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Technical Analysis and Stock Return Predictability: An Aligned Approach

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Abstract

This paper provides an empirical evaluation of the U.S. aggregate stock market predictability based on a new technical analysis index that eliminates the idiosyncratic noise component in technical indicators. I find that the new index exhibits statistically and economically significant in-sample and out-of-sample predictive power and outperforms the well-known technical indicators and macroeconomic variables. In addition, it can predict cross-sectional stock portfolio returns sorted by size, value, momentum, and industry and generate substantial utility gains for a mean-variance investor. A vector autoregression-based stock return decomposition shows that the economic source of the predictive power predominantly comes from time variations in future cash flows (i.e., the cash flow channel).

Keywords**:** Technical analysis; Equity risk premium; Partial least squares method; Predictive regression; Cash flow channel

JEL Classification**:** C53, G11, G12

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1. Introduction

Changes in future excess stock returns affect many fundamental areas of finance, from portfolio theory to capital budgeting (e.g., Spiegel, 2008; Cochrane, 2011). Theoretically, the latent factors that drive the systematic variation of stock returns are not directly observable; therefore, researchers have proposed many predictors as proxies for these unobservable latent factors. Examples include valuation ratios, such as the dividend yield (Campbell and Viceira, 2002; Campbell and Yogo, 2006), the dividend payout ratio (Campbell and Shiller, 1988, 1998; Lamont, 1998), and book-to-market ratio (Kothari and Shanken, 1997; Pontiff and Schall, 1998), as well as nominal interest rates (Fama and Schwert, 1977; Ang and Bekaert, 2007), the inflation rate (Nelson, 1976; Campbell and Vuolteenaho, 2004), term spreads (Campbell, 1987; Fama and French, 1988), and stock market volatility (Guo, 2006). Welch and Goyal (2008), however, show that most of the economic predictors from the literature fail to generate consistently superior out-of-sample forecasts of the U.S. equity premium, and they attribute the weak predictability to their structural instability. Consequently, recent studies have devoted more attention to the application of technical indicators, a widely used strategy by market traders and investors for modern quantitative portfolio management and investment issues (e.g., Chincarini and Kim, 2006).

Technical analysis, going back at least as early as Cowles (1933), uses past prices, trading volume, and other past available data to identify price trends believed to persist into the future.[1] Brock, Lakonishok, and LeBaron (1992) and Lo, Mamaysky, and Wang (2000) find strong evidence of return predictability when using technical analysis, primarily based on a moving average strategy. Similarly, Neely et al. (2014) report that technical indicators and the popular macroeconomic variables from Welch and Goyal (2008) capture different types of information that is relevant for predicting aggregate market returns. Goh et al. (2013) also show that technical analysis can generate better performance in forecasting bond risk premiums than macroeconomic predictors. However, the predictability of technical indicators for aggregate stock market returns remains an open question. Indeed, Neely et al. (2014) show that only three of the Campbell and Thompson's (2008) R_{OS}^2 statistics for the 14 technical indicators are significantly greater than the historical average at the 5% level. Further, the forecasting power of the first principal component (PC) extracted from the technical indicators in out-of-sample periods is quite weak; the mean squared forecast error (MSFE) for the PC is marginally significantly less than the historical average MSFE at the 10% level according to the MSFE-adjusted statistics. Since out-of-sample forecasts are of great interest to practitioners for portfolio allocation and risk management, it is important to provide a method that can improve these forecasts substantially.

In this paper, I propose a new technical analysis index by employing the partial least squares (PLS) method pioneered by Wold (1966, 1975) and extended by Kelly and Pruitt (2013, 2015). Econometrically, the PC that optimally combines the total

[1] See, for example, Zhu and Zhou (2009), Zhou and Zhu (2013), and Neely et al. (2014) for the theoretical implications of technical analysis.

variations of the technical indicators should capture the best information in the predictors. Because all of the predictors are proxies for the true but unobservable latent factors, the PC can potentially contain a substantial amount of the idiosyncratic error or noise components that are irrelevant for the dynamics of the stock returns and thus fails to predict the equity risk premium, even when stock returns are indeed strongly forecastable by the true drivers of technical indicators. By contrast, the PLS method works efficiently in this case as it can identify latent factors that influence the future stock returns while discarding idiosyncratic error components that are irrelevant for forecasting. Huang et al. (2015) confirms the superiority of PLS by showing that its application significantly improves the predictability of investor sentiment. Hence, I implement the PLS method to discipline the dimension reduction and construct a new index, the aligned technical analysis index ($TECH^{PLS}$ hereafter), which indeed efficiently incorporates all the relevant forecasting information from the predictors, as shown by the forecast encompassing tests. This paper is therefore distinct from existing work: using a modern PLS approach, I provide reliable evidence that technical signals based on price patterns exhibit strong predictability of the equity risk premium. For comparison, I also consider an equal-weighted (EW) technical analysis index, $TECH^{EW}$, which places equal weight on the 14 technical indicators from Neely et al. (2014) and a PC index, $TECH^{PC}$, extracted from the same technical indicators.

If technical indicators do contain information about future market returns, the aligned technical analysis index would exhibit stronger return predictability than any individual indicator. Consistent with this expectation, in-sample tests show that the aligned technical analysis index is a statistically and economically significant predictor of the U.S. aggregate stock market over December 1955 through December 2015. In addition, $TECH^{PLS}$ produces a predictive regression R^2 of 9.279%, which is substantially greater than those of $TECH^{EW}$ and $TECH^{PC}$, with in-sample R^2s of 0.620% and 0.622%. I also compare the predictive power of $TECH^{PLS}$ with that of 14 macroeconomic predictor variables from Goyal and Welch (2008). $TECH^{PLS}$ substantially outperforms all of the macroeconomic predictors, and its superior predictability of stock returns remains intact even when I control for each of these economic proxies and their PCs. I also implement a cross-country analysis to examine the robustness of the return predictability of the aligned technical analysis index and find that it continues to substantially outperform the other indices in other developed markets, as reported in the online appendix.

Goyal and Welch (2008) show that the significant evidence of in-sample predictive ability is less relevant to the predictability of the equity risk premium based on out-of-sample tests. Therefore, I also investigate the out-of-sample predictive ability of $TECH^{PLS}$, as well as the technical indicators for the forecast evaluation period over December 1970 through December 2015. I find that the Campbell and Thompson (2008) R_{OS}^2 statistic of $\mathrm{TECH}^{\mathrm{PLS}}$ is 8.640%, which is both statistically and economically significant according to the Clark and West's (2007) MSFE-adjusted statistic, and it substantially exceeds all of the R_{OS}^2 statistics for other forecasting predictors. In addition, to mitigate the inconsistency of factor-augmented regressions, I apply both the Mallows model averaging (MMA; Hansen, 2007) and the leave-*h*-out cross-validation averaging (CVA_h; Hansen, 2010) criteria to the $TECH^{PC}$ forecast, as suggested by Cheng and Hansen (2015). $TECH^{PC}$ still fails to outperform the prevailing average benchmark in terms of MSFE. Using forecast encompassing tests, I show that forecasts based on $TECH^{PLS}$ have superior informational content relative to forecasts based on $TECH^{EW}$ and $TECH^{PC}$, which in turn confirms its superior forecasting performance with respect to out-of-sample forecasting. To address the data-snooping concern that the findings are only a special phenomenon related to the U.S. market, I also examine whether and how well the aligned technical analysis index predicts future aggregate excess stock returns in both in-sample and out-of-sample tests in the largest emerging stock market—the Chinese stock market—and obtain similar results.

In a cross-sectional analysis, I find that all of the regression slope estimates for $TECH^{PLS}$ are significantly positive, with a fairly large dispersion in the cross-section, indicating that the positive predictability of $TECH^{PLS}$ for subsequent stock returns is pervasive across characteristics portfolios sorted by size, book-to-market (BM) ratio, momentum, and industry. $TECH^{EW}$ and $TECH^{PC}$, however, forecast the corresponding characteristics portfolios only marginally. In addition, all the R^2s of $TECH^{PLS}$ are much greater than the corresponding R^2s of $TECH^{EW}$ and $TECH^{PC}$, most of which are even lower than the 0.5% threshold of Campbell and Thompson (2008). Stocks that are small, distressed (high BM ratio), or past winners are more predictable. I also examine the economic significance of the predictive ability of $TECH^{PLS}$ for a mean-variance investor who allocates between equities and risk-free bills using various equity risk premium forecasts via an asset allocation analysis. I find that $TECH^{PLS}$ produces the highest monthly Sharpe ratios for all the portfolios and generates the largest utility gains for a risk-averse investor across different levels of risk aversion. For example, a mean-variance investor would be willing to pay from 5.429% to 6.152% in annualized portfolio management fees in order to have access to the excess return forecast based on $TECH^{PLS}$ with a relatively high transaction cost equal to 50 bps per transaction. These utility gains substantially outweigh those provided by $TECH^{EW}$, $TECH^{PC}$, and 14 technical indicators. In line with the results of the out-of-sample tests, the information contained in $TECH^{PLS}$ appears to be considerably more valuable than that found in myriad commonly used return predictors from the literature.

Why does $TECH^{PLS}$ generate significantly predictive future market returns, whereas $TECH^{EW}$ and $TECH^{PC}$ do not? I present evidence that the predictive ability of $TECH^{PLS}$ predominantly operates via time variations in cash flows instead of discount rates. Specifically, I use the Campbell (1991) and Campbell and Ammer (1993) vector autoregression (VAR) approach and the information contained in macroeconomic predictor variables from Goyal and Welch (2008) to decompose total stock returns into three components: the expected return, the discount rate news component, and the cash flow news component. I find that the strong positive predictability of $TECH^{PLS}$ primarily derives from its ability to predict future cash flow news, supporting the cash flow channel. My result is robust to the use of the set of macroeconomic predictors as proxies for the market information set. This finding suggests that results of technical analyses are predictive of future aggregate market returns owing to analysts' informed anticipation of future aggregate cash flows that cannot be justified by subsequent economic fundamentals. The informational content of technical analysis thus appears to be more economically important than previously thought. The ability of $TECH^{EW}$ and $TECH^{PC}$ to be predictive of future cash flow news, however, is much weaker than that of $TECH^{PLS}$.

The rest of the paper is organized as follows. I describe the data in Section 2, including the construction of the aligned technical analysis index. In Section 3, I present both in-sample and out-of-sample predictive regression results for $TECH^{PLS}$, $TECH^{EW}$, $TECH^{PC}$, and 14 popular technical indicators based on the aggregate market index and characteristics portfolios, as well as the asset allocation analysis. In Section 4, I report the results of the VAR decomposition to glean insight into the economic underpinnings of the predictive ability of $TECH^{PLS}$. Concluding remarks are given in Section 5.

2. Data

In this section, following Kelly and Pruitt (2013, 2015), I implement the PLS method to construct the aligned technical analysis index using the monthly technical indicators from Neely et al. (2014) and then combine the index with data on the equity risk premium and popular macroeconomic predictor variables from the literature.

2.1 Technical indicators

To address the concern of data mining, I employ 14 technical indicators from Neely et al. (2014) that are based on three popular trend-chasing trading strategies. The first strategy is based on the momentum (MOM) rule, which generates a buy or sell signal at the end of month t by comparing the current stock price with its level m months ago:

$$S_{i,t} = \begin{cases} 1 & \text{if} \quad P_{i,t} \geq P_{i,t-m} \\ 0 & \text{if} \quad P_{i,t} < P_{i,t-m} \end{cases}, \tag{1}$$

where $P_{i,t}$ and $P_{i,t-m}$ represent the current price level of stock i and its momentum m months ago. $S_{i,t} = 1$ represents a buy signal as the current stock price is higher than its momentum, which indicates a strong positive market trend, and similarly, $S_{i,t} = 0$ represents a sell signal. The MOM indicator with m months momentum is defined as $MOM(m)$. I then compute the monthly signals for m = 9 and 12.

The second strategy is based on the moving average (MA) rule. I form a trading signal by comparing two MAs at the end of month t as follows:

$$S_{i,t} = \begin{cases} 1 & \text{if} \quad MA_{i,t}^{s} \geq MA_{i,t}^{l} \\ 0 & \text{if} \quad MA_{i,t}^{s} < MA_{i,t}^{l} \end{cases}, \tag{2}$$

where

$$MA_{i,t}^{m} = \frac{1}{m}\sum_{h=0}^{m-1} P_{i,t-h} \tag{3}$$

and $m = s, l$. s and l are the length of the short and long MA, respectively, and $s < l$. The corresponding MA indicator with MA lengths of s and l is thus defined as $MA(s,l)$. I compute monthly signals for s = 1, 2, 3 and l = 9, 12.

The last strategy is based on the trading volume (VOL) rule, as the change in volume is another useful measure that is frequently employed to identify market trends. The trading signal using trading volume is defined as:

$$S_{i,t} = \begin{cases} 1 & \text{if} \quad MA_{i,t}^{OBV,s} \geq MA_{i,t}^{OBV,l} \\ 0 & \text{if} \quad MA_{i,t}^{OBV,s} < MA_{i,t}^{OBV,l} \end{cases}, \tag{4}$$

where

$$MA_{i,t}^{OBV,m} = \frac{1}{m}\sum_{h=0}^{m-1} OBV_{i,t-h}, \tag{5}$$

$m = s, l$, and $OBV_{i,t}$ is the "on-balance" volume (e.g., Granville, 1963) which is calculated as:

$$OBV_{i,t} = \sum_{j=1}^{t} VOL_{i,j} \times D_{i,j}. \tag{6}$$

$OBV_{i,j}$ is a measure of the trading volume during period *j*, and $D_{i,j}$ is a binary variable that takes a value of 1 if the change in stock prices is greater than one and −1 otherwise. Intuitively, a rise in the recent price in conjunction with a relatively high recent trading volume typically indicates a strong positive market trend and thus generates a buy signal. By contrast, a decrease in the recent price together with relatively high recent trading volume usually signals a strong negative market trend. The corresponding VOL indicator with VOL lengths of *s* and *l* is thus defined as $VOL(s,l)$. I compute monthly signals for *s* = 1, 2, 3 and *l* = 9, 12.

