Forecasting the Equity Risk Premium: The Role of Technical Indicators

Christopher J. Neely
Federal Reserve Bank of St. Louis
neely@stls.frb.org

David E. Rapach
Saint Louis University
rapachde@slu.edu

Jun Tu
Singapore Management University
tujun@smu.edu.sg

Guofu Zhou[*]
Washington University in St. Louis and CEMA
zhou@wustl.edu

October 16, 2012

[*]Corresponding author. Send correspondence to Guofu Zhou, Olin School of Business, Washington University in St. Louis, St. Louis, MO 63130; e-mail: zhou@wustl.edu; phone: 314-935-6384. This project began while Rapach and Zhou were Visiting Scholars at the Federal Reserve Bank of St. Louis. We thank seminar participants at Beijing University, the Cheung Kong Graduate School of Business, 2011 China International Conference in Finance, 2012 European Finance Association Meeting, Federal Reserve Bank of St. Louis, Forecasting Financial Markets 2010 Conference, Fudan University, Saint Louis University, Shanghai Advanced Institute of Finance, Singapore Management University 2010 Summer Finance Camp, Southwest University of Business and Finance, Temple University, Third Annual Conference of The Society for Financial Econometrics, University of New South Wales, 2010 Midwest Econometrics Group Meetings, Hank Bessembinder, Michael Brennan, William Brock, Henry Cao, Long Chen, Todd Clark, John Cochrane, Robert Engle, Tom Engsted (2012 EFA discussant), Miguel Ferreira, Mark Grinblatt, Bruce Grundy, Massimo Guidolin, Harrison Hong, Jennifer Huang, Raymond Kan (2011 CICF discussant), Michael McCracken, Adrian Pagan, Jesper Rangvid, Pedro Santa-Clara, Jack Strauss, and George Tauchen for helpful comments. We are especially grateful for the insightful comments of two referees, an Associate Editor, and the Area Editor (Wei Jiang). The usual disclaimer applies. We also thank Amit Goyal for kindly providing data on his web page and Brett Fawley for research assistance. Tu acknowledges support from SMU Internal Research Grant C207/MSS10B001. The views expressed in this paper are those of the authors and do not reflect those of the Federal Reserve Bank of St. Louis or the Federal Reserve System.

Forecasting the Equity Risk Premium: The Role of Technical Indicators

Abstract

Academic research has extensively used macroeconomic variables to forecast the U.S. equity risk premium, with little attention paid to the technical indicators widely employed by practitioners. Our paper fills this gap by comparing the forecasting ability of technical indicators with that of macroeconomic variables. Technical indicators display statistically and economically significant in-sample and out-of-sample forecasting power, matching or exceeding that of macroeconomic variables. Furthermore, technical indicators and macroeconomic variables provide complementary information over the business cycle: technical indicators better detect the typical decline in the equity risk premium near business-cycle peaks, while macroeconomic variables more readily pick up the typical rise in the equity risk premium near cyclical troughs. In line with this behavior, we show that combining information from both technical indicators and macroeconomic variables significantly improves equity risk premium forecasts versus using either type of information alone. Overall, the substantial countercyclical fluctuations in the equity risk premium appear well captured by the combined information in macroeconomic variables and technical indicators.

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

Key words: equity risk premium predictability; macroeconomic variables; moving-average rules; momentum; volume; out-of-sample forecasts; asset allocation; business cycle

1. Introduction

Numerous studies report evidence of U.S. equity risk premium predictability based on an assortment of macroeconomic variables, including the dividend-price ratio (Rozeff 1984, Campbell and Shiller 1988, Fama and French 1988, Cochrane 2008, Pástor and Stambaugh 2009), nominal interest rates and interest rate spreads (Keim and Stambaugh 1986, Campbell 1987, Breen, Glosten, and Jagannathan 1989, Fama and French 1989), the inflation rate (Nelson 1976, Fama and Schwert 1977, Campbell and Vuolteenaho 2004), consumption-wealth ratio (Lettau and Ludvigson 2001), and volatility (Guo 2006). Ang and Bekaert (2007), Hjalmarsson (2010), and Henkel, Martin, and Nadari (2011) find that macroeconomic variables also predict the equity risk premium across countries.[1] The ability of macroeconomic variables to predict the equity risk premium has profoundly shifted the emphasis of asset pricing theory from expected cash flows to discount rates (Cochrane 2011).

Although the literature has extensively investigated the predictive ability of macroeconomic variables (i.e., economic "fundamentals"), it has paid much less attention to technical indicators, despite their widespread use among practitioners (Schwager 1989, 1992, 2012, Billingsley and Chance 1996, Park and Irwin 2007, Covel 2009, Lo and Hasanhodzic 2009, 2010). Technical indicators rely primarily on past price behavior to detect price trends believed to portend future price movements. Whereas early studies were inconclusive about the value of technical indicators (e.g., Cowles 1933, Fama and Blume 1966, Jensen and Benington 1970), more recent studies suggest that technical indicators provide useful information for outperforming a buy-and-hold portfolio. 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) report successful results for automated pattern recognition analysis.[2] These existing studies of technical indicators evaluate the profitability of trading signals—essentially the sign of the market return—rather than forecasting the magnitude of the equity risk premium per se.

Our paper is the first to use technical indicators to forecast the equity risk premium and compare the forecasting performance of technical indicators with that of macroeconomic variables. To directly compare equity risk premium forecasts, we generate all forecasts in a standard predictive regression framework, where the equity risk premium is regressed on a constant and the lag of a macroeconomic variable or technical indicator. To parsimoniously incorporate information from a large number of predictors, we also estimate predictive regressions based on a small number of principal components extracted from the entire set of macroeconomic variables and/or technical indicators.

We employ in-sample and out-of-sample tests in our analysis, because both approaches have relative strengths. Use of the entire sample enables in-sample tests to be more powerful for detecting the existence of return predictability; in-sample estimation also provides more efficient parameter estimates and thus more precise estimates of the expected equity risk premium. On the other hand, out-of-sample methods implicitly test the stability of the data-generating process and guard against in-sample overfitting. Moreover, as emphasized by Goyal and Welch (2003, 2008), out-of-sample tests are clearly the more relevant for investors. Employing both in-sample and out-of-sample tests helps to establish the robustness of our results.

[1]The studies cited are representative and do not constitute an exhaustive list.

[2]LeBaron (1999), Neely (2002), and Hsu and Taylor (2012), among others, find strong support for the profitability of technical indicators in foreign exchange markets, and Menkhoff and Taylor (2007) argue that technical analysis today is as important as fundamental analysis to currency mangers. In independent and subsequent (to this paper) research, Goh, Jiang, Tu, and Zhou (2012) find that technical indicators have much greater predictive power than macroeconomic variables for U.S. bond returns.

We use data spanning 1950:12 to 2011:12 for 14 well-known macroeconomic variables from the literature and 14 technical indicators, including indicators based on popular moving-average, momentum, and volume-based rules. In-sample results demonstrate that individual technical indicators typically perform as well as, or better than, individual macroeconomic variables for predicting the future equity risk premium. Regressions based on principal components extracted from the 14 macroeconomic variables (PC-ECON model) or 14 technical indictors (PC-TECH model) reveal that both macroeconomic variables as a group and technical indicators as a group are significant equity risk premium predictors. Moreover, the in-sample R^2 statistic for a predictive regression based on principal components extracted from the entire set of macroeconomic variables and technical indicators taken together (PC-ALL model) equals the sum of the R^2 statistics for the PC-ECON and PC-TECH models. This result indicates that macroeconomic variables and technical indicators capture different types of information that is relevant for predicting the equity risk premium; put another way, fundamental and technical analyses represent complementary approaches to equity risk premium forecasting.

The PC-ECON and PC-TECH model estimates of the expected equity risk premium display complementary countercyclical patterns. Technical indicators better detect the typical decline in the actual equity risk premium near business-cycle peaks, while macroeconomic variables more readily pick up the typical rise in the actual equity risk premium later in recessions near cyclical troughs. In line with this behavior, the PC-ALL model estimate of the expected equity risk premium displays an even clearer countercyclical pattern. We show that this accentuated countercyclical pattern enables the expected equity risk premium generated by the PC-model to better track the sizable fluctuations in the actual equity risk premium around business-cycle peaks and troughs.

Out-of-sample results corroborate the in-sample results. Forecast encompassing tests suggest that we can improve equity risk premium forecasts by utilizing information from both macroeconomic variables and technical indicators. Indeed, the PC-ALL model forecast outperforms all of the competitors we consider, including the historical average forecast, which Goyal and Welch (2003, 2008) show is a very stringent benchmark. Finally, the PC-ALL model forecast has substantial economic value for a mean-variance investor with a relative risk coefficient of five who optimally allocates across equities and risk-free Treasury bills.

Economically, why do technical indicators contain information useful for forecasting the equity risk premium beyond that found in familiar macroeconomic variables? There are at least three possible intuitive explanations. First, technical indicators could proxy for persistent reactions in equity prices induced by macroeconomic variables not typically employed in the literature, such as changes in government policy and international economic conditions.[3] A second and related reason for the predictive value of technical indicators is that technical indicators potentially better track persistent price trends induced by the market feedback effect: an uptrend in equity prices can positively affect firm fundamentals and lead to even higher prices (e.g., Soros 2003, Edmans, Goldstein, and Jiang 2012). Third, Guiso, Sapienza, and Zingales (2008, 2011) present evidence that risk aversion varies over time with changes in investor trust and psychological factors, which are potentially better captured by technical indicators. In a nutshell, popular macroeconomic variables are insufficient for tracking the myriad of economic forces relevant for forecasting the equity risk premium; by better reflecting certain key

[3]For example, U.S. equity prices increased for five of the six days prior to the Federal Reserve's announcement of its third round of quantitative easing ("QE3") on September 13, 2012. The *Wall Street Journal* reported that "many investors had anticipated a new round of easing," and the market moved up another 1.5% on the day after the announcement because "some said that the Fed declaration...was surprisingly aggressive" (Tom Lauricella and Alex Frangos, "Fed Move Echoes World-Wide," wsj.com, updated September 14, 2012, 6:48 p.m. ET).

economic forces, technical indicators can also play an important role in equity risk premium prediction.

2. In-Sample Analysis

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 the equity risk premium, 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 available at t; and $\varepsilon_{i,t+1}$ is a zero-mean disturbance term. Under the null hypothesis of no equity risk premium predictability, $\beta_i = 0$, and (1) reduces to the constant expected equity risk premium model. Because theory suggests the sign of β_i, Inoue and Kilian (2004) recommend a one-sided alternative hypothesis to increase the power of in-sample tests of predictability; we define $x_{i,t}$ such that β_i is expected to be positive under the alternative. We test H_0: $\beta_i = 0$ against H_A: $\beta_i > 0$ using a heteroskedasticity-consistent t-statistic corresponding to $\hat{\beta}_i$, the ordinary least squares (OLS) estimate of β_i in (1).

The well-known Stambaugh (1999) bias potentially inflates the t-statistic for $\hat{\beta}_i$ in (1) and distorts test size when $x_{i,t}$ is highly persistent, as is the case for a number of popular predictors. We address this concern by computing p-values using a wild bootstrap procedure that accounts for the persistence in regressors, as well as the correlations between equity risk premium and predictor innovations and general forms of heteroskedasticity. The Appendix details the wild bootstrap procedure.[4]

We estimate predictive regressions using updated monthly data from Goyal and Welch (2008).[5] The equity risk premium is the difference between the continuously compounded return on the S&P 500 (including dividends) and the log return on a risk-free bill. The following 14 macroeconomic variables are representative of the literature (Goyal and Welch 2008) and constitute the set of $x_{i,t}$ variables used to predict the equity risk premium in (1):

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.

[4] Amihud and Hurvich (2004), Lewellen (2004), Campbell and Yogo (2006), and Amihud, Hurvich, and Wang (2009) develop predictive regression tests that explicitly account for the Stambaugh bias. These tests, however, are not necessarily robust to general forms of heteroskedasticity. Inferences based on these procedures are qualitatively similar to those based on the wild bootstrap.

[5] The data are available from Amit Goyal's web page at http://www.hec.unil.ch/agoyal/.

5. *Equity risk premium volatility*, RVOL:[6] based on the moving standard deviation estimator,

$$\hat{\sigma}_t = \frac{1}{12}\sum_{i=1}^{12}|r_{t+1-i}|, \tag{2}$$

and subsequently converted to

$$\widehat{\mathrm{Vol}}_t \equiv \sqrt{\frac{\pi}{2}}\sqrt{12}\hat{\sigma}_t. \tag{3}$$

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.
11. *Term spread*, TMS: long-term yield minus the Treasury bill rate.
12. *Default yield spread*, DFY: difference between Moody's BAA- and AAA-rated corporate bond yields.
13. *Default return spread*, DFR: long-term corporate bond return minus the long-term government bond return.
14. *Inflation*, INFL: calculated from the Consumer Price Index (CPI) for all urban consumers; we use $x_{i,t-1}$ in (1) for inflation to account for the delay in CPI releases.

Table 1 reports summary statistics for the equity risk premium and 14 macroeconomic variables for 1950:12–2011:12. The start of the sample reflects data availability for the technical indicators (discussed below). The average monthly equity risk premium is 0.47%, which, together with a monthly standard deviation of 4.26%, produces a monthly Sharpe ratio of 0.11. Most of the macroeconomic variables are strongly autocorrelated, particularly the valuation ratios, nominal interest rates, and interest rate spreads.

To compare technical indicators with the macroeconomic variables, we employ 14 technical indicators based on three popular technical strategies. The first is a moving-average (MA) rule that generates a buy or sell signal ($S_{i,t} = 1$ or $S_{i,t} = 0$, respectively) at the end of t by comparing two moving averages:

$$S_{i,t} = \begin{cases} 1 & \text{if } \mathrm{MA}_{s,t} \geq \mathrm{MA}_{l,t} \\ 0 & \text{if } \mathrm{MA}_{s,t} < \mathrm{MA}_{l,t} \end{cases}, \tag{4}$$

where

$$\mathrm{MA}_{j,t} = (1/j)\sum_{i=0}^{j-1} P_{t-i} \quad \text{for} \quad j = s, l; \tag{5}$$

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 indicator with MA lengths s and l as MA(s,l). Intuitively, the MA rule detects changes in stock price trends, because the short MA will be more sensitive to recent price movement than the long MA. For example, when prices have recently been falling, the short MA will tend to be lower than the long MA. If prices begin trending

[6]This is the volatility measure used by Mele (2007). Goyal and Welch (2008) measure monthly volatility as the sum of squared daily excess stock returns during the month. This measure, however, produces a severe outlier in October of 1987. $\widehat{\mathrm{Vol}}_t$ avoids this problem and yields more plausible estimation results.

upward, then the short MA tends to increase faster than the long MA, eventually exceeding the long MA and generating a buy signal. We analyze monthly MA rules with $s = 1,2,3$ and $l = 9,12$.

