fluctuation of R^2_{OoS} values. However, all the R^2_{OoS} values are above zero after 1960 year, which indicates that new technical indicators can still achieve significant predictability of stock returns. It is noteworthy that from 1978 to 2018, the values of R^2_{OoS} were rising steadily, up to about 8%. Therefore, with the passage of time, the predictor of NMA (1,9) always has stronger predictive ability than other three indicators.

5.4. Alternative out-of-sample period

Numerous relevant literatures (e.g., [Campbell & Thompson, 2008](#); [Rapach et al., 2016](#); [Wang et al., 2019](#)) have found that the

⁷ We get NBER data of economic expansion and recession directly from the FRED Database.

Table 6

Business cycle results.

Panel A: Recession					
Macroeconomic variables		Technical indicators		New technical indicators	
Predictor	R^2_{OoS}	Predictor	R^2_{OoS}	Predictor	R^2_{OoS}
DP	1.779**	MA(1,6)	3.746***	NMA(1,6)	11.650***
DY	2.696***	MA(1,9)	3.275***	NMA(1,9)	9.807***
EP	−2.199	MA(1,12)	2.834**	NMA(1,12)	12.156***
DE	−2.641	MA(2,6)	1.781**	NMA(2,6)	9.438***
SVAR	0.662	MA(2,9)	2.724**	NMA(2,9)	8.389***
BM	−0.374	MA(2,12)	3.159**	NMA(2,12)	10.663***
NTIS	−3.716	MA(3,6)	0.333	NMM(1,9)	10.999***
TBL	1.288	MA(3,9)	1.382*	NMM(1,12)	12.199***
LTY	0.587	MA(3,12)	1.085	NMM(2,9)	7.060***
LTR	0.877	MOM(1)	1.513**	NMM(2,12)	10.957***
TMS	0.888	MOM(3)	0.477*	NM (1)	7.917***
DFY	−0.172	MOM(6)	1.799*	NM (3)	8.154***
DFR	−0.587	MOM(9)	0.815	NM (6)	9.639***
INFL	−0.419	MOM(12)	1.507*	NM (12)	15.273***
Panel B: Expansion					
Macroeconomic variables		Technical indicators		New technical indicators	
Predictor	R^2_{OoS}	Predictor	R^2_{OoS}	Predictor	R^2_{OoS}
DP	−0.727	MA(1,6)	−2.601	NMA(1,6)	4.611***
DY	−1.477	MA(1,9)	−1.213	NMA(1,9)	7.568***
EP	−1.203*	MA(1,12)	−0.391	NMA(1,12)	5.286***
DE	−1.041	MA(2,6)	−0.674	NMA(2,6)	6.639***
SVAR	−0.024	MA(2,9)	−0.576	NMA(2,9)	5.434***
BM	−1.853	MA(2,12)	0.014*	NMA(2,12)	1.513***
NTIS	0.454**	MA(3,6)	−0.199	NMM(1,9)	5.506***
TBL	−0.364	MA(3,9)	−0.065	NMM(1,12)	5.555***
LTY	−1.123	MA(3,12)	−0.509	NMM(2,9)	6.871***
LTR	−1.339	MOM(1)	−1.128	NMM(2,12)	2.160***
TMS	−0.174	MOM(3)	−0.358	NM (1)	1.038***
DFY	−0.167	MOM(6)	−0.776	NM (3)	3.642***
DFR	−0.071	MOM(9)	−1.600	NM (6)	5.576***
INFL	0.066	MOM(12)	−0.633	NM (12)	0.891***

This table reports the out-of-sample results linking to business cycle. The forecast performance is evaluated by out-of-sample R^2 (R^2_{OoS}) multiplied by 100 to denote the percent value. Statistical significance for positive R^2_{OoS} is measured using [Clark and West \(2007\)](#) statistic. *, ** and *** denotes significance at 10%, 5% and 1% levels, respectively. The out-of-sample period is 1947:01–2018:12.

out-of-sample prediction performance is instable due to the influence of out-of-sample period. Therefore, in this subsection, the robustness of the new technology indicators is further tested in two out-of-sample from 1969:01 to 2018:12 and 1989:01 to 2018:12, respectively.

[Tables 7 and 8](#) report the predictive ability of existing predictors and new technical indicators based on different out-of-sample periods, respectively. Two important observations emerge. Firstly, some of the existing predictors have a worse prediction effect with negative R^2_{OoS} values, while all R^2_{OoS} values from new technical indicators are positive, the maximum value exceeding 9.043%. This indicates that it is more stable to use new technical indicators to predict stock returns. Furthermore, all the new technical indicators have significant predictability at the level of 1% during any sample periods, which is consistent with the results in [subsection 4.2](#).

