Forecasting the Equity Risk Premium:
The Role of Technical Indicators

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Abstract

Do existing equity risk premium forecasts ignore useful information, such as technical indicators? Although academics have extensively used macroeconomic variables to forecast the U.S. equity risk premium, they have paid relatively little attention to the technical stock market indicators widely employed by practitioners. Our paper fills this gap by studying the forecasting ability of technical indicators relative to popular macroeconomic variables. We find that technical indicators display statistically and economically significant out-of-sample forecasting power and generate substantial utility gains; moreover, technical indicators tend to 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. In line with this cyclical behavior, utilizing information from both technical indicators and macroeconomic variables substantially increases out-of-sample forecasting performance relative to either alone.

1. Introduction

A voluminous literature studies U.S. equity risk premium prediction with macroeconomic variables. 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. Recent studies confirm 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). Additional macroeconomic variables, such as the consumption-wealth ratio (Lettau and Ludvigson 2001) and volatility (Guo 2006), also exhibit predictive power. Ang and Bekaert (2007), Hjalmarsson (2010), and Henkel, Martin, and Nadari (2011) find equity risk premium predictability based on macroeconomic variables across countries. Cochrane (2011) explains how this predictability literature profoundly shifts the emphasis of asset pricing theory from expected cash flows to discount rates.

The degree of return predictability is small, however. The influential study of Goyal and Welch (2008) argues that out-of-sample criteria are important for assessing stock return predictability. In light of this, recent studies rely on 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, as well as utility gains for investors. In terms of these metrics, Ferreira and Santa-Clara (2011) provide the best-to-date forecast of the U.S. equity risk premium with their intriguing "sum-of-the-parts" approach, which more efficiently exploits macro information. For the 1966:01–2008:12 evaluation period, the sum-of-the-parts forecast generates a monthly R^2_{OS} of 1.18% and annualized utility gain of 2.97% for a mean-variance investor with a risk aversion coefficient of five. By focusing on macroeconomic variables, however, recent studies ignore a specific type of information that practitioners commonly use: technical indicators.

Technical indicators, such as moving averages and price-momentum signals, represent market price reactions and other market statistics. Such indicators potentially capture information relevant for forecasting stock market returns beyond that summarized by macroeconomic variables. Indeed, technical indicators are readily 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, Covel 2005, Park and Irwin 2007, Lo and Hasanhodzic 2010). Despite the widespread use of technical indicators, relatively few academic papers study their predictive ability. Although early studies (e.g., Cowles 1933, Fama and Blume 1966, Jensen and Benington 1970) typically find little ability for technical indicators to track future stock returns, more recent studies provide much stronger evidence that technical indicators work. For example, Brock, Lakonishok, and LeBaron (1992) present evidence that moving averages based on the Dow Jones Industrial Average generate profitable trading signals, while Lo, Mamaysky, and Wang (2000) find that technical analysis implemented via kernel estimators and automated rules provides incremental information that adds value to the investment process.[1] Existing studies of technical analysis focus on the profitability of trading signals, which essentially predict the sign of market

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[1] Relative to equity markets, academic studies generally find stronger support for the efficacy of technical analysis in foreign exchange markets. For example, LeBaron (1999) and Neely (2002) show that moving averages generate substantial portfolio gains for currency trading and that the gains are much larger than those in the stock market. Moreover, Menkhoff and Taylor (2007) argue that technical analysis today is as important as fundamental analysis to currency mangers.

returns, and do not forecast the *magnitude* of the equity risk premium with technical indicators.

Our paper is the first to compare and combine the power of macroeconomic variables and technical indicators for forecasting the equity risk premium. We begin by analyzing equity risk premium forecasts based on technical indicators with the R^2_{OS} statistic. 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.

Following Campbell and Thompson (2008), among others, 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 a number of 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.

Our results indicate 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 popular macroeconomic variables. Furthermore, the out-of-sample forecasting gains are highly concentrated in NBER-dated business-cycle 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 3.58% 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 19.51%. Insofar as predictability is linked to the real economy, we expect that there will be more predictability in the rapidly changing economic conditions of recessions (e.g., Henkel, Martin, and Nadari 2011). The relatively high predictability during recessions is consistent with the stock price continuation/trend story of Zhang (2006), who incorporates behavioral insights from Daniel, Hirshleifer, and Subrahmanyam (1998, 2001) and Hirshleifer (2001). When volatility is high, as in recessions relative to expansions, information uncertainty is also high. In this environment, investors are more likely to underreact to information, which produces stock price trends and greater return predictability based on technical indicators.

Although technical indicators and macroeconomic variables both forecast better than the historical average benchmark during recessions, the two approaches exploit different patterns: technical indicators detect the typical fall in the equity risk premium near cyclical peaks, while macroeconomic variables tend to pick up the typical rise in the equity risk premium later in recessions near cyclical troughs. This suggests that technical indicators and macroeconomic variables provide complementary information over the business cycle. To further investigate this complementarity, we combine information from both technical indicators and macroeconomic variables. In particular, we compute an equity risk premium forecast from a predictive regression with a small

number of principal components extracted from the complete set of technical indicators and macroeconomic variables. This approach guards against in-sample overfitting when estimating the forecasting model in the presence of a large number of potential predictors.[2] Combining information from both technical indicators and macroeconomic variables appears very useful. Relative to the Ferreira and Santa-Clara (2011) sum-of-the-parts approach, the R^2_{OS} increases by about 40%, from 1.18% to 1.66%, while the annualized utility gain increases by nearly 80%, from 2.97% to 5.32%, over the 1966:01–2008:12 evaluation period. These results help to explain the simultaneously prominent roles for the macroeconomic variables used in the academic literature and technical indicators used by practitioners: both approaches seem useful for predicting returns, and they complement each other.

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. Existing theoretical asset pricing models typically ignore the information investors have about technical indicators, and our study calls for new asset pricing models that can improve our understanding of the role of technical indicators and their equilibrium pricing impacts.[3]

2. Econometric Methodology

2.1. Forecast Construction

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

$$r_{t+1} = \alpha_i + \beta_i x_{i,t} + \varepsilon_{i,t+1}, \tag{1}$$

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 t as

$$\hat{r}_{i,t+1} = \hat{\alpha}_{i,t} + \hat{\beta}_{i,t} x_{i,t}, \tag{2}$$

where $\hat{\alpha}_{i,t}$ and $\hat{\beta}_{i,t}$ are the ordinary least squares (OLS) estimates of α_i and β_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: $\{\hat{r}_{i,t+1}\}_{t=q_1}^{T-1}$.[4] The historical average of the equity

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[2]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.

[3]Behavioral 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*. As previously discussed, Zhang (2006) finds that stock-price underreaction is magnified when there is greater information uncertainty. Furthermore, 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.

[4]Observe that the forecasts are generated using a recursive (i.e., expanding) window for estimating α_i and β_i in (1). Forecasts could also be generated using a rolling window (which drops earlier observations as additional observations become available) in recognition

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 β_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. We impose Campbell and Thompson (2008) restrictions on the individual predictive regression forecasts.

We consider three popular types of technical indicators. 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 t by comparing two moving averages:

$$S_t = \begin{cases} 1 & \text{if } MA_{s,t} \geq MA_{l,t} \\ 0 & \text{if } MA_{s,t} < MA_{l,t} \end{cases}, \tag{3}$$

where

$$MA_{j,t} = (1/j)\sum_{i=0}^{j-1} P_{t-i} \quad \text{for } j = s, l, \tag{4}$$

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 momentum rule generates the following signal:

$$S_t = \begin{cases} 1 & \text{if } P_t \geq P_{t-m} \\ 0 & \text{if } P_t < P_{t-m} \end{cases}. \tag{5}$$

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 employ volume data in conjunction with past prices to identify market trends. In light of this, the final type of technical indicator we consider incorporates "on-balance" volume (e.g., Granville 1963). We first define

$$OBV_t = \sum_{k=1}^{t} VOL_k D_k, \tag{6}$$

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of potential structural instability. Pesaran and Timmermann (2007) and Clark and McCracken (2009), however, show that the optimal estimation window for a quadratic loss function can include pre-break data due to the familiar bias-efficiency tradeoff. We use recursive estimation windows in Section 3, although we obtain similar results using rolling estimation windows of various sizes.