2.2 Aligned index

If each individual technical indicator captures different aspects of the true underlying relevant common factors, then adding all of them into a single predictive multivariate regression model, known as the kitchen sink model, should improve the return predictability. However, the kitchen sink model typically behaves poorly because it suffers from a serious over-fitting issue. A solution well known in the economics literature is to use a principal component regression (PCR) as a dimension reduction to aggregate the information from proxies, as in Neely et al. (2014). Since each individual technical indicator may contain some idiosyncratic noise that is irrelevant for forecasting, the PC methodology itself is unable to separate the true yet unobservable drivers of technical indicators (latent factors) from the idiosyncratic error components. In this case, it is possible that the PCR may fail to significantly forecast future stock returns, even when stock returns are indeed strongly forecastable by the true drivers of technical indicators.

To deliver consistent forecasts, following Kelly and Pruitt (2013, 2015), I employ the partial least squares (PLS) method to extract error or noise from the expected stock returns and then construct the aligned technical analysis index. I assume that the realized excess stock return can be decomposed into two components: the conditional expectation and an unpredictable error term,

$$R^e_{t+1} = E_t(R^e_{t+1}) + \epsilon_{t+1}, \tag{7}$$

where the expected excess stock return explained by the true yet unobservable drivers of the technical indicators can be expressed as the following standard linear relation:

$$E_t(R^e_{t+1}) = \alpha + \beta \times \mathrm{TECH}_t \tag{8}$$

and ϵ_{t+1} is irrelevant to the technical indicators. Since the systematic variation of both the predictors (technical indicators) and the one-period ahead expected excess stock return is driven by latent factors, Kelly and Pruitt (2015) suggest using the following two steps of ordinary least squares (OLS) regressions to identify the latent factors from the return predictors. The PLS approach is implemented by using the following two-pass regressions. The technical indicators, $S_{i,t}$, can be decomposed into common components that are related to the expected component of excess stock returns and idiosyncratic error components that are irrelevant for the dynamics of the stock returns. Therefore, in the first step, for technical indicator *i*, I run *N* time series forecasting regressions of $S_{i,t-1}$ to extract the true but unobservable drivers of technical indicators from future stock returns:

$$S_{i,t-1} = a_i + b_i \times R_t^e + \eta_{i,t-1}, \quad t = 1,...,T, \tag{9}$$

where $S_{i,t-1}$ is one of the 14 individual technical indicators described in Section 2.1 and b_i is the coefficient that captures the sensitivity of technical indicator *i*, $S_{i,t-1}$, to the true driver instrumented by future excess stock return R_t^e. In the second step, for each time period *t*, I run *T* cross-sectional regressions of $S_{i,t}$ on the corresponding coefficient estimated in the time series regressions in equation (9), $\hat{b}_i$, to yield the aligned technical analysis index at time *t*,

$$S_{i,t} = \phi_t + TECH_t^{\text{PLS}} \times \hat{b}_i + u_{i,t}, \quad i = 1,...,N, \tag{10}$$

in which the regression coefficient $TECH^{PLS}$ is the aligned technical analysis index. Based on the theoretical results of Kelly and Pruitt (2015), the estimated second-pass coefficient $TECH^{PLS}$ is a consistent estimator of the true return-relevant driver of the technical indicators.

2.3 Macroeconomic predictor variables

To facilitate the comparison of the findings and mitigate the concern of data snooping, I employ the following 14 monthly macroeconomic variables, which are representative of those in the literature on market return predictability (Goyal and

Welch, 2008). Specifically, I include the following predictors:

1. Log dividend-price ratio, *DP*: log of a 12-month moving sum of dividends paid on the S&P 500 index minus the log of the corresponding stock prices (S&P 500 index).

2. Log dividend yield, *DY*: log of a 12-month moving sum of dividends paid on the S&P 500 index minus the log of lagged stock prices.

3. Log earnings-price ratio, *EP*: log of a 12-month moving sum of earnings on the S&P 500 index minus the log of the corresponding stock prices.

4. Log dividend-payout ratio, *DE*: log of a 12-month moving sum of dividends paid on the S&P 500 index minus the log of the corresponding 12-month moving sum of earnings.

5. Equity risk premium volatility, *RVOL*: calculated based on a 12-month moving standard deviation estimator (Mele, 2007).

6. Book-to-market ratio, *BM*: book-to-market ratio for the Dow Jones Industrial Average.

7. Net equity expansion, *NTIS*: the ratio of a 12-month moving sum of net equity issues to the total end-of-year market capitalization of New York Stock Exchange (NYSE) stocks.

8. Treasury bill rate, *TBL*: interest rate on a secondary market three-month Treasury bill.

9. Long-term yield, *LTY*: long-term government bond yield.

10. Long-term return, *LTR*: return on long-term government bonds.

11. Term spread, *TMS*: long-term yield minus the yield on the Treasury bill.

12. Default yield spread, *DFY*: difference between Moody's BAA- and AAA-rated corporate bond yields.

13. Default return spread, *DFR*: long-term corporate bond return minus the long-term government bond return.

14. Inflation, *INFL*: calculated from the Consumer Price Index (CPI) for all urban consumers. To account for the delay in CPI data releases, I use its lagged values when testing the predictive ability of inflation.

The aggregate stock market excess return is the log return on the S&P 500 index (including dividends) minus the risk-free rate. Table 1 reports the summary statistics of the data for December 1955 to December 2015. The monthly excess market return has a mean of 0.409% and a standard deviation of 4.238%, producing a monthly Sharpe ratio of 0.097. In addition, consistent with the low autocorrelation in the individual technical indicators, the persistency of the aligned technical analysis index ($TECH^{PLS}$) is quite low, with an autocorrelation coefficient of 0.430. This result indicates that the well-known Stambaugh (1999) small-sample bias is not a serious issue here. However, both the EW technical analysis index ($TECH^{EW}$) and the PC index ($TECH^{PC}$) exhibit strong autocorrelation, although it is still lower than that of most of the macroeconomic predictors. $TECH^{PC}$ indicates the first PC extracted from the 14 technical indicators, which is selected using the adjusted R^2. Finally, despite the low autocorrelation in the excess market return, 11 out of the 14 economic predictor variables are highly persistent, particularly the valuation ratios (*DP*, *DY*, and

DE) and nominal interest rates (*TBL* and *LTY*), which raises a concern of the persistent predictor bias. Therefore, in the following tests, I employ a wild bootstrap procedure with the Nicholls and Pope (1988) expression for the analytical bias of the OLS estimates (Amihud, Hurvich, and Wang, 2009) to account for this issue. In sum, the summary statistics are generally consistent with the literature.

3. Predictive regression analysis

In this section, I investigate both in-sample and out-of-sample return predictability of the technical analysis-related predictors.

3.1. Univariate in-sample analysis

I use the following standard univariate predictive regression model to analyze excess equity risk premium predictability based on each technical analysis-related predictor:

$$R^e_{t+1} = \alpha + \beta \times \mathrm{TECH}_t + u_{t+1}, \tag{11}$$

where R^e_{t+1} is the equity risk premium for month t+1 (i.e., the monthly log return on the S&P 500 index in excess of the risk-free rate); TECH_t includes the technical analysis-related variables for month t ($TECH^{PLS}$, $TECH^{EW}$, $TECH^{PC}$, and 14 technical indicators); and u_{t+1} is a zero-mean disturbance term. The null hypothesis of interest in equation (11) is that the technical analysis-related variable has an insignificant positive sign; that is, it has no predictive ability. Because finance theory suggests the positive sign of β, Inoue and Kilian (2004) recommend a one-sided alternative hypothesis to increase the power of in-sample tests. In this case, I test $H_0: \beta = 0$ against $H_A: \beta > 0$.

Technically, there are three issues that may affect the statistical inference running in-sample predictive regressions. First, the statistical inference in equation (11) may be biased when a predictor is highly persistent and correlated with the excess market return (Ferson, Sarkissian, and Simin, 2003). In addition, the *t*-statistics in the finite sample can also be distorted due to the well-known Stambaugh (1999) small-sample bias. I address these potential concerns and make more reliable inference using a Newey-West heteroskedasticity- and autocorrelation-robust *t*-statistic and computing a empirical *p*-value using a wild bootstrap procedure, as in Goncalves and Kilian (2004) and Cavaliere, Rahbek, and Taylor (2010), that accounts for the persistence in regressors, correlations between the dependent variable and predictors, and general forms of return distribution. Finally, for return predictability, the time series regression for the aligned technical analysis index $TECH^{PLS}$ in equation (9) introduces a look-forward bias as it is estimated using full-sample information in the first-step time series regressions. When the sample size is sufficiently large, this bias will vanish and thus does not distort the statistical inference (Kelly and Pruitt, 2013, 2015). However, it can still be a concern with the finite sample here. To construct a look-ahead bias-free $TECH^{PLS}$ forecast, I estimate the regression in equation (9) with information up to month t only. I run the first-pass regression using the preceding five years (60 months) of past monthly returns.[2] Then, the first-pass coefficient estimates are used as independent variables for the second-pass regression, equation (10), the coefficient of which therefore is the look-ahead bias-free $TECH^{PLS}$ at time t.

Table 2 reports the results of the predictive regression for the technical

[2] Similar results are obtained if a window size of ten years is used.

analysis-related predictors.[3] Consistent with theory, all of the predictors help predict the excess equity return for the aggregate market, and $TECH^{PLS}$ outperforms the other two indices. Specifically, $TECH^{PC}$ has a regression slope of 0.105, which is statistically significant at the 5% level based on the wild bootstrap *p*-value and an in-sample R^2 of 0.622%. These results are very similar to the earlier findings of Neely et al. (2014). Since the monthly equity risk premium inherently contains a large unpredictable component, Campbell and Thompson (2008) argue that a monthly R^2 of approximately 0.5% can represent an economically significant degree of stock return predictability. In this sense, the R^2 for $TECH^{PC}$ is slightly greater than this threshold. However, a simple index, $TECH^{EW}$, performs as well as $TECH^{PC}$, which generates a similar Newey-West *t*-statistic of 1.823 and an in-sample R^2 of 0.620%. The R^2 of $TECH^{EW}$ demonstrates that it can generate a significant degree of equity risk premium predictability. These similar estimation results also suggest that the constructed indices are robust to different combinations of weights of technical indicators. Similar to $TECH^{PC}$ and $TECH^{EW}$, $TECH^{PLS}$ is a positive return predictor for the stock market. Its *t*-statistic and in-sample R^2 are up to 8.640 and 9.279%, substantially greater than those of $TECH^{PC}$ and $TECH^{EW}$, indicating that $TECH^{PLS}$ displays the most powerful predictive ability in forecasting excess market returns.

For comparison, Panel D of Table 2 presents the predictive abilities of the 14 individual technical indicators on the stock market. As can be seen, the $TECH^{PLS}$ continues to perform the best among all the individual predictors. Specifically, all of

[3] Using the Elliott and Müller (2006) qLL statistic, I find little evidence of structural instability in the predictive regressions.

the 14 technical indicators have regression coefficients that are consistent with the theoretical predictions. However, only half exhibit significant predictive ability at the conventional level: *MA*(1,12), *MA*(2,9), *MA*(2,12), *MA*(3,9), *VOL*(1,9), *VOL*(1,12), and *VOL*(3,12). In addition, three generate *t*-statistics with marginal statistical significance at the 10% level: *MA*(1,9), *VOL*(2,9), and *VOL*(2,12). Only six of the 14 technical indicators have in-sample R^2s that are greater than the 5% threshold of Campbell and Thompson (2008): *MA*(1,12), *MA*(2,12), *MA*(3,9), *VOL*(1,12), *VOL*(2,12), and *VOL*(3,12). Interestingly, none generates a *t*-statistic that is greater than 2.2 or has an in-sample R^2 that is greater than 0.81%, indicating the relatively weak predictive power of the individual indicators. Overall, these results provide supporting evidence that an aggregate technical analysis index is more appropriate than any individual indicator.

From an economic point of view, I am also interested in analyzing the relative strength of the equity return predictability during National Bureau of Economic Research (NBER)-defined business cycles and uncertainty movements to better understand the fundamental driving forces. Following Rapach, Strauss, and Zhou (2010) and Henkel, Martin, and Nardari (2011), I compute the R^2s separately for economic expansions (R^2_{exp}) and recessions (R^2_{rec}), along with upward markets (R^2_{up}) and downward markets (R^2_{down}):

$$R_k^2 = 1 - \frac{\sum_{t=1}^{T}\left[I_t(k)(\hat{u}_{k,t})^2\right]}{\sum_{t=1}^{T}\left[I_t(k)(R_t^e - \frac{1}{T}\sum_{t=1}^{T}R_t^e)^2\right]}, \quad k = exp, rec, \text{or } up, down, \qquad (12)$$

where $I_t(exp/rec)$ is an indicator that takes a value of one when month t is in an

NBER expansion/recession period and zero otherwise. Following Stambaugh, Yu, and Yuan, (2012), $I_t(up/down)$ is defined as an indicator that takes a value of one in month t when the corresponding technical analysis-related predictor is above/below its median value for the sample period; $\widehat{u}_t$ is the fitted residual based on the in-sample estimates of the predictive regression model in equation (11). Note that in contrast to the full sample R^2 s, the subsample R^2 s can take negative values.

The results in columns (4) and (5) in Table 2 indicate that $TECH^{PLS}$ presents the strongest in-sample forecasting ability and that its forecasting power concentrates over economic expansions vis-à-vis recessions, whereas the other the technical analysis-related predictors perform much better during recessions. For example, during recessions, $TECH^{PLS}$ has an R^2_{rec} of 4.753% (versus 2.731% for $TECH^{EW}$ and 2.727% for $TECH^{PC}$). By contrast, during expansions, $TECH^{PLS}$ has an R^2_{exp} of 10.957% (versus 0.068% for $TECH^{EW}$ and 0.071% for $TECH^{PC}$). In Sections 3.2 and 3.7, I report that the relatively weak in-sample predictability of $TECH^{PLS}$ during recessions echoes its out-of-sample forecasting power and is largely due to its poor performance during the Global Financial Crisis. Regarding the individual technical indicators, I find similar results that their predictive power with respect to the equity premium is also concentrated over economic recessions. In the last two columns of Table 2, the equity risk premium predictability is substantially higher during downward markets for all of the technical analysis-related predictors, particularly for $TECH^{PLS}$. The R^2_{down} of $TECH^{PLS}$ is 12.221%, which is much greater than the R^2_{up} of 7.517%, implying that its predictive power mainly comes from downward markets.