The second technical strategy is based on momentum. A simple momentum rule generates the following signal:

$$S_{i,t} = \begin{cases} 1 & \text{if } P_t \geq P_{t-m} \\ 0 & \text{if } P_t < P_{t-m} \end{cases}. \tag{6}$$

Intuitively, a current stock price that is higher than its level m periods ago indicates "positive" momentum and relatively high expected excess returns, thereby generating a buy signal. We denote the momentum indicator that compares P_t to P_{t-m} as MOM(m), and we compute monthly signals for $m = 9,12$.

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

$$OBV_t = \sum_{k=1}^{t} VOL_k D_k, \tag{7}$$

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

$$S_{i,t} = \begin{cases} 1 & \text{if } \mathrm{MA}_{s,t}^{OBV} \geq \mathrm{MA}_{l,t}^{OBV} \\ 0 & \text{if } \mathrm{MA}_{s,t}^{OBV} < \mathrm{MA}_{l,t}^{OBV} \end{cases}, \tag{8}$$

where

$$\mathrm{MA}_{j,t}^{OBV} = (1/j) \sum_{i=0}^{j-1} OBV_{t-i} \quad \text{for} \quad j = s,l. \tag{9}$$

Intuitively, relatively high recent volume together with recent price increases, say, indicate a strong positive market trend and generate a buy signal. We compute monthly signals for $s = 1,2,3$ and $l = 9,12$ and denote the corresponding indicator as VOL(s,l).

The MA, momentum, and volume-based indicators are representative of the trend-following technical indicators analyzed in the academic literature (e.g., Sullivan, Timmermann, and White 1999). We use the S&P 500 index and monthly volume data from Google Finance in (4), (6), and (8).[7] After accounting for the lags in constructing the technical indicators, we have observations for all of the indicators starting in 1950:12.[8] The technical indicators generate buy signals ($S_{i,t} = 1$) between 66% and 72% of the time.

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 $x_{i,t}$ in (1) with $S_{i,t}$ from (4), (6), or (8):

$$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}. \tag{10}$$

Because $S_{i,t} = 1$ ($S_{i,t} = 0$) represents a bullish (bearish) signal, we again test H_0: $\beta_i = 0$ against H_A: $\beta_i > 0$.

Panel A of Table 2 reports estimates of β_i for the bivariate predictive regression given by (1) or (10), as well

[7] The volume data are available at http://www.google.com/finance.

[8] Technical indicators are often computed using monthly, weekly, or daily data. 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 weekly and daily data to generate monthly trading signals to study the more practical problem of maximizing portfolio performance using technical indicators.

as heteroskedasticity-consistent t-statistics and R^2 statistics. After accounting for the lag in the predictive regression, the estimation sample is 1951:01-2011:12 (732 observations). Seven of the 14 macroeconomic variables exhibit significant predictive ability at conventional levels in the second column of Panel A: DP, DY, RVOL, TBL, LTY, LTR, and TMS. Among these seven significant predictors, the dividend-price ratio (and dividend yield), Treasury bill rate, and term spread are among the most studied in the literature. At first glance, the R^2 statistics in the third column of Panel A appear small. However, because monthly stock returns inherently contain a substantial unpredictable component, a monthly R^2 near 0.5% can represent an economically significant degree of equity risk premium predictability (Kandel and Stambaugh 1996, Xu 2004, Campbell and Thompson 2008). Five of the R^2 statistics in the third column of Panel A exceed this 0.5% benchmark.

Turning to the results for the technical indicators, 13 of the 14 indicators evidence significant predictive ability at conventional levels in the fifth column of Table 2, Panel A. The coefficient estimates indicate that a buy signal predicts that the next month's equity risk premium is higher by 48 to 94 basis points than when there is a sell signal. In addition, 10 of the 14 R^2 statistics in the last column of Panel A are above the 0.5% threshold, and the R^2 for MA(2,12) is 1.03%, which is the largest R^2 in Panel A. Overall, the in-sample bivariate regression results in Table 2, Panel A suggest that individual technical indicators generally predict the future equity risk premium as well as, or better than, individual macroeconomic variables.

Next, we incorporate information from multiple macroeconomic variables by estimating a predictive regression based on principal components.[9] Let $x_t = (x_{1,t}, \dots, x_{N,t})'$ denote the N-vector ($N = 14$) of the entire set of macroeconomic variables and let $\hat{F}_t^{\mathrm{ECON}} = (\hat{F}_{1,t}^{\mathrm{ECON}}, \dots, \hat{F}_{K,t}^{\mathrm{ECON}})'$ denote the vector containing the first K principal components extracted from x_t (where $K \ll N$). The principal component predictive regression (PC-ECON model) is given by

$$r_{t+1} = \alpha + \sum_{k=1}^{K} \beta_k \hat{F}_{k,t}^{\mathrm{ECON}} + \varepsilon_{t+1}. \tag{11}$$

Principal components parsimoniously incorporate information from a large number of potential predictors in predictive regressions. The first few principal components identify the key comovements among the entire set of predictors, which filters out much of the noise in individual predictors, thereby guarding against in-sample overfitting.

We again estimate (11) via OLS, compute heteroskedasticity-consistent t-statistics, and base inferences on wild bootstrapped p-values. The first three columns of Table 2, Panel B report estimation results for (11) with $K = 3$, the value selected by the adjusted R^2.[10] The coefficient estimates on the first two principal components are insignificant at conventional levels in (11), while the coefficient estimate on the third principal component is significant at the 1% level. The R^2 for the PC-ECON model is 1.18%, which is greater than the 0.5% benchmark.

To illustrate the the economic content of the principal components, Panels A through C of Figures 1 and 2 present the $\{\hat{F}_{k,t}^{\mathrm{ECON}}\}_{k=1}^{3}$ estimates and corresponding factor loadings, respectively.[11] Panel A of Figure 2 shows

[9] Ludvigson and Ng (2007, 2009) estimate predictive regressions for excess stock and bond returns, respectively, based on principal components.

[10] The AIC also selects $K = 3$. To keep the model reasonably parsimonious, we consider a maximum K value of three, given the 14 macroeconomic variables. Note that we account for the "estimated regressors" in (11) via the wild bootstrap procedure (as explained in the Appendix). Bai and Ng (2006) analyze the asymptotic properties of parameter estimates for predictive regressions based on estimated principal components.

[11] The $x_{i,t}$ variables, estimated principal components (or factors), and estimated factor loadings are related via $x_{i,t} - \bar{x}_i = \sum_{k=1}^{K} \hat{\lambda}_{i,k} \hat{F}_{k,t}^{\mathrm{ECON}} + \hat{e}_{i,t}$ ($i = 1, \dots, N$), where $\bar{x}_i$ is the sample mean of $x_{i,t}$ (so that, following convention, the principal components

that the valuation ratios load heavily on $\hat{F}^{\text{ECON}}_{1,t}$; that is, the first principal component extracted from the macroeconomic variables primarily captures common fluctuations in the valuation ratios. This is also evident in Figure 1, Panel A, where the persistence of $\hat{F}^{\text{ECON}}_{1,t}$ (autocorrelation of 0.99) matches that of the individual valuation ratios in Table 1. From Figure 2, Panel B, we see that RVOL and DFY load most heavily on $\hat{F}^{\text{ECON}}_{2,t}$; accordingly, $\hat{F}^{\text{ECON}}_{2,t}$ spikes during the Global Financial Crisis in Figure 2, Panel B, when stock market volatility and credit spreads increased dramatically. Panel C of Figure 3 indicates that a number of the macroeconomic variables load relatively strongly on $\hat{F}^{\text{ECON}}_{3,t}$, including DP, DY, DE, TBL, LTY, TMS, DFR, and INFL. $\hat{F}^{\text{ECON}}_{3,t}$ thus reflects a wider variety of macroeconomic variables and potentially captures more useful predictive information, which apparently helps $\hat{F}^{\text{ECON}}_{3,t}$ to better forecast the future equity risk premium than $\hat{F}^{\text{ECON}}_{1,t}$ and $\hat{F}^{\text{ECON}}_{2,t}$. $\hat{F}^{\text{ECON}}_{3,t}$ is also less persistent (autocorrelation of 0.92) than $\hat{F}^{\text{ECON}}_{1,t}$ and $\hat{F}^{\text{ECON}}_{2,t}$. Although the three principal components extracted from the 14 macroeconomic variables are contemporaneously uncorrelated by construction, they all exhibit a countercylical tendency in Panels A through C of Figure 2. The countercyclical pattern is especially evident for $\hat{F}^{\text{ECON}}_{2,t}$ and $\hat{F}^{\text{ECON}}_{3,t}$, which have distinct local minima (maxima) near business-cycle peaks (troughs).

To incorporate information from all of the technical indicators, we estimate (1) with $\hat{F}^{\text{TECH}}_{t}$ replacing $\hat{F}^{\text{ECON}}_{t}$ (PC-TECH model):

$$r_{t+1} = \alpha + \sum_{k=1}^{K} \beta_k \hat{F}^{\text{TECH}}_{k,t} + \varepsilon_{t+1}, \tag{12}$$

where $\hat{F}^{\text{TECH}}_{t} = (\hat{F}^{\text{TECH}}_{1,t}, \ldots, \hat{F}^{\text{TECH}}_{K,t})'$ is the vector containing the first K principal components extracted from $S_t = (S_{1,t}, \ldots, S_{N,t})'$, the N-vector of 14 technical indicators. The last three columns of Table 2, Panel B report these estimation results for $K = 1$ (the value selected by the adjusted R^2). The coefficient estimate on the first principal component is significant at the 5% level, and the R^2 for the PC-TECH model is 0.84% (which is again above the 0.5% benchmark). The 14 technical indicators, taken as a group, thus significantly predict the future equity risk premium. The last panels in Figures 1 and 2 show the $\hat{F}^{\text{TECH}}_{1,t}$ estimates and corresponding factor loadings, respectively. The technical indicators load nearly uniformly on $\hat{F}^{\text{TECH}}_{1,t}$ in Figure 2, Panel D, so that the first principal component is essentially a simple average of the 14 indicators. Intuitively, this implies that if the first principal component takes a large (small) value, then most of the individual technical indicators are giving a buy (sell) signal; hence, the first principle component acts like a "consensus" indicator. Panel D of Figure 1 indicates that $\hat{F}^{\text{TECH}}_{1,t}$ is also linked to business-cycle fluctuations. Specifically, $\hat{F}^{\text{TECH}}_{1,t}$ typically falls sharply from its maximum level to its minimum level near cyclical peaks, while the converse usually occurs near cyclical troughs.

We also parsimoniously incorporate information from the entire set of macroeconomic variables and technical indicators by estimating a predictive regression based on $\hat{F}^{\text{ALL}}_{t}$ (PC-ALL model):

$$r_{t+1} = \alpha + \sum_{k=1}^{K} \beta_k \hat{F}^{\text{ALL}}_{k,t} + \varepsilon_{t+1}, \tag{13}$$

where $\hat{F}^{\text{ALL}}_{t} = (\hat{F}^{\text{ALL}}_{1,t}, \ldots, \hat{F}^{\text{ALL}}_{K,t})'$ is the K-vector containing the first K principal components extracted from

have zero mean), $\hat{\lambda}_{i,k}$ is the estimated loading of the ith variable on the kth factor, and $\hat{e}_{i,t}$ is the estimated idiosyncratic component of $x_{i,t}$. Note that the scales of the factors and factor loadings are indeterminant. Principal component estimation uses a normalization to identify the factors and factor loadings. This normalization has no effect on the t-statistics, R^2 statistic, and estimate of the expected equity risk premium in (11).

$z_t = (x_t', S_t')'$, the $2N$-vector of 14 macroeconomic variables and 14 technical indicators.[12] Panel C of Table 2 reveals that the coefficient estimates on $\hat{F}_{1,t}^{\text{ALL}}$, $\hat{F}_{3,t}^{\text{ALL}}$, and $\hat{F}_{4,t}^{\text{ALL}}$ are significant in the PC-ALL model at the 5%, 10%, and 1% levels, respectively. The R^2 for the PC-ALL model is 2.02%, which equals the sum of the R^2 statistics for the PC-ECON and PC-TECH models.[13] This indicates that the macroeconomic variables and technical predictors essentially contain complementary information.

The $\{\hat{F}_{k,t}^{\text{ALL}}\}_{k=1}^{4}$ estimates and corresponding factor loadings, depicted in Figures 3 and 4, respectively, reflect the complementarity of the macroeconomic variables and technical indicators; that is, the principal components extracted from the entire set of predictors are often very similar to those extracted from the set of macroeconomic variables or technical indicators alone. Panel A of Figure 4 shows that the 14 technical indicators load nearly uniformly on the first principal component, while the macroeconomic variables are relatively insensitive to this factor, so that that $\hat{F}_{1,t}^{\text{ALL}}$ is closely related to $\hat{F}_{1,t}^{\text{TECH}}$. Panel A of Figure 3 confirms this relationship, as $\hat{F}_{1,t}^{\text{ALL}}$ behaves very similarly to $\hat{F}_{1,t}^{\text{TECH}}$ in Figure 1, Panel D. Panels B through D of Figures 3 and 4 demonstrate that $\hat{F}_{2,t}^{\text{ALL}}$, $\hat{F}_{3,t}^{\text{ALL}}$, and $\hat{F}_{4,t}^{\text{ALL}}$ closely correspond to $\hat{F}_{1,t}^{\text{ECON}}$, $\hat{F}_{2,t}^{\text{ECON}}$, and $\hat{F}_{3,t}^{\text{ECON}}$, respectively. The same macroeconomic variables that load heavily on $\hat{F}_{1,t}^{\text{ECON}}$, $\hat{F}_{2,t}^{\text{ECON}}$, and $\hat{F}_{3,t}^{\text{ECON}}$ in Panels A through C of Figure 2 load heavily on $\hat{F}_{2,t}^{\text{ALL}}$, $\hat{F}_{3,t}^{\text{ALL}}$, and $\hat{F}_{4,t}^{\text{ALL}}$ in Panels B through D of Figure 4, while the technical indicators respond relatively weakly to the latter three factors.[14] Furthermore, $\hat{F}_{2,t}^{\text{ALL}}$, $\hat{F}_{3,t}^{\text{ALL}}$, and $\hat{F}_{4,t}^{\text{ALL}}$ in Panels B through D of Figure 3 behave similarly to the factors in Panels A through C of Figure 1. The coefficient estimates on $\hat{F}_{2,t}^{\text{ALL}}$ and $\hat{F}_{4,t}^{\text{ALL}}$ in Table 2, Panel C are similar to those on $\hat{F}_{1,t}^{\text{ECON}}$ and $\hat{F}_{3,t}^{\text{ECON}}$, respectively, in Panel B.

