Forecasting the Equity Risk Premium:  
The Role of Technical Indicators

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Forecasting the Equity Risk Premium: The Role of Technical Indicators

Abstract

While macroeconomic variables have been used extensively to forecast the U.S. equity risk premium and build models to explain it, relatively little attention has been paid to the technical stock market indicators widely employed by practitioners. Our paper fills this gap by studying the forecasting ability of a variety of technical indicators in comparison to that of a number of well-known macroeconomic variables from the literature. We find that technical indicators have statistically and economically significant out-of-sample forecasting power and can be as useful as macroeconomic variables. Out-of-sample predictability is closely connected to the business cycle for both technical indicators and macroeconomic variables, although in a complementary manner: technical indicators detect the typical decline in the equity risk premium near cyclical peaks, while macroeconomic variables more readily pick up the typical rise near cyclical troughs. We further show that utilizing information from both technical indicators and macroeconomic variables substantially increases the out-of-sample gains relative to using either macroeconomic variables or technical indicators alone.

JEL classification: C53, C58, E32, G11, G12, G17

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1. Introduction

A voluminous literature exists using various macroeconomic variables (i.e., economic fundamentals) to predict the U.S. equity risk premium. Rozeff (1984), Fama and French (1988), and Campbell and Shiller (1988a, 1988b) present evidence that valuation ratios, such as the dividend yield, predict the U.S. equity risk premium. Similarly, Keim and Stambaugh (1986), Campbell (1987), Breen, Glosten, and Jagannathan (1989), and Fama and French (1989) find predictive ability for nominal interest rates and the default and term spreads, while Nelson (1976) and Fama and Schwert (1977) detect predictive capability for the inflation rate. More recent studies continue to support equity risk premium predictability using valuation ratios (Cochrane, 2008; Pástor and Stambaugh, 2009), interest rates (Ang and Bekaert, 2007), and inflation (Campbell and Vuolteenaho, 2004). Other studies identify additional macroeconomic variables with predictive power, including corporate equity issuing activity (Baker and Wurgler, 2000; Boudoukh, Michaely, Richardson, and Roberts, 2007), the consumption-wealth ratio (Lettau and Ludvigson, 2001), and volatility (Guo, 2006). Hjalmarsson (2010) confirms equity risk premium predictability based on macroeconomic variables across countries. Under the conventional view that asset prices equal expected discounted cash flows, Cochrane (2011) indicates how this literature profoundly shifts the emphasis from expected cash flows to discount rates, reshaping modern asset pricing theory.

While the predictive ability of macroeconomic variables has received considerable attention over the last 40 years, the literature pays relatively little attention to market indicators, also known as technical indicators. Technical indicators attempt to discern market price trends, which are interpreted as signals of future price movements.1 Popular technical indicators include moving-average and momentum signals, and these are often used in conjunction with measures of trading volume. Such indicators are available from newspapers and newsletters and are an important component of the information set used by traders and investors (e.g., Billingsley and Chance, 1996; Park and Irwin, 2007). Indeed, Schwager (1993, 1995), Covel (2005), and Lo and Hasanhodzic (2010) report that many large and successful traders rely extensively on technical indicators.

Despite their popularity among practitioners, technical indicators are often viewed suspiciously by academic researchers (e.g., Malkiel, 2011), largely due to a lack of theoretical underpinnings. Empirically, Cowles (1933), Fama and Blume (1966), and Jensen and Benington (1970) report little ability for a variety of popular technical indicators to provide profitable trading signals. More

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1 Technical analysis dates at least to 1700 (Nison, 1991; Lo and Hasanhodzic, 2010) and was popularized in the late nineteenth and early twentieth centuries by the “Dow Theory” of Charles Dow and William Peter Hamilton.

In the present paper, we analyze the forecasting ability of technical indicators in a predictive regression framework and compare it to the forecasting ability of popular macroeconomic variables from the literature. We seek to answer two questions: (1) Do technical indicators—which are clearly available to investors—provide useful information for forecasting the equity risk premium? (2) Can technical indicators and macroeconomic variables be used in conjunction to improve equity risk premium forecasts?

We first study equity risk premium forecasts based on technical indicators with the Campbell and Thompson (2008) out-of-sample $R^2$ statistic, $R^2_{OS}$, which measures the reduction in mean squared forecast error (MSFE) for a competing forecast relative to the historical average (constant expected excess return) benchmark forecast. Goyal and Welch (2008) show that out-of-sample criteria are important for assessing return predictability. We transform the technical indicators into equity risk premium forecasts using a recursive predictive regression framework. This allows us to directly compare equity risk premium forecasts based on technical indicators with those based on macroeconomic variables in terms of MSFE. We analyze the forecasting ability of a variety of technical indicators, including popular moving-average (MA), momentum, and volume-based technical indicators.

We also analyze the economic value of equity risk premium forecasts based on technical indicators and macroeconomic variables from an asset allocation perspective. Specifically, we calculate utility gains for a mean-variance investor who optimally allocates a portfolio between equities and risk-free Treasury bills using equity risk premium forecasts based on either technical indicators or macroeconomic variables relative to an investor who uses the historical average equity risk premium forecast. While numerous studies investigate the profitability of technical indicators, these studies are ad hoc in that they do not account for risk aversion in the asset allocation decision. Analogous to Zhu and Zhou (2009), we address this drawback and compare the utility gains for a risk-averse investor who forecasts the equity risk premium using technical indicators to those for
an identical investor who forecasts the equity risk premium with macroeconomic variables.

To investigate links between out-of-sample return predictability and the real economy, we compute the $R^2_{OS}$ statistics and utility gains over both NBER-dated cyclical expansions and recessions, and we closely examine the behavior of the equity risk premium forecasts over the course of recessions. Insofar as predictability is linked to the real economy, we expect that there will be more predictability in the rapidly changing macroeconomic conditions of recessions (e.g., Cochrane, 2011; Henkel, Martin, and Nadari, 2011).

Finally, we explore the ability of a principal component forecast to tractably incorporate the information from the technical indicators and macroeconomic variables taken together. From an out-of-sample forecasting perspective, over-parameterization presents a keen challenge: although highly parameterized models fit well in sample, such models typically deliver very poor out-of-sample forecasting performance, due to in-sample “over-fitting.” The large number of technical indicators and macroeconomic variables that we consider makes over-fitting a significant concern. To avoid over-fitting, we generate equity risk premium forecasts based on a predictive regression with a small number of principal components extracted from the complete set of technical indicators and macroeconomic variables. This is similar to Ludvigson and Ng (2007, 2009), who use principal component forecasts to extract information from a very large number of macroeconomic variables to predict stock and bond returns.

 Previewing our results, we find that monthly equity risk premium forecasts based on technical indicators produce economically significant $R^2_{OS}$ statistics and utility gains and frequently outperform forecasts based on macroeconomic variables. Furthermore, the out-of-sample forecasting gains are highly concentrated in recessions for both technical indicators and macroeconomic variables. This is especially evident for the utility metric. For example, a mean-variance investor with a risk aversion coefficient of five would pay an annualized portfolio management fee of 3.31% to have access to the equity risk premium forecast based on a monthly MA(2,12) technical indicator relative to the historical average benchmark forecast for the entire 1966:01–2008:12 forecast evaluation period; during recessions, the same investor would pay a hefty annualized fee of 19.18%.

Although technical indicators and macroeconomic variables both forecast better than the benchmark during recessions, the two approaches exploit different patterns. Technical indicators detect the typical fall in the equity risk premium near business-cycle peaks, while a number of macroeconomic variables correctly pick up the typical rise in the equity risk premium later in recessions near business-cycle troughs. These results may help to explain the simultaneously prominent roles for
macroeconomic variables in the academic literature and technical indicators among practitioners. Both approaches seem useful for predicting returns, and they appear to complement each other.

We also show that the principal component forecast, which incorporates information from both technical indicators and macroeconomic variables, outperforms any of the forecasts based on individual technical indicators or macroeconomic variables in terms of both the $R^2_{OS}$ and utility gain metrics. Furthermore, the principal component forecast produces larger out-of-sample gains than the recently proposed methods of Rapach, Strauss, and Zhou (2010) and Ferreira and Santa-Clara (2011). There is thus considerable value in pooling the information in technical indicators and macroeconomic variables. Like forecasts based on technical indicators, the principal component forecast is typically well below the historical average forecast near cyclical peaks; like the best-performing forecasts based on macroeconomic variables, the principal component forecast is typically well above the historical average near cyclical troughs. The principal component forecast thus utilizes important information from both technical indicators and macroeconomic variables.