By contrast, the predictive power of other proxies, including $TECH^{EW}$ and $TECH^{PC}$, is very weak during upward markets. For the technical analysis-related predictors except $TECH^{PLS}$, the predictive power during downward markets is weaker than that during recessions.

Overall, the in-sample regression results suggest that the aligned technical analysis index, $TECH^{PLS}$, displays the strongest forecasting power for aggregate stock market returns, and this forecasting power is much better than that of both $TECH^{PC}$ and $TECH^{EW}$. In addition, $TECH^{PLS}$ predicts the aggregate market during both expansions/recessions and upward/downward markets, although the power is generally stronger during expansions and downward markets. As such, the results confirm the superiority of the PLS approach extended by Kelly and Pruitt (2013, 2015) by eliminating the common noise component of the predictors. $TECH^{PC}$ and $TECH^{EW}$ also display significant forecasting power for the market. However, in Section 3.2, I show that the in-sample predictability of these two predictors is not sustainable out of sample.

3.2 Out-of-sample R^2_{OS}

Considering the in-sample over-fitting issue and the aim to provide more relevant information for assessing stock return predictability in real time, it is of interest to investigate out-of-sample forecasting statistics for the technical analysis-related predictors. Goyal and Welch (2008) show that the out-of-sample predictive ability of a variety of popular macroeconomic predictors seems to be less relevant than that of in-sample predictive tests. To examine the robustness of the in-sample results, we implement an out-of-sample analysis by estimating the following predictive regression model recursively, based on different measures of the technical analysis-related predictors,

$$R^e_{t+1} = \hat{\alpha}_t + \hat{\beta}_t \times \mathrm{TECH}_{1:t} \tag{13}$$

$$R^e_{t+1} = \hat{\alpha}_t + \hat{\beta}_t \times \mathrm{TECH}_{1:t}, \tag{1}$$

where TECH_t includes the technical analysis-related variables for month t ($TECH^{PLS}$, $TECH^{EW}$, $TECH^{PC}$, and 14 technical indicators), and $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the OLS estimates of α_t and β_t, respectively, based on data from the beginning of the sample through month t. I use a 15-year initial estimation window, and thus the forecast evaluation period spans December 1970 through December 2015.[4]

Following Goyal and Welch (2003, 2008), Campbell and Thompson (2008), and Neely et al. (2014), among others, I use the average excess return (HA) from the beginning of the sample through month t to serve as a prevailing and strict out-of-sample benchmark, which implies that there is no predictability in the predictor ($\beta = 0$ in equation (13)). Rapach, Strauss, and Zhou (2010) show that combination forecasts of the equity risk premium can significantly improve the forecasting performance of macroeconomic predictors. This improvement occurs because a predictive regression model that uses an individual predictor may perform well during some particular periods. Therefore, combining information in all predictors together can generate more reliable forecasts over time by reducing the model uncertainty and parameter instability associated with a single model. As such, I also employ the mean

[4] Using either rolling or recursive estimation with a window size of 10 or 15 years, I obtain similar results.

combination index ($TECH^{POST\text{-}EW}$), which is constructed using equal weights for each individual technical indicator model forecast. To compare the out-of-sample forecasting performance across different technical analysis-related predictors, I employ the Campbell and Thompson (2008) R^2_{OS} statistic, which measures the proportional reduction in MSFE for the predictive regression forecast vis-à-vis the historical average benchmark forecast,

$$R^2_{OS} = 1 - \frac{\sum_{t=p}^{T-1}(R^e_{t+1} - \hat{R}^e_{t+1})^2}{\sum_{t=p}^{T-1}\left[R^e_{t+1} - (\frac{1}{t}\sum_{j=1}^{t} R^e_j)\right]^2}. \quad (14)$$

The R^2_{OS} statistic lies in the range $(-\infty,1]$. A positive value for the R^2_{OS} statistic indicates that the out-of-sample forecast $\hat{R}^e_{t+1}$ outperforms the prevailing average benchmark forecast in terms of MSFE, whereas a negative value signals the opposite. Statistically, it is also important to ascertain whether the predictive regression forecast exhibits a significant improvement in MSFE. Hence, I use the Clark and West (2007) MSFE-adjusted statistic (CW-test hereafter) to test the null hypothesis that $H_0 : R^2_{OS} \le 0$ against $H_A : R^2_{OS} > 0$, i.e., the historical average MSFE is less than or equal to the predictive regression MSFE against the alternative hypothesis that the historical average MSFE is greater than the predictive regression MSFE. Note that the MSFE-adjusted statistic can reject the null hypothesis even if the R^2_{OS} statistic is negative since it also accounts for the negative expected difference between the historical average MSFE and the predictive regression MSFE under the null hypothesis (McCracken, 2007).

Panels A and B of Table 3 report the out-of-sample results for the predictive regression forecasts based on $TECH^{PLS}$, $TECH^{EW}$, $TECH^{PC}$, $TECH^{POST\text{-}EW}$, and the 14 technical indicators. Only the monthly R^2_{OS} statistic for $TECH^{PLS}$ reveals a positive and significant sign with the CW-test at the conventional level and thus delivers a lower MSFE than the prevailing average benchmark in terms of MSFE. Its R^2_{OS} statistic is 8.838%, which is largely comparable to the in-sample one in Table 2 and substantially exceeds all the R^2_{OS} statistics for other forecasting predictors. Matching the in-sample results, the R^2_{OS} statistics also indicate that the strong predictability of $TECH^{PLS}$ manifests over economic expansions vis-à-vis recessions. In addition, both $TECH^{EW}$ and $TECH^{POST\text{-}EW}$ display better out-of-sample predictive ability for the aggregate stock market than $TECH^{PC}$. For example, the economic magnitude of the monthly R^2_{OS} statistics for both $TECH^{EW}$ and $TECH^{POST\text{-}EW}$ are 0.425% and 0.330%, which are larger than that of $TECH^{PC}$, 0.221%, suggesting that the EW approach reduces estimation errors for index weights and that the combination forecasting approach accommodates forecast uncertainty. However, their R^2_{OS} statistics are well below that of $TECH^{PLS}$, and the CW statistics indicate that none can significantly lower the MSFE at the conventional level. The evidence for $TECH^{EW}$ and $TECH^{PC}$ further supports the notion that the forecasting performance generally does not hold up in out-of-sample analysis. A similar situation prevails when examining the individual technical indicators: only three of the predictors do not fail to outperform the historical average benchmark forecast at the 10% level, suggesting that they are instable predictors and thus have weak out-of-sample predictive ability.

To further investigate the potential bias-efficiency trade-offs in the forecasts, following Theil (1971) and Rapach, Strauss, and Zhou (2010), we decompose MSFE into two parts: the squared forecast bias, $(\bar{\hat{R}} - \bar{R})^2$, and a remainder term, $(\sigma_{\hat{R}} - \rho\sigma_R)^2 + (1-\rho^2)\sigma_R^2$, where $\bar{R} / \bar{\hat{R}}$ and $\sigma_R / \sigma_{\hat{R}}$ are the mean and standard deviation of the actual/forecasted values and ρ is the correlation coefficient between the actual and forecasted values. The squared bias (remainder term) is 0.011 (19.505) for the historical average forecast. Surprisingly, $TECH^{PLS}$ has a squared bias (0.023) slightly larger than that of the historical mean, whereas $TECH^{EW}$, $TECH^{PC}$, and $TECH^{POST\text{-}EW}$ have smaller squared biases. Nevertheless, $TECH^{PLS}$ generates the lowest remainder term (only 17.767), implying that its superior forecasting ability predominantly stems from an improvement in estimation efficiency instead of bias reduction. The smaller remainder term and slightly greater squared bias enable forecasts based on $TECH^{PLS}$ to be more efficient than the historical mean, which in turn generates a smaller MSFE (17.791) and better out-of-sample forecasting performance. All 14 predictors also exhibit MSFEs less than or equal to the historical mean. The squared biases for these variables are also smaller than or equal to that for the historical average with one exception, *VOL*(3,12), which ranges from 0.004 to 0.011. However, the individual forecasts that are less biased than the historical average do not sufficiently generate significantly lower MSFEs according to the MSFE-adjusted statistics.

One concern is that the predictive results are based on estimated regressors rather than on the original predictors. In contrast to the PLS method (Kelly and Pruitt, 2015), which is designed to handle many predictors, factor-augmented regressions can lead to biased forecasting. Hence, to address this issue, I apply the frequentist model averaging criteria to the factor-augmented forecast as suggested by Cheng and Hansen (2015). In their influential studies, Cheng and Hansen (2015) show that the Mallows model averaging (MMA; Hansen, 2007) and the leave-*h*-out cross-validation averaging (CVA$_h$; Hansen, 2010) criteria are asymptotically unbiased estimators of the MSFE in one-step and multi-step forecasts, respectively, because they are designed to minimize the MSFE, even in the presence of estimated factors. These two estimators also outperform a variety of model averaging methods, including the jackknife model averaging, the Bayesian model averaging, and the simple averaging with equal weights. The results based on MMA and CVA$_h$ are presented in Panel C of Table 3. When I account for the potential bias of the estimated factors, the PC forecast still fails to outperform the prevailing average benchmark, with R^2_{OS} statistics of -0.074% for the $TECH^{MMA}$ forecasts and -0.082% for the $TECH^{CVA}$ forecasts, respectively, both of which are insignificant.

To better understand the out-of-sample forecasting performance over time, following Goyal and Welch (2008) and Rapach, Strauss, and Zhou (2010), I present the time series plots of the differences between the cumulative squared forecast error (CSFE) for the historical average benchmark forecast and the CSFE for the predictive regression forecasts based on six indices including $TECH^{PLS}$, $TECH^{EW}$, $TECH^{PC}$, $TECH^{POST\text{-}EW}$, $TECH^{MMA}$, and $TECH^{CVA}$ in Figure 1. This figure shows that $TECH^{PLS}$ consistently outperforms the historical average from the whole sample period, with the predominantly positive curve slopes, except during certain special episodes, thus confirming the findings in Table 3 that the $TECH^{PLS}$ forecast has a lower MSFE and a greater R^2_{OS} statistic than the historical average. By contrast, the alternative indices fail to consistently outperform the historical average benchmark. Most of the indices perform slightly better in the past decade; however, their curves are negatively sloped over the periods from the mid-1980s to the early 2000s.

In summary, the out-of-sample results in Table 3 echo the in-sample results in Table 2 that the $TECH^{PLS}$ strategy substantially outperforms the prevailing mean benchmark portfolio strategy and exhibits the strongest statistically and economically significant predictability.

3.3. Forecast encompassing tests

Next, to further compare the informational content of the predictive regression forecast based on three technical analysis-related predictors ($TECH^{PLS}$, $TECH^{EW}$, and $TECH^{PC}$) to that of the individual predictive regression forecasts based on the 14 technical indicators, I conduct a forecast encompassing test. An optimal combination forecast of market return is defined as a weighted average of two competing forecasts: a predictive regression forecast based on one of the technical analysis-related predictors and the predictive regression forecast based on one of the 14 technical indicators:

$$\hat{R}^e_{t+1} = (1-\lambda)\hat{R}^e_{s,t+1} + \lambda\hat{R}^e_{m,t+1}, \quad 0 \le \lambda \le 1, \tag{15}$$

where $\hat{R}^e_{m,t+1}$ is the predictor of interest and $\hat{R}^e_{s,t+1}$ is the corresponding variable used for comparison: the predictive regression forecast based on $TECH^{PLS}$, $TECH^{EW}$, or $TECH^{PC}$ and one of the 14 technical indicators. If $\lambda > 0$, then the optimal combination forecast given by equation (15) indicates that the predictor of interest incorporates relevant information that is beyond that in the corresponding variable used for comparison and that is useful for forecasting excess returns. Alternatively, if $\lambda = 0$, then the optimal combination forecast given by equation (15) is simply $\hat{R}^{e}_{s,t+1}$, indicating that the corresponding variable used for comparison is a preferred predictor as it contains all the information present in the predictor of interest. I use a statistic developed by Harvey, Leybourne, and Newbold (1998) to test the null hypothesis that the weight on the forecast based on the predictor of interest is equal to zero against the alternative that the weight on the forecast based on the predictor of interest is greater than zero. For example, $\hat{\lambda}_{TECH \to PLS}$ represents the null hypothesis that the forecast based on a given technical indicator encompasses the competitor based on $TECH^{PLS}$ against the alternative that the competing forecast based on $TECH^{PLS}$ incorporates relevant information beyond that in the forecast based on the given technical indicator.Table 4 reports the estimates of λ in equation (15). First, in accordance with the out-of-sample tests in Table 3, the $\hat{\lambda}_{TECH \to PLS}$ estimates for $TECH^{PLS}$ are all significant at the 1% significance level and most of their magnitudes are very close to one, whereas the $\hat{\lambda}_{PLS \to TECH}$ estimates are indistinguishable from zero for all 14 technical indicators. Therefore, I reject the null hypothesis that the predictive regression forecast based on the 14 technical indicators encompasses that based on $TECH^{PLS}$ and confirm the superior informational content of $TECH^{PLS}$ relative to the technical indicators from the literature with respect to out-of-sample forecasting. Second, only four of the 14 technical indicators fail to encompass the forecasts based on $TECH^{EW}$, whereas none of the $\hat{\lambda}_{EW \rightarrow TECH}$ estimates are significant at the 10% significance level, indicating that the optimal forecast incorporates only part of the relevant information from $TECH^{EW}$. Third, in line with the weak out-of-sample performance in Table 3, $TECH^{PC}$ and the 14 technical indicators encompass each other as none can reject the null hypothesis at the conventional significance level. This finding implies that $TECH^{PC}$ does not make full use of all of the relevant forecasting information in the technical indicators.

Overall, the forecast encompassing test in Table 4 provides strong evidence that there are substantial gains from using the superior informational content of $TECH^{PLS}$ regardless of the technical indicators included in equation (15), which confirms its superior forecasting performance as reported in Table 3 with respect to out-of-sample forecasting.

3.4. Subsample analysis

In this subsection, I investigate the extent to which equity risk premium predictability of the aligned technical analysis index may remain across different sample lengths. First, the sample is divided into two periods of approximately equal length. For the in-sample regression model, the subsamples span from December 1955 to November 1985 and from December 1985 to December 2015 and the results are presented in Panel A of Table 5.