The PC-ALL model estimation results thus imply that the macroeconomic variables and technical indicators provide complementary approaches to equity risk premium prediction. The first principal component in the PC-ALL model is primarily driven by common fluctuations in the technical indicators and only weakly related to the macroeconomic variables; the second through fourth principal components predominantly reflect comovements in subsets of the macroeconomic variables. The significant coefficient estimates on $\hat{F}_{1,t}^{\text{ALL}}$, $\hat{F}_{3,t}^{\text{ALL}}$, and $\hat{F}_{4,t}^{\text{ALL}}$ in the PC-ALL model demonstrate that macroeconomic variables and technical indicators provide nonredundant information for predicting the future equity risk premium.

Figure 5 provides another perspective on the complementary roles of macroeconomic variables and technical indicators. The figure shows in-sample forecasts of the equity risk premium for the PC-ECON, PC-TECH, and PC-ALL models, which represent in-sample estimates of the expected equity risk premium. The expected equity risk premium for the PC-ECON model in Figure 5, Panel A displays a relatively smooth countercyclical pattern, in line with the estimated factors in Panels A through C of Figure 1.[15] The countercyclical movements in the expected equity risk premium for the PC-TECH model in Panel B are much more abrupt, in line with Figure 1, Panel D. When the information in the macroeconomic variables and technical indicators is combined in the PC-ALL model in Figure 5, Panel C, the expected equity risk premium falls more abruptly near business-cycle peaks relative to Panel A, while it rises to higher levels around cyclical troughs relative to Panel B. The comple-

[12] $K = 4$ is selected by the adjusted R^2, considering a maximum value of four, since we now extract principal components from 28 potential predictors. The value of four is also the sum of the respective K values selected for the PC-ECON and PC-TECH models.

[13] We checked this result for various subsamples and found that the R^2 for the PC-ALL model is not always exactly equal to the sum of the R^2 statistics for the PC-ECON and PC-TECH models, but they are always quite close.

[14] The volume-based technical indicators are possible exceptions, as they respond somewhat strongly to $\hat{F}_{3,t}^{\text{ALL}}$ and $\hat{F}_{4,t}^{\text{ALL}}$.

[15] The countercyclical pattern in the expected equity risk premium in Figure 5, Panel A is similar to the countercyclical pattern reported in Fama and French (1989), Ferson and Harvey (1991), Whitelaw (1994), Harvey (2001), and Lettau and Ludvigson (2010), among others.

mentary information in macroeconomic variables and technical indicators thus accentuates the countercyclical fluctuations in the expected equity risk premium for the PC-ALL model.

We glean further insight into the behavior of the expected equity risk premium around business-cycle peaks and troughs via the following regressions:

$$r_t = a_{\mathrm{A}} + \sum_{m=-4}^{2} b^{\mathrm{P}}_{\mathrm{A},m} I^{\mathrm{P}}_{t-m} + \sum_{m=-4}^{2} b^{\mathrm{T}}_{\mathrm{A},m} I^{\mathrm{T}}_{t-m} + u_{\mathrm{A},t}, \tag{14}$$

$$\hat{r}_t = a_{\mathrm{FC}} + \sum_{m=-4}^{2} b^{\mathrm{P}}_{\mathrm{FC},m} I^{\mathrm{P}}_{t-m} + \sum_{m=-4}^{2} b^{\mathrm{T}}_{\mathrm{FC},m} I^{\mathrm{T}}_{t-m} + u_{\mathrm{FC},t}, \tag{15}$$

where $\hat{r}_t$ is the in-sample equity risk premium forecast for the PC-ECON, PC-TECH, or PC-ALL model and I^{P}_t (I^{T}_t) is an indicator variable equal to unity when month t is an NBER-dated business-cycle peak (trough) and zero otherwise. Each $b^{\mathrm{P}}_{\mathrm{A},m}$ ($b^{\mathrm{T}}_{\mathrm{A},m}$) coefficient in (14) measures the average change in the actual equity risk premium m months after a cyclical peak (trough), while each $b^{\mathrm{P}}_{\mathrm{FC},m}$ ($b^{\mathrm{T}}_{\mathrm{FC},m}$) coefficient does likewise for the expected equity risk premium. Because the equity market is forward looking, we use an asymmetric window that includes the fourth months before and two months after a peak or trough.[16]

Figure 6 presents OLS estimates of the slope coefficients in (14) and (15), along with 90% confidence intervals. Panel A of Figure 6 indicates that the actual equity risk premium declines significantly on average for most of the months around a cyclical peak, with an average decline of nearly 400 basis points for some months. Panel B shows that the expected equity risk premium for the PC-ECON model only experiences a significant decline for a few of the months around a peak. In contrast, the PC-TECH model's expected equity risk premium in Panel C falls significantly for all of the months near a peak, better matching the depressed actual equity risk premium. Similarly to the PC-TECH model, Panel D shows that the expected equity risk premium for the PC-ALL model also falls significantly for most of the months around a peak. In addition, the coefficient magnitudes are larger for the PC-ALL model in Panel D relative to those for the PC-ECON and PC-TECH models in Panels B and C, respectively, so that the PC-ALL model better captures the typically depressed actual equity risk premium near a peak.

Panel E of Figure 6 demonstrates that, in contrast to a cyclical peak, the actual equity risk premium typically rises significantly on average several months prior to a cyclical trough. Generally in line with this behavior, the expected equity risk premium for the PC-ECON model in Panel F increases significantly during the months around a trough. The expected equity risk premium for the PC-TECH model in Panel G rises around a trough, but does not become significantly positive. The PC-ALL model's average expected equity risk premium increases significantly for many of the months around a trough, and the increase in the expected equity risk premium is relatively large in magnitude for the month of and two months following a trough, again helping the PC-ALL model to better match the rise in the actual equity risk premium prior to a trough.

Overall, Figure 6 indicates that the information in technical indicators is more useful than that in macroeconomic variables for detecting the typical decline in the equity risk premium around a business-cycle peak, while macroeconomic variables provide more useful information than technical indicators for ascertaining the typical rise in the equity risk premium near a cyclical trough. By incorporating information from both macroeconomic variables and technical indicators, the PC-TECH model exploits the information in each set of predictors to

[16]The results for other windows are similar.

produce an expected equity risk premium that better tracks the substantial countercyclical fluctuations in the equity risk premium.

3. Out-of-Sample Analysis

This section reports out-of-sample forecasting statistics for the 14 macroeconomic variables and 14 technical indicators. The month-$(t+1)$ out-of-sample equity risk premium forecast based on an individual macroeconomic variable in (1) and data through month t is given by

$$\hat{r}_{t+1} = \hat{\alpha}_{t,i} + \hat{\beta}_{t,i} x_{i,t}, \tag{16}$$

where $\hat{\alpha}_{t,i}$ and $\hat{\beta}_{t,i}$ are the OLS estimates from regressing $\{r_s\}_{s=2}^{t}$ on a constant and $\{x_{i,s}\}_{s=1}^{t-1}$. We use 1951:01–1965:12, the first 15 years of the available sample, as the initial estimation period, so that the forecast evaluation period spans 1966:01–2011:12 (552 observations). The length of the initial in-sample estimation period balances having enough observations for reasonably precisely estimating the initial parameters with our desire for a relatively long out-of-sample period for forecast evaluation.[17]

The out-of-sample forecast based on an individual technical indicator in (10) is given by

$$\hat{r}_{t+1} = \hat{\alpha}_{t,i} + \hat{\beta}_{t,i} S_{i,t}, \tag{17}$$

where $\hat{\alpha}_{t,i}$ and $\hat{\beta}_{t,i}$ are the OLS estimates from regressing $\{r_s\}_{s=2}^{t}$ on a constant and $\{S_{i,s}\}_{s=1}^{t-1}$. We also generate out-of-sample forecasts based on principal components, as in (11), (12), and (13):

$$\hat{r}_{t+1}^{j} = \hat{\alpha}_t + \sum_{k=1}^{K} \hat{\beta}_{t,k} \hat{F}_{1:t,k,t}^{j} \quad \text{for} \quad j = \text{ECON, TECH, or ALL}, \tag{18}$$

where $\hat{F}_{1:t,k,t}^{j}$ is the kth principal component extracted from the 14 macroeconomic variables ($j = $ ECON), 14 technical indicators ($j = $ TECH), or 14 macroeconomic variables and 14 technical indicators taken together ($j = $ ALL) based on data through t and $\hat{\alpha}_t$ and $\hat{\beta}_{t,k}$ ($k = 1, \ldots, K$) are the OLS estimates from regressing $\{r_s\}_{s=2}^{t}$ on a constant and $\{\hat{F}_{1:t,k,s}^{j}\}_{s=1}^{t-1}$ ($k = 1, \ldots, K$).[18]

We compare the forecasts given by (16), (17), and (18) to the historical average forecast:

$$\hat{r}_{t+1}^{\text{HA}} = (1/t) \sum_{s=1}^{t} r_s. \tag{19}$$

This popular benchmark forecast (e.g., Goyal and Welch 2003, 2008, Campbell and Thompson 2008, Ferreira and Santa-Clara 2011) assumes a constant expected equity risk premium ($r_{t+1} = \alpha + \varepsilon_{t+1}$). Goyal and Welch (2003, 2008) show that (19) is a very stringent benchmark: predictive regression forecasts based on individual

[17] Hansen and Timmermann (2012) show that out-of-sample tests of predictive ability have better size properties when the forecast evaluation period is a relatively large proportion of the available sample, as in our case. Note that we generate forecasts using a recursive (i.e., expanding) window for estimating α_i and β_i in (1). We could also generate forecasts using a rolling window (which drops earlier observations as additional observations become available), in recognition 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 generally includes pre-break data due to the familiar bias-efficiency tradeoff. Although we use a recursive estimation window, we obtain similar results using rolling estimation windows of various sizes.

[18] We select K via the adjusted R^2 based on data through t.

macroeconomic variables typically fail to outperform the historical average.

We analyze forecasts in terms of mean squared forecast error (MSFE). We compute the Campbell and Thompson (2008) out-of-sample R^2 (R^2_{OS}) and Clark and West (2007) *MSFE-adjusted* statistics to compare the predictive regression forecasts to the historical average benchmark. The former measures the proportional reduction in MSFE for the predictive regression forecast relative to the historical average, while the latter tests the null hypothesis that the historical average MSFE is less than or equal to the predictive regression MSFE against the one-sided (upper-tail) alternative hypothesis that the historical average MSFE is greater than the predictive regression MSFE.[19]

Panel A of Table 3 reports out-of-sample results for bivariate predictive regression forecasts based on individual macroeconomic variables and technical indicators. Only three of the R^2_{OS} statistics are positive in the third column of Panel A; the vast majority of individual macroeconomic variables thus fail to outperform the historical average benchmark in terms of MSFE. The three positive R^2_{OS} statistics (for DY, RVOL, and LTR) only range from 0.05% to 0.29%. Nevertheless, the MSFEs for these three predictors are significantly less than the historical average MSFE at conventional levels according to the *MSFE-adjusted* statistics in the fourth column. It interesting to note that the *MSFE-adjusted* statistics indicate that the MSFEs for TBL, LTY, and TMS are significantly less than that the historical average, despite the negative R^2_{OS} statistics for these forecasts. Although this result appears strange, it is possible when comparing nested model forecasts (Clark and McCracken 2001, Clark and West 2007, McCracken 2007).[20] Reminiscent of Goyal and Welch (2003, 2008), individual macroeconomic variables display limited out-of-sample predictive ability in Table 3, Panel A.

All of the R^2_{OS} statistics are positive in the ninth column of Table 3, Panel A; each of the technical indicators thus delivers a lower MSFE than the historical average benchmark. Three of the R^2_{OS} statistics exceed 0.7%, and the MSFEs for six of the technical indicators are significantly less than the historical average MSFE based on the *MSFE-adjusted* statistics. Overall, individual technical indicators appear to perform as well as, or better than, individual macroeconomic variables in terms of MSFE.

To get a sense of potential bias-efficiency tradeoffs in the forecasts, Table 3 also report a decomposition of MSFE into squared-bias and variance components:

$$\text{MSFE} = (\bar{\hat{e}})^2 + \text{Var}(\hat{e}), \tag{20}$$

where $\hat{e}$ signifies the forecast error, $(\bar{\hat{e}})^2$ is the squared forecast bias, and $\text{Var}(\hat{e})$ is forecast error variance. The squared bias (error variance) is 0.07 (20.16) for the historical average forecast. DP, DY, EP, DE, and INFL have squared biases well below that of the historical average. These five variables, however, have forecast error variances that exceed that of the historical average, and only DY has a smaller MSFE than the historical average. The squared biases are substantially higher than that of the historical average for RVOL, NTIS, TMS, and DFY,

[19]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 a predictive regression forecast to the historical average entails comparing nested models, as the predictive regression model reduces to the constant expected equity risk premium model under the null hypothesis.

[20]Intuitively, under the null hypothesis that the constant expected equity risk premium model generates the data, the predictive regression model produces a noisier forecast than the historical average benchmark, because it estimates slope parameters with zero population values. We thus expect the benchmark model MSFE to be smaller than the predictive regression model MSFE under the null. The *MSFE-adjusted* statistic accounts for the negative expected difference between the historical average MSFE and predictive regression MSFE under the null, so that it can reject the null even if the R^2_{OS} statistic is negative.

ranging from 0.13 to 0.23. Among these variables, only RVOL has a smaller forecast error variance (and MSFE) than the historical average. The squared biases are much more similar across the technical indicators, and all of them are less than or equal to the historical average squared bias. In addition, the forecast error variances for the technical indicators are all less than or equal to (or only slightly above) that of the historical average. Thus, forecasts based on the technical indicator are generally both less biased and more efficient that the historical average.

