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Forecasting the Equity Risk Premium: The Role of Technical Indicators

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Academic research relies extensively on macroeconomic variables to forecast the U.S. equity risk premium, with relatively little attention paid to the technical indicators widely employed by practitioners. Our paper fills this gap by comparing the predictive ability of technical indicators with that of macroeconomic variables. Technical indicators display statistically and economically significant in-sample and out-of-sample predictive 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, whereas macroeconomic variables more readily pick up the typical rise in the equity risk premium near cyclical troughs. Consistent 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 technical indicators and macroeconomic variables.

Data, as supplemental material, are available at http://dx.doi.org/10.1287/mnsc.2013.1838.

Keywords: equity risk premium predictability; macroeconomic variables; moving averages; momentum; volume; sentiment; out-of-sample forecasts; asset allocation; business cycle

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1. Introduction

Numerous studies report evidence of U.S. equity risk premium predictability based on assorted macroeconomic variables, including valuation ratios, interest rates, and interest rate spreads; see Cochrane (2011) and Rapach and Zhou (2013) for recent surveys. Relative to macroeconomic variables (i.e., "economic fundamentals"), technical indicators have received significantly less attention in the literature, despite their widespread use among practitioners (e.g., Schwager 1989, Lo and Hasanhodzic 2010). Technical indicators rely on past price and volume patterns to identify price trends believed to persist into the future. Existing studies analyze the profitability of trading strategies based on a variety of technical indicators, including filter rules (Fama and Blume 1966), moving averages (Brock et al. 1992, Zhu and Zhou 2009), momentum (Conrad and Kaul 1998, Ahn et al. 2003), and automated pattern recognition (Lo et al. 2000). These studies, however, do not specifically analyze how well technical indicators directly predict the equity risk premium, which is the focus of the vast literature on equity risk premium predictability based on macroeconomic variables.

In this paper, we investigate the capacity of technical indicators to directly forecast the equity risk premium and compare their performance to that of macroeconomic variables. In comparing the technical and macroeconomic predictors, 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 many 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. Our investigation complements existing studies of equity risk premium predictability, which ignore technical indicators, as well as existing studies of technical indicators, which focus on the profitability of technical strategies.

We use data spanning from December 1950 to December 2011 for 14 well-known macroeconomic variables from the literature and 14 common technical indicators, including those based on moving averages, momentum, and volume. In-sample results demonstrate that individual technical indicators typically predict the equity risk premium as well as, or better than, individual macroeconomic variables. Regressions based on principal components extracted from the 14 macroeconomic variables (PC-ECON model) or 14 technical indicators (PC-TECH model) reveal that both macroeconomic variables as a group and technical indicators as a group significantly predict the equity risk premium. 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. The additive nature of the predictability indicates that macroeconomic variables and technical indicators capture different types of information relevant for predicting the equity risk premium and thus represent complementary approaches to equity risk premium forecasting.

Consistent with differential information, 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, whereas macroeconomic variables more readily pick up the typical rise in the actual equity risk premium later in recessions near cyclical troughs. The PC-ALL model estimate of the expected equity risk premium exhibits an even clearer countercyclical pattern. This accentuated countercyclical pattern enables the expected equity risk premium generated by the PC-ALL model to better track the sizable fluctuations in the actual equity risk premium around business-cycle peaks and troughs.

Out-of-sample results confirm the in-sample results. Forecast encompassing tests suggest that utilizing information from both macroeconomic variables and technical indicators can improve equity risk premium forecasts. Indeed, the PC-ALL model performs the best and significantly outperforms the historical average forecast, which Goyal and Welch (2003, 2008) show to be a very stringent benchmark. Furthermore, the PC-ALL 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. In particular, the investor realizes substantial utility gains by using the PC-ALL forecast versus ignoring any forecastability or using the information in macroeconomic variables alone.

Theoretically, why do macroeconomic variables and technical indicators predict the equity risk premium? In dynamic asset pricing models, the future state of the economy is the fundamental driver of time-varying expected stock returns. Macroeconomic variables track changing macroeconomic conditions and should thus have predictive power for the equity risk premium. This predictive ability reflects time-varying compensation to investors for bearing aggregate risk and is consistent with rational asset pricing; see Cochrane (2011) and references therein. Explanations of the predictive power of technical indicators are not as well known, however, and require more discussion. There are basically four types of theoretical models that explain why technical indicators can have predictive ability, all of which point to an informationally inefficient market.