Similar to the findings using the full sample in Table 2, all the predictors generate positive signs and $TECH^{PLS}$ continues to display the strongest in-sample forecasting ability during the two subsample periods, indicating that the results are less likely due to the choice of sample length. In addition, the forecasting power of $TECH^{PLS}$ is slightly stronger in the first subsample, although $TECH^{PLS}$ displays statistically significant predictive ability at the 1% level based on the wild bootstrap *p*-values during both subsample periods. This is not surprising as the second subsample contains the recent Global Financial Crisis and the power of $TECH^{PLS}$ is generally stronger during expansions (Table 2). $TECH^{PLS}$ has a regression slope of 1.394 and an in-sample R^2 of 11.051% in the first subsample, which are substantially greater than those of the alterative predictors. The regression slope and in-sample R^2 of $TECH^{PLS}$ are slightly lower than those in the first subsample, 1.237 and 8.253%, but still the strongest predictor in the second subsample.

Next, I implement the out-of-sample analysis and use a 15-year initial estimation window such that the forecast evaluation period covers from December 1970 to December 2015. Therefore, the two corresponding subsamples span from December 1970 to November 1992 and from December 1992 to December 2015, separately. The out-of-sample forecasting results are presented in Panel B of Table 5. In line with the in-sample evidence, only the monthly R^2_{OS} statistic for $TECH^{PLS}$ reveals positive and significant signs according to the CW-test at the 1% significance level and thus delivers a significantly lower MSFE than the prevailing average benchmark. In addition, the R^2_{OS} statistic for $TECH^{PLS}$ is greater in the second subsample than in the first subsample, 10.389% versus 7.468%. This result is reasonable because the first subsample incorporates a severe market downfall period in the mid-1980s. As shown in Figure 1, the CSFE curve for $TECH^{PLS}$ is negatively sloped over that period, which indicates that the $TECH^{PLS}$ forecast fails to outperform the forecast based on the historical average benchmark. Nevertheless, $TECH^{PLS}$ continues to remain the strongest predictor in both subsamples, as it delivers the lowest MSFEs and the greatest R_{OS}^2 statistics.

Taken together, the subsample evidence demonstrates that the findings in Tables 2 and 3 are robust, as $TECH^{PLS}$ presents the strongest forecasting ability across different sample lengths, whereas the alternative predictors cannot.

3.5. Can the aligned index predict aggregate market returns in China?

In this subsection, I investigate whether and how well the aligned technical analysis index can predict changes in future aggregate excess stock returns in the Chinese equity market. As such, the research helps determine whether the superior performance of the aligned technical analysis index is a special phenomenon related to the U.S. market. If not, to what extent can it help predict monthly excess stock returns in the case of China? Furthermore, providing out-of-sample evidence to support results beyond the U.S. market can mitigate the data snooping concern pointed out by Lo and MacKinlay (1990). The Chinese data come from the China Stock Market & Accounting Research (CSMAR) Database and cover from February 1992 to December 2016 for the Shanghai Stock Exchange (SHSE) and from October 1993 to December 2016 for the Shenzhen Stock Exchange (SZSE). The aggregate stock market excess returns are the log return on the A-share composite index (including dividends) minus the risk-free rate on the SHSE and the SZSE, respectively. For the out-of-sample forecast, I use a five-year initial estimation window.

Panels A and B of Table 6 present the results of the in-sample predictive regression. There is strong evidence that $TECH^{PLS}$ is also predictive of the excess stock returns in the Chinese markets, confirming the findings in the U.S. market. Specifically, $TECH^{PLS}$ generates Newey-West t-statistics of 3.896 and 2.821 and in-sample R^2 of 3.705% and 5.358% for the SHSE and the SZSE, respectively, both of which clear the Campbell and Thompson (2008) hurdle. By contrast, among the alternative predictors (14 technical indicators, $TECH^{EW}$, and $TECH^{PC}$), only two on both the SHSE and the SZSE are significant at the conventional level. Most of the R^2s for these predictors, however, are greater than those for the U.S. results but are still well below that of $TECH^{PLS}$.

Panels C and D of Table 6 report the out-of-sample results. Only the monthly R^2_{OS} statistics for $TECH^{PLS}$ reveal statistically significantly positive signs with the CW-test at the 1% level and thus deliver lower MSFEs than the prevailing average benchmark. Its R^2_{OS} statistics are 2.337% and 5.908% for the SHSE and the SZSE, respectively, exceeding all of the R^2_{OS} statistics. When examining the alternative predictors, both $TECH^{EW}$ and $TECH^{PC}$ and almost all 14 technical indicators fail to outperform the historical average benchmark forecast in terms of the CW-tests, consistent with the in-sample results that they have weak predictive ability.

It is somewhat surprising that the Chinese equity market appears to be less predictive than the U.S., as the return predictability of the technical analysis-related predictors in Table 6 is weaker than that in Tables 2 and 3. Intuitively, the U.S. market is more sophisticated and should have less predictability. I show that there are three essential reasons for the difference in return predictability between China and the U.S. First, technical analysis is closely related to the momentum anomaly, whereas the momentum effect is much weaker in China than that in the U.S. For example, Rouwenhorst (1999) and Griffin, Ji, and Martin (2003) find weaker momentum profits for emerging markets. Cheema and Nartea (2014) further confirm that the momentum effect in China is less persistent than that in the U.S. Accordingly, the weak momentum anomaly may deteriorate the predictive ability of the technical analysis, which in turn weakens the technical analysis index. Indeed, none of the MOM predictors (*MOM*(9) and *MOM*(12)) in Table 6 exhibit significant forecasting power in the out-of-sample tests, and half even reveal negative R_{OS}^2 s. Second, the Chinese equity market is less trending than in the U.S. Han, Yang, and Zhou (2013) show that the MA timing strategy greatly outperforms the buy-and-hold strategy and generates substantial gains in the cross-section of stock returns. The abnormal returns remain mostly over 5% per annum even when considering a lag length of 200 days for the MAs. However, Han et al. (2014) find that using the same MA strategy in the Chinese equity market generates significant abnormal returns only for much shorter MA prices. Therefore, the weaker performance of the technical indicators may reflect the application of the same lag length to the technical indicators as in the U.S. Third, the SHSE was established in December 19, 1990 and the SZSE was established in July 3, 1991, and the data used in the above tests cover the initial periods for both the SHSE and the SZSE, whereas the return patterns may be different in the initial periods; both exchanges adopted daily price change limits of 10% after December 16, 1996. In unreported tables, I show that using shorter lag lengths and adopting the post-1996 sample indeed significantly improves return predictability in the Chinese equity market. The SHSE and SZSE are both found to be more predictive than the U.S. market, with greater in-sample R^2 and R^2_{OS} statistics. For example, the monthly R^2_{OS} statistics for $TECH^{PLS}$ are 8.364% for the SHSE and 11.370% for the SZSE, respectively, both of which are statistically significant at the 1% level according to the CW-test. In addition, $TECH^{PLS}$ continues to outperform all the competing predictors with substantial margins.

Overall, both in-sample and out-of-sample predictive regression results suggest that $TECH^{PLS}$ exhibits the strongest statistically and economically significant market return predictability in the Chinese stock markets.

3.6 Forecasting characteristics portfolios

In this subsection, I investigate the cross-sectional implications of the $TECH^{PLS}$ predictor. That is, I test whether and how well it can forecast portfolios sorted by size, BM, momentum, and industry, which helps enhance our understanding of the economic sources of equity risk premium predictability.

To address the concern that the predictability of technical analysis-related variables arises because they share comovements with macroeconomic predictors, we consider the following in-sample predictive regression model:

$$R^{e,p}_{t+1} = \alpha_p + \beta_p \times \mathrm{TECH}_t + \sum_{i=1}^{2} \gamma_i^p \times \widehat{f}_{i,t} + u^p_{t+1}, \qquad (16)$$

where TECH_t includes the technical analysis-related variables for month t ($TECH^{PLS}$, $TECH^{EW}$, and $TECH^{PC}$), $\widehat{f}_1$, and $\widehat{f}_2$ are the first two PCs extracted from the entire set of Goyal and Welch (2008) variables, and $R_{t+1}^{e,p}$ denotes the monthly excess returns for the 10 size, 10 BM, 10 momentum, and 10 industry portfolios, respectively. The null hypothesis of interest in equation (16) is that $TECH_t$ has no predictive ability, $H_0: \beta_p = 0$, against the alternative hypothesis, $H_A: \beta_p > 0$.

Table 7 reports the estimation results for in-sample predictive regressions for 10 size-sorted (Panel A), 10 BM-sorted (Panel B), 10 momentum-sorted (Panel C), and 10 industry (Panel D) portfolios, using data from Kenneth French's Data Library. In accordance with the findings for aggregate stock market predictability in Tables 2 and 3, $TECH^{PLS}$ substantially enhances the return forecasting performance relative to $TECH^{EW}$ and $TECH^{PC}$ across all portfolios: the in-sample R^2s of $TECH^{PLS}$ are much greater than the corresponding R^2s of the latter two predictors. This finding indicates that the results are robust in different portfolio specifications. Specifically, the regression slope βs on $TECH^{PLS}$ are statistically significant at the conventional level, whereas a variety of the slopes on $TECH^{EW}$ and $TECH^{PC}$ are insignificant at the 5% or lower level of significance. The R^2s also indicate that $TECH^{PLS}$ exhibits strong significant predictive ability. Most of the R^2s for $TECH^{EW}$ and $TECH^{PC}$, however, are even lower than the 0.5% threshold demonstrated in Campbell and Thompson (2008).

In addition, there is a fairly large dispersion of regression estimates in the cross-section. The results from $TECH^{PLS}$ show that stocks that are small, with less growth opportunity (high BM ratio), or that are past winners are more predictable. $TECH^{PLS}$ also sharply improves the forecasting performance of portfolios formed on nondurable, durable, manufacture, telecom, utility, and other industries, whereas shop and energy present the lowest predictabilities. Interestingly, the regression coefficients on the size portfolios monotonically increase in absolute value from large to small firms, and this increasing pattern is found to be a true feature of the data that is statistically significant at the 5% significance level based on the monotonicity test of Patton and Timmermann (2010).

3.7. Asset allocation

In this subsection, I measure the economic value of the technical analysis-related predictors' predictive ability from an asset allocation perspective. Following Campbell and Thompson (2008) and Neely et al. (2014), among others, I compute the certainty equivalent return (CER) gain (i.e., the risk-free rate of return that a risk-averse investor is willing to accept rather than adopting the given risky equity portfolio) and Sharpe ratio for a mean-variance investor who optimally allocates across equities and the risk-free asset using the out-of-sample predictive regression forecasts of excess stock returns. At the end of month *t*, the investor optimally allocates the following share of his/her portfolio to equities during month *t*+1:

$$\omega_t = \frac{1}{\gamma} \frac{R^e_{s,t+1}}{Var(R^e_{s,t+1})}, \tag{17}$$

where γ is the coefficient of relative risk aversion, $R^e_{s,t+1}$ is the out-of-sample forecast of the excess market return, and $Var(R^e_{s,t+1})$ is the corresponding forecast of the excess return variance. As such, the investor allocates the share $1-\omega_t$ to the risk-free asset, and the realized portfolio return at month *t*+1 is:

$$R^e_{p,t+1} = \omega_t R^e_{s,t+1} + R^f_{t+1}, \tag{18}$$

where R_{t+1}^{f} is the risk-free return. Following Neely et al. (2014), I assume that the variance of the equity risk premium is estimated using a five-year moving window of past monthly returns. To impose the investor's leverage ability and produce better-behaved portfolio weights, I also assume that the share that the investor allocates to the risky portfolio is constrained between -0.5 and 1.5. The investor's CER or the average utility of the portfolio is given by:

$$\text{CER}_{p} = \mathbb{E}(R_{p,t+1}^{e}) - \frac{\gamma}{2} Var(R_{p,t+1}^{e}), \tag{19}$$

where $\mathbb{E}(R_{p,t+1}^{e})$ and $Var(R_{p,t+1}^{e})$ are the sample mean and variance, respectively, for the investor's portfolio over the forecast evaluation period. We also compute the CER for the historical average forecast. The CER gain is defined as the difference between the CER for the investor who uses an out-of-sample predictive regression forecast of market return based on equation (19) and that for an investor who uses the historical average benchmark forecast. In this way, we can interpret the CER gain as the portfolio management fee that an investor would be willing to pay to have access to the predictive regression forecast instead of the prevailing average benchmark forecast. For comparison, I annualize the CER gain by multiplying it by 1200. To examine the effect of relative risk aversion, I consider portfolio performance based on risk aversion coefficients of 1, 3, and 5, respectively. In addition, I also consider the case of a relatively high transactions cost equal to 50 bps per transaction.

The results for the 14 technical indicators, along with the corresponding $TECH^{PLS}$, $TECH^{EW}$, and $TECH^{PC}$ are presented in Table 8. Of all the technical analysis-related indices, the performance of $TECH^{PLS}$ clearly stands out across the levels of risk aversion. Consistent with the large R_{OS}^2 statistics in Table 3, the forecast based on $TECH^{PLS}$ outperforms the prevailing average benchmark forecast in terms of the Sharpe ratio and provides a hefty CER gain for a mean-variance investor, from 11.181% when the risk aversion is one to 7.268% when the relative risk aversion coefficient is five. The net-of-transactions-costs CER gains for $TECH^{PLS}$ is a little lower but also reaches a very sizable amount, ranging from 5.429% to 6.152%. The gains accruing to $TECH^{PLS}$ are approximately two to seven times higher than those accruing to the best of the technical indicators. In addition, $TECH^{PLS}$ produces the highest monthly Sharpe ratio among the portfolios, ranging from 0.199 to 0.273, which is always greater than the prevailing average and more than double the market Sharpe ratio, 0.096, with a buy-and-hold strategy (Table 1). For both $TECH^{EW}$ and $TECH^{PC}$, the forecast based on $TECH^{EW}$ performs slightly better than the forecast based on $TECH^{PC}$, consistent with the out-of-sample results in Table 3. The CER gains for these two predictors remain well above 700 bps when the risk aversion is one, whereas they are reduced substantially to below 160 bps when the relative risk aversion coefficient is five, indicating that the gains generated from $TECH^{EW}$ and $TECH^{PC}$ are somewhat sensitive. Their volatile CER gains also lead to relatively smaller Sharpe ratios that vary from 0.106 to 0.144.