Panel B of Table 3 reports out-of-sample results for the principal component predictive regression forecasts based on macroeconomic variables or technical indicators. Although the R^2_{OS} is negative for the PC-ECON forecast, its MSFE is significantly less (at the 1% level) than that of the historical average according to the *MSFE-adjusted* statistic.[21] The R^2_{OS} is 0.65% for the PC-TECH forecast, and the *MSFE-adjusted* statistic indicates that the MSFE for the PC-TECH forecast is significantly below that of the historical average. The PC-ECON and PC-TECH forecasts have smaller squared biases than the historical average. The PC-ECON forecast error variance, however, substantially exceeds that of the historical average; in contrast, the PC-TECH forecast error variance is well below that of the historical average.

We next compare the information content of the PC-ECON and PC-TECH forecasts using encompassing tests. Harvey, Leybourne, and Newbold (1998) develop a statistic for testing the null hypothesis that a given forecast contains all of the relevant information found in a competing forecast (i.e., the given forecast encompasses the competitor) against the alternative that the competing forecast contains relevant information beyond that in the given forecast. We reject the null hypothesis that the PC-ECON forecast encompasses the PC-TECH forecast, as well as the null that the PC-TECH forecast encompasses the PC-ECON (both at the 1% level). The PC-ECON and PC-TECH forecasts thus fail to encompass each other, indicating that there are gains to using information from macroeconomic variables and technical indicators in conjunction.

In accord with the encompassing test results, the PC-ALL forecast has an R^2_{OS} of 1.79% in Table 3, Panel C, which easily exceeds all of the other R^2_{OS} statistics in Table 3. The PC-ALL MSFE is also significantly less than the historical average MSFE at the 1% level according to the *MSFE-adjusted* statistic. The squared bias and forecast error variance for the PC-ALL forecast are below the respective values for the historical average; indeed, the PC-ALL forecast error variance is well below that of any of the other forecast error variances. The out-of-sample results in Table 3 thus confirm the in-sample results in Section 2: macroeconomic variables and technical indicators capture different types of information relevant for forecasting the equity risk premium.[22]

Figure 7 reveals that the PC-ECON, PC-TECH, and PC-ALL out-of-sample equity risk premium forecasts behave similarly to the in-sample forecasts in Figure 5. The PC-ECON and PC-ALL out-of-sample forecasts are considerably more volatile during the early stages of the forecast evaluation period, however, due to the relatively small samples available for estimating the principal components and predictive regression parameters. The PC-ALL forecast in Figure 7 again exhibits a marked countercyclical pattern.

[21] See footnote 20 for the intuition for this seemingly strange result.

[22] The PC-ALL forecast also has a lower MSFE than the constant 0.5% equity risk premium benchmark forecast used by Simin (2008). 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 14 bivariate predictive regression forecasts in Table 3, Panel A, and its R^2_{OS} is 1.16%. Ferreira and Santa-Clara (2011) propose an intriguing "sum-of-the-parts" equity risk premium forecast as the sum of a 20-year moving average of earnings growth and the current dividend-price ratio (minus the risk-free rate). We compute a sum-of-the-parts forecast, and its R^2_{OS} is 1.32%. The PC-ALL forecast thus appears to be the best-to-date out-of-sample forecast of the equity risk premium.

To control for data snooping, which becomes a concern when considering many predictors, we use Clark and McCracken's (2012) modified version of White's (2000) reality check. The Clark and McCracken (2012) reality check is based on a wild fixed-regressor bootstrap and is appropriate for comparing forecasts from multiple models, all of which nest the benchmark model, as in our framework. We use the Clark and McCracken (2012) maxMSFE-F statistic to test the null hypothesis that the historical average MSFE is less than or equal to the MSFE for all of the 28 bivariate predictive regression forecasts and three principal component predictive regression forecasts in Table 3 against the alternative that the historical average MSFE is greater than the MSFE for at least one of the 31 competing forecasts. The maxMSFE-F statistic rejects the null that none of the competing forecasts outperforms the historical average, with a bootstrapped p-value of 0.03. This reality check indicates that data snooping cannot readily explain the significant out-of-sample predictive power of the PC-ALL forecast.[23]

4. Asset Allocation Exercise

As a final exercise, we directly measure the economic value of equity risk premium forecasts for a risk-averse investor. Following Campbell and Thompson (2008) and Ferreira and Santa-Clara (2011), among others, we compute the certainty equivalent return (CER) for a mean-variance investor who optimally allocates across equities and risk-free bills using various equity risk premium forecasts. This exercise also addresses the weakness of many existing studies of technical indicators that fail to incorporate the degree of risk aversion into the asset allocation decision.

The mean-variance investor's expected utility can be expressed as

$$U(R_p) = E(R_p) - \frac{1}{2}\gamma \mathrm{Var}(R_p), \tag{21}$$

where R_p is the (simple) return on the investor's portfolio, $E(R_p)$ is the expected portfolio return, $\mathrm{Var}(R_p)$ is the variance of the portfolio return, and γ is the investor's coefficient of relative risk aversion. At the end of month t, the investor optimally allocates the following share of the portfolio to equities during month $t+1$ by obeying the Markowitz rule:

$$w_t = \left(\frac{1}{\gamma}\right)\left(\frac{\hat{r}_{t+1}}{\hat{\sigma}^2_{t+1}}\right), \tag{22}$$

where $\hat{r}_{t+1}$ is a forecast of the (simple) equity risk premium and $\hat{\sigma}^2_{t+1}$ is a forecast of its variance. The share $1-w_t$ is allocated to risk-free bills, and the month-$(t+1)$ portfolio return is given by

$$R_{p,t+1} = w_t r_{t+1} + R_{f,t+1}, \tag{23}$$

where $R_{f,t+1}$ is the risk-free return. 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 w_t to lie between 0 and 1.5.[24]

[23] Ferson, Sarkissian, and Simin (2003) demonstrate that size distortions related to the Stambaugh bias can exacerbate data snooping problems for in-sample predictive regressions with persistent predictors. Busetti and Marcucci (2012), however, show that out-of-sample tests of predictive ability are not afflicted by size distortions in the presence of persistent predictors, so that the issues raised by Ferson, Sarkissian, and Simin (2003) do not appear of great concern for our out-of-sample analysis.

[24] This imposes realistic portfolio constraints by precluding short sales and preventing more than 50% leverage.

The CER for the portfolio is

$$\text{CER}_p = \hat{\mu}_p - \frac{1}{2}\gamma\hat{\sigma}_p^2, \tag{24}$$

where $\hat{\mu}_p$ and $\hat{\sigma}_p^2$ are the mean and variance, respectively, for the investor's portfolio over the forecast evaluation period. The CER can be interpreted as the risk-free rate of return that an investor is willing to accept instead of adopting the given risky portfolio. The CER gain is the difference between the CER for the investor who uses a predictive regression forecast of the equity risk premium based on (16), (17), or (18) and the CER for an investor who uses the historical average forecast given by (19).[25] 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 predictive regression forecast instead of the historical average forecast.

The second and seventh columns of Table 4, Panel A present CER gains for an investor with a relative risk coefficient of five who relies on the bivariate predictive regression forecast given by (16) or (17), respectively, instead of the historical average forecast; for the historical average forecast, the table reports the CER level.[26] Table 4 also reports additional portfolio performance measures. The monthly Sharpe ratio in the third and eighth columns is the mean portfolio return in excess of the risk-free rate divided by the standard deviation of the excess portfolio return. The fourth and ninth columns report average monthly turnover, where monthly turnover is the percentage of wealth traded each month (DeMiguel, Garlappi, and Uppal 2009, DeMiguel, Garlappi, Nogales, and Uppal 2009). For the portfolio based on the historical average forecast, the table gives the average monthly turnover; for the other portfolios, it gives the relative average turnover (average monthly turnover divided by the average monthly turnover for the portfolio based on the historical average). The fifth and tenth columns report CER gains net of transactions costs, where the costs are calculated using the monthly turnover measures and assuming a proportional transactions cost equal to 50 basis points per transaction (Balduzzi and Lynch 1999).

Table 4 reports that the CER for the portfolio based on the historical average forecast is 3.54%. The CER gains are positive for nine of the macroeconomic variables in the second column of Table 4, Panel A, with TBL, LTY, LTR, and TMS providing gains of over 100 basis points. Eight of the macroeconomic predictors produce higher Sharpe ratios than that of the historical average, with TMS generating the highest ratio of 0.12. The average turnover is 2.09% for the historical average. Portfolios based on many of the macroeconomic variables turn over approximately three to five times more often than the historical average portfolio, and the LTR portfolio turns over nearly 24 times as much. After accounting for transactions costs, the relatively high turnovers for NTIS, LTR, DFR, and INFL reduce the CER gains from positive to negative values.

The last four columns of Table 4, Panel A reveal that portfolios based on technical indicators generally outperform those based on macroeconomic variables. The CER gains in the seventh column are positive for all of the technical indicators, reaching a maximum of 317 basis points. Portfolios based on the technical indicators turn over approximately two to five times more often than the historical average portfolio. Despite this turnover, the net-of-transactions-costs CER gains are positive—and as high as 282 basis points—for all of the technical indicators.

Panels B and C of Table 4 report performance measures for portfolios based on the principal component predictive regression forecasts given by (18). PC-ECON delivers a sizable CER gain of 224 basis points in the

[25]The investor always uses the same five-year moving window to estimate the equity risk premium variance, so that differences in the portfolio weights are solely due to differences in equity risk premium forecasts.

[26]We obtain similar returns for other reasonable relative risk coefficient values.

second column of Panel B, and its Sharpe ratio of 0.10 is twice that of the historical average. Although the PC-ECON portfolio turns over nearly seven times more often than the historical average portfolio, it still improves the net-of-transactions-costs CER by 151 basis points. PC-TECH generates a CER gain of 249 basis points in the seventh column of Panel B, 25 basis points more than PC-ECON, and a Sharpe ratio of 0.10, matching that of PC-ECON. Because the PC-TECH portfolio turns over much less than the PC-ECON portfolio, the net-of-transactions-costs CER gain for PC-TECH remains well above 200 basis points.

The performance of PC-ALL in Table 4, Panel C stands out. The CER gain for PC-ALL in the second column of Panel C is more than 170 basis points higher than that of any of the other portfolios in Table 4. PC-ALL also produces the highest Sharpe ratio, 0.16, and the highest net-of-transactions-costs CER gain, 412 basis points, of all the portfolios. The asset allocation exercise demonstrates the substantial economic value of combining information from macroeconomic variables and technical indicators.

5. Conclusion

This paper is the first to utilize technical indicators to forecast the equity risk premium and compare their performance with that of macroeconomic variables. We find that technical indicators exhibit statistically and economically significant in-sample and out-of-sample forecasting power for the monthly equity risk premium, clearly on par with that of well-known macroeconomic variables from the literature. Furthermore, we find that technical indicators and macroeconomic variables capture different types of information relevant for forecasting the equity risk premium; in particular, technical indicators (macroeconomic variables) better detect the typical decline (rise) in the equity risk premium near business-cycle peaks (troughs). In line with this finding, we demonstrate that combining information from both technical indicators and macroeconomic variables produces superior equity risk premium forecasts and offer substantial utility gains to investors by better tracking the substantial countercyclical fluctuations in the equity risk premium.

Our empirical findings call for new theoretical models than can explain the forecasting power of technical indicators. Existing asset pricing models typically include only a limited number of state variables, such as consumption growth and the dividend-price ratio, so that the stochastic discount factors can only explain the predictive ability of these variables and their cross-sectional pricing effects. On the other hand, as mentioned previously, technical indicators could be a good proxy for persistent reactions in equity prices induced by macroeconomic variables not typically employed in the literature and could capture trends in equity prices that affect fundamentals themselves via the feedback effect (e.g., Edmans, Goldstein, and Jiang 2012). Given these considerations, as well as the significant empirical predictive ability of technical indicators, there appears to be a pressing need to develop new asset pricing models that include technical indicators among the state variables that agents use for decision making (in line with the actual behavior of practitioners). Such models hold the promise of substantially improving our understanding of the economic forces affecting the equity risk premium and cross-sectional pricing of assets.

Appendix: Wild Bootstrap Procedure

This appendix describes the wild bootstrap procedure used to compute p-values for the t-statistics in Table 2. Let

$$\hat{\varepsilon}_{t+1} = r_{t+1} - (\hat{\alpha} + \sum_{i=1}^{N} \hat{\beta}_{i,x} x_{i,t} + \sum_{i=1}^{N} \hat{\beta}_{i,S} S_{i,t}), \tag{25}$$

where $\hat{\alpha}$, $\hat{\beta}_{i,x}$ ($i = 1,\ldots,N$), and $\hat{\beta}_{i,S}$ ($i = 1,\ldots,N$) are OLS parameter estimates for the general multiple predictive regression model that includes a constant and all of the N macroeconomic variables and N technical indicators as regressors. Following convention, we assume that each macroeconomic variable follows an AR(1) process:

$$x_{i,t+1} = \rho_{i,0} + \rho_{i,1} x_{i,t} + v_{i,t+1} \ \text{ for } \ i = 1,\ldots,N. \tag{26}$$

Define

$$\hat{v}^c_{i,t+1} = x_{i,t+1} - (\hat{\rho}^c_{i,0} + \hat{\rho}^c_{i,1} x_{i,t}) \ \text{ for } \ i = 1,\ldots,N, \tag{27}$$

where $\hat{\rho}^c_{i,0}$ and $\hat{\rho}^c_{i,1}$ are reduced-bias estimates of the AR(1) parameters in (26). The reduced-bias estimates of the AR parameters are computed by iterating on the Nicholls and Pope (1988) expression for the analytical bias of the OLS estimates. Based on these AR parameter estimates and fitted residuals, we build up a pseudo sample of observations for the equity risk premium and N macroeconomic variables under the null hypothesis of no return predictability:

$$r^*_{t+1} = \bar{r} + \hat{\varepsilon}_{t+1} w_{t+1} \ \text{ for } \ t = 0,\ldots,T-1, \tag{28}$$

$$x^*_{i,t+1} = \hat{\rho}^c_{i,0} + \hat{\rho}^c_{i,1} x^*_{i,t} + \hat{v}^c_{i,t+1} w_{t+1} \ \text{ for } \ i = 1,\ldots,N \ \text{ and } \ t = 0,\ldots,T-1, \tag{29}$$

where $\bar{r}$ is the sample mean of the equity risk premium, w_{t+1} is a draw from the standard normal distribution, and $x^*_{i,0} = x_{i,0}$ ($i = 1,\ldots,N$). Observe that we multiply $\hat{\varepsilon}_{t+1}$ in (28) and each $\hat{v}^c_{i,t+1}$ in (29) by the same scalar, w_{t+1}, when generating the month-$(t+1)$ pseudo residuals, thereby making it a wild bootstrap. In addition to preserving the contemporaneous correlations in the data, the wild bootstrap accounts for general forms of conditional heteroskedasticity. Employing reduced-bias parameter estimates in (29) helps to ensure that we adequately capture the persistence in the macroeconomic variables. To generate a pseudo sample of observations for the N technical indicators, we assume that each indicator follows a first-order, two-state, Markov-switching process with the following transition matrix:

$$P_i = \begin{pmatrix} p_i^{0,0} & p_i^{0,1} \\ p_i^{1,0} & p_i^{1,1} \end{pmatrix} \ \text{ for } \ i = 1,\ldots,N, \tag{30}$$

where

$$p_i^{j,k} = \Pr(S_{i,t} = k | S_{i,t-1} = j) \ \text{ for } \ j,k = 0,1, \tag{31}$$

and $p_i^{0,0} + p_i^{0,1} = p_i^{1,0} + p_i^{1,1} = 1$. Based on estimates of the transition probabilities in (30) and $S_{i,0}$ ($i = 1,\ldots,N$), we can build up a pseudo sample of observations for the N technical indicators via simulations.