The first type of theoretical model recognizes differences in the time for investors to receive information. Under this friction, Treynor and Ferguson (1985) show that technical analysis is useful for assessing whether information has been fully incorporated into equity prices, whereas Brown and Jennings (1989) demonstrate that past prices enable investors to make better inferences about price signals. In addition, Grundy and McNichols (1989) and Blume et al. (1994) show that trading volume can provide useful information beyond prices.

The second type of model posits different responses to information by heterogeneous investors. Cespa and Vives (2012) recently show that asset prices can deviate from their fundamental values if there is a positive level of asset residual payoff uncertainty and/or persistence in liquidity trading. In this setting, rational long-term investors follow trends. In the real world, different responses to information are more likely during recessions because of, for example, consumption-smoothing asset sales by households that experience job losses and liquidation sales of margined assets by some investors. These factors help to explain why we find that technical indicators display enhanced predictive ability during recessions.

The next type of model allows for underreaction and overreaction to information. Hong and Stein (1999) explain that, at the start of a trend, investors underreact to news because of behavioral biases; as the market rises, investors subsequently overreact, leading to even higher prices. Similarly, positive feedback traders—who buy (sell) after asset prices rise (fall)—can create price trends that technical indicators detect. Hedge fund guru Soros (2003) argues that positive feedback can actually alter firm fundamentals, thereby justifying to a certain extent the price trends. Edmans et al. (2012)

recently show that such feedback trading can occur in a rational model of investors with private information.

Finally, models of investor sentiment shed light on the efficacy of technical analysis. Since Keynes (1936), researchers have analyzed how investor sentiment can drive asset prices away from their fundamental values. DeLong et al. (1990) show that in the presence of limits to arbitrage, noise traders with irrational sentiment can cause prices to deviate from their fundamentals, even when informed traders recognize the mispricing. Baker and Wurgler (2006, 2007) find that measures of investor sentiment help to explain the cross-section of U.S. equity returns. In this paper, the monthly sentiment-changes index from Baker and Wurgler (2007) is significantly and positively contemporaneously correlated with the realized equity risk premium, and we show that technical indicators significantly predict the sentiment-changes index, whereas macroeconomic variables do not. The differential information useful for predicting the equity risk premium in technical indicators thus appears related to their ability to anticipate changes in investor sentiment.

In sum, theoretical models based on information frictions help to explain the predictive value of technical indicators. Empirically, Moskowitz et al. (2012) recently find that pervasive price trends exist across commonly traded equity index, currency, commodity, and bond futures. Insofar as the stock market is not a pure random walk and exhibits periodic trends, technical indicators should prove informative because they are primarily designed to detect trends.

2. In-Sample Analysis

2.1. Bivariate Predictive Regressions

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

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

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 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 and correlations between equity risk premium and predictor innovations as well as general forms of heteroskedasticity. The online appendix (available at http://sites.slu.edu/rapachde/home/research) accompanying this paper details the wild bootstrap procedure.

We estimate predictive regressions using updated monthly data from Goyal and Welch (2008).[1] The equity risk premium is the difference between the log 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 12-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 12-month moving sum of dividends minus the log of lagged stock prices.
3. Earnings-price ratio (log), EP: log of a 12-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 12-month moving sum of dividends minus the log of a 12-month moving sum of earnings.
5. Equity risk premium volatility, RVOL: based on a 12-month moving standard deviation estimator (Mele 2007).[2]
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 12-month moving sum of net equity issues by NYSE-listed stocks to the total end-of-year market capitalization of New York Stock Exchange (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.

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

[2] 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 1987. The Mele (2007) measure avoids this problem and yields more plausible estimation results.

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

14. Inflation, INFL: calculated from the 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 December 1950 to December 2011. 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 to the macroeconomic variables, we employ 14 technical indicators based on three popular trend-following 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:

$$S_{i,t}=\begin{cases}1 & \text{if } \mathrm{MA}_{s,t}\geq \mathrm{MA}_{l,t},\\ 0 & \text{if } \mathrm{MA}_{s,t}< \mathrm{MA}_{l,t},\end{cases} \tag{2}$$

where

$$\mathrm{MA}_{j,t}=(1/j)\sum_{i=0}^{j-1}P_{t-i} \quad \text{for } j=s,\,l; \tag{3}$$

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 by MA(s,l).

Table 1 Summary Statistics, December 1950 to December 2011

Variable	Mean	Std. dev.	Min	Max	Auto-correlation	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. This table reports summary statistics for the log equity risk premium (in percent) and 14 macroeconomic variables. LTR, DFR, and INFL (TBL, LTY, TMS, and DFY) are measured in percent (annual percent). The Sharpe ratio is the mean of the log equity risk premium divided by its standard deviation.