Overall, our findings suggest that technical indicators are at least as useful as macroeconomic variables and capture additional relevant information for forecasting the equity risk premium. Hence, empirical asset pricing may need to pay more attention to technical indicators in explaining asset returns. Furthermore, our results raise the open question of why technical indicators predict the equity risk premium. Existing asset pricing models typically ignore the information investors have about technical indicators, so that our study calls for new asset pricing models that can improve our understanding of the role of technical indicators and their equilibrium pricing impacts.²

The remainder of the paper is organized as follows. Section 2 outlines the construction of equity risk premium forecasts based on macroeconomic variables and technical indicators, as well as the forecast evaluation criteria. Section 3 reports out-of-sample test results. Section 4 analyzes the principal component forecast. Section 5 concludes.

²Behavioral models offer potential explanations for the predictive ability of technical indicators, especially during recessions, although these models have not typically been formalized for technical indicators per se. Hong and Stein (1999) and Hong, Lim, and Stein (2000) provide both theory and empirical evidence on the slow transmission of bad news in financial markets. Recessions are presumably associated with large adverse macroeconomic news shocks, which may take longer to be fully incorporated into stock prices. As a result, the market will exhibit stronger trending patterns during recessions, creating greater scope for trend-based technical indicators to forecast equity prices. Consistent with this is the disposition effect—investors tend to hold losers too long and sell winners too early (Odean, 1998). During the early stages of recessions, there are more share price declines and hence more losers; this implies that the disposition effect is stronger in recessions, thereby reinforcing the stronger trend.
2. Econometric methodology

This section describes the construction and evaluation of out-of-sample equity risk premium forecasts based on macroeconomic variables and technical indicators.

2.1. Forecast construction

The conventional framework for analyzing equity risk premium predictability based on macroeconomic variables is the following predictive regression model:

\[ r_{t+1} = \alpha_i + \beta_i x_{i,t} + \varepsilon_{i,t+1}, \]

where \( r_{t+1} \) is the return on a broad stock market index in excess of the risk-free rate from period \( t \) to \( t+1 \), \( x_{i,t} \) is a predictor (e.g., the dividend yield), and \( \varepsilon_{i,t+1} \) is a zero-mean disturbance term. Following Campbell and Thompson (2008) and Goyal and Welch (2003, 2008), we generate an out-of-sample forecast of \( r_{t+1} \) based on (1) and information through period \( t \) as

\[ \hat{r}_{i,t+1} = \hat{\alpha}_{i,t} + \hat{\beta}_{i,t} x_{i,t}, \]

where \( \hat{\alpha}_{i,t} \) and \( \hat{\beta}_{i,t} \) are the ordinary least squares (OLS) estimates of \( \alpha_i \) and \( \beta_i \), respectively, in (1) computed by regressing \( \{r_k\}_{k=2}^T \) on a constant and \( \{x_{i,k}\}_{k=1}^{t-1} \). Dividing the total sample of \( T \) observations into \( q_1 \) in-sample and \( q_2 \) out-of-sample observations, where \( T = q_1 + q_2 \), we can calculate a series of out-of-sample equity risk premium forecasts based on \( x_{i,t} \) over the last \( q_2 \) observations: \( \{\hat{r}_{i,t+1}\}_{t=q_1}^{T-1} \). The historical average of the equity risk premium, \( \bar{r}_{t+1} = (1/t) \sum_{k=1}^T r_k \), is a natural benchmark forecast corresponding to the constant expected excess return model (\( \beta_i = 0 \) in (1)). Goyal and Welch (2003, 2008) show that \( \bar{r}_{t+1} \) is a stringent benchmark: predictive regression forecasts based on macroeconomic variables frequently fail to outperform the historical average forecast in out-of-sample tests.

Campbell and Thompson (2008) demonstrate that parameter and forecast sign restrictions improve individual forecasts based on macroeconomic variables, allowing them to more consistently outperform the historical average equity risk premium forecast. For example, theory often indicates the expected sign of \( \beta_i \) in (1), so that we set \( \beta_i = 0 \) when forming a forecast if the estimated slope
coefficient does not have the expected sign. Campbell and Thompson (2008) also suggest setting
the equity risk premium forecast to zero if the predictive regression forecast is negative, since risk
considerations typically imply a positive expected equity risk premium based on macroeconomic
variables.

In addition to macroeconomic variables, we consider three popular types of technical indica-
tors. The first is an MA rule that, in its simplest form, generates a buy or sell signal \( S_t = 1 \) or
\( S_t = 0 \), respectively) at the end of period \( t \) by comparing two moving averages:

\[
S_t = \begin{cases} 
1 & \text{if } \text{MA}_{s,t} \geq \text{MA}_{l,t} \\
0 & \text{if } \text{MA}_{s,t} < \text{MA}_{l,t}
\end{cases}
\]

(3)

where

\[
\text{MA}_{j,t} = \frac{1}{j} \sum_{i=0}^{j-1} P_{t-i} \quad \text{for } j = s, l,
\]

(4)

\( P_t \) is the level of a stock price index, and \( s \) (\( l \)) is the length of the short (long) MA (\( s < l \)). We
denote the MA rule with MA lengths \( s \) and \( l \) as MA\((s,l)\). Intuitively, the MA rule is designed to
detect changes in stock price trends. For example, when prices have recently been falling, the short
MA will tend to be lower than the long MA. If prices begin trending upward, then the short MA
tends to increase faster than the long MA, eventually exceeding the long MA and generating a buy
signal. In Section 3, we analyze monthly MA rules with \( s = 1, 2, 3 \) and \( l = 9, 12 \).

The second type of technical indicator we consider is based on momentum. A simple momen-
tum rule generates the following signal:

\[
S_t = \begin{cases} 
1 & \text{if } P_t \geq P_{t-m} \\
0 & \text{if } P_t < P_{t-m}
\end{cases}
\]

(5)

Intuitively, a current stock price that is higher than its level \( m \) periods ago indicates “positive”
momentum and relatively high expected excess returns, which generates a buy signal. We denote
the momentum rule that compares \( P_t \) to \( P_{t-m} \) as MOM\((m)\), and we compute monthly signals for
\( m = 9, 12 \) in Section 3.

Technical analysts frequently use volume data in conjunction with past prices to identify market
trends. In light of this, the final type of technical indicator we consider employs “on-balance”
volume (e.g., Granville, 1963). We first define

\[
\text{OBV}_t = \sum_{k=1}^{t} \text{VOL}_k D_k,
\]

(6)

6
where $VOL_k$ is a measure of the trading volume during period $k$ and $D_k$ is a binary variable that takes a value of 1 if $P_k - P_{k-1} \geq 0$ and $-1$ otherwise. We then form a trading signal from $OBV_t$ as

$$S_t = \begin{cases} 1 & \text{if } MA^{OBV}_{s,t} \geq MA^{OBV}_{l,t} \\ 0 & \text{if } MA^{OBV}_{s,t} < MA^{OBV}_{l,t} \end{cases},$$

(7)

where

$$MA^{OBV}_{j,t} = \frac{1}{j} \sum_{i=0}^{j-1} OBV_{t-i} \text{ for } j = s, l.$$

(8)

Intuitively, relatively high recent volume together with recent price increases, say, indicate a strong positive market trend and generate a buy signal. In Section 3, we compute monthly signals for $s = 1, 2, 3$ and $l = 9, 12$.

The three types of indicators that we consider (MA, momentum, and volume-based) conveniently capture the trend-following idea at the center of technical analysis and are representative of the technical indicators analyzed in the academic literature (e.g., Brock, Lakonishok, and LeBaron, 1992; Sullivan, Timmermann, and White, 1999). To directly compare these technical indicators to equity risk premium forecasts based on macroeconomic variables, we transform the technical indicators to point forecasts of the equity risk premium by replacing the macroeconomic variable $x_{i,t}$ in the predictive regression, (1), with $S_t$ from (3), (5), or (7). We then generate out-of-sample equity risk premium forecasts using $S_t$ as the explanatory variable in a manner analogous to the forecasts based on macroeconomic variables described earlier. To further facilitate comparison with predictive regression forecasts based on macroeconomic variables, we set the predictive regression forecast based on a technical indicator to zero if the unrestricted forecast is negative.