6. Conclusion

The goal of this paper is to propose some new technical indicators to obtain superior out-of-sample prediction performance for stock returns where those indicators are constructed by the trend of stock returns where the original stock returns are de-noised by wavelet transform.

Our in-sample results show that there is a significant predictive power from new technical indexes to stock returns. The out-of-sample results also indicate new technical indicators can obtain superior prediction performance. Moreover, the new technology indicators as predictors are more significant than the relative counterparts economically. Mean-variance investors are willing to use new technical indicators to predict stock returns and allocate portfolios.

Considering the multivariate information of prediction, significant predictability is also found through several combination methods. In addition, our results also have important implications for a series of other extensions and robustness analyses, including the relationship with business cycles, the predictive performance over time, and alternative out-of-sample period. Those evidences explain why new technical indicators can predict stock returns.

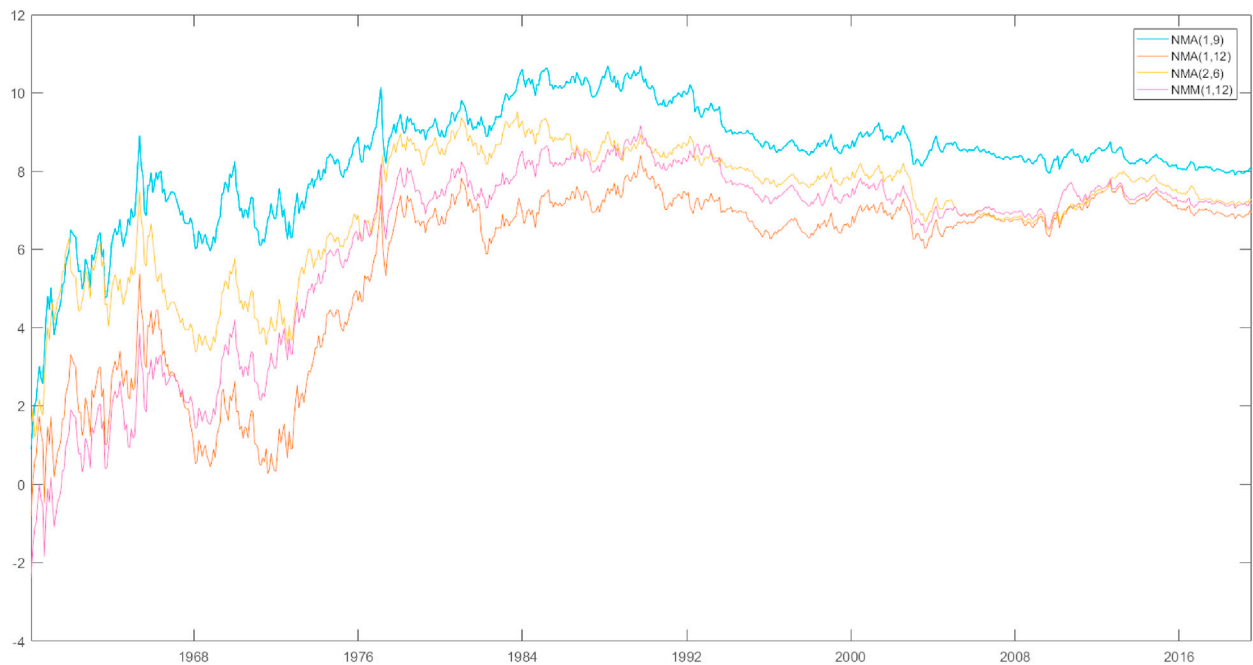


Fig. 3. Recursive out-of-sample of four new technical indicators.

Table 7

Out-of-sample results (1969.01–2018.12).