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where VOL_k is a measure of the trading volume during 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

$$S_t = \begin{cases} 1 & \text{if } \text{MA}_{s,t}^{OBV} \geq \text{MA}_{l,t}^{OBV} \\ 0 & \text{if } \text{MA}_{s,t}^{OBV} < \text{MA}_{l,t}^{OBV} \end{cases}, \tag{7}$$

where

$$\text{MA}_{j,t}^{OBV} = (1/j) \sum_{i=0}^{j-1} OBV_{t-i} \quad \text{for } j = s, l. \tag{8}$$

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 $l = 9, 12$ and denote the corresponding rule as VOL(s,l).

The MA, momentum, and volume-based indicators 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., 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_{OS}^2 statistic, which measures the proportional reduction in MSFE for a competing model relative to the historical average benchmark:

$$R_{OS}^2 = 1 - \frac{\sum_{k=1}^{q_2} (r_{q_1+k} - \hat{r}_{q_1+k})^2}{\sum_{k=1}^{q_2} (r_{q_1+k} - \bar{r}_{q_1+k})^2}, \tag{9}$$

where $\hat{r}_{q_1+k}$ represents an equity risk premium forecast based on a macroeconomic variable or technical indicator. Clearly, when $R_{OS}^2 > 0$, 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 $H_0 : R_{OS}^2 \leq 0$ against $H_A : R_{OS}^2 > 0$.[5]

R_{OS}^2 statistics are typically small for equity risk premium forecasts, but even a relatively small R_{OS}^2 statistic can 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

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[5]Clark and West (2007) develop the *MSFE-adjusted* statistic by modifying the familiar Diebold and Mariano (1995) and West (1996) statistic so that it has an approximately standard normal asymptotic distribution when comparing forecasts from nested models. Comparing the forecasts based on technical indicators or macroeconomic variables with the historical average forecast entails comparing nested models, since setting $\beta_i = 0$ in (1) yields the constant expected excess return model.

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 technical indicator or macroeconomic variable relative to the historical average forecast.

3. Empirical Results

This section describes the data and reports out-of-sample test results for the R^2_{OS} 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).[6] 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:

1. *Dividend-price ratio (log)*, DP: log of a twelve-month moving sum of dividends paid on the S&P 500 index minus the log of stock prices (S&P 500 index).
2. *Dividend yield (log)*, DY: log of a twelve-month moving sum of dividends minus the log of lagged stock prices.
3. *Earnings-price ratio (log)*, EP: log of a twelve-month moving sum of earnings on the S&P 500 index minus the log of stock prices.
4. *Dividend-payout ratio (log)*, DE: log of a twelve-month moving sum of dividends minus the log of a twelve-month moving sum of earnings.
5. *Stock variance*, SVAR: monthly sum of squared daily returns on the S&P 500 index.
6. *Book-to-market ratio*, BM: book-to-market value ratio for the Dow Jones Industrial Average.
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).
9. *Long-term yield*, LTY: long-term government bond yield.
10. *Long-term return*, LTR: return on long-term government bonds.

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[6]The data are available at http://www.hec.unil.ch/agoyal/.

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

12. *Default yield spread*, DFY: difference between 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 CPI (all urban consumers); we follow Goyal and Welch (2008) and use $x_{i,t-1}$ 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).[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. R^2_{OS} statistics are computed separately for the full 1966:01–2008:12 forecast evaluation period, as well as NBER-dated expansions and recessions.[8] 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 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

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[7]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.

[8]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.

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.[9] 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 1927:12–1965:12 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.[10] Data availability limits the starting date for the volume rules' in-sample period to 1950:12.[11] 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 around 1.5% 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

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[9]Goyal and Welch (2003, 2008) employ this device to assess the consistency of out-of-sample predictive ability.

[10]These starting dates allow for the lags necessary to compute the initial MA or momentum signal in (3) or (5).

[11]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.

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 out-of-sample equity risk premium predictability using either macroeconomic variables or technical indicators.

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).[12] The results in Panel A indicate that forecasts based on macroeconomic variables often produce sizable utility gains vis-á-vis the historical average benchmark. The utility gain is above 1% for seven of the individual macroeconomic variables in the second column, so that the investor would be willing to pay an annual management fee of more than 100 basis points 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 (2.47%) for the full 1966:01–2008:12 forecast evaluation period. The utility gain is negative (−0.21%) during expansions, while it is a very sizable 17.17% during recessions. DP, TBL, LTY, and TMS also provide utility gains above 8% 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 (gray line) is procyclical, which, given that the historical average forecast of the equity risk premium is relatively smooth, primarily reflects countercyclical changes in expected volatility.[13] The equity weights based on macroeconomic variables (black lines) 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. Twelve of the individual technical forecasts provide utility gains above 1.5%, with the MA(2,12) forecast generating the largest gain (3.58%). 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 (−0.51%), while it jumps to 16.95% during recessions. In all, ten of the individual technical forecasts produce utility gains above 12% during recessions. The fifth and seventh columns reveal that the

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[12]For the asset allocation exercises, we measure the equity risk premium and compute forecasts in terms of simple (instead of log) returns, so that the portfolio return is given by the sum of the individual portfolio weights multiplied by the asset returns.

[13]French, Schwert, and Stambaugh (1987), Schwert (1989, 1990), Whitelaw (1994), Harvey (2001), Ludvigson and Ng (2007), Lundblad (2007), and Lettau and Ludvigson (2009), among others, also find evidence of countercyclical expected volatility using alternative volatility estimators.

average equity weight is substantially lower during recessions than expansions for all of the technical forecasts.

Figure 6 further illustrates that technical forecast weights (black lines) 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:

$$r_t - \bar{r}_t = a_P + \sum_{k=-2}^{4} b_{P,k} I_{k,t}^P + e_{P,t}, \tag{10}$$

where $I_{k,t}^P$ 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:

$$\hat{r}_t - \bar{r}_t = a_P + \sum_{k=-2}^{4} b_{P,k} I_{k,t}^P + e_{P,t}. \tag{11}$$

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:

$$r_t - \bar{r} = a_T + \sum_{k=-4}^{2} b_{T,k} I_{k,t}^T + e_{T,t}, \tag{12}$$

$$\hat{r}_t - \bar{r}_t = a_T + \sum_{k=-4}^{2} b_{T,k} I_{k,t}^T + e_{T,t}, \tag{13}$$

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

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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, EP, 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. Technical Indicators and Macro Variables in Conjunction

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?

Including all of the potential regressors simultaneously or using in-sample model selection methods can overfit the data, leading to poor out-of-sample forecasts. 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}:

$$\hat{r}_{PC,t+1} = \hat{\alpha}_{PC,t} + \hat{\beta}'_{PC,t} \hat{f}_{t,t}, \tag{14}$$

where $\hat{\alpha}_{PC,t}$ and $\hat{\beta}_{PC,t}$ are the OLS intercept and J-vector of 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 (2011) 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 (2011). 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.[14]

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 enhances 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 or 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 5.32% 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 1.39% and 27.25% 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-á-vis expansions (0.10 and 0.39, respectively). Inspection of the bottom panel of Figure 11 shows that the average equity weight of 0.10 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 cyclical 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 (2012). The Clark and McCracken (2012) 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.[15]

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[14]We also generated a PC forecast based on the first prinicpal component of the 14 macroeconomic variables, so that information from the technical indicators is excluded. The PC forecast based on macroeconomic variables alone has an R^2_{OS} of 0.96% for the full 1966:01–2008:12 forecast evaluation period (significant at the 1% level). This is less than the R^2_{OS} of 1.66% for the PC forecast that includes information from both the macroeconomic variables and technical indicators, so that incorporating information from the technical indicators improves the PC forecast. Furthermore, the Clark and West *MSFE-adjusted* statistic indicates that the MSFE for the PC forecast based on the 14 macroeconomic variables and 14 technical indicators taken together is significantly less than the MSFE for the PC forecast based only on the 14 macroeconomic variables at the 5% level.