Intuitively, the MA rule detects changes in stock price trends because the short MA will be more sensitive to recent price movement than will the long MA. We analyze monthly MA rules with $s=1,2,3$ and $l=9,12$.

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

$$S_{i,t}=\begin{cases}1 & \text{if } P_t\geq P_{t-m},\\ 0 & \text{if } P_t< P_{t-m}.\end{cases} \tag{4}$$

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} by 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 strategy we consider incorporates "on-balance" volume (e.g., Granville 1963). We first define

$$\mathrm{OBV}_t=\sum_{k=1}^{t}\mathrm{VOL}_k D_k, \tag{5}$$

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

$$S_{i,t}=\begin{cases}1 & \text{if } \mathrm{MA}^{\mathrm{OBV}}_{s,t}\geq \mathrm{MA}^{\mathrm{OBV}}_{l,t},\\ 0 & \text{if } \mathrm{MA}^{\mathrm{OBV}}_{s,t}< \mathrm{MA}^{\mathrm{OBV}}_{l,t},\end{cases} \tag{6}$$

where

$$\mathrm{MA}^{\mathrm{OBV}}_{j,t}=(1/j)\sum_{i=0}^{j-1}\mathrm{OBV}_{t-i} \quad \text{for } j=s,\,l. \tag{7}$$

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 by 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 et al. 1999). We use the S&P 500 Index and monthly volume data from Google Finance in (2), (4), and (6).[3] After accounting for the lags in constructing the technical indicators, we have observations for all of the indicators starting in December 1950.[4] The technical

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

[4] 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.

Table 2 Predictive Regression Estimation Results, January 1951 to December 2011

Macroeconomic variables					Technical indicators				
Predictor	Slope coefficient	R^2 (%)	R^2_{EXP} (%)	R^2_{REC} (%)	Predictor	Slope coefficient	R^2 (%)	R^2_{EXP} (%)	R^2_{REC} (%)
Panel A: Bivariate predictive regressions									
DP	0.78 [1.98]	0.58	0.40	1.00	MA(1, 9)	0.67 [1.78]**	0.54	−0.39	2.66
DY	0.84 [2.13]**	0.67	0.32	1.48	MA(1, 12)	0.87 [2.22]**	0.87	−0.18	3.27
EP	0.43 [0.97]	0.20	0.22	0.14	MA(2, 9)	0.70 [1.88]**	0.59	−0.26	2.53
DE	0.59 [0.93]	0.17	0.09	0.35	MA(2, 12)	0.94 [2.42]***	1.03	−0.09	3.58
RVOL	7.41 [2.45]***	0.73	0.54	1.18	MA(3, 9)	0.77 [2.04]**	0.69	0.03	2.22
BM	0.54 [0.75]	0.10	0.01	0.29	MA(3, 12)	0.54 [1.39]*	0.34	−0.12	1.39
NTIS	0.66 [0.06]	0.00	0.04	−0.08	MOM(9)	0.55 [1.40]*	0.34	−0.09	1.33
TBL	0.11 [1.90]**	0.56	0.42	0.90	MOM(12)	0.58 [1.45]*	0.37	−0.36	2.04
LTY	0.08 [1.25]**	0.23	0.22	0.23	VOL(1, 9)	0.68 [1.86]**	0.56	−0.51	3.02
LTR	0.13 [2.05]**	0.76	−0.41	3.41	VOL(1, 12)	0.89 [2.31]***	0.92	−0.20	3.49
TMS	0.20 [1.74]**	0.44	0.03	1.38	VOL(2, 9)	0.74 [2.02]**	0.67	−0.17	2.58
DFY	0.16 [0.37]	0.03	0.04	0.00	VOL(2, 12)	0.74 [1.94]**	0.65	−0.04	2.21
DFR	0.16 [0.89]	0.26	0.05	0.74	VOL(3, 9)	0.48 [1.27]	0.27	−0.17	1.29
INFL	0.10 [0.18]	0.01	0.07	−0.14	VOL(3, 12)	0.85 [2.25]***	0.85	0.21	2.30
Panel B: Principal component predictive regressions									
$\hat{F}_1^{\mathrm{ECON}}$	0.04 [0.48]	1.18	0.79	2.07	$\hat{F}_1^{\mathrm{TECH}}$	0.12 [2.12]**	0.84	−0.19	3.18
$\hat{F}_2^{\mathrm{ECON}}$	0.07 [0.61]								
$\hat{F}_3^{\mathrm{ECON}}$	0.31 [2.48]***								
Panel C: Principal component predictive regression, all predictors taken together									
$\hat{F}_1^{\mathrm{ALL}}$	0.11 [1.98]**	2.02	0.29	5.95					
$\hat{F}_2^{\mathrm{ALL}}$	0.08 [0.93]								
$\hat{F}_3^{\mathrm{ALL}}$	0.18 [1.51]*								
$\hat{F}_4^{\mathrm{ALL}}$	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 (sixth) 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 ($j = \mathrm{ECON}$), 14 technical indicators ($j = \mathrm{TECH}$), or the 14 macroeconomic variables and 14 technical indicators taken together ($j = \mathrm{ALL}$). We select K via the adjusted R^2. The brackets to the immediate right of the estimated slope coefficients report heteroskedasticity-consistent t-statistics. The R^2 statistics in the third and eighth columns are computed for the full sample. The R^2_{EXP} (R^2_{REC}) statistics in the fourth and ninth (fifth and tenth) columns are computed for National Bureau of Economic Research-dated business-cycle expansions (recessions), as given by (9) in the text.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, based on one-sided (upper-tail) wild bootstrapped p-values; 0.00 indicates less than 0.005 in absolute value.