Using the pseudo sample of observations for the equity risk premium $[\{r^*_{t+1}\}_{t=0}^{T-1}]$, N macroeconomic variables $[\{x^*_{i,t}\}_{t=0}^{T-1}$ $(i = 1,\ldots,N)]$, and N technical indicators $[\{S^*_{i,t}\}_{t=0}^{T-1}$ $(i = 1,\ldots,N)]$, we estimate the slope coefficients and corresponding t-statistics for the bivariate predictive regressions given by (1) and (10) for each i, as well as the principal component predictive regressions given by (11), (12), and (13). Note that we compute the principal components in (11), (12), and (13) using $\{x^*_{i,t}\}_{t=0}^{T-1}$ and $\{S^*_{i,t}\}_{t=0}^{T-1}$ ($i = 1,\ldots,N$), so that the pseudo sample accounts for the estimated regressors in the principal component predictive regressions. We store the t-statistics for all of the predictive regressions. Repeating this process 2,000 times yields empirical distributions for each of the t-statistics. For a given t-statistic, the empirical p-value is the proportion of the bootstrapped t-statistics greater than the t-statistic for the original sample.

References

Amihud, Y., C. M. Hurvich. 2004. Predictive regressions: A reduced-bias estimation method. *Journal of Financial and Quantitative Analysis* **39** 813–841.

Amihud, Y., C. M. Hurvich, Y. Wang. 2009. Multiple-predictor regressions: Hypothesis tests. *Review of Financial Studies* **22** 413–434.

Ang, A., G. Bekaert. 2007. Return predictability: Is it there? *Review of Financial Studies* **20** 651–707.

Bai, J., S. Ng. 2006. Confidence intervals for diffusion index forecasts and inferences for factor-augmented regressions. *Econometrica* **74** 1133–1150.

Balduzzi, P., A. W. Lynch. 1999. Transaction costs and predictability: Some utility cost calculations. *Journal of Financial Economics* **52** 47–78.

Billingsley, R. S., D. M. Chance. 1996. The benefits and limits of diversification among commodity trading advisors. *Journal of Portfolio Management* **23** 65–80.

Breen, W., L. R. Glosten, R. Jagannathan. 1989. Economic significance of predictable variations in stock index returns. *Journal of Finance* **64** 1177–1189.

Brock, W., J. Lakonishok, B. LeBaron. 1992. Simple technical trading rules and the stochastic properties of stock returns. *Journal of Finance* **47** 1731–1764.

Busetti, F., J. Marcucci. 2012. Comparing forecast accuracy: A Monte Carlo investigation. *International Journal of Forecasting* **29** 13–27.

Campbell, J. Y. 1987. Stock returns and the term structure. *Journal of Financial Economics* **18** 373–399.

Campbell, J. Y., R. J. Shiller. 1988. The dividend-price ratio and expectations of future dividends and discount factors. *Review of Financial Studies* **1** 195–228.

Campbell, J. Y., S. B. Thompson. 2008. Predicting the equity premium out of sample: Can anything beat the historical average? *Review of Financial Studies* **21** 1509–1531.

Campbell, J. Y., T. Vuolteenaho. 2004. Inflation illusion and stock prices. *American Economic Review* **94** 19–23.

Campbell, J. Y., M. Yogo. 2006. Efficient tests of stock return predictability. *Journal of Financial Economics* **81** 27–60.

Clark, T. E., M. W. McCracken. 2001. Test of equal forecast accuracy and encompassing for nested models. *Journal of Econometrics* **105** 85–110.

Clark, T. E., M. W. McCracken. 2009. Improving forecast accuracy by combining recursive and rolling forecasts. *International Economic Review* **50** 363–395.

Clark, T. E., M. W. McCracken. 2012. Reality checks and nested forecast model comparisons. *Journal of Business and Economic Statistics* **30** 53–66.

Clark, T. E., K. D. West. 2007. Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics* **138** 291–311.

Cochrane, J. H. 2008. The dog that did not bark: A defense of return predictability. *Review of Financial Studies* **21** 1533–1575.

Cochrane, J. H. 2011. Discount rates. *Journal of Finance* **66** 1047–1108.

Covel, M. W. 2009. *Trend Following (Updated Edition): Learn to Make Millions in Up or Down Markets*. FT Press, Upper Saddle River, New Jersey.

Cowles, A. 1933. Can stock market forecasters forecast? *Econometrica* **1** 309–324.

DeMiguel, V., L. Garlappi, R. Uppal. 2009. Optimal versus naive diversification: How inefficient is the 1/*N* Portfolio Strategy? *Review of Financial Studies* **22** 1915–1953.

DeMiguel, V., L. Garlappi, F. J. Nogales, R. Uppal. 2009. A generalized approach to portfolio optimization: Improving performance by constraining portfolio norms. *Management Science* **55** 798–812.

Diebold, F. X., R. S. Mariano. 1995. Comparing predictive accuracy. *Journal of Business and Economic Statistics* **13** 253–263.

Edmans, A., I. Goldstein, W. Jiang. 2012. Feedback effects and the limits to arbitrage. Working paper, University of Pennsylvania.

Fama, E. F., M. F. Blume. 1966. Filter rules and stock market trading. *Journal of Business* **39** 226–241.

Fama, E. F., K. R. French. 1988. Dividend yields and expected stock returns. *Journal of Financial Economics* **22** 3–25.

Fama, E. F., K. R. French. 1989. Business conditions and expected returns on stocks and bonds. *Journal of Financial Economics* **25** 23–49.

Fama, E. F., G. W. Schwert. 1977. Asset returns and inflation. *Journal of Financial Economics* **5** 115–146.

Ferreira, M. A., P. Santa-Clara. 2011. Forecasting stock market returns: The sum of the parts is more than the whole. *Journal of Financial Economics* **100** 514–537.

Ferson, W. E., C. R. Harvey. 1991. The variation of equity risk premiums. *Journal of Political Economy* **99** 385–415.

Ferson, W. E., Sarkissian, S., T. T. Simin. Spurious regressions in financial economics? *Journal of Finance* **58** 1393–1413.

Goh, J., F. Jiang, J. Tu, and G. Zhou. 2012. Forecasting bond risk premia using technical indicators. Working paper, Washington University in St. Louis.

Goyal, A., I. Welch. 2003. Predicting the equity premium with dividend ratios. *Management Science* **49** 639–654.

Goyal, A., I. Welch. 2008. A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies* **21** 1455–1508.

Granville, J. 1963. *Granville's New Key to Stock Market Profits*. Prentice-Hall, New York.

Guiso, L., P. Sapienza, L. Zingales. 2008. Trusting the stock market. *Journal of Finance* **63** 2557–2600.

Guiso, L., P. Sapienza, L. Zingales. 2011. Time varying risk aversion. Working paper, Northwestern University.

Guo, H. 2006. On the out-of-sample predictability of stock market returns. *Journal of Business* **79** 645–670.

Hansen, P. R., A. Timmermann. 2012. Choice of sample split in out-of-sample forecast evaluation. Working paper, European University Institute and University of California at San Diego.

Harvey, C. R. 2001. The specification of conditional expectations. *Journal of Empirical Finance* **8** 573–637.

Harvey, D. I., S. J. Leybourne, P. Newbold. 1998. Tests for forecast encompassing. *Journal of Business and Economic Statistics* **16** 254–259.

Henkel, S. J., J. S. Martin, F. Nadari. 2011. Time-varying short-horizon predictability. *Journal of Financial Economics* **99** 560–580.

Hjalmarsson, E. 2010. Predicting global stock returns. *Journal of Financial and Quantitative Analysis* **45** 49–80.

Hsu, P.-H., M. P. Taylor. 2012. Technical analysis: Is it still beating the foreign exchange market? Working paper, University of Warwick.

Inoue, A., L. Kilian. 2004. In-sample or out-of-sample tests of predictability: Which one should we use? *Econometric Reviews* **23** 371–402.

Jensen, M. C., G. A. Benington. 1970. Random walks and technical theories: Some additional evidence. *Journal of Finance* **25** 469–482.

Kandel, S., R. F. Stambaugh. 1996. On the predictability of stock returns: An asset allocation perspective. *Journal of Finance* **51** 385–424.

Keim, D. B., R. F. Stambaugh. 1986. Predicting returns in the stock and bond markets. *Journal of Financial Economics* **17** 357–390.

LeBaron, B. 1999. Technical trading rule profitability and foreign exchange intervention. *Journal of International Economics* **49** 125–143.

Lettau, M., S. C. Ludvigson. 2001. Consumption, aggregate wealth, and expected stock returns. *Journal of Finance* **56** 815–849.

Lettau, M., S. C. Ludvigson. 2010. Measuring and modeling variation in the risk-return tradeoff. Y. Aït-Sahalïa, L. P. Hansen, eds. *Handbook of Financial Econometrics: Tools and Techniques*. Elsevier, Amsterdam, 617–690.

Lewellen, J. 2004. Predicting returns with financial ratios. *Journal of Financial Economics* **74** 209–235.

Lo, A. W., J. Hasanhodzic. 2009. *The Heretics of Finance*. Bloomberg Press, New York, New York.

Lo, A. W., J. Hasanhodzic. 2010. *The Evolution of Technical Analysis: Financial Prediction from Babylonian Tablets to Bloomberg Terminals*. John Wiley & Sons, Hoboken, New Jersey.

Lo, A. W., H. Mamaysky, J. Wang. 2000. Foundations of technical analysis: Computational algorithms, statistical inference, and empirical implementation. *Journal of Finance* **55** 1705–1765.

Ludvigson, S. C., S. Ng. 2007. The empirical risk-return relation: A factor analysis approach. *Journal of Financial Economics* **83** 171–222.

Ludvigson, S. C., S. Ng. 2009. Macro factors in bond risk premia. *Review of Financial Studies* **22** 5027–5067.

McCracken, M. W. 2007. Asymptotics for out of sample tests of Granger casuality. *Journal of Econometrics* **140** 719–752.

Mele, A. 2007. Asymmetric stock market volatility and the cyclical behavior of expected returns. *Journal of Financial Economics* **86** 446–478.

Menkhoff, L., M. P. Taylor. 2007. The obstinate passion of foreign exchange professionals: Technical analysis. *Journal of Economic Literature* **45** 936–972.

Neely, C. J. 2002. The temporal pattern of trading rule returns and exchange rate intervention: Intervention does not generate technical trading profits. *Journal of International Economics* **58** 211–232.

Nelson, C. R. 1976. Inflation and the rates of return on common stock. *Journal of Finance* **31** 471–483.

Nicholls, D. F., Pope, A.L. 1988. Bias in the estimation of multiple autoregressions. *Australian Journal of Statistics* **30A** 296–309.

Park, C.-H., S. H. Irwin. 2007. What do we know about the profitability of technical analysis? *Journal of Economic Surveys* **21** 786–826.

Pástor, L., R. F. Stambaugh. 2009. Predictive systems: Living with imperfect predictors. *Journal of Finance* **64** 1583–1628.

Pesaran, M. H., A. Timmermann. 2007. Selection of estimation window in the presence of breaks. *Journal of*

Econometrics **137** 134–161.

Rapach, D. E., J. K. Strauss, G. Zhou. 2010. Out-of-sample equity premium prediction: Combination forecasts and links to the real economy. *Review of Financial Studies* **23** 821–862.

Rozeff, M. S. 1984. Dividend yields are equity risk premiums. *Journal of Portfolio Management* **11** 68–75.

Schwager, J. D. 1989. *Market Wizards*. John Wiley & Sons, Hoboken, New Jersey.

Schwager, J. D. 1992. *The New Market Wizards*. John Wiley & Sons, Hoboken, New Jersey.

Schwager, J. D. 2012. *Hedge Fund Market Wizards*. John Wiley & Sons, Hoboken, New Jersey.

Simin, T. T. 2008. The poor predictive performance of asset pricing models. *Journal of Financial and Quantitative Analysis* **43** 355–380.

Soros, G. 2003. *The Alchemy of Finance*, updated edition. John Wiley & Sons, Hoboken, New Jersey.

Stambaugh, R. F. 1999. Predictive regressions. *Journal of Financial Economics* **54** 375–421.

Sullivan, R., A. Timmermann, H. White. 1999. Data-snooping, technical trading rule performance, and the bootstrap. *Journal of Finance* **54** 1647–1691.

West, K. D. 1996. Asymptotic inference about predictive ability. *Econometrica* **64** 1067–1084.

White, H. 2000. A reality check for data snooping. *Econometrica* **68** 1097–1126.

Whitelaw, R. F. 1994. Time variations and covariations in the expectation and volatility of stock market returns. *Journal of Finance* **49** 515–541.

Xu, Y. 2004. Small levels of predictability and large economic gains. *Journal of Empirical Finance* **11** 247–275.