[15]As Clark and McCracken (2012) emphasize, the asymptotic and finite-sample properties of the non-parametric bootstrap procedure in White's (2000) reality check, as well as Hansen's (2005) modified reality check, do not generally apply when comparing forecasts

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: $R^2_{OS,m} \leq 0$ for all $m = 1, \ldots, M$, where m indexes a competing model, against H_A: $R^2_{OS,m} > 0$ for at least one m. We implement this test using the Clark and McCracken (2012) maxMSFE-F_m statistic:

$$\text{maxMSFE-}F_m = \max_{m=1,\ldots,M} q_2 \frac{\bar{d}_m}{MSFE_m}, \tag{15}$$

where q_2 is the size of the forecast evaluation period,

$$\bar{d}_m = (1/q_2) \sum_{k=1}^{q_2} \left[(r_k - \bar{r}_k)^2 - (r_k - \hat{r}_{m,k})^2 \right], \tag{16}$$

$$MSFE_m = (1/q_2) \sum_{k=1}^{q_2} (r_k - \hat{r}_{m,k})^2. \tag{17}$$

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 4.7%, 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.[16] 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 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 1.62% for the 1966:01–2008:12 forecast evaluation period.[17] These values are both well below the R^2_{OS} of 1.66% and utility gain of 5.32% 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).[18] They show that the SOP fore-

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from multiple models that all nest the benchmark model. Clark and McCracken (2012) 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.

[16]The wild fixed-regressor bootstrap used to compute the p-value is described in detail in the appendix.

[17]Rapach, Strauss, and Zhou (2010) report an R^2_{OS} of 3.58% and utility gain of 2.34% for quarterly (instead of monthly) equity risk premium forecasts for the 1965:1–2005:4 forecast evaluation period.

[18]Ferreira and Santa-Clara (2011) focus on forecasting the market return, but note that they obtain similar results for the equity risk premium.

cast 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 1.18% and utility gain of 2.97%.[19] 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 substantially lower than the corresponding values of 1.66% and 5.32% 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 a set of well-known macroeconomic variables. 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, 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. 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 delivers substantially larger out-of-sample gains than any of the forecasts based on individual technical indicators or macroeconomic variables. These gains show that both technical indicators and macroeconomic variables are important for forecasting the U.S. equity risk premium.

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 $\{r_t^b\}_{t=1}^{T}$ 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 boostrapped 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.

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[19]The R^2_{OS} of 1.18% 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.

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Table 1 Out-of-Sample Equity Risk Premium Forecasting Results, 1966:01–2008:12

Predictor	Overall		Expansion		Recession	
	R^2_{OS} (%)	Average forecast (%)	R^2_{OS} (%)	Average forecast (%)	R^2_{OS} (%)	Average forecast (%)
Panel A: Forecasts Based on Individual Macroeconomic Variables						
DP	0.54**	0.21	−0.10	0.18	2.06**	0.41
DY	0.77**	0.18	−0.20	0.14	3.06***	0.39
EP	−0.37	0.40	−0.42	0.35	−0.27	0.71
DE	−1.63	0.76	−1.42	0.77	−2.13	0.72
SVAR	−0.07	0.51	−0.09	0.51	−0.01	0.48
BM	−0.99	0.41	−1.06	0.33	−0.83	0.85
NTIS	−1.58	0.77	0.01*	0.74	−5.29	0.91
TBL	0.13	0.26	−0.19	0.27	0.85	0.18
LTY	0.35*	0.22	−0.03	0.23	1.23	0.16
LTR	0.24	0.56	−0.72	0.55	2.49***	0.61
TMS	0.02	0.63	−0.54	0.65	1.31*	0.48
DFY	0.001	0.50	−0.03	0.49	0.08	0.52
DFR	0.21	0.50	0.03	0.51	0.64	0.46
INFL	0.12	0.46	0.12	0.48	0.13	0.35
Panel B: Forecasts Based on Individual Technical Indicators						
MA(1,9)	0.31	0.51	−1.18	0.57	3.79***	0.15
MA(1,12)	1.14**	0.54	0.19	0.62	3.36***	0.11
MA(2,9)	0.71**	0.51	−0.53	0.58	3.59***	0.13
MA(2,12)	1.23***	0.55	0.26	0.62	3.49***	0.11
MA(3,9)	0.63**	0.50	−0.07	0.56	2.28**	0.17
MA(3,12)	0.50*	0.50	0.02	0.56	1.63*	0.15
MOM(9)	0.52*	0.58	−0.22	0.66	2.24**	0.11
MOM(12)	0.65**	0.52	−0.13	0.59	2.47**	0.14
VOL(1,9)	0.18	0.55	−0.76	0.60	2.40**	0.25
VOL(1,12)	0.57*	0.55	−0.41	0.61	2.85**	0.19
VOL(2,9)	0.01	0.56	−0.61	0.60	1.47*	0.33
VOL(2,12)	−0.16	0.54	−0.43	0.58	0.48	0.33
VOL(3,9)	−0.32	0.54	−0.76	0.58	0.69	0.31
VOL(3,12)	0.38	0.53	−0.24	0.59	1.82*	0.21

Notes. R^2_{OS} measures the percent reduction in mean squared forecast error (MSFE) for the forecasting model based on the predictor given in the first column relative to the historical average benchmark forecast. R^2_{OS} statistics and average forecasts 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). 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.

Table 2 Asset allocation results, 1966:01–2008:12

|	Overall		Expansion		Recession	
Predictor	Δ (ann. %)	Average equity weight	Δ (ann. %)	Average equity weight	Δ (ann. %)	Average equity weight
Panel A: Forecasts Based on Individual Macroeconomic Variables						
DP	1.79	0.30	−0.06	0.24	11.80	0.68
DY	2.47	0.25	−0.21	0.19	17.17	0.62
EP	1.45	0.58	0.56	0.53	6.00	0.88
DE	−0.74	0.91	−0.44	0.92	−2.36	0.89
SVAR	−0.28	0.82	−0.24	0.82	−0.52	0.83
BM	−0.29	0.50	−1.17	0.43	4.12	0.94
NTIS	−0.74	1.00	0.38	0.99	−6.97	1.08
TBL	1.90	0.47	0.71	0.49	8.48	0.31
LTY	1.97	0.40	0.69	0.42	8.97	0.30
LTR	0.69	0.87	−0.66	0.87	7.88	0.89
TMS	1.43	0.93	0.17	0.96	8.28	0.71
DFY	0.55	0.79	0.26	0.76	1.97	0.94
DFR	1.05	0.84	0.07	0.85	6.46	0.79
INFL	0.80	0.77	0.22	0.80	4.07	0.58
Panel B: Forecasts Based on Individual Technical Indicators						
MA(1,9)	2.16	0.79	−0.51	0.85	16.95	0.41
MA(1,12)	3.37	0.81	0.64	0.90	18.60	0.34
MA(2,9)	2.41	0.80	−0.08	0.87	16.23	0.43
MA(2,12)	3.58	0.81	0.72	0.90	19.51	0.32
MA(3,9)	1.53	0.83	0.08	0.88	9.62	0.57
MA(3,12)	1.76	0.83	0.33	0.88	9.79	0.53
MOM(9)	3.24	0.80	0.61	0.90	17.91	0.23
MOM(12)	2.09	0.84	0.23	0.89	12.46	0.50
VOL(1,9)	1.86	0.78	−0.49	0.84	14.94	0.43
VOL(1,12)	2.84	0.76	−0.14	0.85	19.41	0.30
VOL(2,9)	1.62	0.79	−0.30	0.84	12.26	0.53
VOL(2,12)	1.39	0.78	−0.13	0.82	9.88	0.54
VOL(3,9)	0.90	0.78	−0.41	0.83	8.25	0.53
VOL(3,12)	2.32	0.76	−0.09	0.83	15.73	0.35

Notes. 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 3   Out-of-Sample Equity Risk Premium Forecasting and Asset Allocation Results Based on Technical Indicators and Macroeconomic Variables Taken Together, 1966:01–2008:12

Overall		Expansion		Recession	

Panel A: Out-of-Sample Equity Risk Premium Forecasting Results

R^2_{OS} (%)	Average forecast (%)	R^2_{OS} (%)	Average forecast (%)	R^2_{OS} (%)	Average forecast (%)
1.66***	0.25	0.50*	0.28	4.37***	0.08

Panel B: Asset Allocation Results

Δ (ann. %)	Average equity weight	Δ (ann. %)	Average equity weight	Δ (ann. %)	Average equity weight
5.32	0.34	1.39	0.39	27.25	0.10

Notes. 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 (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 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).