To further investigate the behavior of the monthly portfolio based on the aligned technical analysis index, Figure 2 depicts equity weights and the cumulative wealth for the monthly portfolios based on $TECH^{PLS}$, $TECH^{EW}$, $TECH^{PC}$, and the prevailing average benchmark. The equity weight for the portfolio based on the prevailing average is relatively stable throughout the out-of-sample period, largely because of its smooth prevailing average benchmark forecasts. By contrast, the equity weight for the portfolio based on $TECH^{PLS}$ exhibits substantial fluctuations, which enables it to respond more quickly to the changes in the market. The timely adjustment of equity weights, however, comes at a cost as they generate much higher average turnovers, nearly twice the historical average portfolio. Nevertheless, the adept market timing improves the net-of-transactions-costs CER by approximately 500 bps.

Panels B and C of Figure 2 reveal that both $TECH^{PLS}$ and the prevailing average portfolio suffer from a major drawdown during the Global Financial Crisis as they take the "wrong" position in equity investment during this period. Specifically, unlike the portfolios based on $TECH^{EW}$ and $TECH^{PC}$, which remain aggressively short during the Great Recession, the portfolio based on $TECH^{PLS}$ takes a short equity position in the early stages, abruptly moves to an aggressive long position in early 2008, and then takes a short equity position with increasing weights during the "recovery" from the Great Recession. The evidence presented here echoes the in-sample and out-of-sample results in Tables 2 and 3 that the forecasting power of $TECH^{PLS}$ concentrates over economic expansions vis-à-vis recessions. The prevailing average portfolio also tells a similar story. Despite this drawdown during the Financial Crisis, $TECH^{PLS}$ performs significantly well in other situations, as the timely adjustment of equity weights for $TECH^{PLS}$ enables it to take aggressive short (long) positions and therefore offers striking gains in both bull and bear markets.

The results demonstrate that the information in $TECH^{PLS}$ has substantial economic value for a mean-variance investor, much more than for $TECH^{EW}$, $TECH^{PC}$, and the 14 technical indicators (as well as the buy-and-hold strategy). Accounting for the transaction costs, an investor with a risk aversion of 1, 3, or 5 would be willing to pay an annual portfolio management fee of up to 5.645%, 6.152%, and 5.429%, respectively, to have access to the predictive regression forecast based on $\mathrm{TECH}^{\mathrm{PLS}}$ instead of using the prevailing average benchmark forecast. Despite a major drawdown during the recent Global Financial Crisis, $TECH^{PLS}$ performs significantly well in other situations, as the timely adjustment of equity weights for $TECH^{PLS}$ enables it to take aggressive short (long) positions and therefore generates substantial gains in both bull and bear markets. Zhu and Zhou (2009) provide theoretical explanations for an investor to use a standard asset allocation model and show that the use of technical signals based on price patterns adds value to allocation rules that invest fixed proportions of wealth in equities. My empirical results complement their theoretical models and provide strong evidence that technical analysis improves investors' asset allocation performance even with time-varying weights of wealth in equities.

4. Economic explanations

Why is the aligned technical analysis index predictive of future market returns? In this section, I explore the economic driving force of the predictability of $TECH^{PLS}$ by implementing stock return decomposition. Following Campbell (1991) and Campbell and Ammer (1993), I first decompose the log market return into the news components by using the VAR methodology, and then analyze whether the technical analysis-related predictors are able to forecast future aggregate stock returns by anticipating the discount rate and/or cash flow news. As in Campbell and Shiller (1988), the log-linear approximation of r_{t+1} is defined as:

$$r_{t+1} \approx k + \rho p_{t+1} + (1-\rho) d_{t+1} - p_t, \tag{20}$$

where $r_{t+1} = \log(P_{t+1} + D_{t+1}) - \log(P_t)$, P_t, and D_t are the stock price and dividend in month *t*; p_t and d_t are their corresponding log values; and the coefficient ρ is slightly smaller than one and is defined as $\rho = 1/[1 + exp(\overline{d-p})]$, in which $\overline{d-p}$ is the mean of $d_t - p_t$; $k = -\log(\rho) - (1-\rho)\log[(1/\rho) - 1]$.

By imposing the no-bubble transversality condition ($\lim_{j\to\infty} \rho^j p_{t+j} = 0$), Campbell and Shiller (1988) show that the log stock return can be decomposed into three components: the expected return component $E_t[r_{t+1}]$, the cash flow news component, and the discount rate news component:

$$r_{t+1} = E_t[r_{t+1}] + \xi_{t+1}^{CF} - \xi_{t+1}^{DR}, \tag{21}$$

where E_t denotes the expectation operator conditional on information through month *t*. The cash flow news component is given by $\xi_{t+1}^{CF} = (E_{t+1} - E_t)\sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j}$, and the discount rate news component is given by $\xi_{t+1}^{DR} = (E_{t+1} - E_t)\sum_{j=1}^{\infty} \rho^j r_{t+1+j}$. Equation (21) indicates that the stock returns represent the time variation in cash flow news (changes in market expectations of current and future cash flows), time variation in discount rate news (changes in market expectations of future discount rates), and/or an expected return component. I define the stock return innovation as $\xi_{t+1}^{r} = r_{t+1} - E_t[r_{t+1}]$.

Following Campbell (1991) and Campbell and Ammer (1993), the cash flow and discount rate news components are extracted by applying a VAR framework. To implement the return decomposition, I use the following first-order VAR model:

$$y_{t+1} = \Phi y_t + \epsilon_{t+1}, \tag{22}$$

in which y_t is a vector of *n* elements and the variables are $y_t = (r_t, d_t - p_t, x_t')'$, x_t' is vector of $n-2$ predictor variables, which is a series of predictors from Goyal and Welch (2008) as proxies for the market information set; Φ is an $n \times n$ matrix of VAR slope coefficients; ϵ_t is a zero-mean innovation vector of *n* elements. Note that we always include the log dividend-price ratio $d_t - p_t$ in the VAR, as Engsted, Pedersen, and Tanggaard (2012) show that it is important to include this variable in the VAR to properly estimate the cash flow and discount rate news components. Defining $e_1' \equiv [1, 0, \ldots, 0]$, the stock return innovation and the discount rate news component can be expressed as

$$\xi_{t+1}^{r} = e_1' \epsilon_{t+1}, \tag{23}$$

$$\xi_{t+1}^{DR} = e_1' \rho \Phi (I - \rho \Phi)^{-1} \epsilon_{t+1}. \tag{24}$$

Similarly, in terms of equation (22), the expected stock return for *t*+1 based on information through *t* is given by $E_t[r_{t+1}] = e_1' \Phi y_t$. Using equation (21), the cash flow news component is then defined as:

$$\xi_{t+1}^{CF} = \xi_{t+1}^{r} + \xi_{t+1}^{DR}. \tag{25}$$

To explore the economic underpinnings of the technical analysis-related predictors' predictability, I consider the following predictive regression models for the estimates of the individual components in equation (21) for $t = 1, \ldots, T-1$:

$$\hat{E}_t[r_{t+1}] = \alpha_{\hat{E}} + \beta_{\hat{E}} \times \mathrm{TECH}_t + u_{t+1}^{\hat{E}}, \tag{26}$$

$$\hat{\xi}_{t+1}^{CF} = \alpha_{CF} + \beta_{CF} \times \mathrm{TECH}_t + u_{t+1}^{CF}, \tag{27}$$

$$\hat{\xi}_{t+1}^{DR} = \alpha_{DR} + \beta_{DR} \times \mathrm{TECH}_t + u_{t+1}^{DR}, \tag{28}$$

where TECH_t includes the technical analysis-related variables for month *t* ($TECH^{PLS}$, $TECH^{EW}$, and $TECH^{PC}$). By comparing the estimated coefficients, β, in equations (26)–(28), we can ascertain the extent to which the technical analysis-related predictors can forecast aggregate stock market returns. In order to implement the VAR methodology, I need to address the concern on the high degree of persistency in the Goyal and Welch (2008) predictors. Because employing unit-root series in the VAR system can lead to biased estimates, I start by presenting both augmented Dickey-Fuller and Phillips-Perron test statistics. The results show that I can reject at the 5% significance level the null hypothesis that six economic predictors (i.e., *RVOL*, *LTR*, *TMS*, *DFY*, *DFR*, and *INFL*) are unit root processes. Hence, I use first-order difference variables for the remaining nonstationary predictors before estimating the VAR.

Table 9 reports the results. The $\hat{\beta}_{CF}$ and $\hat{\beta}_{DR}$ slope estimates of $TECH^{PLS}$ for two different components in the predictive regression, equations (27) and (28), are all statistically significant at the 5% level, signaling the strong market return predictability of $TECH^{PLS}$ in Tables 2 and 3. However, the $\hat{\beta}_{\hat{E}}$ slope estimates are insignificant in most of the regressions and thus contribute little to the predictability of $\mathrm{TECH}^{\mathrm{PLS}}$. In addition, the $\hat{\beta}_{DR}$ slope estimates contribute only a relatively small portion of equity risk premium predictability, although they are more statistically significant and typically larger in magnitude than the OLS estimates of $\hat{\beta}_{\hat{E}}$. By contrast, the $\hat{\beta}_{CF}$ slope estimates are statistically significant and much more sizable (about three to five times larger than the $\hat{\beta}_{DR}$ slope estimates), signaling an economically important source of $TECH^{PLS}$'s predictive power for aggregate stock market returns.

In sharp contrast to $TECH^{PLS}$, nearly all the $\hat{\beta}_{CF}$ and $\hat{\beta}_{DR}$ slope estimates are statistically insignificant at the 5% level for both $TECH^{EW}$ and $TECH^{PC}$. The weak predictability for both the cash flow and discount rate news components jointly indicate their weak predictive power for excess market returns.

Note that equation (21) indicates that the log stock return is the sum of the three components: the expected return component, the cash flow news component, and the discount rate news component. Hence, based on the properties of OLS, the sum of the OLS estimates of $\hat{\beta}_{\hat{E}}$, $\hat{\beta}_{CF}$, and $\hat{\beta}_{DR}$ should be equal to the OLS estimate of $\hat{\beta}_{\mathrm{PLS}}$, which is estimated using the following predictive regression model for the log stock return based on $TECH^{PLS}$:

$$R_{t+1} = \alpha_{\mathrm{PLS}} + \beta_{\mathrm{PLS}} \times TECH_t^{PLS} + v_{t+1}. \tag{29}$$

The OLS estimate of $\hat{\beta}_{\mathrm{PLS}}$ is 1.299, with a Newey-West *t*-statistic of 8.928, which is very similar to excess return results presented in Table 2. This finding makes sense because changes in log stock returns clearly dominate the fluctuations in log excess returns. More importantly, the sum of the three OLS estimates ($\hat{\beta}_{\hat{E}}$, $\hat{\beta}_{CF}$, and $\hat{\beta}_{DR}$) always equals the $\hat{\beta}_{\mathrm{PLS}}$ slope estimate for all the VAR variable sets. On average, the $\hat{\beta}_{CF}$ slope estimate explains approximately 77.9% of the OLS estimate of $\hat{\beta}_{\mathrm{PLS}}$, whereas the $\hat{\beta}_{DR}$ slope estimate only explains approximately 18.8%. The $\hat{\beta}_{\hat{E}}$ slope estimate contributes the least: approximately 3.3%.

Taken together, the VAR-based return decomposition reiterates the notion that the strong positive predictability of $TECH^{PLS}$ derives from its ability to forecast the cash flow news component, while the discount rate news component has little explanatory power. In addition, I fail to find consistent evidence that $TECH^{EW}$ and $TECH^{PC}$ affect any components of stock returns, consistent with their weak return predictability in both in-sample and out-of-sample forecasting.

5. Concluding remarks

In this paper, I propose a new aligned technical analysis index ($TECH^{PLS}$) that is constructed by incorporating 14 well-known technical indicators from Neely et al. (2014) using the PLS method suggested by Kelly and Pruitt (2013, 2015). I document that the $TECH^{PLS}$ index is a statistically and economically significant predictor of the aggregate stock market over December 1955 through December 2015. Indeed, this index is a powerful predictor of future market excess returns. In-sample results show that the $TECH^{PLS}$ index consistently exhibits stronger predictive power than the EW index, the PC index, and 14 individual technical indicators and that its predictability is both statistically and economically significant. $TECH^{PLS}$ continues to perform well after I control for 14 popular macroeconomic predictor variables from Goyal and Welch (2008). In out-of-sample tests for the forecast evaluation period spanning from December 1970 to December 2015, a predictive regression forecast based on $TECH^{PLS}$ outperforms the prevailing average benchmark in terms of MSFE by a statistically and economically significant margin according to the CW-test statistic. The information contained in the $TECH^{PLS}$-based forecast dominates the information found in forecasts based on 14 individual technical indicators. Consistently, the evidence from the Chinese equity market confirms that $TECH^{PLS}$ does a good job of forecasting returns based on both in-sample and out-of-sample tests, which mitigates the data-snooping concern. Furthermore, $TECH^{PLS}$ successfully forecasts cross-sectional stock returns, including portfolios sorted by size, BM, momentum, and industry, and generates substantial utility gains for a mean-variance investor across levels of risk aversion relative to $TECH^{EW}$ and $TECH^{PC}$, where the gains are especially large due to better tracking of the substantial fluctuations in economic expansions. Finally, after I control for the information in popular macroeconomic predictors from the literature, $TECH^{PLS}$ anticipates future aggregate cash flows, suggesting that the strong ability of $TECH^{PLS}$ to forecast aggregate stock market returns largely stems from the cash flow channel rather than discount rate channel.

Overall, the results show that the aligned technical analysis index substantially improves the forecastability of the equity risk premium at either the aggregate level or the portfolio level. The work complements early studies by Neely et al. (2014) and many others, who document that technical analysis plays an important role in equity risk premium predictability. Its superior performance arises because the PLS approach eliminates the idiosyncratic error components of predictors that is irrelevant to returns from the estimation process and thus more efficiently exploits all the relevant forecasting information in the technical indicators. These findings are of economic importance from an investment perspective. Various investment and forecasting issues that have been previously investigated can also be examined with the PLS strategy. All of these are interesting topics for future research.