Table 1 Summary Statistics, 1950:12–2011:12

Variable	Mean	Standard deviation	Minimum	Maximum	Autocorrelation	Sharpe ratio
Log equity risk premium	0.47	4.26	−24.84	14.87	0.06	0.11
DP	−3.49	0.42	−4.52	−2.60	0.99	
DY	−3.48	0.42	−4.53	−2.59	0.99	
EP	−2.78	0.44	−4.84	−1.90	0.99	
DE	−0.71	0.30	−1.24	1.38	0.99	
RVOL	0.14	0.05	0.05	0.32	0.96	
BM	0.54	0.25	0.12	1.21	0.99	
NTIS	0.02	0.02	−0.06	0.05	0.98	
TBL	4.67	2.95	0.01	16.30	0.99	
LTY	6.32	2.68	2.21	14.82	0.99	
LTR	0.56	2.76	−11.24	15.23	0.05	
TMS	1.64	1.42	−3.65	4.55	0.96	
DFY	0.96	0.45	0.32	3.38	0.97	
DFR	0.01	1.38	−9.75	7.37	−0.09	
INFL	0.30	0.35	−1.92	1.79	0.61	

Notes. The table reports summary statistics for the log equity risk premium (in percent) and 14 macroeconomic variables. The data are from Amit Goyal's web page at http://www.hec.unil.ch/agoyal/. The mnemonics are defined as follows: DP = log dividend-price ratio, DY = log dividend yield, EP = log earnings-price ratio, DE = log dividend-payout ratio, RVOL = equity risk premium volatility, BM = book-to-market ratio, NTIS = net equity expansion, TBL = Treasury bill rate (annual %), LTY = long-term bond yield (annual %), LTR = long-term bond return (%), TMS = term spread (annual %), DFY = default yield spread (annual %), DFR = default return spread (%), INFL = inflation rate (%). The Sharpe ratio is the mean of the log equity risk premium divided by its standard deviation.

Table 2 Predictive Regression Estimation Results, 1951:01–2011:12

Macroeconomic variables			Technical indicators		
Predictor	Slope coefficient	R^2	Predictor	Slope coefficient	R^2
Panel A: Bivariate Predictive Regressions					
DP	0.78 [1.98]*	0.58%	MA(1,9)	0.67 [1.78]**	0.54%
DY	0.84 [2.13]**	0.67%	MA(1,12)	0.87 [2.22]**	0.87%
EP	0.43 [0.97]	0.20%	MA(2,9)	0.70 [1.88]**	0.59%
DE	0.59 [0.93]	0.17%	MA(2,12)	0.94 [2.42]***	1.03%
RVOL	7.41 [2.45]***	0.73%	MA(3,9)	0.77 [2.04]**	0.69%
BM	0.54 [0.75]	0.10%	MA(3,12)	0.54 [1.39]*	0.34%
NTIS	0.66 [0.06]	0.001%	MOM(9)	0.55 [1.40]*	0.34%
TBL	0.11 [1.90]**	0.56%	MOM(12)	0.58 [1.45]*	0.37%
LTY	0.08 [1.25]**	0.23%	VOL(1,9)	0.68 [1.86]**	0.56%
LTR	0.13 [2.05]**	0.76%	VOL(1,12)	0.89 [2.31]***	0.92%
TMS	0.20 [1.74]**	0.44%	VOL(2,9)	0.74 [2.02]**	0.67%
DFY	0.16 [0.37]	0.03%	VOL(2,12)	0.74 [1.94]**	0.65%
DFR	0.16 [0.89]	0.26%	VOL(3,9)	0.48 [1.27]	0.27%
INFL	0.10 [0.18]	0.01%	VOL(3,12)	0.85 [2.25]***	0.85%
Panel B: Principal Component Predictive Regressions					
$\hat{F}_1^{\text{ECON}}$	0.04 [0.48]	1.18%	$\hat{F}_1^{\text{TECH}}$	0.12 [2.12]**	0.84%
$\hat{F}_2^{\text{ECON}}$	0.07 [0.61]				
$\hat{F}_3^{\text{ECON}}$	0.31 [2.48]***				
Panel C: Principal Component Predictive Regression, All Predictors Taken Together					
$\hat{F}_1^{\text{ALL}}$	0.11 [1.98]**	2.02%			
$\hat{F}_2^{\text{ALL}}$	0.08 [0.93]				
$\hat{F}_3^{\text{ALL}}$	0.18 [1.51]*				
$\hat{F}_4^{\text{ALL}}$	0.26 [2.30]***				

Notes. Panel A reports estimation results for the bivariate predictive regression model,

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

where r_{t+1} is the log equity risk premium (in percent) and $q_{i,t}$ is one of the 14 macroeconomic variables (14 technical indicators) given in the first (fourth) column. Panels B and C report estimation results for a predictive regression model based on principal components,

$$r_{t+1} = \alpha + \sum_{k=1}^{K} \beta_k \hat{F}_{k,t}^{j} + \varepsilon_{t+1},$$

where $\hat{F}_{k,t}^{j}$ is the kth principal component extracted from the 14 macroeconomic variables ($j =$ ECON), 14 technical indicators ($j =$ TECH), or the 14 macroeconomic variables and 14 technical indicators taken together ($j =$ ALL). K is selected via the adjusted R^2. The brackets to the immediate right of the estimated slope coefficients report heteroskedasticity-consistent t-statistics; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, based on one-sided (upper-tail) wild bootstrapped p-values.

Table 3 Out-of-Sample Forecasting Results, 1966:01–2011:12

Macroeconomic variables						Technical indicators					
Predictor	MSFE	R^2_{OS}	*MSFE-adjusted*	$(\bar{\hat{e}})^2$	Var($\hat{e}$)	Predictor	MSFE	R^2_{OS}	*MSFE-adjusted*	$(\bar{\hat{e}})^2$	Var($\hat{e}$)
Historical average	20.23			0.07	20.16						
Panel A: Bivariate Predictive Regression Forecasts											
DP	20.23	−0.02%	1.27	0.00	20.23	MA(1,9)	20.18	0.24%	0.98	0.05	20.13
DY	20.22	0.05%	1.41*	0.00	20.22	MA(1,12)	20.10	0.63%	1.52*	0.05	20.05
EP	20.35	−0.58%	0.02	0.02	20.32	MA(2,9)	20.16	0.32%	1.16	0.05	20.11
DE	20.39	−0.78%	0.73	0.00	20.39	MA(2,12)	20.07	0.78%	1.69**	0.05	20.02
RVOL	20.19	0.19%	1.59*	0.13	20.06	MA(3,9)	20.15	0.41%	1.41*	0.05	20.09
BM	20.48	−1.23%	−1.27	0.08	20.40	MA(3,12)	20.21	0.08%	0.63	0.06	20.16
NTIS	20.43	−0.97%	0.38	0.17	20.26	MOM(9)	20.21	0.11%	0.61	0.06	20.15
TBL	20.46	−1.12%	2.04**	0.08	20.38	MOM(12)	20.20	0.15%	0.69	0.06	20.14
LTY	20.42	−0.95%	1.56*	0.09	20.33	VOL(1,9)	20.15	0.40%	1.25	0.06	20.09
LTR	20.17	0.29%	2.00**	0.10	20.07	VOL(1,12)	20.07	0.80%	1.76**	0.05	20.02
TMS	20.43	−0.99%	2.08**	0.23	20.20	VOL(2,9)	20.14	0.44%	1.36*	0.07	20.07
DFY	20.36	−0.64%	−0.34	0.13	20.23	VOL(2,12)	20.16	0.33%	1.12	0.06	20.10
DFR	20.32	−0.46%	0.05	0.06	20.26	VOL(3,9)	20.23	0.01%	0.46	0.06	20.17
INFL	20.32	−0.45%	0.32	0.02	20.30	VOL(3,12)	20.09	0.71%	1.68**	0.05	20.04
Panel B: Principal Component Predictive Regression Forecasts											
PC-ECON	20.40	−0.86%	2.58***	0.02	20.38	PC-TECH	20.10	0.65%	1.46*	0.05	20.04
Panel C: Principal Component Predictive Regression Forecasts, All Predictors Taken Together											
PC-ALL	19.87	1.79%	3.28***	0.04	19.83						

Notes. The historical average forecast is given by

$$\hat{r}^{\text{HA}}_{t+1} = (1/t)\sum_{s=1}^{t} r_t,$$

where r_t is the log equity risk premium (in percent). Each bivariate predictive regression forecast in Panel A is given by

$$\hat{r}_{t+1} = \hat{\alpha}_{t,i} + \hat{\beta}_{t,i} q_{i,t},$$

where $q_{i,t}$ is one of the 14 macroeconomic variables (14 technical indicators) given in the first (seventh) column and $\hat{\alpha}_{t,i}$ and $\hat{\beta}_{t,i}$ are the OLS estimates computed from regressing $\{r_s\}_{s=2}^{t}$ on a constant and $\{q_{i,s}\}_{s=1}^{t-1}$. The PC-ECON, PC-TECH, and PC-ALL forecasts in Panels B and C are given by

$$\hat{r}_{t+1}^{j} = \hat{\alpha}_t + \sum_{k=1}^{K} \hat{\beta}_{t,k} \hat{F}_{1:t,k,t}^{j} \text{ for } j = \text{ECON, TECH, or ALL},$$

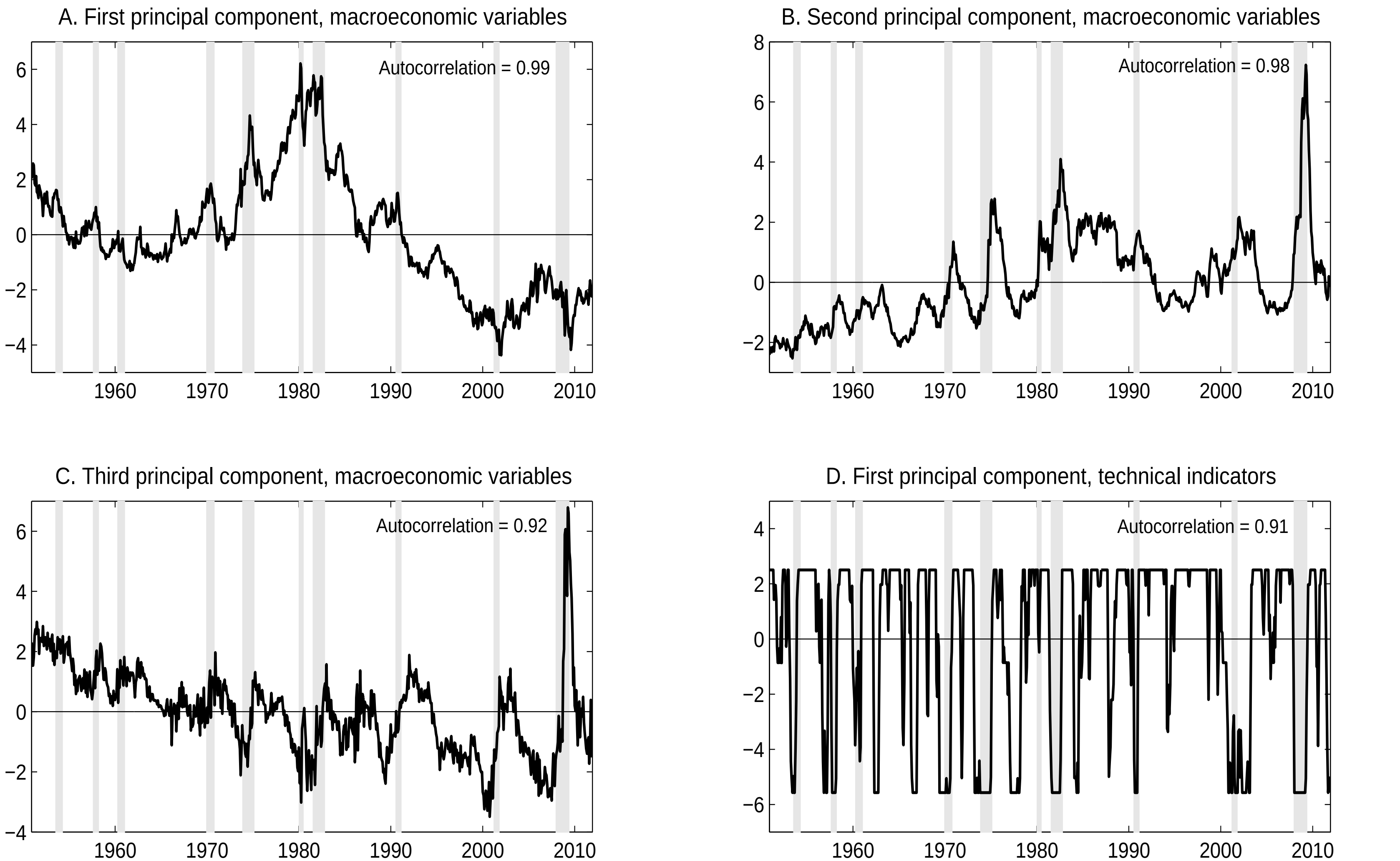
where $\hat{F}_{1:t,k,t}^{j}$ is the kth principal component extracted from the 14 macroeconomic variables ($j = \text{ECON}$), 14 technical indicators ($j = \text{TECH}$), or 14 macroeconomic variables and 14 technical indicators taken together ($j = \text{ALL}$) based on data through t and $\hat{\alpha}_t$ and $\hat{\beta}_{t,k}$ ($k = 1,\ldots,K$) are the OLS estimates computed from regressing $\{r_s\}_{s=2}^{t}$ on a constant and $\{\hat{F}_{1:t,s,k}^{j}\}_{s=1}^{t-1}$ ($k = 1,\ldots,K$). K is selected via the adjusted R^2 based on data through t. MSFE is the mean squared forecast error. R_{OS}^2 measures the reduction in MSFE for the competing forecast given in the first or seventh column relative to the historical average forecast. *MSFE-adjusted* is the Clark and West (2007) statistic for testing the null hypothesis that the historical average forecast MSFE is less than or equal to the competing forecast MSFE against the one-sided (upper-tail) alternative hypothesis that the historical average forecast MSFE is greater than the competing forecast MSFE; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. $(\bar{\hat{e}})^2$ and VAR$(\hat{e})$ are the squared forecast bias and forecast error variance, respectively. 0.00 indicates less than 0.005 in absolute value.