Figure 1   Out-of-Sample Equity Risk Premium Forecasts Based on Individual Macroeconomic Variables, 1966:01–2008:12
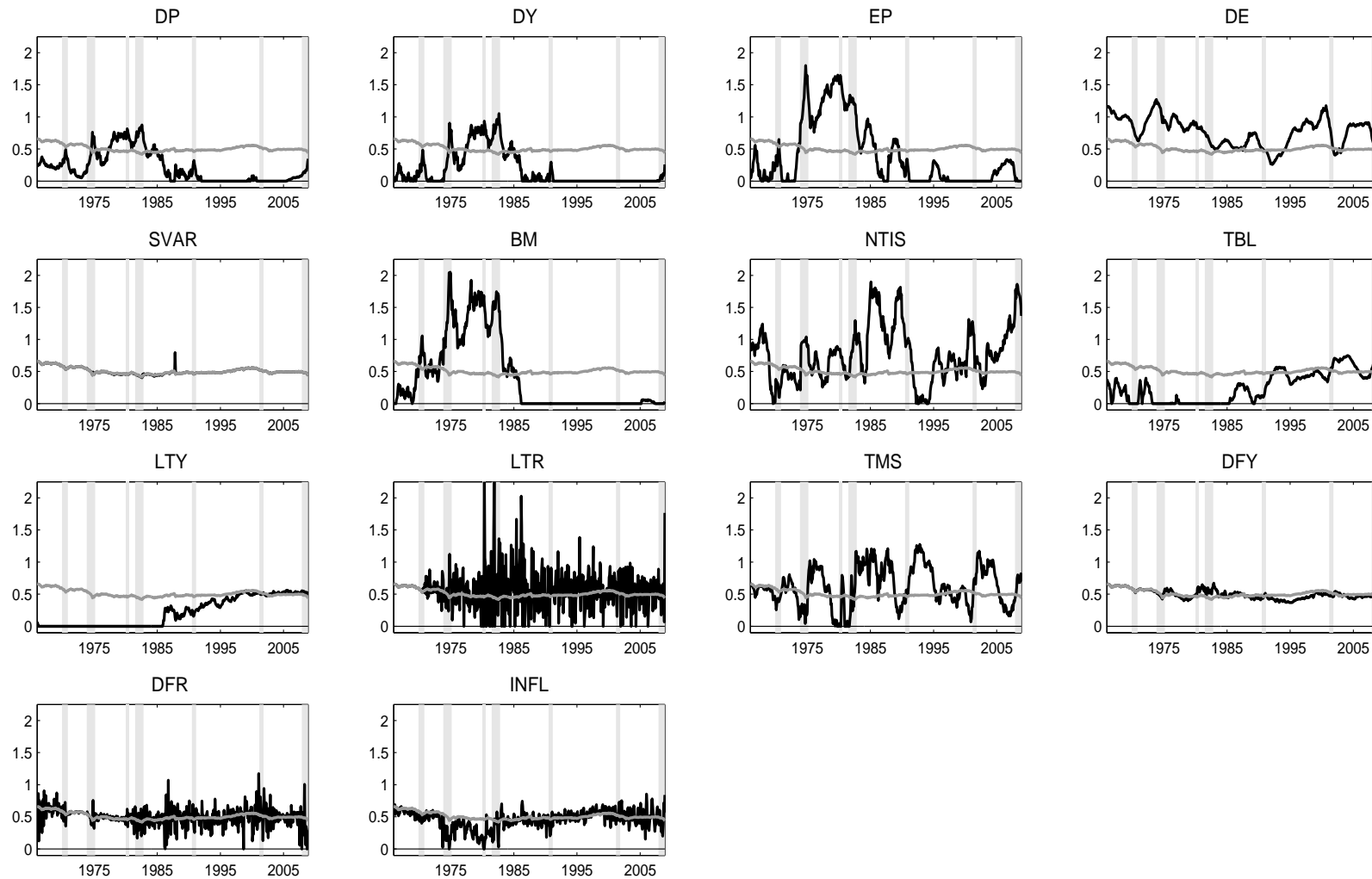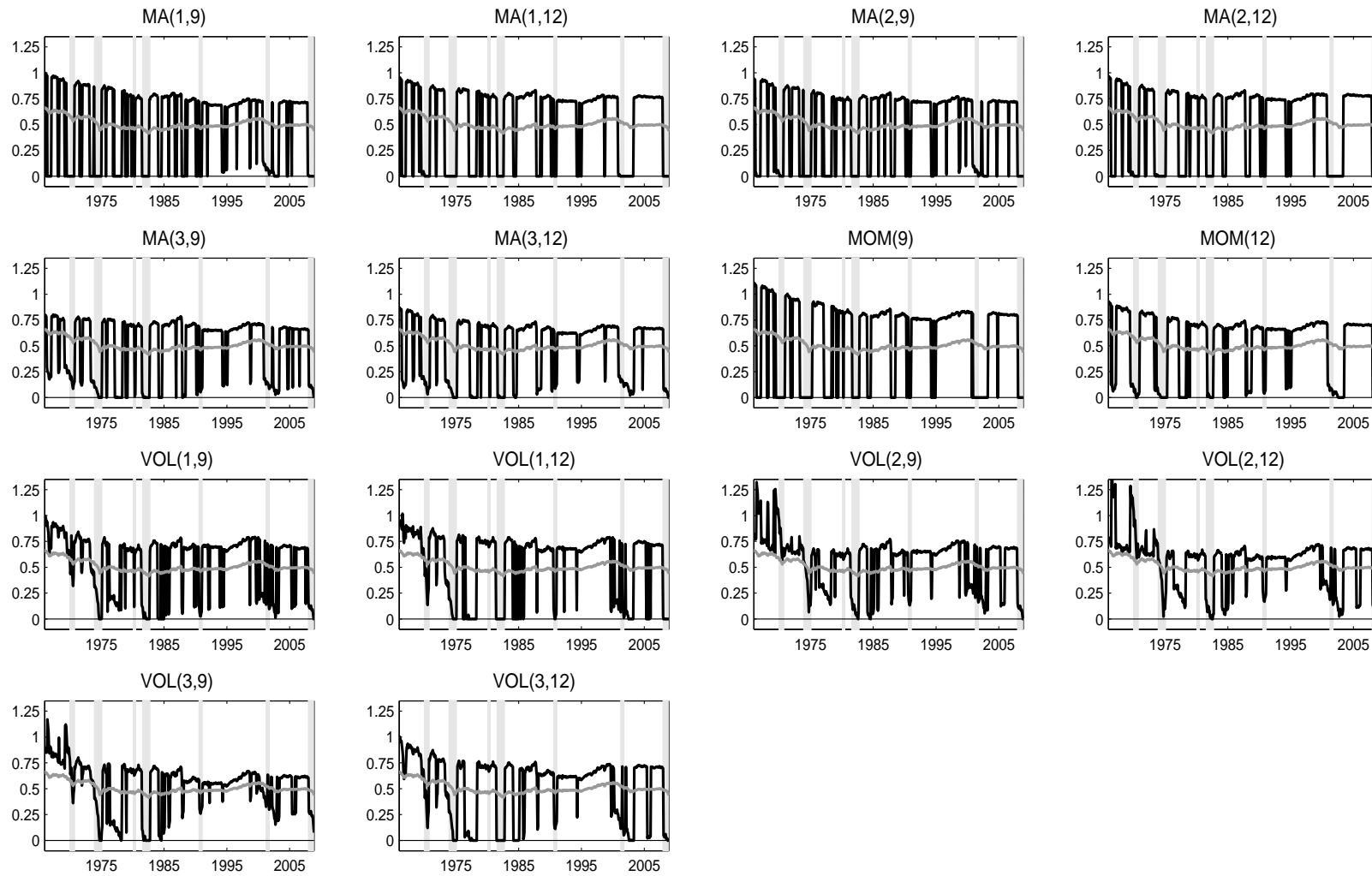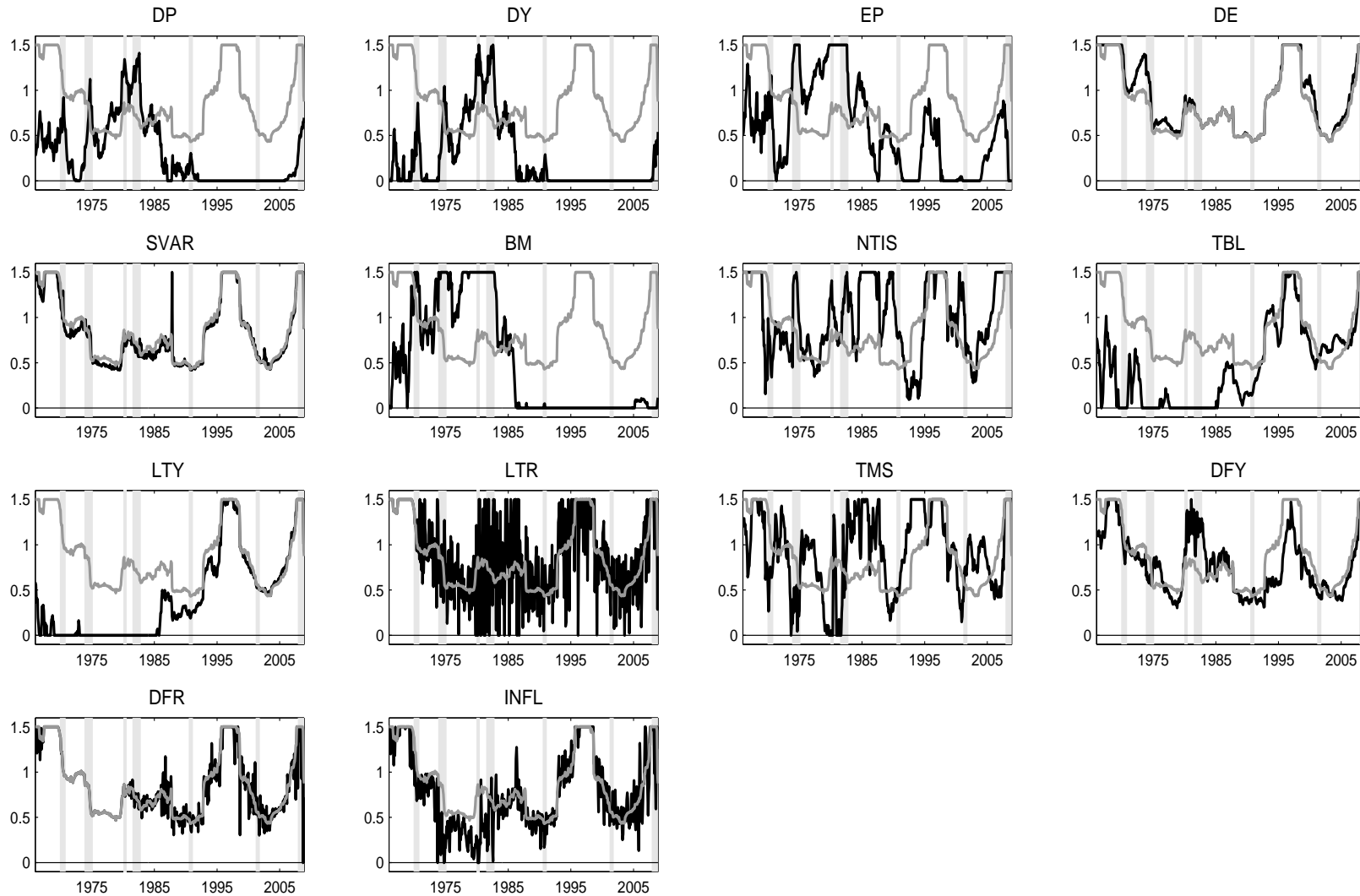