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Table 1. Summary statistics

The table ***provides summary statistics for the equity risk premium, the*** aligned technical analysis index ***(**$TECH^{PLS}$**), the equal-weighted index (**$TECH^{EW}$**), and the principal component index (**$TECH^{PC}$**). We also consider 14 technical indicators from Neely et al. (2014): six moving-average indicators (**$MA(s, l)$for s = 1, 2, 3 and l = 9, 12***), two momentum indicators (***$MOM(m)$ for m = 9 and 12***), and six trading volume indicators (***$VOL(s, l)$ for s = 1, 2, 3 and l = 9, 12***), and 14 economic predictor variables from Goyal and Welch (2008): the log dividend-price ratio (*DP*), log dividend yield (*DY*), log earnings-price ratio (*EP*), log dividend-payout ratio (*DE*), stock return variance (RVOL), book-to-market ratio (*BM*), net equity expansion (*NTIS*), Treasury bill rate (*TBL*), long-term bond yield (*LTY*), long-term bond return (*LTR*), term spread (*TMS*), default yield spread (*DFY*), default return spread (*DFR*), and inflation rate (*INFL*). For each variable, the time-series average (Mean), median (***Median***), standard deviation (***Std. dev.***),*** 1st percentile***,*** 99th percentile, ***and first-order autocorrelation (***rho***) are reported. The sample period is*** December 1955 to December 2015.

Variable	Mean	Median	1st percentile	99th percentile	Std. dev.	rho
Equity Return (%)	0.409	0.832	-11.060	10.192	4.238	0.057
$TECH^{PLS}$	0.000	0.030	-3.312	3.133	1.000	0.430
$TECH^{EW}$	0.694	0.929	0.000	1.000	0.392	0.911
$TECH^{PC}$	0.000	1.939	-5.632	2.480	3.184	0.911
$MA(1,9)$	0.679	1.000	0.000	1.000	0.467	0.694
$MA(1,12)$	0.706	1.000	0.000	1.000	0.456	0.773
$MA(2,9)$	0.681	1.000	0.000	1.000	0.467	0.757
$MA(2,12)$	0.703	1.000	0.000	1.000	0.457	0.820
$MA(3,9)$	0.686	1.000	0.000	1.000	0.464	0.790
$MA(3,12)$	0.704	1.000	0.000	1.000	0.457	0.823
$MOM(9)$	0.701	1.000	0.000	1.000	0.458	0.757
$MOM(12)$	0.721	1.000	0.000	1.000	0.449	0.807
$VOL(1,9)$	0.674	1.000	0.000	1.000	0.469	0.595
$VOL(1,12)$	0.701	1.000	0.000	1.000	0.458	0.695
$VOL(2,9)$	0.671	1.000	0.000	1.000	0.470	0.755
$VOL(2,12)$	0.703	1.000	0.000	1.000	0.457	0.814
$VOL(3,9)$	0.690	1.000	0.000	1.000	0.463	0.762
$VOL(3,12)$	0.697	1.000	0.000	1.000	0.460	0.832

DP	-3.565	-3.498	-4.459	-2.865	0.390	0.994
DY	-3.559	-3.491	-4.465	-2.860	0.390	0.994
EP	-2.823	-2.856	-4.372	-1.988	0.418	0.989
DE	-0.742	-0.740	-1.237	0.817	0.306	0.987
RVOL	14.268	13.517	5.959	30.185	4.967	0.963
BM	0.509	0.487	0.132	1.122	0.250	0.994
NTIS	0.013	0.015	-0.048	0.045	0.019	0.979
TBL	0.046	0.046	0.000	0.147	0.031	0.990
LTY	0.064	0.060	0.022	0.138	0.027	0.994
LTR	0.006	0.004	-0.060	0.084	0.029	0.037
TMS	0.017	0.017	-0.018	0.044	0.015	0.957
DFY	0.010	0.009	0.004	0.026	0.004	0.969
DFR	0.000	0.001	-0.042	0.039	0.014	-0.080
INFL	0.003	0.003	-0.005	0.012	0.003	0.622

Table 2. *Predictive regression estimation results*

The table ***presents the*** *results for the following in-sample predictive regression model*

$$R^e_{t+1} = \alpha + \beta \times \mathrm{TECH}_t + u_{t+1}\,,$$

where R^e_{t+1} ***is the equity risk premium for month*** t+*1* ***(i.e., the monthly log return on the S&P 500 index in excess of the risk-free rate);*** TECH_t ***includes the technical analysis***-related ***variables for month*** **t*; and*** u_{t+1} *is* ***a zero-mean disturbance term.*** *Panels A, B, C, and D present estimates of* β *and* R^2*s for the* aligned technical analysis index ***(***$TECH^{PLS}$***), the equal-weighted index (***$TECH^{EW}$***), the principal component index (***$TECH^{PC}$***), and*** *the 14 individual* ***technical indicators from Neely et al. (2014), respectively.*** *The* R^2_{exp} ***and*** R^2_{rec} ***statistics are calculated over the NBER-dated business-cycle expansions and recessions, and the*** R^2_{up} ***and*** R^2_{down} ***statistics are calculated over upward and downward market periods, respectively.*** The table also reports the ***corresponding heteroskedasticity- and autocorrelation-robust*** t***-statistics (with a lag of 12) for testing*** $H_0: \beta = 0$ *against* $H_A: \beta > 0$. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively***, according to one-sided wild bootstrapped*** p***-values.***

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
	β *(%)*	**t**-*stat*	R^2 *(%)*	R^2_{exp} *(%)*	R^2_{rec} *(%)*	R^2_{up} *(%)*	R^2_{down} *(%)*
Panel A: Aligned technical analysis ***index***							
$TECH^{PLS}$	1.291	8.640***	9.279	10.957	4.753	7.517	12.221
Panel B: Equal-weighted index							
$TECH^{EW}$	0.334	1.823**	0.620	0.068	2.731	0.008	1.050
Panel C: Principal component index							
$TECH^{PC}$	0.105	1.825**	0.622	0.071	2.727	-0.113	1.065
Panel D: Individual technical indicators							
MA(1,9)	0.271	1.537*	0.407	-0.207	2.548	0.254	0.569
MA(1,12)	0.345	1.854**	0.661	0.234	2.310	0.365	1.000

MA(2,9)	0.273	1.619**	0.416	-0.227	2.649	0.250	0.602
MA(2,12)	0.380	2.182**	0.804	0.262	2.856	0.448	1.213
MA(3,9)	0.306	1.697**	0.520	-0.011	2.371	0.301	0.779
MA(3,12)	0.185	0.985	0.191	-0.105	1.215	0.102	0.302
MOM(9)	0.220	1.207	0.269	0.037	1.121	0.148	0.412
MOM(12)	0.209	1.133	0.243	0.010	1.147	0.118	0.413
VOL(1,9)	0.288	1.632**	0.461	-0.008	2.472	0.288	0.650
VOL(1,12)	0.359	1.940**	0.718	0.304	2.645	0.403	1.078
VOL(2,9)	0.289	1.550*	0.466	0.031	2.378	0.298	0.643
VOL(2,12)	0.303	1.614*	0.512	0.263	1.748	0.285	0.773
VOL(3,9)	0.218	1.133	0.265	-0.114	1.410	0.154	0.391
VOL(3,12)	0.327	1.800**	0.595	0.222	2.173	0.327	0.924

Table 3. Out-of-sample test results

The table *presents the* Campbell and Thompson (2008) R_{OS}^2 ***statistics*** that measure *the proportional reduction in MSFE for a predictive regression forecast of the excess market return based on the predictor in the first column vis-à-vis the prevailing* average *benchmark forecast, where statistical significance is based on the Clark and West (2007)* ***MSFE-adjusted*** *statistic* for testing $H_0: R_{OS}^2 \leq 0$ ***against*** $H_A: R_{OS}^2 > 0$. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. ***Panel A presents the results for historical average (*****HA*****) forecast,*** *the* aligned technical analysis index ***(*****TECH^{PLS}*****), the equal-weighted index (*****TECH^{EW}*****), the principal component index (*****TECH^{PC}*****), and*** the mean combination index (**TECH**$^{POST\text{-}EW}$), ***respectively. Panel B reports the results for one of the 14 technical indicators. Panel C reports the results for the principal component index using the Mallows model averaging and the leave-*****h*****-out cross-validation averaging criteria separately.*** *The* $R_{OS,exp}^2$ ***and*** $R_{OS,rec}^2$ ***statistics are calculated over the NBER-dated business-cycle expansions and recessions. The*** $(\bar{\hat{e}})^2$ and ***Rem. term represent the squared forecast bias and the remainder term for the Theil (1971) MSFE decomposition.*** The out-of-sample evaluation period is December 1970 through December 2015.

	MSFE	R_{OS}^2 (%)	CW-test	$R_{OS,exp}^2$ *(%)*	CW-test	$R_{OS,rec}^2$ *(%)*	CW-test	$(\bar{\hat{e}})^2$	***Rem. term***
Panel A: ***historical average, the PLS index, the EW index, the EW index, and the*** POST-EW index									
HA	19.515							0.011	19.505
TECH^{PLS}	17.791	8.838	6.855***	9.587	6.211***	6.388	2.899***	0.023	17.767
TECH^{EW}	19.432	0.425	1.156	-0.061	0.425	1.175	0.935	0.007	19.426
TECH^{PC}	19.472	0.221	0.858	-0.346	0.042	1.180	0.937	0.006	19.466
TECH$^{POST\text{-}EW}$	19.451	0.330	1.056	-0.056	0.260	0.942	0.931	0.008	19.443
Panel B: 14 individual technical indicators									
MA(1,9)	19.487	0.148	0.734	-0.361	-0.328	1.121	1.166	0.008	19.479
MA(1,12)	19.419	0.493	1.310*	-0.132	0.407	1.650	1.256	0.005	19.414
MA(2,9)	19.477	0.195	0.849	-0.308	-0.115	1.148	1.146	0.005	19.472
MA(2,12)	19.388	0.653	1.531*	0.018	0.676	1.787	1.310*	0.005	19.383
MA(3,9)	19.471	0.228	1.036	-0.160	0.520	0.953	0.867	0.004	19.467
MA(3,12)	19.528	-0.062	0.132	-0.223	-0.328	0.215	0.362	0.008	19.519
MOM(9)	19.510	0.028	0.385	-0.265	-0.354	0.595	0.697	0.008	19.502
MOM(12)	19.514	0.009	0.290	-0.255	-0.494	0.455	0.581	0.009	19.505

VOL(1,9)	19.467	0.249	0.991	-0.508	-0.221	1.462	1.273	0.007	19.460
VOL(1,12)	19.413	0.523	1.387*	-0.110	0.551	1.360	1.044	0.010	19.404
VOL(2,9)	19.482	0.173	0.840	-0.206	0.078	0.482	0.663	0.007	19.475
VOL(2,12)	19.473	0.215	0.893	0.086	0.636	0.044	0.238	0.009	19.464
VOL(3,9)	19.513	0.010	0.400	-0.158	-0.018	0.448	0.598	0.011	19.503
VOL(3,12)	19.438	0.394	1.212	0.174	0.876	0.484	0.579	0.012	19.427
Panel C: ***the PC index using the Mallows model averaging and the leave-*****h*****-out cross-validation averaging criteria***									
TECH^{MMA}	19.530	-0.074	0.230	-0.692	-1.146	1.110	1.078	0.048	19.482
TECH^{CVA}	19.531	-0.082	0.191	-0.683	-1.201	1.092	1.118	0.050	19.481

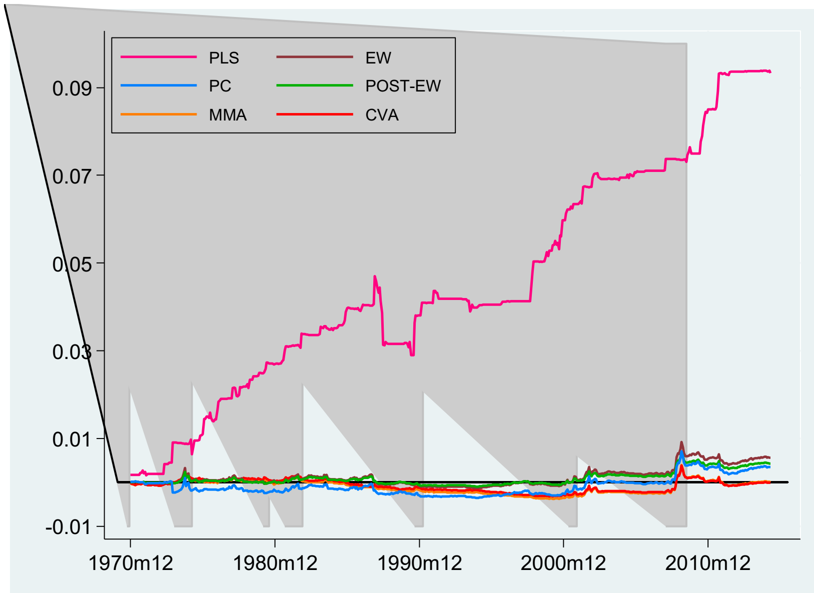


Figure 1. The difference in CSFE, December 1970 through December 2015

The solid lines delineate the difference between the CSFE for the historical average benchmark and the CSFE for the out-of-sample predictive regression forecast based on *the* aligned technical analysis index ***(*PLS,** solid pink line***), the equal-weighted index (*EW,** solid maroon line***), the principal component index (*PC,** solid blue line***),*** the mean combination index (*POST-EW,* solid green line), and ***the principal component index using the MMA and the CVA$_h$ criteria (*MMA,** solid orange line and *CVA*, solid red line***), respectively***. The vertical bars depict NBER-defined recessions.