2.2. Forecast evaluation

We consider two metrics for evaluating forecasts based on macroeconomic variables and technical indicators. The first is the Campbell and Thompson (2008) $R^2_{OS}$ statistic, which measures the proportional reduction in MSFE for a competing model relative to the historical average benchmark:

$$R^2_{OS} = 1 - \frac{\sum_{k=1}^{q_2} (r_{q_1+k} - \hat{r}_{q_1+k})^2}{\sum_{k=1}^{q_2} (r_{q_1+k} - \bar{r}_{q_1+k})^2},$$

(9)

where $\hat{r}_{q_1+k}$ represents an equity risk premium forecast based on a macroeconomic variable or technical indicator. Clearly, when $R^2_{OS} > 0$, the competing forecast outperforms the historical average benchmark in terms of MSFE. We employ the Clark and West (2007) MSFE-adjusted
statistic to test the null hypothesis that the competing model MSFE is greater than or equal to the historical average MSFE against the one-sided alternative hypothesis that the competing forecast has a lower MSFE, corresponding to $H_0: R^2_{OS} \leq 0$ against $H_A: R^2_{OS} > 0$. Clark and West (2007) develop the \textit{MSFE-adjusted} statistic by modifying the familiar Diebold and Mariano (1995) and West (1996) statistic so that it has a standard normal asymptotic distribution when comparing forecasts from nested models. Comparing the forecasts based on macroeconomic variables or technical indicators with the historical average forecast entails comparing nested models, since setting $\beta_i = 0$ in (1) yields the constant expected excess return model.$^4$

$R^2_{OS}$ statistics are typically small for equity risk premium forecasts, since aggregate excess returns inherently contain a large unpredictable component, but a relatively small $R^2_{OS}$ statistic can still signal economically important gains for an investor (Kandel and Stambaugh, 1996; Xu, 2004; Campbell and Thompson, 2008). From an asset allocation perspective, however, the utility gain itself is the key metric. As a second metric for evaluating forecasts, we thus compute realized utility gains for a mean-variance investor who optimally allocates across stocks and risk-free bills, as in, among others, Marquering and Verbeek (2004) and Campbell and Thompson (2008). As discussed in the introduction, this procedure addresses the weakness of many existing studies of technical indicators that fail to incorporate the degree of risk aversion into the asset allocation decision.

In particular, we compute the average utility for a mean-variance investor with risk aversion coefficient of five who monthly allocates between stocks and risk-free bills using an equity risk premium forecast based on a macroeconomic variable or technical indicator. Following Campbell and Thompson (2008), we assume that the investor uses a five-year moving window of past monthly returns to estimate the variance of the equity risk premium, and we constrain the equity weight in the portfolio to lie between 0% and 150%. We then calculate the average utility for the same investor using the historical average forecast of the equity risk premium. The utility gain is the difference between the two average utilities. We multiply this difference by 1200, so that it can be interpreted as the annual percentage portfolio management fee that an investor would be willing to pay to have access to the equity risk premium forecast based on a macroeconomic variable or technical indicator relative to the historical average forecast.

$^4$While the Diebold and Mariano (1995) and West (1996) statistic has a standard normal asymptotic distribution when comparing forecasts from non-nested models, Clark and McCracken (2001) and McCracken (2007) show that it has a complicated non-standard distribution when comparing forecasts from nested models. The non-standard distribution can lead the Diebold and Mariano (1995) and West (1996) statistic to be severely undersized when comparing forecasts from nested models, thereby substantially reducing power.
3. Empirical results

This section describes the data and reports the out-of-sample test results for the $R_{OS}^2$ statistics and average utility gains.

3.1. Data

Our monthly data span 1927:01–2008:12. The data are from Amit Goyal’s web page, which provides updated data from Goyal and Welch (2008). The aggregate market return is the continuously compounded return on the S&P 500 (including dividends), and the equity risk premium is the difference between the aggregate market return and the log return on a risk-free bill. The following 14 macroeconomic variables, which are well representative of the literature (Goyal and Welch, 2008), constitute the set of macroeconomic variables used to forecast the equity risk premium:


2. Dividend yield (log), DY: log of a twelve-month moving sum of dividends minus the log of lagged stock prices.


7. Net equity expansion, NTIS: ratio of a twelve-month moving sum of net equity issues by NYSE-listed stocks to the total end-of-year market capitalization of NYSE stocks.

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


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5The data are available at http://www.hec.unil.ch/agoyal/.


14. **Inflation**, INFL: calculated from the CPI (all urban consumers); we follow Goyal and Welch (2008) and use $x_{t, i-1}$ in (1) for inflation to account for the delay in CPI releases.

We use the S&P 500 index for $P_t$ when computing the technical indicators based on the MA and momentum rules in (3) and (5), respectively. In addition to the S&P 500 index, we use monthly volume data (beginning in 1950:01) from Google Finance to compute the trading signal in (7).

### 3.2. $R^2_{OS}$ statistics

Panel A of Table 1 reports $R^2_{OS}$ statistics (in percent) for monthly predictive regression forecasts based on macroeconomic variables over the 1966:01–2008:12 forecast evaluation period. We use 1927:01–1965:12 as the initial in-sample period when forming the recursive out-of-sample forecasts. We assess the statistical significance of $R^2_{OS}$ using the Clark and West (2007) MSFE-adjusted statistic, as described in Section 2.2. We compute $R^2_{OS}$ statistics separately for the full 1966:01–2008:12 forecast evaluation period, as well as NBER-dated expansions and recessions. The U.S. economy is in recession for 77 of the 516 months (15%) spanning 1966:01–2008:12.

According to the second column of Table 1, Panel A, nine of the 14 individual macroeconomic variables produce positive $R^2_{OS}$ statistics over the full 1966:01–2008:12 out-of-sample period, so that they outperform the historical average benchmark forecast in terms of MSFE. Three of the nine positive $R^2_{OS}$ statistics for the individual macroeconomic variables are significant at the 10% level or better. DP and DY have the highest $R^2_{OS}$ statistics, 0.54% and 0.77%, respectively, among the individual macroeconomic variables. The fourth and sixth columns of Table 1 report $R^2_{OS}$ statistics separately for business-cycle expansions and recessions, respectively. Recessions markedly enhance the out-of-sample predictive ability of most macroeconomic variables compared to the

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The volume data are available at http://www.google.com/finance. While daily data are frequently used to generate technical indicators, we compute technical indicators using monthly data to put the forecasts based on macroeconomic variables and technical indicators on a more equal footing. In ongoing research, we are investigating the use of daily data to generate monthly trading signals to study the more practical problem of maximizing portfolio performance using technical indicators.

NBER peak and trough dates that define the expansion and recession phases of the U.S. business cycle are available at http://www.nber.org/cycles.html.
historical average. For example, the predictive ability of DP and DY is highly concentrated in recessions: the $R^2_{OS}$ statistics for DP (DY) are $-0.10\%$ and $2.06\%$ ($-0.20\%$ and $3.06\%$) during expansions and recessions, respectively. The $R^2_{OS}$ statistics for DP, DY, LTR, and TMS are significant at the 10$\%$ level during recessions, despite the reduced number of available observations; the $R^2_{OS}$ for NTIS (0.01$\%$) is the only statistic that is significant during expansions for the macroeconomic variables.

To illustrate how equity risk premium forecasts vary over the business cycle, Figure 1 graphs predictive regression forecasts based on individual macroeconomic variables, along with the historical average benchmark. The vertical bars in the figure depict NBER-dated recessions. Many of the individual predictive regression forecasts—especially those that perform the best during recessions, such as DP, DY, and TMS—often increase substantially above the historical average forecast over the course of recessions, reaching distinct local maxima near cyclical troughs. This is particularly evident during more severe recessions, such as the mid 1970s and early 1980s. The countercyclical fluctuations in equity risk premium forecasts in Figure 1 are similar to the countercyclical fluctuations in in-sample expected equity risk premium estimates reported in, for example, Fama and French (1989), Ferson and Harvey (1991), Whitelaw (1994), Harvey (2001), and Lettau and Ludvigson (2009). The fifth and seventh columns of Table 1, Panel A show that the average equity risk premium forecast is higher during recessions than expansions for a number of macroeconomic variables, including DP and DY.

Figure 2 provides a time-series perspective on the out-of-sample predictive ability of macroeconomic variables over the business cycle. The figure portrays the cumulative differences in squared forecast errors between the historical average forecast and forecasts based on individual macroeconomic variables.$^8$ A segment of the curve that is higher (lower) at its end point relative to its initial point indicates that the competing forecast outperforms (underperforms) the historical average forecast in terms of MSFE over the period corresponding to the segment. The curves are predominantly positively sloped—sometimes quite steeply—during many recessions in Figure 2 (with the notable exception of NTIS); outside of recessions, the curves are often flat or negatively sloped. Overall, Figure 2 provides further evidence of the enhanced predictive power of macroeconomic variables during recessions.

We turn next to the forecasting performance of the technical indicators in Table 1, Panel B. For the MA and momentum indicators in (3) and (5), respectively, we use data for 1927:12–1965:12

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$^8$Goyal and Welch (2003, 2008) employ this device to assess the consistency of out-of-sample predictive ability.
or 1928:01–1965:12 as the initial in-sample period to estimate the predictive regression model that transforms the trading signals to point forecasts.\textsuperscript{9} Data availability limits the starting date for the volume rules’ in-sample period to 1950:12.\textsuperscript{10} The second column of Table 1, Panel B shows that twelve of the 14 individual technical forecasts have positive $R^2_{OS}$ statistics for 1966:01–2008:12, so that they outperform the historical average forecast according to the MSFE metric. Eight of the twelve positive $R^2_{OS}$ statistics are significant at conventional levels. Comparing the results in Panels A and B of Table 1, equity risk premium forecasts based on technical indicators generally provide more sizable out-of-sample gains than forecasts based on macroeconomic variables.