Notes. Black (gray) lines delineate equity risk premium forecasts in percent based on the macroeconomic variable given in the panel heading (historical average). Vertical bars depict NBER-dated recessions.

Figure 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
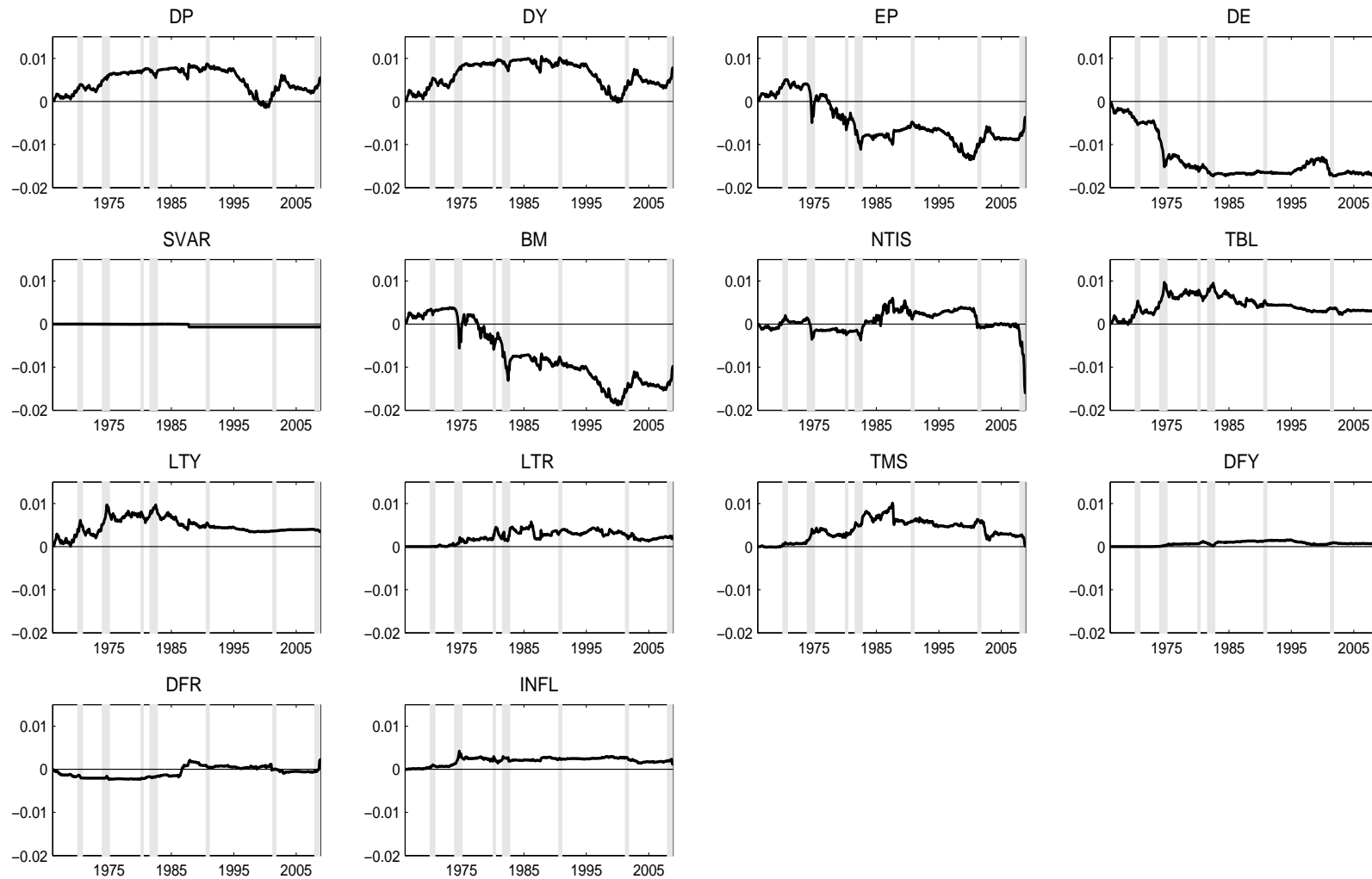

Notes. The figure depicts cumulative differences between squared forecast errors for the historical average equity risk premium forecast and the equity risk premium forecast based on the macroeconomic variable given in the panel heading. Vertical bars depict NBER-dated recessions.

Figure 3 Out-of-Sample Equity Risk Premium Forecasts Based on Individual Technical Indicators, 1966:01–2008:12

Notes. 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.