Table 4 ***Forecast encompassing tests***

The table presents the estimated weight on the predictive regression forecast based on one of the technical analysis-related index (**TECH^{PLS}**, **TECH^{EW}**, and **TECH^{PC}**) given in columns (2), (4), and (6) or one of the 14 individual technical indicators given in columns (3), (5), and (7) in a combination forecast that takes the form of a convex combination of a predictive regression forecast based on one of the technical analysis-related index (**TECH^{PLS}**, **TECH^{EW}**, and **TECH^{PC}**) and a predictive regression forecast based on one of the 14 individual technical indicators given in column (1). The statistical significance is based on the Harvey, Leybourne, and Newbold (1998) statistic for testing the null hypothesis that the weight on the forecast based on the predictor of interest is equal to zero against the alternative that the weight on the forecast based on the predictor of interest is greater than zero. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	TECH^{PLS}		**TECH^{EW}**		**TECH^{PC}**	
(1)	***(2)***	***(3)***	***(4)***	***(5)***	***(6)***	***(7)***
TECH	$\hat{\lambda}_{TECH\to PLS}$	$\hat{\lambda}_{PLS\to TECH}$	$\hat{\lambda}_{TECH\to EW}$	$\hat{\lambda}_{EW\to TECH}$	$\hat{\lambda}_{TECH\to PC}$	$\hat{\lambda}_{PC\to TECH}$
MA(1,9)	1.000***	0.000	1.000	0.000	0.741	0.259
MA(1,12)	0.984***	0.016	0.087	0.913	0.000	1.000
MA(2,9)	1.000***	0.000	1.000	0.000	0.615	0.385
MA(2,12)	0.985***	0.015	0.000	1.000	0.000	1.000*
MA(3,9)	0.991***	0.009	1.000	0.000	0.483	0.517
MA(3,12)	1.000***	0.000	1.000**	0.000	1.000	0.000
MOM(9)	1.000***	0.000	1.000*	0.000	1.000	0.000
MOM(12)	1.000***	0.000	1.000*	0.000	1.000	0.000
VOL(1,9)	0.991***	0.009	1.000	0.000	0.427	0.573
VOL(1,12)	0.985***	0.015	0.150	0.850	0.000	1.000
VOL(2,9)	1.000***	0.000	1.000	0.000	0.626	0.374
VOL(2,12)	0.995***	0.005	1.000	0.000	0.520	0.480
VOL(3,9)	1.000***	0.000	1.000*	0.000	1.000	0.000
VOL(3,12)	0.985***	0.015	0.671	0.329	0.000	1.000

Table **5. *Predictive regression estimation results for subsample analysis: two periods of roughly equal length***

Panel A presents *in-sample estimates of* β *and* R^2s *for the* aligned technical analysis index ***(*TECH^{PLS}*), the equal-weighted index (*TECH^{EW}*), the principal component index (*TECH^{PC}*), and*** *14 individual* ***technical indicators***. The table also reports the ***corresponding heteroskedasticity- and autocorrelation-robust*** t***-statistics (with a lag of 12) for testing*** $H_0: \beta = 0$ *against* $H_A: \beta > 0$. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively***, according to one-sided wild bootstrapped*** p***-values.*** *Panel B presents the* Campbell and Thompson (2008) R_{OS}^2 ***statistics*** that measure *the proportional reduction in MSFE for a predictive regression forecast of the excess market return based on the predictor in the first column vis-à-vis the prevailing* average *benchmark forecast (*HA*), where statistical significance is based on the Clark and West (2007)* ***MSFE-adjusted*** *statistic* for testing $H_0: R_{OS}^2 \le 0$ ***against*** $H_A: R_{OS}^2 > 0$. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: ***In-sample predictive regressions***						*Panel B: Out-of-sample forecasting results*					
	December 1955 to November 1985			*December 1985 to December 2015*			December 19***70 to*** November 1992			December 1992 ***to*** December 2015		
	β	**t**-*stat*	R^2 *(%)*	β	**t**-*stat*	R^2 *(%)*	***MSFE***	R_{OS}^2 (%)	CW-test	***MSFE***	R_{OS}^2 (%)	CW-test
TECH^{PLS}	1.394***	8.229	11.051	1.237***	5.343	8.253	19.644	7.468***	4.682	16.024	10.389***	5.031
TECH^{EW}	0.238	1.191	0.390	0.421	1.193	0.748	21.268	-0.181	0.107	17.683	1.111*	1.403
TECH^{PC}	0.075	1.197	0.393	0.132	1.192	0.748	21.350	-0.569	-0.254	17.683	1.116*	1.406
MA(1,9)	0.231	1.193	0.355	0.281	0.851	0.356	21.324	-0.446	-0.331	17.736	0.819*	1.551
MA(1,12)	0.300*	1.507	0.612	0.365	1.017	0.578	21.240	-0.051	0.360	17.684	1.107*	1.407
MA(2,9)	0.236	1.346	0.378	0.276	0.812	0.332	21.259	-0.140	0.116	17.779	0.574	1.065
MA(2,12)	0.306*	1.618	0.636	0.438	1.341	0.849	21.212	0.079	0.519	17.649	1.302*	1.514
MA(3,9)	0.387**	2.025	1.020	0.156	0.448	0.105	21.260	-0.144	0.453	17.766	0.649	1.125
MA(3,12)	0.146	0.770	0.146	0.190	0.515	0.157	21.302	-0.345	-0.552	17.836	0.258	0.640
MOM(9)	0.090	0.466	0.056	0.345	0.990	0.501	21.304	-0.351	-0.758	17.800	0.456	0.867
MOM(12)	0.085	0.417	0.050	0.329	0.961	0.463	21.297	-0.321	-0.790	17.814	0.382	0.797
VOL(1,9)	0.229	1.113	0.352	0.320	0.997	0.445	21.199	0.140	0.556	17.815	0.373	0.834
VOL(1,12)	0.228	1.025	0.357	0.494*	1.526	1.038	21.228	0.008	0.478	17.684	1.107*	1.446
VOL(2,9)	0.173	0.761	0.203	0.392	1.210	0.670	21.299	-0.329	-0.449	17.749	0.742	1.252
VOL(2,12)	0.119	0.517	0.097	0.502*	1.580	1.086	21.329	-0.470	-0.711	17.705	0.991*	1.517
VOL(3,9)	0.147	0.664	0.148	0.290	0.831	0.364	21.309	-0.378	-0.311	17.802	0.450	1.054
VOL(3,12)	0.186	0.905	0.236	0.496*	1.529	1.070	21.298	-0.326	-0.111	17.666	1.209**	1.692
HA							21.229			17.882		

Table 6. *Predictive regression estimation results in the Chinese equity market*

Panel A presents *in-sample estimates of* β *and* R^2s *for* **TECH$^{\mathbf{PLS}}$, TECH$^{\mathbf{EW}}$, TECH$^{\mathbf{PC}}$, *and*** *14 individual* ***technical indicators from Neely et al. (2014) using data*** for both the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE) in the Chinese equity market. The table also reports the ***corresponding heteroskedasticity- and autocorrelation-robust*** ***t-statistics (with a lag of 12) for testing*** $H_0 : \beta = 0$ *against* $H_A : \beta > 0$**.** ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively**,** ***according to one-sided wild bootstrapped p-values.*** *Panel B presents the* Campbell and Thompson (2008) R^2_{OS} ***statistics*** that measure *the proportional reduction in MSFE for a predictive regression forecast of the excess market return based on the predictor in the first column vis-à-vis the prevailing* average *benchmark forecast (*HA*), where statistical significance is based on the Clark and West (2007)* ***MSFE-adjusted*** *statistic*.

	Panel A: ***Univariate predictive regressions***						*Panel B: Out-of-sample forecasting results*					
	SHSE			*SZSE*			SHSE			*SZSE*		
	β	**t**-*stat*	R^2 (%)	β	**t**-*stat*	R^2 (%)	***MSFE***	R^2_{OS} (%)	CW-test	***MSFE***	R^2_{OS} (%)	CW-test
TECH$^{\mathbf{PLS}}$	1.626***	3.896	3.705	2.163***	2.821	5.358	74.087	2.337***	2.858	94.034	5.908***	3.876
TECH$^{\mathbf{EW}}$	0.937*	1.434	1.229	1.067	1.403	1.308	75.551	0.408	0.831	99.423	0.516	0.968
TECH$^{\mathbf{PC}}$	0.312*	1.429	1.220	0.344	1.395	1.298	76.031	-0.225	0.633	100.369	-0.431	0.711
MA(1,9)	0.990*	1.581	1.373	0.975*	1.432	1.089	75.120	0.976	1.164	99.489	0.450	0.941
MA(1,12)	0.918*	1.446	1.180	1.281**	1.968	1.881	75.392	0.617	0.984	98.547	1.392*	1.408
MA(2,9)	0.737	1.166	0.762	0.505	0.577	0.292	75.778	0.109	0.640	101.517	-1.579	-0.278
MA(2,12)	1.044*	1.692	1.527	0.791	1.084	0.717	75.016	1.113	1.267	99.947	-0.008	0.629
MA(3,9)	0.830	1.305	0.965	0.387	0.511	0.172	75.578	0.372	0.847	101.488	-1.550	-0.634
MA(3,12)	0.590	1.004	0.487	0.695	0.965	0.553	76.096	-0.310	0.186	100.169	-0.230	0.413
MOM(9)	0.981**	1.931	1.347	1.016*	1.582	1.184	75.280	0.765	1.131	99.493	0.446	0.883

MOM(12)	0.721	1.108	0.727	0.800	1.172	0.731	76.162	-0.398	0.291	99.941	-0.003	0.525
VOL(1,9)	0.851*	1.458	1.016	1.172*	1.640	1.576	75.580	0.369	0.902	98.856	1.083*	1.302
VOL(1,12)	0.502	0.852	0.354	0.688	0.828	0.544	76.493	-0.834	-0.131	100.238	-0.299	0.531
VOL(2,9)	0.599	0.932	0.503	0.962	1.220	1.062	76.377	-0.681	0.031	99.580	0.359	0.951
VOL(2,12)	0.493	0.763	0.341	0.888	1.131	0.906	76.568	-0.933	0.010	99.768	0.170	0.781
VOL(3,9)	0.641	1.146	0.577	1.074	1.560	1.323	75.892	-0.041	0.421	99.245	0.694	1.048
VOL(3,12)	0.516	0.832	0.374	1.151*	1.568	1.520	76.403	-0.715	0.028	99.103	0.836	1.235
HA							75.860			99.939		

Table 7.Forecasting characteristics portfolios

The table ***presents*** *estimates of* β *and* R^2 s *for the following in-sample predictive regression model:*

$$R_{t+1}^{e,p} = \alpha_p + \beta_p \times \mathrm{TECH}_t + \sum_{i=1}^{2} \gamma_i^p \times \hat{f}_{i,t} + u_{t+1}^p,$$

where TECH_t ***includes the technical analysis***-related ***variables for month*** t ***(*****TECH**$^{\mathbf{PLS}}$, **TECH**$^{\mathbf{EW}}$***, and*** **TECH**$^{\mathbf{PC}}$***),***

$\hat{f}_1$, and $\hat{f}_2$ are the first two principal components extracted from the set of Goyal and Welch (2008) variables and $R_{t+1}^{e,p}$ ***denotes the monthly excess returns for the 10 size, 10 book-to-market, 10 momentum, and 10 industry portfolios, respectively.*** The table also reports the ***corresponding heteroskedasticity- and autocorrelation-robust t-statistics (with a lag of 12) for testing*** $H_0 : \beta_p = 0$ *against* $H_A : \beta_p > 0$.

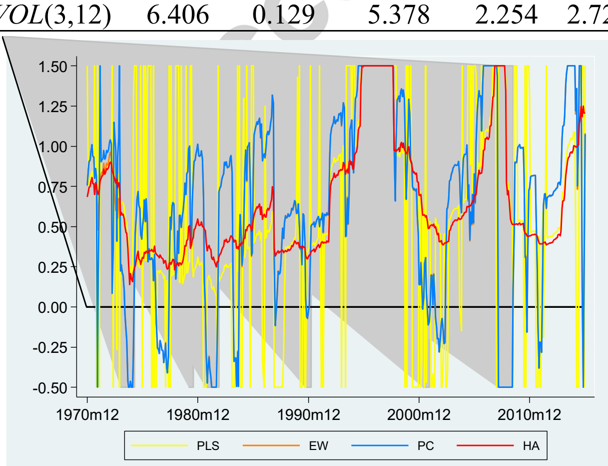
	TECH^{PLS}			TECH^{EW}			TECH^{PC}		
	β	**t**-*stat*	R^2 *(%)*	β	**t**-*stat*	R^2 *(%)*	β	**t**-*stat*	R^2 *(%)*
Panel A: Size portfolios									
Small	1.186	4.689	3.604	0.336	1.136	0.290	0.104	1.130	0.287
2	1.139	4.994	3.402	0.231	0.865	0.140	0.071	0.856	0.137
3	1.126	5.165	3.635	0.207	0.852	0.123	0.064	0.846	0.121
4	1.138	5.287	3.998	0.210	0.900	0.136	0.065	0.894	0.135
5	1.027	4.852	3.475	0.228	1.013	0.172	0.071	1.011	0.171
6	1.022	5.137	3.924	0.158	0.755	0.094	0.049	0.751	0.093
7	0.927	4.859	3.329	0.182	0.856	0.129	0.057	0.854	0.128
8	0.946	5.387	3.639	0.173	0.891	0.122	0.054	0.888	0.122
9	0.884	5.042	3.745	0.245	1.341	0.289	0.076	1.339	0.289
Large	0.728	4.312	2.961	0.264	1.649	0.390	0.082	1.647	0.389
Panel B: Book-to-market portfolios									
Growth	1.024	4.701	4.012	0.273	1.556	0.285	0.084	1.548	0.282
2	0.854	4.525	3.410	0.247	1.411	0.285	0.077	1.406	0.284
3	0.817	4.716	3.141	0.187	1.048	0.165	0.058	1.043	0.164
4	0.734	3.722	2.553	0.223	1.181	0.235	0.069	1.176	0.232
5	0.851	4.210	3.740	0.303	1.716	0.474	0.094	1.713	0.471
6	0.996	6.161	5.402	0.335	1.959	0.614	0.104	1.960	0.613
7	0.910	5.722	3.911	0.263	1.283	0.327	0.082	1.284	0.327
8	0.983	7.251	4.445	0.207	1.088	0.197	0.064	1.088	0.197
9	0.866	4.926	3.172	0.234	1.105	0.231	0.073	1.103	0.230
Value	1.235	7.817	4.365	0.179	0.709	0.092	0.056	0.710	0.092
Panel C: Momentum portfolios									
Loser	1.479	3.915	3.606	0.221	0.677	0.081	0.069	0.673	0.080
2	0.939	3.980	2.373	0.179	0.713	0.087	0.056	0.709	0.086
3	0.754	4.115	2.079	0.174	0.832	0.111	0.054	0.826	0.109
4	0.981	6.569	4.303	0.192	0.945	0.166	0.060	0.941	0.164
5	0.954	6.751	4.696	0.239	1.397	0.295	0.074	1.389	0.292
6	0.802	4.559	3.224	0.211	1.235	0.223	0.065	1.232	0.222
7	0.867	4.774	3.979	0.211	1.395	0.235	0.065	1.390	0.233
8	0.914	3.750	4.209	0.255	1.499	0.329	0.080	1.501	0.329
9	1.033	3.917	4.618	0.313	1.773	0.425	0.097	1.771	0.422
Winner	1.259	3.087	4.251	0.304	1.412	0.248	0.094	1.411	0.247
Panel D: Industry portfolios									
Nondurable	0.859	6.279	4.022	0.123	0.804	0.082	0.038	0.796	0.081
Durable	1.246	5.943	4.191	0.307	1.279	0.255	0.096	1.285	0.258
Manufacture	1.004	5.518	4.179	0.180	0.967	0.134	0.056	0.969	0.134
Energy	0.951	2.427	3.266	0.243	1.086	0.213	0.075	1.085	0.212
Technology	1.208	3.970	3.447	0.234	1.115	0.130	0.072	1.107	0.128
Telecom	0.993	5.805	4.643	0.131	0.774	0.081	0.041	0.776	0.082
Shop	0.887	3.810	2.966	0.203	1.084	0.155	0.063	1.085	0.156
Health	0.968	4.675	3.717	0.309	1.879	0.380	0.096	1.872	0.378
Utility	1.107	7.791	7.743	0.279	2.008	0.491	0.086	2.001	0.487