The fourth and sixth columns of Table 1, Panel B show even starker differences in forecasting performance across business-cycle phases for the forecasts based on technical indicators in Panel B compared to the forecasts based on macroeconomic variables in Panel A. Eleven of the 14 individual technical forecasts exhibit negative $R^2_{OS}$ statistics during expansions, while all forecasts have positive $R^2_{OS}$ statistics during recessions; twelve of the positive statistics during recessions are significant at conventional levels. Moreover, the $R^2_{OS}$ statistics for the technical forecasts are quite sizable during recessions, with many ranging from over 1% to close to 4%.

Figure 3 shows that the technical forecasts almost always drop below the historical average forecast—often substantially so—throughout recessions. There are also expansionary episodes where some of the technical forecasts frequently fall below the historical average forecast. The fourth column of Table 1, Panel B indicates that these declines detract from the accuracy of these technical forecasts during expansions. The fifth and seventh columns of Panel B show that the average technical forecasts of the equity risk premium are uniformly lower during recessions than expansions.

Analogous to Figure 2, Figure 4 graphs the cumulative differences in squared forecast errors between the historical average forecast and technical forecasts. The positive slopes of the curves during recessions in Figure 4 show that most of the technical forecasts consistently produce out-of-sample gains during these periods. But the curves are almost always flat or negatively sloped for expansions, so that out-of-sample gains are nearly limited to recessions. Taken together, the results in Table 1 and Figures 2 and 4 highlight the relevance of business-cycle fluctuations for equity risk premium predictability using either macroeconomic variables or technical indicators.

\textsuperscript{9}These starting dates allow for the lags necessary to compute the initial MA or momentum signal in (3) or (5).
\textsuperscript{10}This starting date for the volume rules’ in-sample period motivates our selection of 1966:01 as the start of the forecast evaluation period, since this provides us with approximately 15 years of data for estimating the predictive regression parameters used to compute the initial forecast based on a volume rule.
3.3. Utility gains

Table 2 reports average utility gains, in annualized percent, for a mean-variance investor with risk aversion coefficient of five who allocates monthly across stocks and risk-free bills using equity risk premium forecasts derived from macroeconomic variables (Panel A) or technical indicators (Panel B). The results in Panel A indicate that forecasts based on macroeconomic variables often produce sizable utility gains vis-à-vis the historical average benchmark. The utility gain is above 0.75% for five of the individual macroeconomic variables in the second column, so that the investor would be willing to pay an annual management fee of 75 basis points or more to have access to forecasts based on macroeconomic variables relative to the historical average forecast. Similar to Table 1, the out-of-sample gains are concentrated in recessions. Consider, for example, DY, which generates the largest utility gain (2.22%) for the full 1966:01–2008:12 forecast evaluation period. The utility gain is negative (−0.06%) during expansions, while it is a very sizable 14.85% during recessions. DP, LTY, LTR, and DFR also provide utility gains above 5% during recessions.

Figure 5 portrays the equity portfolio weights computed using equity risk premium forecasts based on macroeconomic variables and historical average forecasts. Because the investor uses the same volatility forecast for all of the portfolio allocations, only the equity risk premium forecasts produce differences in the equity weights. Figure 5 shows that the equity weight computed using the historical average forecast is procyclical, which, given that the historical average forecast of the equity risk premium is relatively smooth, primarily reflects countercyclical changes in expected volatility. The equity weights based on macroeconomic variables often deviate substantially from the equity weight based on the historical average, with a tendency for the weights computed using macroeconomic variables to lie below the historical average weight during expansions and move closer to or above the historical average weight during recessions. Panel A of Table 2 indicates that these deviations create significant utility gains for our mean-variance investor, especially during recessions.

The second column of Table 2, Panel B shows that all 14 of the utility gains for forecasts based on technical indicators are positive for the full 1966:01–2008:12 out-of-sample period. Eleven of the individual technical forecasts provide utility gains above 1%, with the MA(2,12) forecast generating the largest gain (3.31%). Comparing the fourth and sixth columns, the utility gains are substantially higher and more consistent during recessions than during expansions. The MA(1,9)

forecast provides a leading example: the utility gain is negative during expansions (−0.99%), while it jumps to 19.82% during recessions. In all, twelve of the individual technical forecasts produce utility gains above 10% during recessions. The fifth and seventh columns reveal that the average equity weight is substantially lower during recessions than expansions for all of the technical forecasts.

Figure 6 further illustrates that technical forecast weights tend to decrease during recessions, dropping below the weight based on the historical average forecast during cyclical downturns. Again recalling that the investor uses the same rolling-window variance estimator for all portfolio allocations, these declining weights reflect decreases in the technical forecasts during recessions, as discussed in the context of Figure 3.

Overall, Table 2 shows that equity risk premium forecasts based on both macroeconomic variables and technical indicators usually generate sizable utility gains, especially during recessions, highlighting the economic significance of equity risk premium predictability using either approach. Comparing Panels A and B of Table 2, forecasts based on technical indicators typically provide larger utility gains than forecasts based on macroeconomic variables over the full 1966:01–2008:12 forecast evaluation period and during recessions.

3.4. A closer look at forecast behavior near cyclical peaks and troughs

Tables 1 and 2 and Figures 1–6 present somewhat of a puzzle. Out-of-sample gains are typically concentrated in recessions for equity risk premium forecasts based on both macroeconomic variables and technical indicators. However, equity risk premium forecasts based on macroeconomic variables often increase during recessions, while forecasts based on technical indicators are usually substantially lower during recessions than expansions. Despite the apparent differences in the behavior of the two types of forecasts during recessions, the out-of-sample gains are concentrated in cyclical downturns for both approaches. Why?

We investigate this issue by examining the behavior of the actual equity risk premium and forecasts around cyclical peaks and troughs, which define the beginnings and ends of recessions, respectively. We first estimate the following regression model around cyclical peaks:

\[ r_t - \bar{r}_t = a_P + \sum_{k=-2}^{4} b_{P,k} I^P_{k,t} + \epsilon_{P,t}, \]  

(10)

where \( I^P_{k,t} \) is an indicator variable that takes a value of unity \( k \) months after an NBER-dated peak and zero otherwise. The estimated \( b_{P,k} \) coefficients measure the incremental change in the average
difference between the realized equity risk premium and historical average forecast $k$ months after a cyclical peak. We then estimate a corresponding model that replaces the actual equity risk premium, $r_t$, with an equity risk premium forecast based on a macroeconomic variable or technical indicator:

$$\hat{r}_t - \bar{r}_t = a_P + \sum_{k=-2}^{4} b_{P,k} I_{P,k,t} + e_{P,t},$$

(11)

The slope coefficients describe the incremental change in the average difference between a forecast based on a macroeconomic variable or technical indicator relative to the historical average forecast $k$ periods after a cyclical peak. Similarly, we measure the incremental change in the average behavior of the realized equity risk premium and the forecasts around cyclical troughs:

$$r_t - \bar{r}_t = a_T + \sum_{k=-4}^{2} b_{T,k} I_{T,k,t} + e_{T,t},$$

(12)

$$\hat{r}_t - \bar{r}_t = a_T + \sum_{k=-4}^{2} b_{T,k} I_{T,k,t} + e_{T,t},$$

(13)

where $I_{T,k,t}$ is an indicator variable equal to unity $k$ months after an NBER-dated trough and zero otherwise.

The top-left panel of Figure 7 graphs OLS slope coefficient estimates (in percent) and 90% confidence bands for (10), and the remaining panels depict corresponding estimates for (11) based on individual macroeconomic variables. The top-left panel shows that the actual equity risk premium tends to move significantly below the historical average forecast one month before through two months after a cyclical peak. The remaining panels in Figure 7 indicate that most macroeconomic variables fail to pick up this decline in the equity risk premium early in recessions. Only the LTR, TMS, and INFL forecasts are significantly below the historical average forecast for any of the months early in recessions when the equity risk premium itself is lower than average, although the size of the decline in the INFL forecast is very small. The TMS forecast does the best job of matching the lower-than-average actual equity risk premium for the month before through two months after a peak. However, the TMS forecast is also significantly lower than the historical average forecast two months before and three and four months after a peak, unlike the actual equity risk premium. Overall, Figure 7 suggests that equity risk premium forecasts based on macroeconomic variables fail to detect the decline in the equity risk premium near cyclical peaks.