Table 4 Portfolio Performance Measures, 1966:01–2011:12

Macroeconomic variables					Technical indicators				
Predictor	Δ (annualized)	Sharpe ratio	Relative avg. turnover	Δ (annualized), cost = 50bps	Predictor	Δ (annualized)	Sharpe ratio	Relative avg. turnover	Δ (annualized), cost = 50bps
Historical average	3.54%	0.05	2.09%	3.40%					
Panel A: Bivariate predictive regression forecasts									
DP	−0.26%	0.03	2.17	−0.38%	MA(1,9)	1.69%	0.08	4.40	1.22%
DY	0.27%	0.04	3.05	0.02%	MA(1,12)	2.91%	0.11	3.94	2.51%
EP	0.42%	0.05	1.72	0.34%	MA(2,9)	2.08%	0.09	4.48	1.63%
DE	−0.19%	0.04	2.17	−0.34%	MA(2,12)	3.17%	0.12	3.62	2.82%
RVOL	−0.52%	0.08	4.20	−0.90%	MA(3,9)	2.54%	0.11	4.60	2.08%
BM	−1.26%	0.03	2.52	−1.45%	MA(3,12)	1.40%	0.08	2.69	1.18%
NTIS	0.15%	0.08	3.52	−0.18%	MOM(9)	1.38%	0.07	2.58	1.16%
TBL	1.62%	0.08	1.52	1.56%	MOM(12)	1.32%	0.07	2.19	1.16%
LTY	1.65%	0.07	1.03	1.65%	VOL(1,9)	1.61%	0.08	5.21	1.05%
LTR	1.07%	0.09	23.94	−1.87%	VOL(1,12)	2.63%	0.11	4.59	2.25%
TMS	1.88%	0.12	4.45	1.44%	VOL(2,9)	1.48%	0.08	2.94	1.23%
DFY	−0.82%	0.05	2.70	−1.03%	VOL(2,12)	1.32%	0.08	2.40	1.13%
DFR	0.26%	0.06	10.16	−0.91%	VOL(3,9)	0.71%	0.06	2.52	0.52%
INFL	0.38%	0.06	7.77	−0.49%	VOL(3,12)	2.22%	0.10	2.80	1.99%
Panel B: Principal Component Predictive Regression Forecasts									
PC-ECON	2.24%	0.10	6.73	1.51%	PC-TECH	2.49%	0.10	3.58	2.15%
Panel C: Principal Component Predictive Regression Forecasts, All Predictors Taken Together									
PC-ALL	4.94%	0.16	7.51	4.12%					

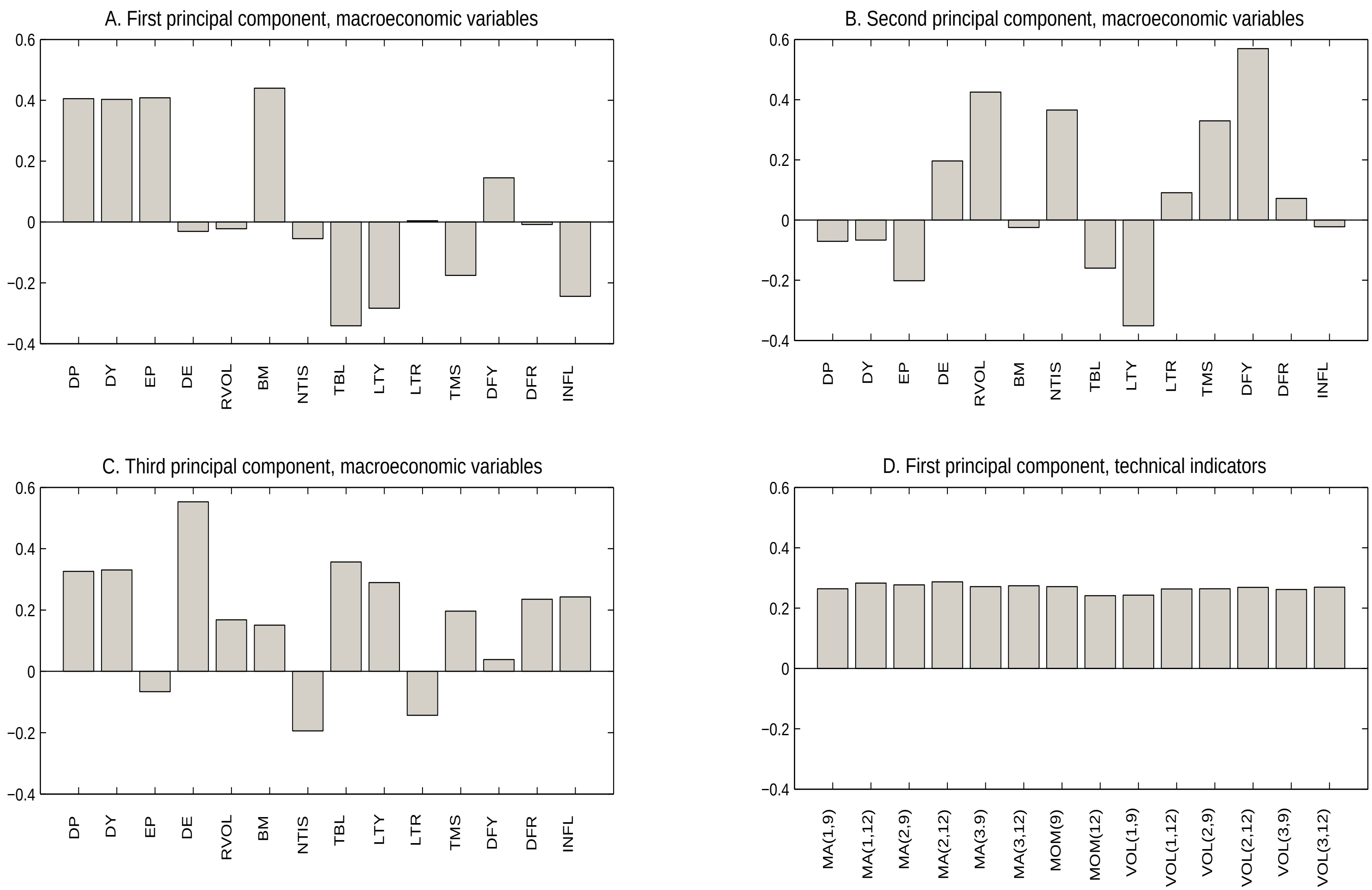
Notes. The table reports portfolio performance measures for a mean-variance investor with relative risk aversion coefficient of five who allocates monthly between equities and risk-free bills using either an historical average or predictive regression equity risk premium forecast. Each forecast in Panel A is based on one of the 14 macroeconomic variables (14 technical indicators) given in the first (sixth) column. The forecasts in Panels B and C are based on the 14 macroeconomic variables (PC-ECON), 14 technical indicators (PC-TECH), or all 14 macroeconomic variables and 14 technical indicators taken together (PC-ALL). Δ is the annualized certainty equivalent return (CER) gain for an investor who uses the predictive regression forecast instead of the historical average forecast; for the historical average forecast, the table reports the CER level. Relative average turnover is the average turnover for the portfolio based on the predictive regression forecast divided by the average turnover for the portfolio based on the historical average forecast; for the historical average forecast, the table reports the average turnover level. Δ, cost = 50bps is the CER gain assuming a proportional transactions cost of 50 basis points per transaction.

Figure 1 Principal Components Extracted From 14 Macroeconomic Variables and 14 Technical Indicators, 1950:12–2011:12



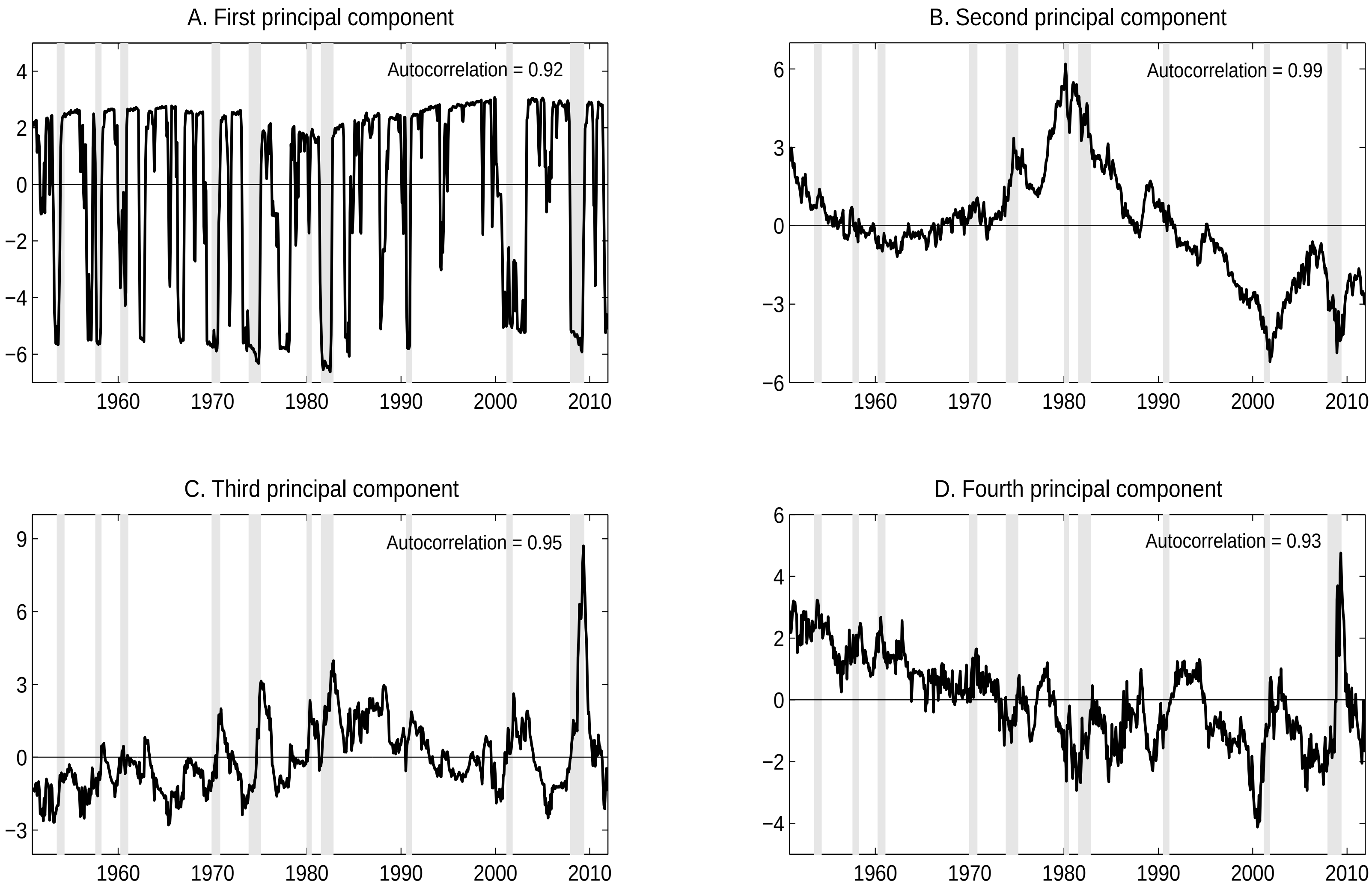
Notes. Panels A through C depict the first three principal components, respectively, extracted from 14 macroeconomic variables. Panel D depicts the first principal component extracted from 14 technical indicators. Autocorrelations for the principal components are reported in the upper right corner of the panels. Vertical bars depict NBER-dated recessions.

Figure 2 Factor Loadings, Principal Components Extracted From 14 Macroeconomic Variables and 14 Technical Indicators, 1950:12–2011:12



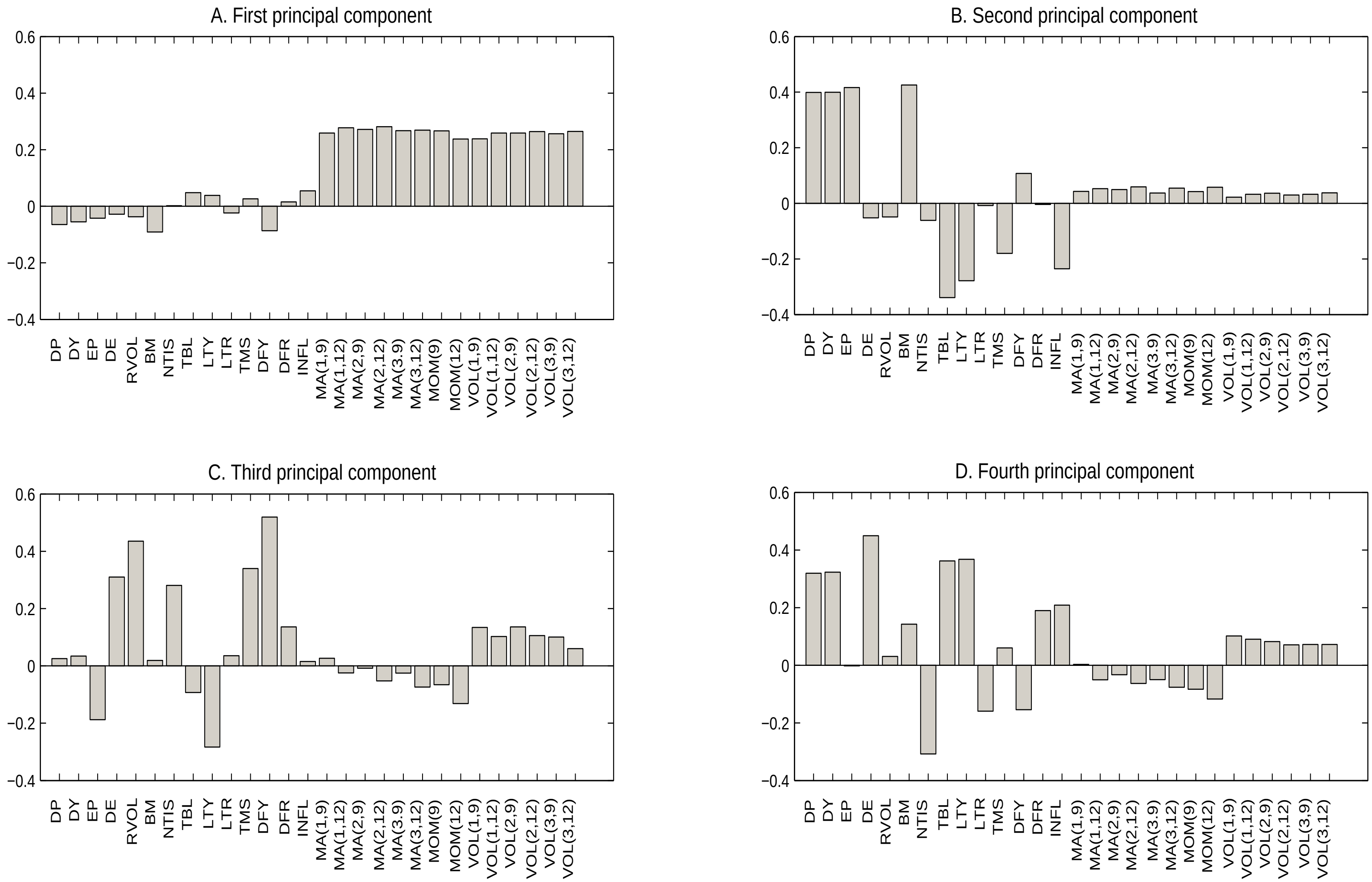
Notes. Panels A through C depict factor loadings corresponding to the first three principal components, respectively, extracted from 14 macroeconomic variables. Panel D depicts factor loadings corresponding to the first principal component extracted from 14 technical indicators.