Figure 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
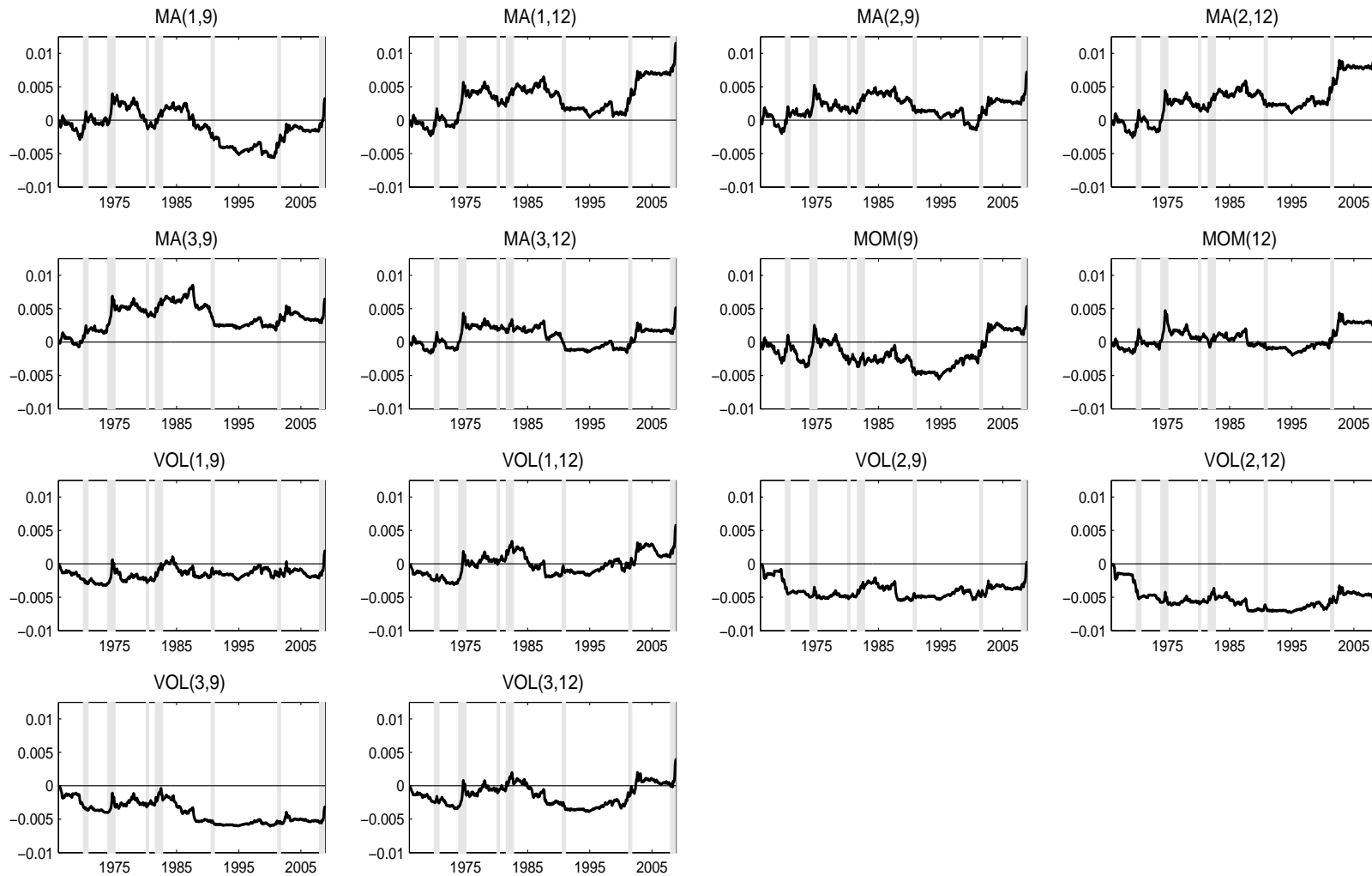
Notes. The figure depicts cumulative differences between squared forecast errors for the historical average equity risk premium forecast and the equity risk premium forecast based on the technical indicator given in the panel heading. Vertical bars depict NBER-dated recessions.

Figure 5 **Equity Portfolio Weights Computed Using Equity Risk Premium Forecasts Based on Individual Macroeconomic Variables, 1966:01–2008:12**
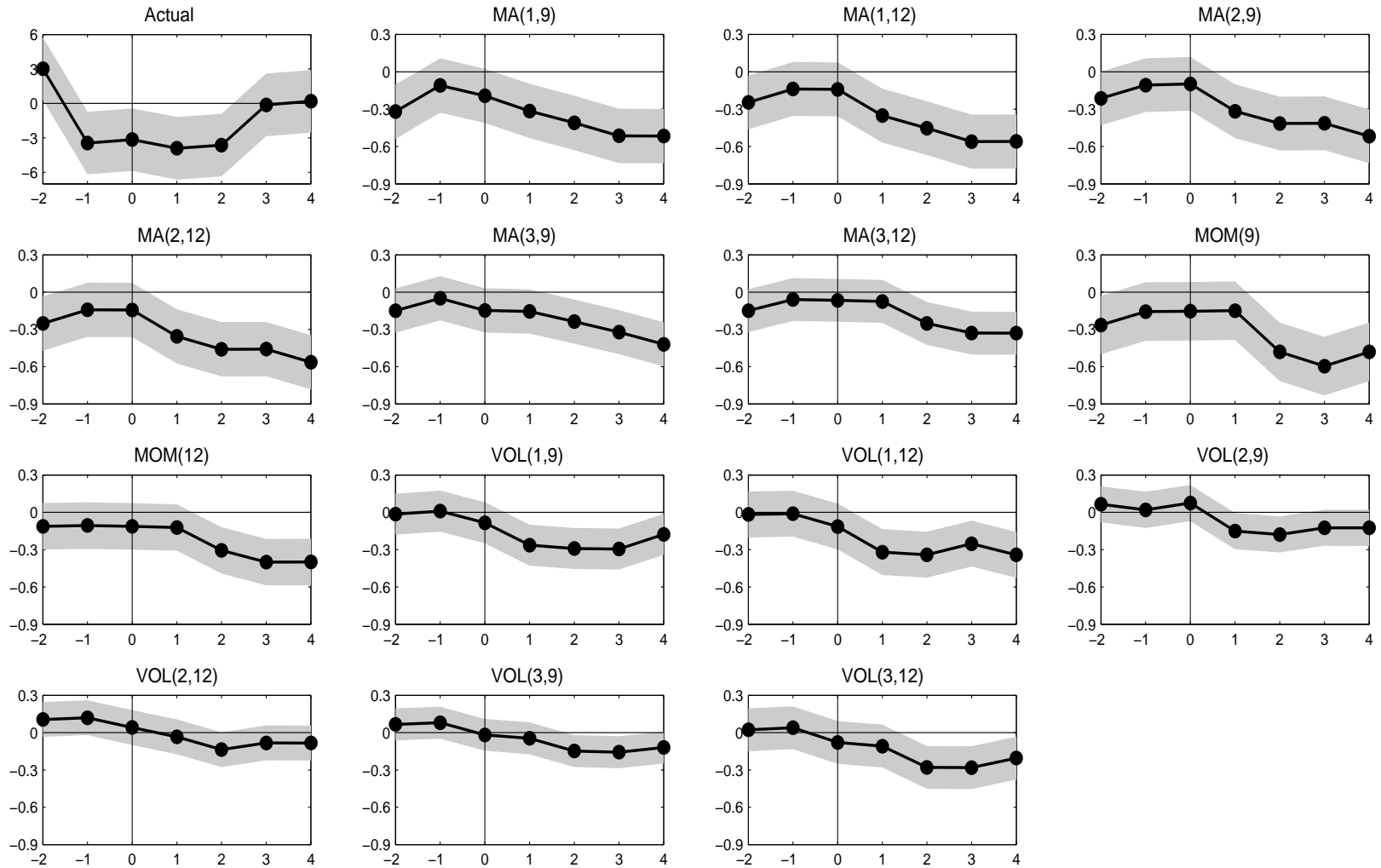

Notes. Black (gray) lines delineate equity portfolio weights for an investor with mean-variance preferences and risk aversion coefficient of five who uses an equity risk premium forecast based on the macroeconomic variable given in the panel heading (historical average forecast). Vertical bars depict NBER-dated recessions.