How do the equity risk premium forecasts based on technical indicators behave near cyclical peaks? The top-left panel of Figure 8 again shows estimates for (10), while the other panels graph estimates for (11) based on individual technical indicators. Figure 8 reveals that most of the technical forecasts move substantially below the historical average forecast in the months immediately
following a cyclical peak, in accord with the behavior of the actual equity risk premium. Given that the actual equity risk premium moves substantially below average in the month before and month of a cyclical peak, it is not surprising that technical forecasts are nearly all lower than the historical average in the first two months after a peak, since the technical forecasts are based on signals that recognize trends in equity prices. This trend-following behavior early in recessions apparently helps to generate the sizable out-of-sample gains during recessions for the technical forecasts in Tables 1 and 2. The forecasts based on technical indicators in Figure 8 tend to remain well below the historical average for too long after a peak, however.

Figures 9 and 10 depict estimates of the slope coefficients in (12) and (13) for forecasts based on macroeconomic variables and technical indicators, respectively. The top-left panel in each figure shows that the actual equity risk premium moves significantly above the historical average forecast in the third and second months before a cyclical trough, so that the equity risk premium is higher than usual in the late stages of recessions. Figure 9 indicates that many of the forecasts based on macroeconomic variables, particularly those based on DP, DY, BM, and LTR, are also significantly higher than the historical average forecast in the third and second months before a trough. The TMS forecast is also well above the historical average in the later stages of recessions, although by less than the previously mentioned macroeconomic variables. The ability of many of the forecasts based on macroeconomic variables to match the higher-than-average equity risk premium late in recessions helps to account for the sizable out-of-sample gains during recessions for forecasts based on macroeconomic variables in Tables 1 and 2.

Figure 10 shows that forecasts based on technical indicators typically start low but rise quickly late in recessions, in contrast to the pattern in the actual equity risk premium. The out-of-sample gains for the technical forecasts during recessions in Tables 1 and 2 thus occur despite the relatively poor performance of technical forecasts late in recessions. While the trend-following technical forecasts detect the decrease in the actual equity risk premium early in recessions (see Figure 8), they do not recognize the unusually high actual equity risk premium late in recessions.

In summary, Figures 7–10 paint the following nuanced picture with respect to the sizable out-of-sample gains during recessions in Tables 1 and 2. Macroeconomic variables typically fail to detect the decline in the actual equity risk premium early in recessions, but generally do detect the increase in the actual equity risk premium late in recessions. Technical indicators exhibit the opposite pattern: they pick up the decline in the actual premium early in recessions, but fail to match the unusually high premium late in recessions. Although both types of forecasts generate
substantial out-of-sample gains during recessions, they capture different aspects of equity risk premium fluctuations during cyclical downturns. This suggests that fundamental and technical analysis provide complementary approaches to out-of-sample equity risk premium predictability. We explore this complementarity further in the next section.

4. Principal component forecast

Heretofore, we have generated equity risk premium forecasts using individual macroeconomic variables and technical indicators. Can employing macroeconomic variables and technical indicators in conjunction produce additional out-of-sample gains? This immediately raises an important forecasting issue, since we analyze a large number of potential predictors. Including all of the potential regressors simultaneously in a multiple regression model can produce a very good in-sample fit, but typically leads to in-sample over-fitting and thus very poor out-of-sample forecasts. Another approach employs a model selection criterion over the in-sample period to select the relevant predictors for out-of-sample forecasting, but, again, this can lead to in-sample over-fitting and poor out-of-sample performance.

To tractably incorporate information from all of the macroeconomic variables and technical indicators while avoiding in-sample over-fitting, we use a principal component approach. Let \( x_t = (x_{1,t}, \ldots, x_{N,t})' \) denote the \( N \)-vector of potential predictors; \( N = 28 \) in our application, since we have 14 macroeconomic variables and 14 technical indicators. Let \( \hat{f}_k, t = (\hat{f}_{1,k,t}, \ldots, \hat{f}_{J,k,t})' \) for \( k = 1, \ldots, t \) represent the vector comprised of the first \( J \) principal components of \( x_t \) estimated using data available through \( t \), where \( J \ll N \). Intuitively, the principal components conveniently detect the key comovements in \( x_t \), while filtering out much of the noise in individual predictors. We then use a predictive regression framework to generate a principal component (PC) forecast of \( r_{t+1} \):

\[
\hat{r}_{PC,t+1} = \hat{\alpha}_{PC,t} + \hat{\beta}_{PC,t}\hat{f}_{i,t}, \tag{14}
\]

where \( \hat{\alpha}_{PC,t} \) and \( \hat{\beta}_{PC,t} \) are the OLS intercept and slope coefficient estimates, respectively, from regressing \( \{r_k\}_{k=2}^{t} \) on a constant and \( \{\hat{f}_{k,t}\}_{k=1}^{t-1} \). Ludvigson and Ng (2007, 2009) use a PC approach to predict stock and bond market returns based on a very large number of macroeconomic variables, while we use such an approach to incorporate information from a large number of macroeconomic variables and technical indicators to forecast the equity risk premium. For consistency, we continue to impose the non-negativity forecast restriction.

An important issue in constructing the PC forecast is the selection of \( J \), the number of principal
components to include in (14). We need \( J \) to be relatively small to avoid an overly parameterized model; at the same time, we do not want to include too few principal components, thereby neglecting important information in \( x_t \). We select \( J \) using the Onatski (2009) ED algorithm. This algorithm displays good properties for selecting the true number of factors in approximate factor models for sample sizes near ours in simulations in Onatski (2009). The ED algorithm typically selects \( J = 3 \) when forming recursive PC forecasts using the 14 macroeconomic variables and 14 technical indicators.

Panel A of Table 3 reports \( R^2_{OS} \) statistics for the PC forecast for the full 1966:01–2008:12 forecast evaluation period and separately during expansions and recessions. The \( R^2_{OS} \) statistic is 1.66% for the full period, which is significant at the 1% level and well above all of the corresponding \( R^2_{OS} \) statistics for the forecasts based on individual macroeconomic variables and technical indicators in Table 1. Similar to the results in Table 1, the PC forecast \( R^2_{OS} \) is substantially higher during recessions (4.37%, significant at the 1% level) than expansions (0.50%, significant at the 10% level). The \( R^2_{OS} \) statistics for the PC forecast during expansions and recessions are higher than each of the corresponding \( R^2_{OS} \) statistics in Table 1.

The top panel of Figure 11 depicts the time series of PC equity risk premium forecasts. The PC forecast exhibits a close connection to the business cycle. In particular, the PC forecast is typically well below the historical average forecast near cyclical peaks. At the same time, the PC forecast moves well above the historical average forecast near cyclical troughs corresponding to more severe recessions. This cyclical pattern in the PC forecast indicates that it incorporates the relevant information from both macroeconomic variables and technical indicators that enhance equity risk premium predictability, as discussed in Section 3.

Analogous to Figures 2 and 4, the middle panel of Figure 11 graphs the difference in cumulative squared forecast errors for the historical average forecast relative to the PC forecast. The curve is predominantly positively sloped throughout the 1966:01–2008:12 period, so that the PC forecast delivers out-of-sample gains on a consistent basis over time, much more consistently than any of the forecasts based on individual macroeconomic variables and technical indicators in Figures 2 and 4. The curve is frequently steeply sloped during recessions, again highlighting the importance of business-cycle fluctuations for equity risk premium predictability.

The PC forecast also generates substantial utility gains from an asset allocation perspective, as evidenced by Table 3, Panel B. The utility gain is 4.35% for the full 1966:01–2008:12 forecast evaluation period, which is well above any of the corresponding utility gains for forecasts based
on individual macroeconomic variables and technical indicators in Table 2. Continuing the familiar pattern, the utility gains are concentrated during economic contractions, with gains of 1.21% and 21.97% during expansions and recessions, respectively. The gains during expansions and recessions are again greater than any of the corresponding gains in Table 2. The average equity weights reported in the last row of Table 2 show that the average equity weight is lower during recessions vis-à-vis expansions (0.08 and 0.31, respectively). Inspection of the bottom panel of Figure 11 shows that the average equity weight of 0.08 during recession masks sizable shifts in asset allocation during recessions: the PC forecast typically leads the investor to move entirely out of stocks near cyclical peaks and throughout much of the downturn; however, the investor tends to move aggressively back into stocks late in recessions near cyclical troughs of severe recessions. In contrast, the historical forecast is much less capable of “timing” the market near recession peaks and troughs.