Macroeconomic variables			Technical indicators			New technical indicators		
Predictor	MSPE	R^2_{Oos}	Predictor	MSPE	R^2_{Oos}	Predictor	MSPE	R^2_{Oos}
DP	19.177	−0.190	MA(1,6)	19.311	−0.891	NMA(1,6)	17.677	7.649***
DY	19.217	−0.400	MA(1,9)	19.091	0.261*	NMA(1,9)	17.504	8.551***
EP	19.452	−1.627	MA(1,12)	19.004	0.717**	NMA(1,12)	17.410	9.043***
DE	19.456	−1.644	MA(2,6)	19.124	0.087	NMA(2,6)	17.537	8.381***
SVAR	19.095	0.240	MA(2,9)	19.052	0.462*	NMA(2,9)	17.916	6.399***
BM	19.554	−2.156	MA(2,12)	18.954	0.978**	NMA(2,12)	18.183	5.002***
NTIS	19.325	−0.963	MA(3,6)	19.171	−0.158	NMM(1,9)	17.563	8.245***
TBL	19.124	0.090*	MA(3,9)	19.063	0.404*	NMM(1,12)	17.504	8.554***
LTY	19.259	−0.619	MA(3,12)	19.115	0.133	NMM(2,9)	17.814	6.931***
LTR	19.138	0.013	MOM(1)	19.162	−0.113	NMM(2,12)	17.970	6.119***
TMS	19.107	0.178	MOM(3)	19.157	−0.082	NM (1)	18.318	4.301***
DFY	19.148	−0.036	MOM(6)	19.115	0.135	NM (3)	17.844	6.777***
DFR	19.118	0.120	MOM(9)	19.146	−0.027	NM (6)	17.709	7.479***
INFL	19.158	−0.090	MOM(12)	19.088	0.276	NM (12)	17.840	6.798***

Notes. This table reports the out-of-sample forecasting performance of macroeconomic variables, technical indicators and new technical indicators from out-of-sample from 1969.01 to 2018.12. The forecast performance is evaluated by out-of-sample R^2 (R^2_{Oos}) multiplied by 100 to denote the percent value. Univariate predictive regression model is used to generate stock returns forecasts with each predictor. *MSPE* are the mean squared predictive errors by $MSPE = \frac{1}{T-M} \sum_{t=M+1}^T (r_t - \hat{r}_t)^2$. Statistical significance for positive R^2_{Oos} is measured using Clark and West (2007) statistic. *, **, and *** denotes significance at 10%, 5% and 1% levels, respectively.

Author statement

Dr. Zhifeng Dai has made substantial contributions to the conception, design of the work, and drafted the work or revised it. Miss Huan Zhu has made substantial contributions to the acquisition, analysis, design of the work and drafted the work or revised it. Mr. Jie Kang has made contributions to the acquisition, analysis, interpretation of data for the work. All persons who have made substantial contributions to the work are reported in the manuscript. All persons have approved the final version to be published.

Table 8

Out-of-sample results (1989.01–2018.12).

Macroeconomic variables			Technical indicators			New technical indicators		
Predictor	MSPE	R^2_{OOS}	Predictor	MSPE	R^2_{OOS}	Predictor	MSPE	R^2_{OOS}
DP	17.167	−1.643	MA(1,6)	16.915	−0.151	NMA(1,6)	15.712	6.971***
DY	17.310	−2.490	MA(1,9)	16.756	0.792	NMA(1,9)	15.885	5.948***
EP	17.187	−1.762	MA(1,12)	16.760	0.765	NMA(1,12)	15.789	6.516***
DE	16.998	−0.646	MA(2,6)	16.878	0.069	NMA(2,6)	15.885	5.946***
SVAR	16.786	0.609	MA(2,9)	16.799	0.535	NMA(2,9)	16.675	1.268***
BM	17.329	−2.601	MA(2,12)	16.695	1.148	NMA(2,12)	16.592	1.763***
NTIS	17.304	−2.455	MA(3,6)	16.925	−0.211	NMM(1,9)	15.880	5.978***
TBL	16.932	−0.255	MA(3,9)	16.884	0.031	NMM(1,12)	15.843	6.194***
LTY	16.899	−0.060	MA(3,12)	16.875	0.086	NMM(2,9)	16.368	3.088***
LTR	16.884	0.032	MOM(1)	16.986	−0.576	NMM(2,12)	16.646	1.440***
TMS	17.006	−0.692	MOM(3)	16.909	−0.117	NM (1)	16.293	3.530***
DFY	16.935	−0.272	MOM(6)	16.840	0.293	NM (3)	15.617	7.532***
DFR	16.929	−0.236	MOM(9)	16.809	0.478	NM (6)	16.144	4.414***
INFL	16.976	−0.512	MOM(12)	16.781	0.643	NM (12)	15.400	8.816***

This table reports the out-of-sample forecasting performance of macroeconomic variables, technical indicators and new technical indicators for out-of-sample period is 1989:01–2018:12. The forecast performance is evaluated by out-of-sample R^2 (R^2_{OOS}) which is multiplied by 100 to denote the percent value. Univariate predictive regression model is used to generate stock returns forecasts with each predictor. MSPE are the mean squared predictive errors by $MSPE = \frac{1}{T-M} \sum_{t=M+1}^T (r_t - \hat{r}_t)^2$. Statistical significance for positive R^2_{OOS} is measured using Clark and West (2007) statistic. *, ** and *** denotes significance at 10%, 5% and 1% levels, respectively.

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