Figure 6 Equity Portfolio Weights Computed Using Equity Risk Premium Forecasts Based on Individual Technical Indicators, 1966:01–2008:12
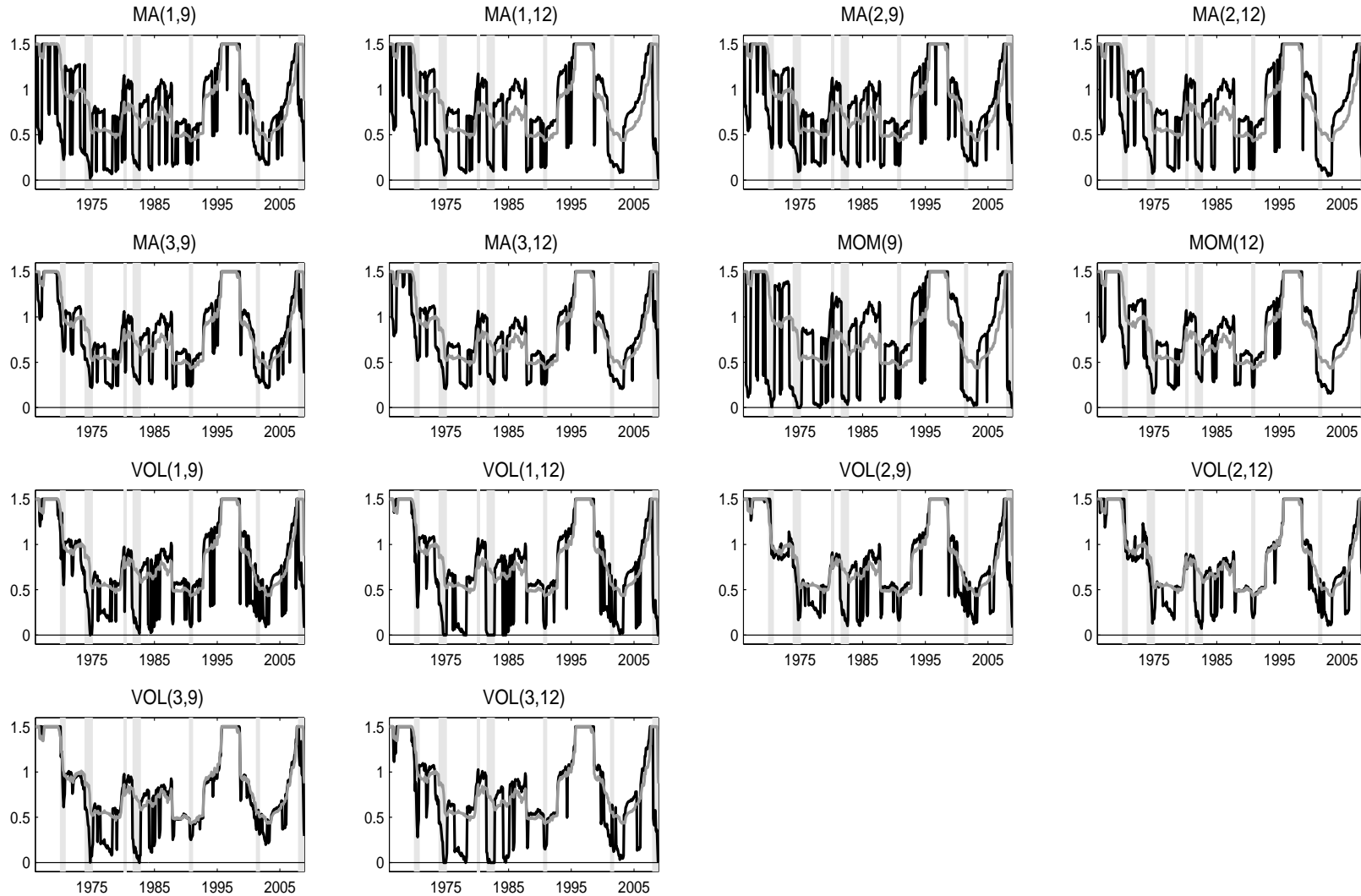
Notes. Black (gray) lines delineate equity portfolio weights for an investor with mean-variance preferences and risk aversion coefficient of five who uses an equity risk premium forecast based on the technical indicator given in the panel heading (historical average forecast). Vertical bars depict NBER-dated recessions.

Figure 7   Actual Equity Risk Premium and Equity Risk Premium Forecasts Based on Individual Macroeconomic Variables Near a U.S. Business-Cycle Peak
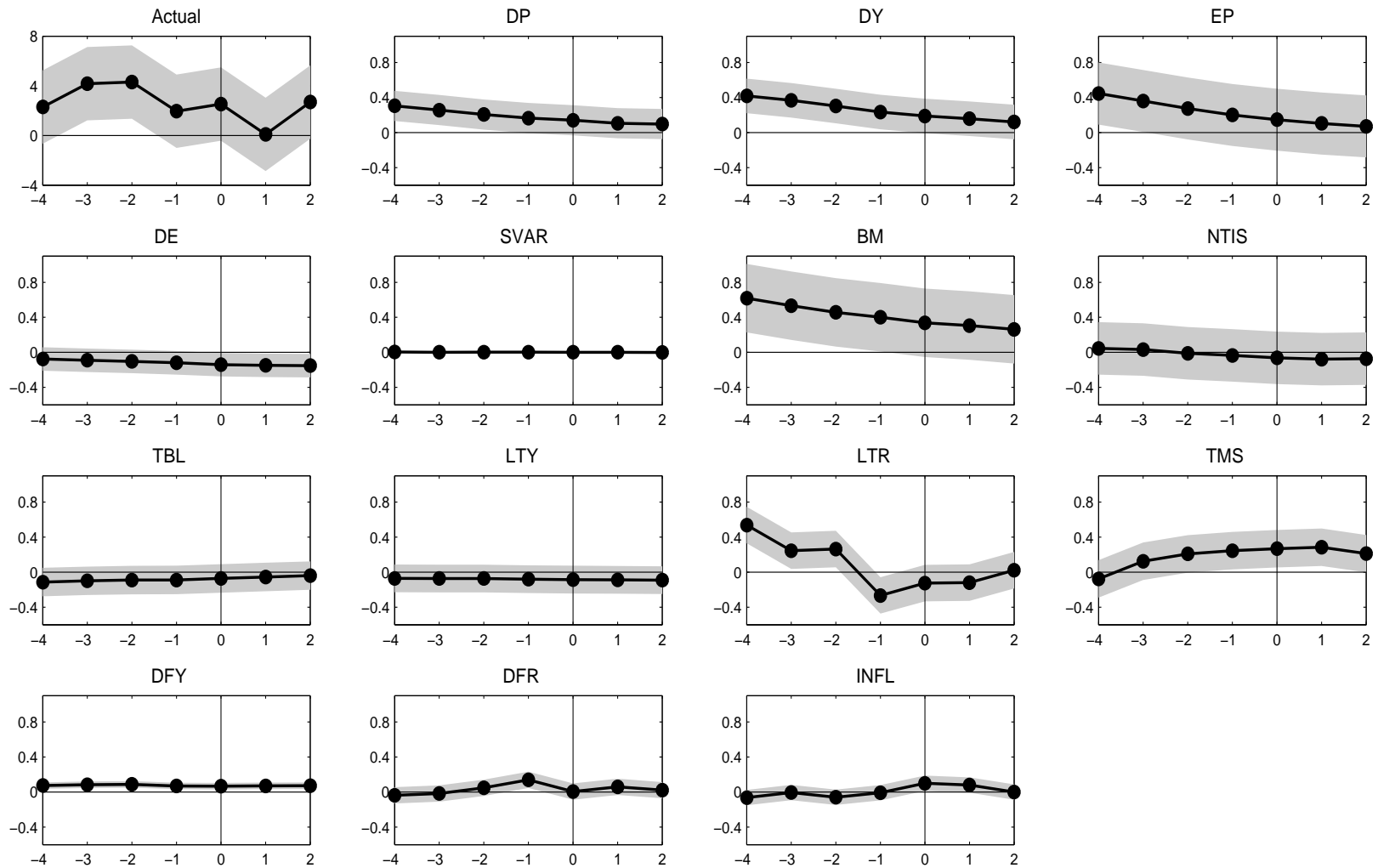

Notes. The panels show the incremental change in the average difference between the actual equity risk premium or equity risk premium forecast based on the macroeconomic variable given in the panel heading and the historical average equity risk premium forecast two months before through four months after an NBER-dated peak. Actual and forecast values are measured in percent. Circles indicate point estimates and shaded areas depict 90% confidence bands.