“Data snooping” concerns naturally arise when considering a host of potential predictors. To control for data snooping, we use a modified version of White’s (2000) reality check due to Clark and McCracken (2010). The Clark and McCracken (2010) reality check is based on a wild fixed-regressor bootstrap and is appropriate for comparing forecasts from multiple models that all nest the benchmark model, as in our framework.\textsuperscript{12} Specifically, we test the null hypothesis that the MSFE for each of the competing models is greater than or equal to the MSFE for the historical average benchmark against the alternative hypothesis that at least one of the competing models has a lower MSFE. This corresponds to a test of \( H_0: R^2_{\text{OS},m} \leq 0 \) for all \( m = 1, \ldots, M \), where \( m \) indexes a competing model, against \( H_A: R^2_{\text{OS},m} > 0 \) for at least one \( m \). We implement this test using the Clark and McCracken (2010) maxMSFE\(-F_m\) statistic:

\[
\text{maxMSFE-F}_m = \max_{m=1,\ldots,M} q_2 \frac{\tilde{d}_m}{\text{MSFE}_m},
\]

where \( q_2 \) is the size of the forecast evaluation period,

\[
\tilde{d}_m = \left( \frac{1}{q_2} \sum_{k=1}^{q_2} \left[ (r_k - \bar{r}_k)^2 - (r_k - \hat{r}_{m,k})^2 \right] \right),
\]

\[
\text{MSFE}_m = \left( \frac{1}{q_2} \sum_{k=1}^{q_2} (r_k - \hat{r}_{m,k})^2 \right).
\]

\textsuperscript{12}As Clark and McCracken (2010) emphasize, the asymptotic and finite-sample properties of the non-parametric bootstrap procedures in White’s (2000) reality check (as well as Hansen’s (2005) modified reality check) do not generally apply when comparing forecasts from multiple models that all nest the benchmark model. Clark and McCracken (2010) show that a wild fixed-regressor bootstrap procedure for maximum statistics delivers asymptotically valid critical values. They also find that this bootstrap procedure has good finite-sample properties.
In our application, \( M = 29 \), corresponding to the 14 forecasts based on individual macroeconomic variables, 14 forecasts based on individual technical indicators, and the PC forecast. For the 1966:01–2008:12 forecast evaluation period, the maxMSFE-\( F_m \) statistic equals 8.70, with a wild fixed-regressor bootstrap \( p \)-value of 4.71\%, so that we reject the null hypothesis that none of the competing models outperforms the historical average benchmark in terms of MSFE at conventional significance levels.\(^{13}\) This reality check indicates that data snooping cannot readily explain the out-of-sample equity risk premium predictability in Tables 1 and 3.

Finally, we briefly compare the out-of-sample gains from the PC forecast, which incorporates information from both macroeconomic variables and technical indicators, to two recently proposed methods for improving out-of-sample equity risk premium forecasts. Rapach, Strauss, and Zhou (2010) show that a combination forecast delivers consistent out-of-sample gains relative to equity risk premium forecasts based on individual macroeconomic variables. Using the same approach, we form a combination forecast as the mean of the forecasts based on the 14 individual macroeconomic variables that we consider. This combination forecast produces an \( R^2_{OS} \) of 0.63\% and utility gain of 1.36\% for the 1966:01–2008:12 forecast evaluation period.\(^{14}\) These values are both well below the \( R^2_{OS} \) of 1.66\% and utility gain of 4.35\% for the PC forecast in Table 3 during this period.

Ferreira and Santa-Clara (2011) develop an intriguing “sum-of-the-parts” (SOP) approach to forecast the market return. Specifically, they decompose the log market return into the sum of the growth in the price-earnings ratio, growth in earnings, and the dividend-price ratio. Treating earnings growth as largely unforecastable and the dividend-price and earnings-price ratios as approximately random walks, Ferreira and Santa-Clara (2011) propose the SOP equity risk premium forecast as the sum of a 20-year moving average of earnings growth rates and the current dividend-price ratio (minus the risk-free rate).\(^{15}\) They show that the SOP forecast outperforms equity risk premium forecasts based on individual macroeconomic variables over the postwar period, primarily by reducing estimation error. For the 1966:01–2008:12 forecast evaluation period, the SOP forecast generates an \( R^2_{OS} \) of 1.19\% and utility gain of 2.34\%.\(^{16}\) These values are larger than the corresponding values for any of the individual macroeconomic variables in Tables 1 and 2, as well as those for the combination forecast. However, the \( R^2_{OS} \) and utility gain for the SOP forecast are

\(^{13}\)The wild fixed-regressor bootstrap used to compute the \( p \)-value is described in detail in the appendix.


\(^{15}\)Ferreira and Santa-Clara (2011) focus on forecasting the market return, but note that they obtain similar results for the equity risk premium.

\(^{16}\)The \( R^2_{OS} \) of 1.19\% is reasonably near the \( R^2_{OS} \) of 1.32\% (0.98\%) for the market return reported by Ferreira and Santa-Clara (2011) for the 1948:01–2007:12 (1977:01–2007:12) forecast evaluation period.
substantially lower than the corresponding values of 1.66% and 4.35% for the PC forecast in Table 3. In short, the ability of the PC forecast to outperform the combination and SOP forecasts further establishes the relevance of technical indicators for equity risk premium forecasting.

5. Conclusion

We analyze monthly out-of-sample forecasts of the U.S. equity risk premium based on popular technical indicators in comparison to that of a set of well-known macroeconomic variables using two out-of-sample metrics: (1) the Campbell and Thompson (2008) $R^2_{OS}$ statistic and (2) the average utility gain for a mean-variance investor who optimally reallocates a monthly portfolio between equities and risk-free Treasury bills using equity risk premium forecasts based on technical indicators or macroeconomic variables relative to the historical average benchmark forecast. We find that technical indicators have statistically and economically significant out-of-sample forecasting power and frequently outperform macroeconomic variables. While both approaches perform disproportionately well during recessions, a careful analysis of their performance during cyclical downturns reveals that they exploit very different patterns: technical indicators recognize the typical drop in the equity risk premium near cyclical peaks; macroeconomic variables identify the typical increase in the equity risk premium near cyclical troughs. Thus, technical indicators and macroeconomic variables represent complementary approaches to equity risk premium forecasting.

Building on this complementarity, we generate a principal component equity risk premium forecast, which incorporates information from all of the technical indicators and macroeconomic variables taken together. The principal component forecast performs very well, delivering substantially larger out-of-sample gains than any of the forecasts based on individual technical indicators or macroeconomic variables. These gains stem in large measure from the principal component forecast’s ability to utilize the complementary information in technical indicators and macroeconomic variables and thus better track the equity risk premium during recessions.

Our results suggest avenues for future research. We show that technical market indicators can be used in a predictive regression framework to improve equity risk premium forecasts. However, forecasting the equity risk premium using technical market indicators in this manner is a special case of employing the information generally available in a broad range of technical indicators. More sophisticated use of past information has the potential to further improve forecasting power. A leading example is Cochrane and Piazzesi (2005), who show that a factor formed as a “tent-
shaped” linear combination of forward rates has substantial predictor power for U.S. bond risk premia. While our principal component forecast is in the spirit of this approach, alternative methods for forming factors based on technical indicators are worth investigating. Given that numerous empirical studies use various economic variables to explain the cross section of expected asset returns, it would also be interesting to incorporate technical indicators into this analysis.

Our paper provides empirical evidence calling for the incorporation of past information, especially technical market indicators, into asset pricing models. Leading asset pricing models, such as the Campbell and Cochrane (1999) habit-formation and Bansal and Yaron (2004) long-run risks models, as well as their recent extensions by Bekaert, Engstrom, and Xing (2009) and Bollerslev, Tauchen, and Zhou (2009), provide theoretical explanations for equity risk premium predictability based on macroeconomic variables in general equilibrium settings. It is not clear, however, the extent to which these models can account for the forecasting ability of technical indicators. Do technical indicators correlate with aggregate risk factors? Alternatively (or additionally), do they represent behavioral influences or information processing limitations? Given that technical indicators appear to provide useful information for equity risk premium forecasting, these are important theoretical questions.
Appendix: Wild fixed-regressor bootstrap

This appendix outlines the wild fixed-regressor bootstrap used to calculate the $p$-value for the maxMSFE-$F_m$ statistic given by (15). We first estimate the constant expected equity risk premium model, corresponding to the null of no predictability: $\bar{r} = (1/T) \sum_{t=1}^{T} r_t$. We next estimate an unrestricted model that includes all of the potential predictors as regressors using OLS; denote the OLS residuals from this model as $\{\hat{u}_t\}_{t=1}^{T}$. We then generate a pseudo sample of equity risk premium observations under the null of no predictability as $r_t^b = \bar{r} + v_t^b \hat{u}_t$ for $t = 1, \ldots, T$, where $v_t^b$ is a draw from an i.i.d. $N(0,1)$ process. Generating pseudo disturbance terms in this manner allows for conditional heteroskedasticity and makes this a “wild” bootstrap. Denote the pseudo sample of equity risk premium observations as $\{r_t^b\}_{t=1}^{T}$. We compute forecasts based on individual macroeconomic variables and technical indicators, as well as the PC forecast, for the last $q_2$ simulated equity risk premium observations using $\{r_t^b\}_{t=q_1+1}^{T}$ in conjunction with the macroeconomic variables and technical indicators from the original sample. Using macroeconomic variables and technical indicators from the original sample makes this a “fixed-regressor” bootstrap. Based on $\{r_t^b\}_{t=q_1+1}^{T}$ and the simulated forecasts, we compute the maxMSFE-$F_m$ statistic for the pseudo sample, maxMSFE-$F_m^b$. Generating $B = 10,000$ pseudo samples in this manner yields an empirical distribution of maxMSFE-$F_m$ statistics, $\{\text{maxMSFE-$F_m^b$}\}_{b=1}^{B}$. The bootstrapped $p$-value is given by $B^{-1} \sum_{b=1}^{B} I_b$, where $I_b = 1$ for maxMSFE-$F_m^b \geq \text{maxMSFE-$F_m$}$ and zero otherwise and maxMSFE-$F_m$ is the relevant statistic computed from the original sample.
References