Figure 3 Principal Components Extracted From 14 Macroeconomic Variables and 14 Technical Indicators Taken Together, 1950:12–2011:12



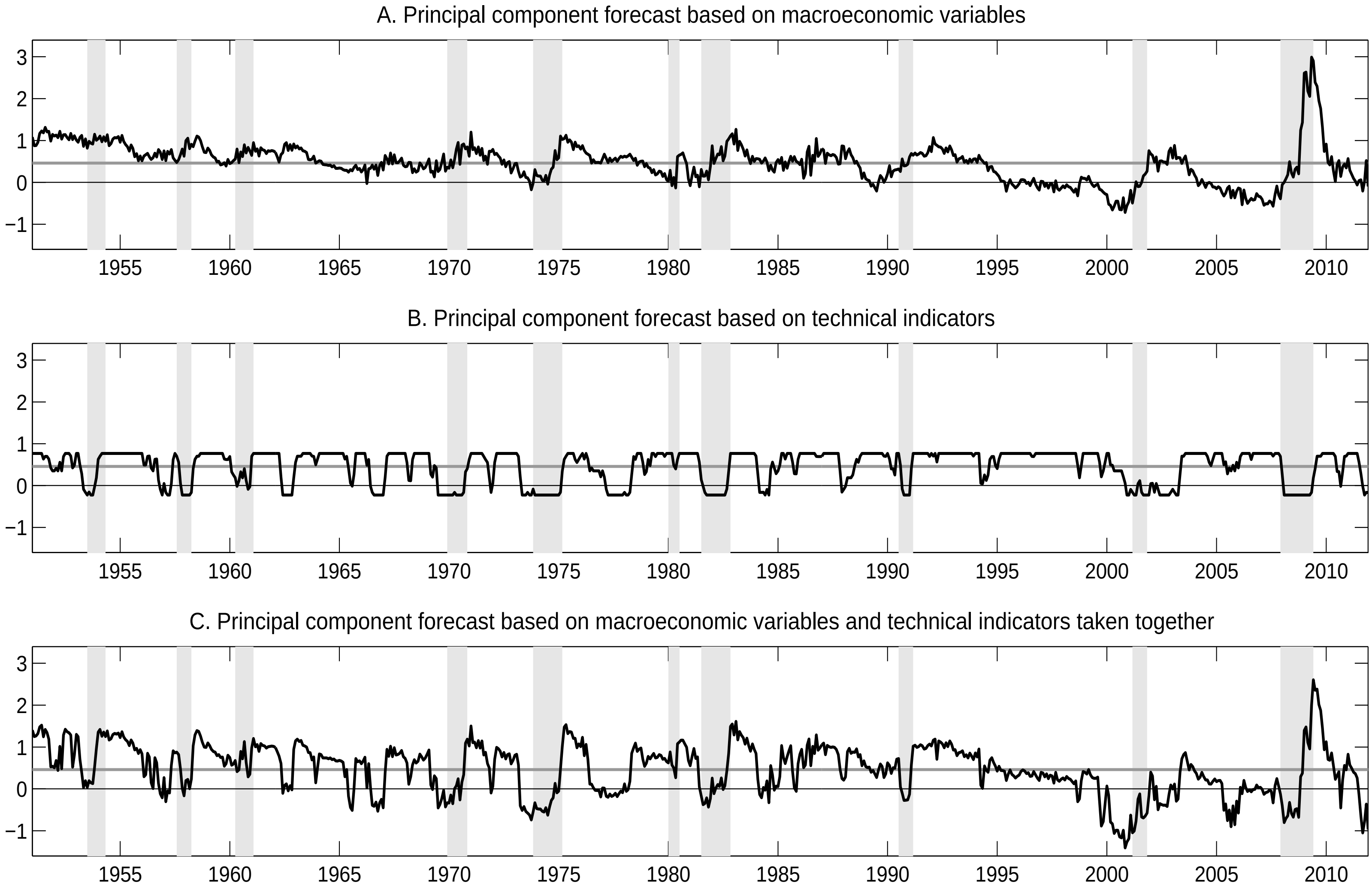
Notes. Panels A through D depict the first four principal components, respectively, extracted from 14 macroeconomic variables and 14 technical indicators taken together. Autocorrelations for the principal components are reported in the upper right corner of the panels. Vertical bars depict NBER-dated recessions.

Figure 4 Factor Loadings, Principal Components Extracted From 14 Macroeconomic Variables and 14 Technical Indicators Taken Together, 1950:12–2011:12



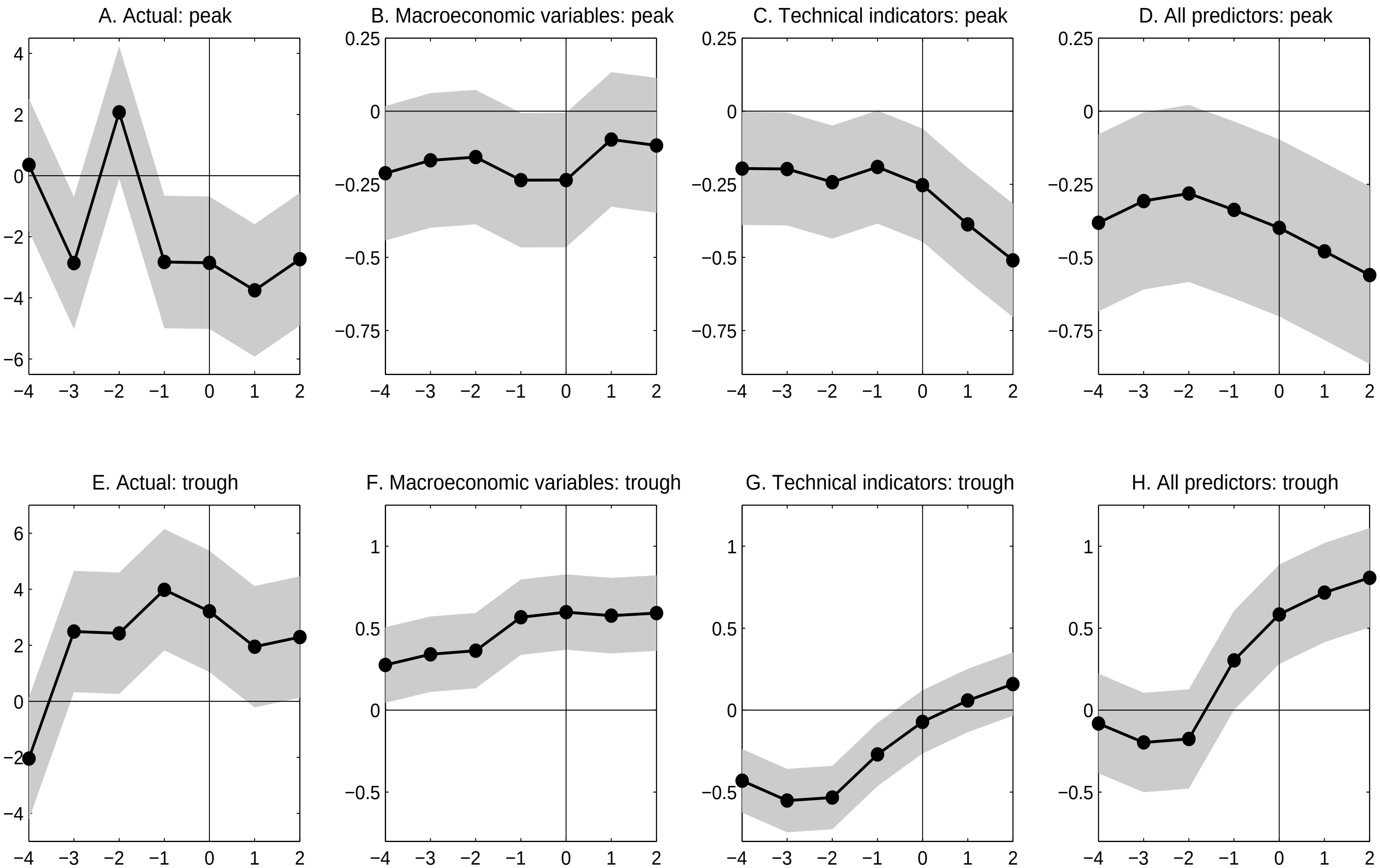
Notes. Panels A through D depict factor loadings corresponding to the first four principal components, respectively, extracted from 14 macroeconomic variables and 14 technical indicators taken together.

Figure 5 In-Sample Log Equity Risk Premium Forecasts Based on 14 Macroeconomic Variables and 14 Technical Indicators, 1951:01–2011:12



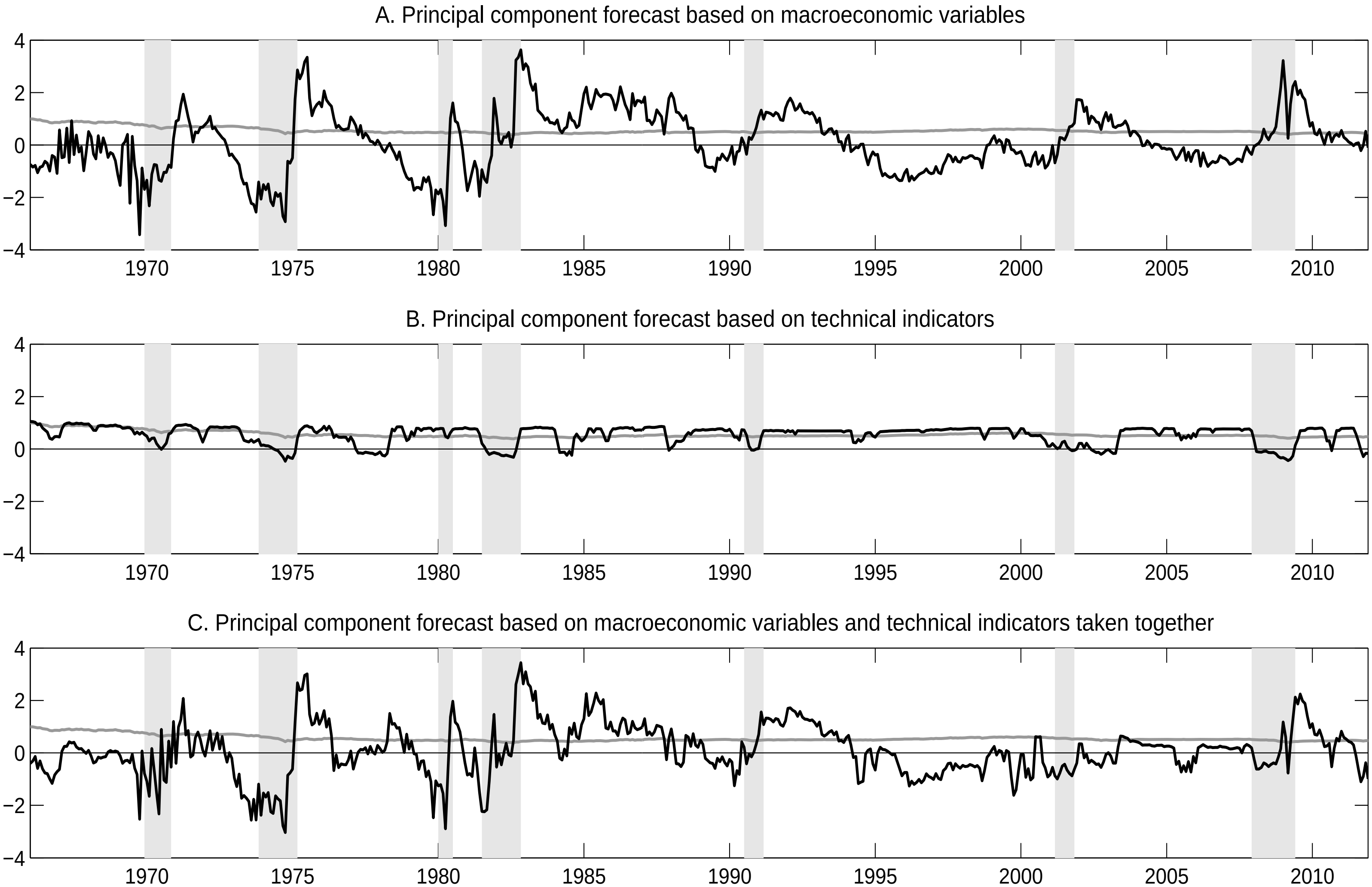
Notes. Black lines delineate monthly log equity risk premium forecasts (in percent); gray lines delineate the average log equity risk premium over the sample. Panel A (B) depicts the forecast for a predictive regression model with a constant and the first three principal components extracted from 14 macroeconomic variables (first principal component extracted from 14 technical indicators) serving as regressors. Panel C depicts the forecast for a predictive regression model with a constant and the first four principal components extracted from the 14 macroeconomic variables and 14 technical indicators taken together serving as regressors. Vertical bars depict NBER-dated recessions.

Figure 6 Average Behavior of the Log Equity Risk Premium and Forecasts Around Business-Cycle Peaks and Troughs, 1951:01–2011:12



Notes. Panel A (E) depicts the average change in the monthly log equity risk premium (in percent) around a business-cycle peak (trough). Panel B (F) depicts the average change in an in-sample forecast based on 14 macroeconomic variables around a peak (trough). Panel C (G) depicts the average change in an in-sample forecast based on 14 technical indicators around a peak (trough). Panel D (H) depicts the average change in an in-sample forecast based on the 14 macroeconomic variables and 14 technical indicators taken together around a peak (trough). Average changes are reported for the four months preceding, month of, and two months following a peak or trough. Bands indicate 90% confidence intervals.

Figure 7 Out-of-Sample Log Equity Risk Premium Forecasts Based on 14 Macroeconomic Variables and 14 Technical Indicators, 1966:01–2011:12



Notes. Black lines delineate monthly principal component log equity risk premium forecasts (in percent); gray lines delineate the historical average log equity risk premium forecast. Panel A (B) depicts the forecast for a predictive regression model with a constant and up to the first three principal components (first principal component) extracted from 14 macroeconomic variables (14 technical indicators) serving as regressors. Panel C depicts the forecast for a predictive regression model with a constant and up to the first four principal components extracted from the 14 macroeconomic variables and 14 technical indicators taken together serving as regressors. Vertical bars depict NBER-dated recessions.