Figure 8   Actual Equity Risk Premium and Equity Risk Premium Forecasts Based on Individual Technical Indicators Near a U.S. Business-Cycle Peak
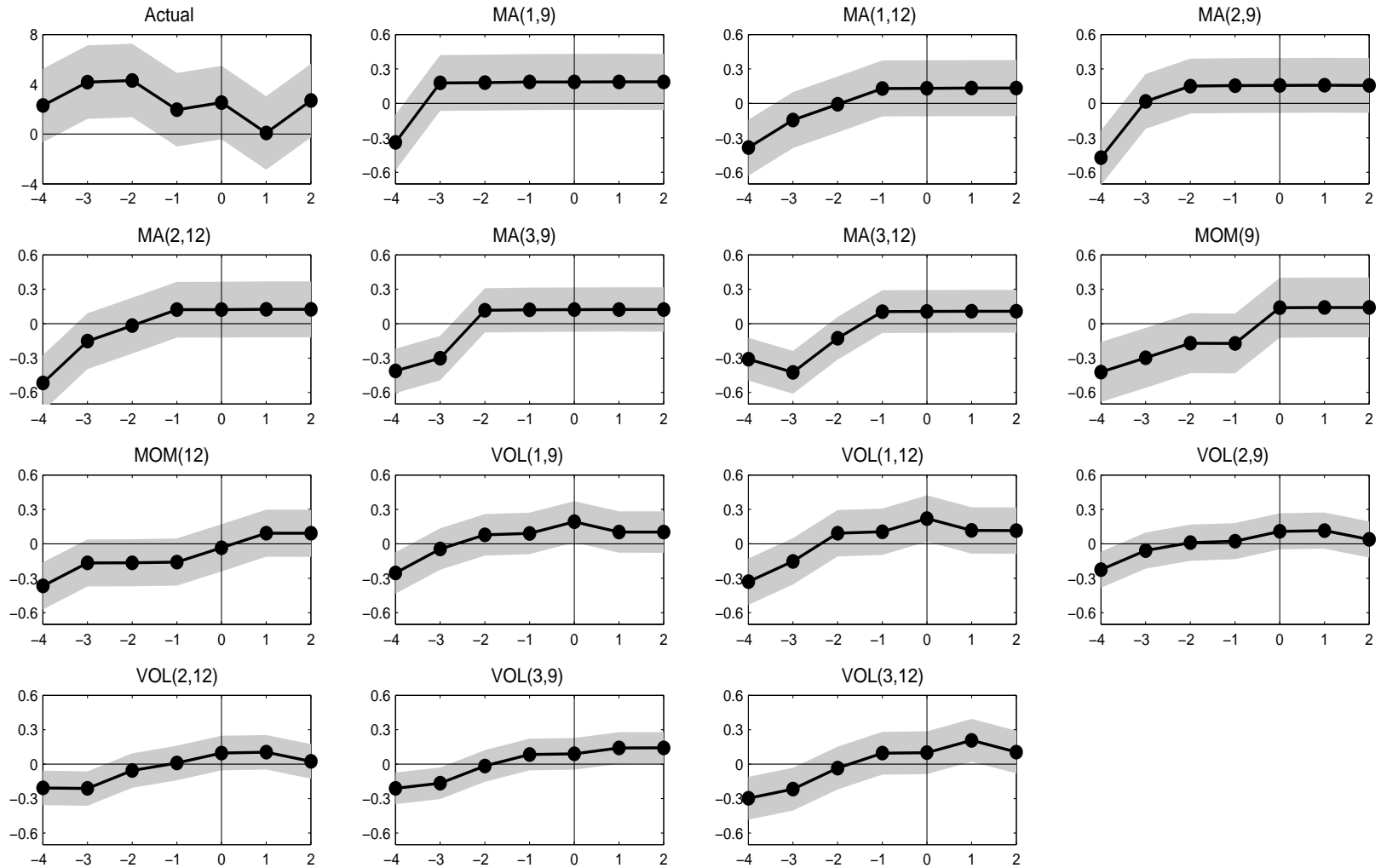

Notes. The panels show the incremental change in the average difference between the actual equity risk premium or equity risk premium forecast based on the technical indicator given in the panel heading and the historical average equity risk premium forecast two months before through four months after an NBER-dated peak. Actual and forecast values are measured in percent. Circles indicate point estimates and shaded areas depict 90% confidence bands.

Figure 9 Actual Equity Risk Premium and Equity Risk Premium Forecasts Based on Individual Macroeconomic Variables near a U.S. Business-Cycle Trough


Notes. 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.

Figure 10   Actual Equity Risk Premium and Equity Risk Premium Forecasts Based on Individual Technical Indicators Near a U.S. Business-Cycle Trough

Notes. 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.

Figure 11   Out-of-Sample Equity Risk Premium Forecasts Based on Macroeconomic Variables and Technical Indicators Taken Together, 1966:01–2008:12
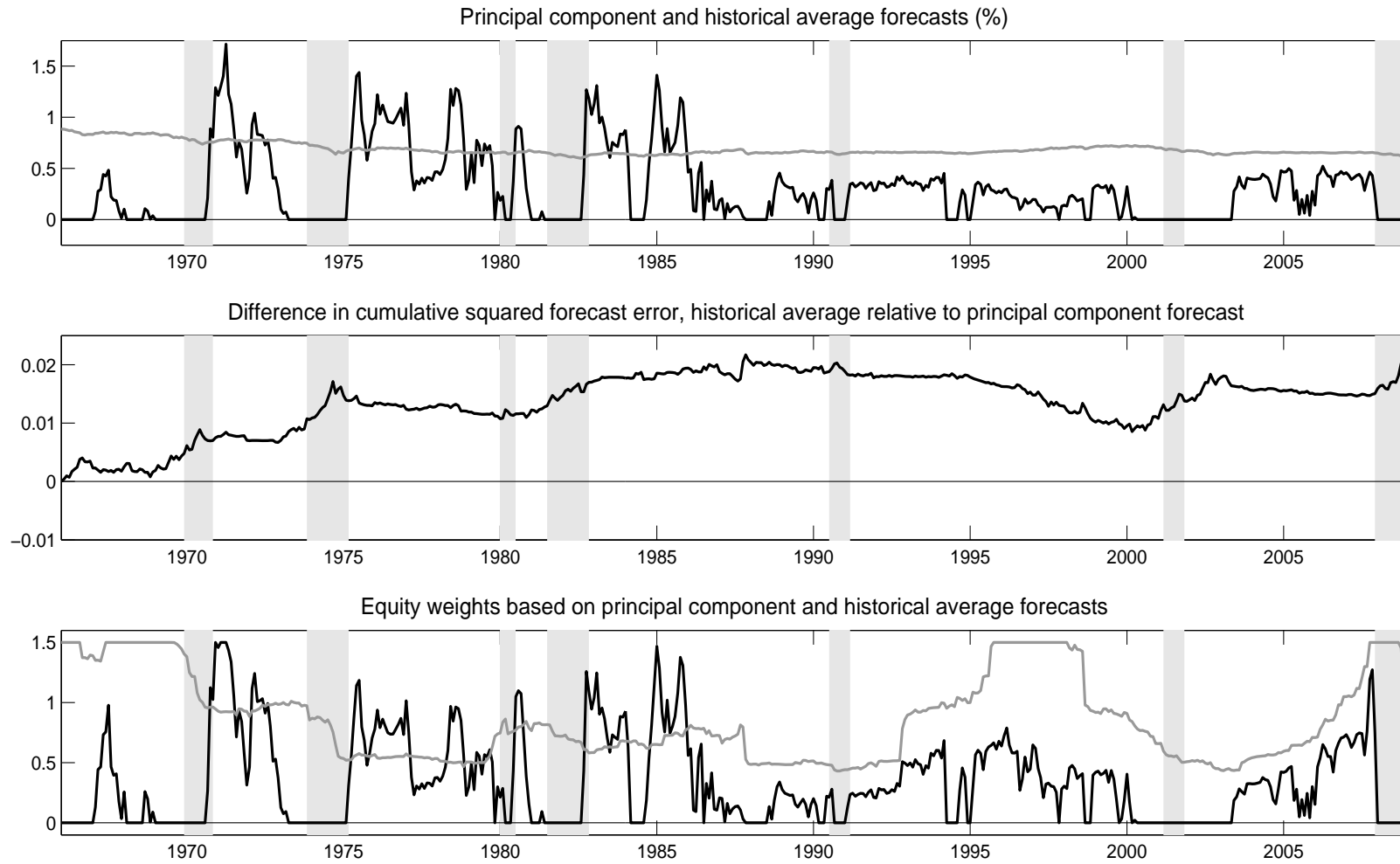
Notes. Black (gray) line in the top panel delineates the principal component (historical average) equity risk premium forecast. The principal component (PC) equity risk premium forecast is based on the first *k* principal components of the 14 macroeconomic variables and 14 technical indicators taken 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.