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<th>Average forecast (%)</th>
<th>Overall $R^2_{OS}$ (%)</th>
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<td><strong>Panel B: Forecasts based on individual technical indicators</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>MA(1,9)</td>
<td>0.31</td>
<td>0.51</td>
<td>−1.18</td>
<td>0.57</td>
<td>3.79***</td>
<td>0.15</td>
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</tr>
<tr>
<td>MA(1,12)</td>
<td>1.14**</td>
<td>0.54</td>
<td>0.19</td>
<td>0.62</td>
<td>3.36***</td>
<td>0.11</td>
<td></td>
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</tr>
<tr>
<td>MA(2,9)</td>
<td>0.71**</td>
<td>0.51</td>
<td>−0.53</td>
<td>0.58</td>
<td>3.59***</td>
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<tr>
<td>MA(2,12)</td>
<td>1.23***</td>
<td>0.55</td>
<td>0.26</td>
<td>0.62</td>
<td>3.49***</td>
<td>0.11</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MA(3,9)</td>
<td>0.63**</td>
<td>0.50</td>
<td>−0.07</td>
<td>0.56</td>
<td>2.28**</td>
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<tr>
<td>MA(3,12)</td>
<td>0.50*</td>
<td>0.50</td>
<td>0.02</td>
<td>0.56</td>
<td>1.63*</td>
<td>0.15</td>
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</tr>
<tr>
<td>MOM(9)</td>
<td>0.52*</td>
<td>0.58</td>
<td>−0.22</td>
<td>0.66</td>
<td>2.24**</td>
<td>0.11</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MOM(12)</td>
<td>0.65**</td>
<td>0.52</td>
<td>−0.13</td>
<td>0.59</td>
<td>2.47**</td>
<td>0.14</td>
<td></td>
<td></td>
</tr>
<tr>
<td>VOL(1,9)</td>
<td>0.18</td>
<td>0.55</td>
<td>−0.76</td>
<td>0.60</td>
<td>2.40**</td>
<td>0.25</td>
<td></td>
<td></td>
</tr>
<tr>
<td>VOL(1,12)</td>
<td>0.57*</td>
<td>0.55</td>
<td>−0.41</td>
<td>0.61</td>
<td>2.85**</td>
<td>0.19</td>
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</tr>
<tr>
<td>VOL(2,9)</td>
<td>0.01</td>
<td>0.56</td>
<td>−0.61</td>
<td>0.60</td>
<td>1.47*</td>
<td>0.33</td>
<td></td>
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</tr>
<tr>
<td>VOL(2,12)</td>
<td>−0.16</td>
<td>0.54</td>
<td>−0.43</td>
<td>0.58</td>
<td>0.48</td>
<td>0.33</td>
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</tr>
<tr>
<td>VOL(3,9)</td>
<td>−0.32</td>
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<td>−0.76</td>
<td>0.58</td>
<td>0.69</td>
<td>0.31</td>
<td></td>
<td></td>
</tr>
<tr>
<td>VOL(3,12)</td>
<td>0.38</td>
<td>0.53</td>
<td>−0.24</td>
<td>0.59</td>
<td>1.82*</td>
<td>0.21</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 2
Asset allocation results, 1966:01–2008:12

Average utility gain (Δ) is the portfolio management fee (in annualized percent return) that an investor with mean-variance preferences and risk aversion coefficient of five would be willing to pay to have access to the forecasting model based on the predictor given in the first column relative to the historical average benchmark forecast. Utility gains and average equity weights are computed for the entire 1966:01–2008:12 forecast evaluation period (second and third columns) and separately for NBER-dated expansions (fourth and fifth columns) and recessions (sixth and seventh columns).

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Δ (ann. %)</th>
<th>Average equity weight</th>
<th>Δ (ann. %)</th>
<th>Average equity weight</th>
<th>Δ (ann. %)</th>
<th>Average equity weight</th>
</tr>
</thead>
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<tr>
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<td></td>
</tr>
<tr>
<td>Recession</td>
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<td></td>
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<td></td>
</tr>
</tbody>
</table>

Panel A: Forecasts based on individual macroeconomic variables

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Δ (ann. %)</th>
<th>Average equity weight</th>
<th>Δ (ann. %)</th>
<th>Average equity weight</th>
<th>Δ (ann. %)</th>
<th>Average equity weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>DP</td>
<td>1.49</td>
<td>0.25</td>
<td>−0.15</td>
<td>0.20</td>
<td>10.46</td>
<td>0.50</td>
</tr>
<tr>
<td>DY</td>
<td>2.22</td>
<td>0.19</td>
<td>−0.06</td>
<td>0.14</td>
<td>14.85</td>
<td>0.45</td>
</tr>
<tr>
<td>EP</td>
<td>0.59</td>
<td>0.42</td>
<td>0.27</td>
<td>0.36</td>
<td>2.02</td>
<td>0.75</td>
</tr>
<tr>
<td>DE</td>
<td>−2.04</td>
<td>0.91</td>
<td>−1.04</td>
<td>0.92</td>
<td>−7.53</td>
<td>0.89</td>
</tr>
<tr>
<td>SVAR</td>
<td>−0.07</td>
<td>0.67</td>
<td>−0.08</td>
<td>0.68</td>
<td>−0.01</td>
<td>0.64</td>
</tr>
<tr>
<td>BM</td>
<td>−0.54</td>
<td>0.42</td>
<td>−0.60</td>
<td>0.34</td>
<td>−0.61</td>
<td>0.86</td>
</tr>
<tr>
<td>NTIS</td>
<td>−0.87</td>
<td>0.84</td>
<td>0.57</td>
<td>0.84</td>
<td>−8.80</td>
<td>0.89</td>
</tr>
<tr>
<td>TBL</td>
<td>0.84</td>
<td>0.36</td>
<td>0.43</td>
<td>0.37</td>
<td>3.03</td>
<td>0.28</td>
</tr>
<tr>
<td>LTY</td>
<td>1.30</td>
<td>0.30</td>
<td>0.54</td>
<td>0.31</td>
<td>5.45</td>
<td>0.26</td>
</tr>
<tr>
<td>LTR</td>
<td>0.51</td>
<td>0.70</td>
<td>−0.56</td>
<td>0.70</td>
<td>6.32</td>
<td>0.70</td>
</tr>
<tr>
<td>TMS</td>
<td>−0.03</td>
<td>0.76</td>
<td>−0.44</td>
<td>0.79</td>
<td>2.12</td>
<td>0.59</td>
</tr>
<tr>
<td>DFR</td>
<td>−0.23</td>
<td>0.65</td>
<td>−0.07</td>
<td>0.65</td>
<td>−1.12</td>
<td>0.68</td>
</tr>
<tr>
<td>INFL</td>
<td>0.33</td>
<td>0.61</td>
<td>0.22</td>
<td>0.64</td>
<td>0.98</td>
<td>0.46</td>
</tr>
</tbody>
</table>