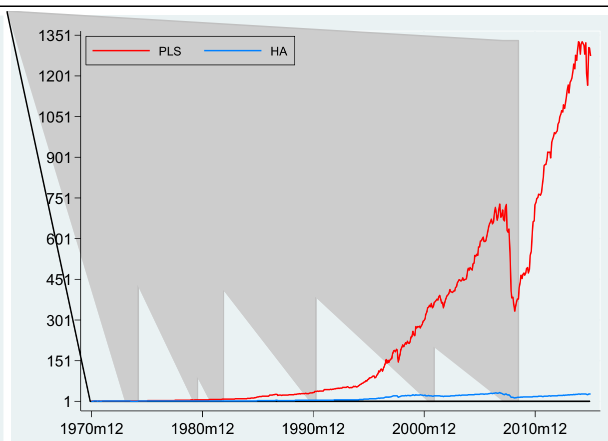
Other	1.050	5.754	4.031	0.323	1.423	0.383	0.100	1.419	0.381

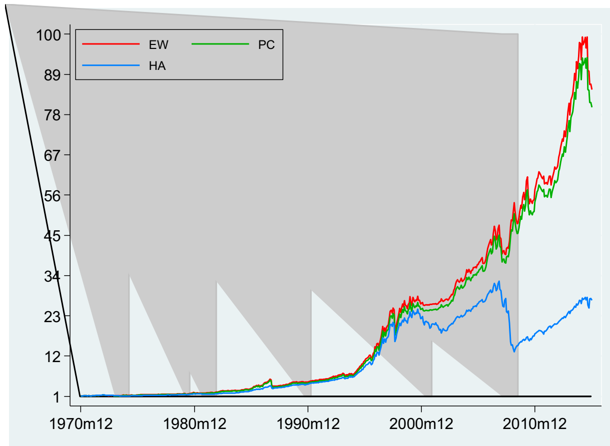
Table 8. Asset allocation results

The table presents the annualized CER gain (in percent), the Sharpe ratio, the average turnover, and the annualized net-of-tr***ansactions-costs*** CER gain (in percent) for a mean-variance investor with a risk-aversion coefficient (γ). of 1, 3, and 5, respectively, who ***optimally allocates across equities and the risk-free asset*** using the out-of-sample forecasts of the excess market returns based on *the* aligned technical analysis index ***(TECH^{PLS}), the equal-weighted index (TECH^{EW}), the principal component index (TECH^{PC}), and*** *14 individual* ***technical indicators from Neely et al. (2014)***, respectively.

Risk aversion	$\gamma = 1$				$\gamma = 3$				$\gamma = 5$			
Cost	***No***			***50 bps***	***No***			***50 bps***	***No***			***50 bps***
	CER gain (%)	Sharpe ratio	Relative average turnover	CER gain (%)	CER gain (%)	Sharpe ratio	Relative average turnover	CER gain (%)	CER gain (%)	Sharpe ratio	Relative average turnover	CER gain (%)
Panel A												
HA	5.560	0.081	2.427	8.921	5.521	0.064	2.328	5.908	5.504	0.059	1.860	5.496
TECH^{PLS}	11.181	0.199	14.729	5.645	8.575	0.241	14.553	6.152	7.268	0.273	16.838	5.429
TECH^{EW}	7.292	0.144	5.481	3.127	2.862	0.121	4.823	1.773	1.595	0.116	4.019	1.126
TECH^{PC}	7.247	0.144	5.973	3.009	2.672	0.116	5.384	1.500	1.232	0.106	4.695	0.677
Panel B												
MA(1,9)	4.647	0.101	7.700	0.158	1.942	0.099	4.761	0.851	1.031	0.095	3.812	0.578
MA(1,12)	7.018	0.140	6.983	2.633	3.252	0.129	4.847	2.139	1.907	0.126	3.949	1.430
MA(2,9)	5.349	0.112	7.076	0.950	2.187	0.105	4.852	1.096	1.175	0.101	3.946	0.718
MA(2,12)	7.527	0.148	6.088	3.273	3.499	0.135	4.548	2.445	2.077	0.132	3.740	1.636
MA(3,9)	5.898	0.122	7.618	1.415	2.590	0.115	5.688	1.382	1.291	0.109	4.523	0.766
MA(3,12)	4.026	0.090	4.490	0.007	1.441	0.087	2.789	0.650	0.683	0.082	2.238	0.425
MOM(9)	4.585	0.100	5.127	0.473	1.997	0.101	3.262	1.133	1.016	0.094	2.622	0.708
MOM(12)	4.145	0.093	4.404	0.139	1.724	0.094	2.665	0.949	0.849	0.087	2.150	0.599
VOL(1,9)	5.551	0.117	12.620	0.336	2.320	0.108	8.401	0.695	1.247	0.105	6.593	0.463
VOL(1,12)	7.013	0.141	10.507	2.102	3.255	0.129	7.506	1.762	1.830	0.124	6.071	1.112
VOL(2,9)	4.506	0.100	6.734	0.156	1.884	0.098	4.486	0.850	1.025	0.096	3.595	0.613
VOL(2,12)	5.235	0.112	5.707	1.035	2.004	0.101	3.971	1.040	0.974	0.093	3.214	0.599
VOL(3,9)	4.247	0.093	5.468	0.084	1.429	0.086	3.696	0.514	0.641	0.081	2.966	0.304
VOL(3,12)	6.406	0.129	5.378	2.254	2.729	0.118	3.899	1.775	1.346	0.107	3.194	0.973







A. Equity weight B. Cumulative wealth ***(PLS and HA)***

C. Cumulative wealth ***(EW, PC, and HA)***

Figure 2. Equity weights and cumulative wealth: December 1970 through December 2015

Panel A delineates the equity weight for a mean-variance investor with relative risk aversion coefficient of three who ***optimally allocates across equities and the risk-free asset*** using a predictive regression excess return forecast based on *the* aligned technical analysis index ***(*PLS*,*** solid yellow line***), the equal-weighted index (*EW*,*** solid orange line***), the principal component index (*PC*,*** solid blue line) or the prevailing mean benchmark forecast (*HA*, solid red line). Panel B delineates the cumulative wealth for the mean-variance investor who ***optimally allocates across equities and the risk-free asset*** using a predictive regression excess return forecast based on *the* aligned technical analysis index ***(*PLS*,*** solid red line***)*** or the prevailing mean benchmark forecast (*HA*, solid blue line). Panel C delineates the cumulative wealth for the mean-variance investor who ***optimally allocates across equities and the risk-free asset*** using a predictive regression excess return forecast based on ***the equal-weighted index (*EW*,*** solid red line***), the principal component index (*PC*,*** solid green line***)*** or the prevailing mean benchmark forecast (*HA*, solid blue line). The vertical bars depict NBER-defined recessions.

Table 9. *Predictive regression estimation results from* ***stock return decomposition***

The table presents the estimates for the predictive regression model, where the dependent variable is one of three estimated components of the market return and the regressor is *the* aligned technical analysis index ***(*****TECH**$^{\text{PLS}}$***), the equal-weighted index (*****TECH**$^{\text{EW}}$***), and the principal component index (*****TECH**$^{\text{PC}}$***), respectively***. The components of the market return are estimated using the vector autoregression (VAR) approach based on a combination of the variables in the first column, ***where "*****R*****" stands for the S&P 500 log return.*** The three estimated components of the market return are ***the estimated expected stock return (*** $\hat{E}_t r_{t+1}$***), the cash flow news component (*** $\hat{\xi}_{t+1}^{CF}$ ***) and the discount rate news component (*** $\hat{\xi}_{t+1}^{DR}$ ***), respectively***, corresponding to $\hat{\beta}_{\hat{E}}$, $\hat{\beta}_{CF}$, and $\hat{\beta}_{DR}$, respectively. The table also reports the ***corresponding heteroskedasticity- and autocorrelation-robust t-statistics (with a lag of 12)***.

	TECH$^{\text{PLS}}$			**TECH**$^{\text{EW}}$			**TECH**$^{\text{PC}}$		
VAR variables	$\hat{\beta}_{\hat{E}}$	$\hat{\beta}_{CF}$	$\hat{\beta}_{DR}$	$\hat{\beta}_{\hat{E}}$	$\hat{\beta}_{CF}$	$\hat{\beta}_{DR}$	$\hat{\beta}_{\hat{E}}$	$\hat{\beta}_{CF}$	$\hat{\beta}_{DR}$
R, *DP*	0.039	1.000	-0.260	0.007	0.260	-0.041	0.006	0.261	-0.041
R, *DP*, *DY*	0.034	0.978	-0.287	-0.066	0.308	-0.065	-0.066	0.309	-0.065
R, *DP*, *EP*	0.042	1.012	-0.246	0.056	0.239	-0.013	0.055	0.240	-0.013
R, *DP*, *DE*	0.042	1.012	-0.246	0.056	0.239	-0.013	0.055	0.240	-0.013
R, *DP*, *RVOL*	0.039	0.926	-0.334	-0.057	0.151	-0.214	-0.058	0.152	-0.214
R, *DP*, *BM*	0.044	0.994	-0.261	0.005	0.261	-0.041	0.004	0.262	-0.042
R, *DP*, *NTIS*	0.023	0.985	-0.291	-0.040	0.270	-0.077	-0.040	0.271	-0.077
R, *DP*, *TBL*	0.033	1.010	-0.255	-0.056	0.265	-0.099	-0.056	0.265	-0.099
R, *DP*, *LTY*	0.051	0.983	-0.265	-0.023	0.278	-0.053	-0.024	0.279	-0.053
R, *DP*, *LTR*	0.052	0.977	-0.270	-0.024	0.279	-0.053	-0.025	0.280	-0.053
R, *DP*, *TMS*	0.024	0.987	-0.287	0.016	0.150	-0.141	0.016	0.151	-0.141
R, *DP*, *DFY*	0.037	0.991	-0.271	-0.017	0.234	-0.091	-0.017	0.235	-0.091
R, *DP*, *DFR*	0.029	1.004	-0.267	0.005	0.257	-0.045	0.004	0.258	-0.045
R, *DP*, *INFL*	0.036	1.000	-0.263	0.012	0.257	-0.038	0.012	0.258	-0.038
R, *DP*, *PC-ECON*	0.048	0.966	-0.286	-0.072	0.292	-0.088	-0.072	0.292	-0.088
VAR variables	$t_{\hat{E}}$	t_{CF}	t_{DR}	$t_{\hat{E}}$	t_{CF}	t_{DR}	$t_{\hat{E}}$	t_{CF}	t_{DR}
R, *DP*	1.506	8.364	-8.882	0.175	1.840	-1.128	0.160	1.848	-1.132
R, *DP*, *DY*	1.439	8.451	-8.953	-1.868	2.230	-1.660	-1.882	2.239	-1.665
R, *DP*, *EP*	1.403	8.270	-6.857	0.974	1.658	-0.326	0.965	1.667	-0.326
R, *DP*, *DE*	1.403	8.270	-6.857	0.974	1.658	-0.326	0.965	1.667	-0.326
R, *DP*, *RVOL*	0.932	8.489	-7.631	-1.538	1.136	-3.498	-1.556	1.142	-3.508
R, *DP*, *BM*	1.705	8.365	-8.819	0.135	1.846	-1.151	0.122	1.854	-1.155
R, *DP*, *NTIS*	0.946	8.271	-9.981	-0.899	1.900	-2.090	-0.911	1.909	-2.095
R, *DP*, *TBL*	1.239	8.216	-6.440	-1.473	1.884	-2.364	-1.488	1.891	-2.369
R, *DP*, *LTY*	2.211	8.435	-7.303	-0.630	1.987	-1.437	-0.639	1.993	-1.443
R, *DP*, *LTR*	2.242	8.422	-7.355	-0.642	1.995	-1.430	-0.652	2.001	-1.437
R, *DP*, *TMS*	0.661	8.033	-6.239	0.382	1.093	-2.558	0.368	1.101	-2.563
R, *DP*, *DFY*	1.374	8.354	-8.221	-0.444	1.670	-2.053	-0.459	1.678	-2.057

R, *DP*, *DFR*	1.008	8.335	-9.394	0.132	1.823	-1.298	0.116	1.832	-1.302
R, *DP*, *INFL*	1.384	8.364	-9.016	0.332	1.821	-1.084	0.317	1.829	-1.090
R, *DP*, *PC-ECON*	1.970	8.398	-6.851	-1.952	2.116	-1.829	-1.964	2.122	-1.836

Highlights

• I construct an aligned technical analysis index by employing the partial least squares (PLS) method.
• The aligned index is a statistically and economically significant predictor of the US aggregate stock market.
• The aligned index outperforms the well-known technical indicators and macroeconomic variables in both in-sample and out-of-sample tests.
• The economic source of its predictive power predominantly stems from time variations in future cash flows