Panel B: Forecasts based on individual technical indicators

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Δ (ann. %)</th>
<th>Average equity weight</th>
<th>Δ (ann. %)</th>
<th>Average equity weight</th>
<th>Δ (ann. %)</th>
<th>Average equity weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>MA(1,9)</td>
<td>2.16</td>
<td>0.62</td>
<td>−0.99</td>
<td>0.71</td>
<td>19.82</td>
<td>0.15</td>
</tr>
<tr>
<td>MA(1,12)</td>
<td>3.23</td>
<td>0.66</td>
<td>0.44</td>
<td>0.76</td>
<td>18.83</td>
<td>0.11</td>
</tr>
<tr>
<td>MA(2,9)</td>
<td>2.50</td>
<td>0.63</td>
<td>−0.55</td>
<td>0.72</td>
<td>19.56</td>
<td>0.14</td>
</tr>
<tr>
<td>MA(2,12)</td>
<td>3.31</td>
<td>0.67</td>
<td>0.47</td>
<td>0.77</td>
<td>19.18</td>
<td>0.11</td>
</tr>
<tr>
<td>MA(3,9)</td>
<td>2.30</td>
<td>0.64</td>
<td>0.15</td>
<td>0.72</td>
<td>14.27</td>
<td>0.21</td>
</tr>
<tr>
<td>MA(3,12)</td>
<td>2.11</td>
<td>0.64</td>
<td>0.13</td>
<td>0.72</td>
<td>13.11</td>
<td>0.18</td>
</tr>
<tr>
<td>MOM(9)</td>
<td>2.61</td>
<td>0.69</td>
<td>0.40</td>
<td>0.79</td>
<td>14.92</td>
<td>0.13</td>
</tr>
<tr>
<td>MOM(12)</td>
<td>2.36</td>
<td>0.67</td>
<td>0.07</td>
<td>0.76</td>
<td>15.13</td>
<td>0.16</td>
</tr>
<tr>
<td>VOL(1,9)</td>
<td>1.22</td>
<td>0.70</td>
<td>−0.95</td>
<td>0.77</td>
<td>13.34</td>
<td>0.31</td>
</tr>
<tr>
<td>VOL(1,12)</td>
<td>2.05</td>
<td>0.70</td>
<td>−0.54</td>
<td>0.78</td>
<td>16.49</td>
<td>0.22</td>
</tr>
<tr>
<td>VOL(2,9)</td>
<td>0.95</td>
<td>0.72</td>
<td>−0.72</td>
<td>0.77</td>
<td>10.20</td>
<td>0.41</td>
</tr>
<tr>
<td>VOL(2,12)</td>
<td>0.73</td>
<td>0.70</td>
<td>−0.44</td>
<td>0.75</td>
<td>7.26</td>
<td>0.41</td>
</tr>
<tr>
<td>VOL(3,9)</td>
<td>0.34</td>
<td>0.70</td>
<td>−0.80</td>
<td>0.76</td>
<td>6.65</td>
<td>0.41</td>
</tr>
<tr>
<td>VOL(3,12)</td>
<td>1.61</td>
<td>0.68</td>
<td>−0.45</td>
<td>0.76</td>
<td>13.05</td>
<td>0.25</td>
</tr>
</tbody>
</table>
Table 3
Results for the principal component forecast, 1966:01–2008:12

$R^2_{OS}$ measures the percent reduction in mean squared forecast error (MSFE) for the principal component forecast relative to the historical average benchmark forecast. The principal component forecast is based on the first $k$ principal components of the 14 macroeconomic variables and 14 technical indicators taken together, where $k$ is selected using the Onatski (2009) ED algorithm. Statistical significance of $R^2_{OS}$ is assessed with the Clark and West (2007) MSFE-adjusted statistic corresponding to $H_0: R^2_{OS} \leq 0$ against $H_A: R^2_{OS} > 0$; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Average utility gain ($\Delta$) is the portfolio management fee (in annualized percent return) that an investor with mean-variance preferences and risk aversion coefficient of five would be willing to pay to have access to the principal component forecast relative to the historical average benchmark forecast. $R^2_{OS}$ statistics, average forecasts, utility gains, and average equity weights are computed for the entire 1966:01–2008:12 forecast evaluation period (first and second columns) and separately for NBER-dated expansions (third and fourth columns) and recessions (fifth and sixth columns).

<table>
<thead>
<tr>
<th>Overall</th>
<th>Expansion</th>
<th>Recession</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R^2_{OS}$ (%)</td>
<td>Average forecast (%)</td>
<td>$R^2_{OS}$ (%)</td>
</tr>
<tr>
<td>1.66***</td>
<td>0.25</td>
<td>0.50*</td>
</tr>
</tbody>
</table>

Panel A: Out-of-sample equity risk premium forecasting results

Panel B: Asset allocation results

<table>
<thead>
<tr>
<th>$\Delta$ (ann. %)</th>
<th>Average equity weight</th>
<th>$\Delta$ (ann. %)</th>
<th>Average equity weight</th>
<th>$\Delta$ (ann. %)</th>
<th>Average equity weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.35</td>
<td>0.28</td>
<td>1.21</td>
<td>0.31</td>
<td>21.97</td>
<td>0.08</td>
</tr>
</tbody>
</table>
Fig. 1. Out-of-sample equity risk premium forecasts based on individual macroeconomic variables, 1966:01–2008:12. Black (gray) lines delineate equity risk premium forecasts in percent based on the macroeconomic variable given in the panel heading (historical average). Vertical bars depict NBER-dated recessions.
Fig. 2. Cumulative squared forecast error differences, out-of-sample equity risk premium forecasts based on the historical average and individual macroeconomic variables, 1966:01–2008:12. The figure depicts cumulative differences between the squared forecast errors for the historical average equity risk premium forecast and the equity risk premium forecast based on the macroeconomic variable given in the panel heading. Vertical bars depict NBER-dated recessions.
Fig. 3. Out-of-sample equity risk premium forecasts based on individual technical indicators, 1966:01–2008:12. Black (gray) lines delineate equity risk premium forecasts in percent based on the technical indicator given in the panel heading (historical average). Vertical bars depict NBER-dated recessions.
Fig. 4. Cumulative squared forecast error differences, out-of-sample equity risk premium forecasts based on the historical average and individual technical indicators, 1966:01–2008:12. The figure depicts cumulative differences between the squared forecast errors for the historical average equity risk premium forecast and the equity risk premium forecast based on the technical indicator given in the panel heading. Vertical bars depict NBER-dated recessions.
Fig. 5. Equity portfolio weights computed using equity risk premium forecasts based on individual macroeconomic variables, 1966:01–2008:12. Black (gray) lines delineate equity portfolio weights for an investor with mean-variance preferences and risk aversion coefficient of five who uses an equity risk premium forecast based on the macroeconomic variable given in the panel heading (historical average forecast). Vertical bars depict NBER-dated recessions.
Fig. 6. Equity portfolio weights computed using equity risk premium forecasts based on individual technical indicators, 1966:01–2008:12. Black (gray) lines delineate equity portfolio weights for an investor with mean-variance preferences and risk aversion coefficient of five who uses an equity risk premium forecast based on the technical indicator given in the panel heading (historical average forecast). Vertical bars depict NBER-dated recessions.
Fig. 7. Actual equity risk premium and equity risk premium forecasts based on individual macroeconomic variables near a U.S. business-cycle peak. The panels show the incremental change in the average difference between the actual equity risk premium or equity risk premium forecast based on the macroeconomic variable given in the panel heading and the historical average equity risk premium forecast two months before through four months after an NBER-dated peak. Actual and forecast values are measured in percent. Circles indicate point estimates and shaded areas depict 90% confidence bands.
Fig. 8. Actual equity risk premium and equity risk premium forecasts based on individual technical indicators near a U.S. business-cycle peak. The panels show the incremental change in the average difference between the actual equity risk premium or equity risk premium forecast based on the technical indicator given in the panel heading and the historical average equity risk premium forecast two months before through four months after an NBER-dated peak. Actual and forecast values are measured in percent. Circles indicate point estimates and shaded areas depict 90% confidence bands.
Fig. 9. Actual equity risk premium and equity risk premium forecasts based on individual macroeconomic variables near a U.S. business-cycle trough. The panels show the incremental change in the average difference between the actual equity risk premium or equity risk premium forecast based on the macroeconomic variable given in the panel heading and the historical average equity risk premium forecast four months before through two months after an NBER-dated trough. All forecasts are measured in percent. Circles indicate point estimates and shaded areas depict 90% confidence bands.
Fig. 10. Actual equity risk premium and equity risk premium forecasts based on individual technical indicators near a U.S. business-cycle trough. The panels show the incremental change in the average difference between the actual equity risk premium or equity risk premium forecast based on the technical indicator given in the panel heading and the historical average equity risk premium forecast four months before through two months after an NBER-dated trough. All forecasts are measured in percent. Circles indicate point estimates and shaded areas depict 90% confidence bands.
Fig. 11. Out-of-sample equity risk premium forecasts based on macroeconomic variables and technical indicators taken together, 1966:01–2008:12. Black (gray) line in the top panel delineates the principal component (historical average) equity risk premium forecast. The principal component (PC) equity risk premium forecast is based on the first $k$ principal components of the 14 macroeconomic variables and 14 technical indicators taken together, where $k$ is selected using the Onatski (2009) ED algorithm. The middle panel depicts cumulative differences between the squared forecast errors for the historical average and PC equity risk premium forecasts. Black (gray) line in the bottom panel delineates the equity portfolio weight for an investor with mean-variance preferences and risk aversion coefficient of five who uses the PC equity risk premium forecast (historical average forecast). Vertical bars depict NBER-dated recessions.