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 (2), (4), or (6):

$$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}. \qquad (8)$$

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 regressions given by (1) and (8) as well as heteroskedasticity-consistent t-statistics and R^2 statistics. After accounting for the lag in the predictive regression, the estimation sample is from January 1951 to December 2011 (732 observations). Six of the 14 macroeconomic variables exhibit significant predictive ability at conventional levels in the second column of panel A: DY, RVOL, TBL, LTY, LTR, and TMS. Among these six significant predictors, the 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 (e.g., 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 evince significant predictive ability at conventional levels in the seventh 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 eighth 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 panel A of Table 2 suggest that individual technical indicators generally predict the equity risk premium as well as, or better than, individual macroeconomic variables.

We are interested in gauging the relative strength of equity risk premium predictability during National Bureau of Economic Research (NBER)-dated business-cycle expansions and recessions. Computing R^2 statistics separately for cyclical expansions and recessions is the most natural way to proceed. Because of the nature of the R^2 statistic, however, there is no clean decomposition of the full-sample R^2 statistic into subsample R^2 statistics based on the full-sample parameter estimates. To compare the degree of return predictability across expansions and recessions, we compute the following intuitive versions of the conventional R^2 statistic:

$$R_c^2 = 1 - \frac{\sum_{t=1}^{T} I_t^c \hat{\varepsilon}_{i,t}^2}{\sum_{t=1}^{T} I_t^c (r_t - \bar{r})^2} \quad \text{for } c = \text{EXP, REC}, \tag{9}$$

where I_t^{EXP} (I_t^{REC}) is an indicator variable that takes a value of unity when month t is an expansion (recession) and zero otherwise, $\hat{\varepsilon}_{i,t}$ is the fitted residual based on the full-sample estimates of the predictive regression model in (1) or (8), $\bar{r}$ is the full-sample mean of r_t, and T is the number of usable observations for the full sample. Observe that, unlike the full-sample R^2 statistic, the R^2_{EXP} and R^2_{REC} statistics can be negative. The fourth and fifth columns of panel A in Table 2 indicate that equity risk premium predictability is substantially higher for recessions vis-à-vis expansions for a number of the macroeconomic variables, including DP, DY, RVOL, TBL, LTR, TMS, and DFR. According to the last two columns of panel A, predictability is highly concentrated during recessions for all of the technical indicators.

2.2. Predictive Regressions Based on Principal Components

Next, we incorporate information from multiple macroeconomic variables by estimating a predictive regression based on principal components.[5] Let $x_t = (x_{1,t}, \ldots, x_{N,t})'$ denote the N-vector ($N = 14$) of the entire set of macroeconomic variables and let $\hat{F}_t^{\text{ECON}} = (\hat{F}_{1,t}^{\text{ECON}}, \ldots, \hat{F}_{K,t}^{\text{ECON}})'$ 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

$$r_{t+1} = \alpha + \sum_{k=1}^{K} \beta_k \hat{F}_{k,t}^{\text{ECON}} + \varepsilon_{t+1}. \tag{10}$$

Principal components parsimoniously incorporate information from a large number of potential predictors in a predictive regression. 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. Following convention, we standardize the individual predictors before computing the principal components.

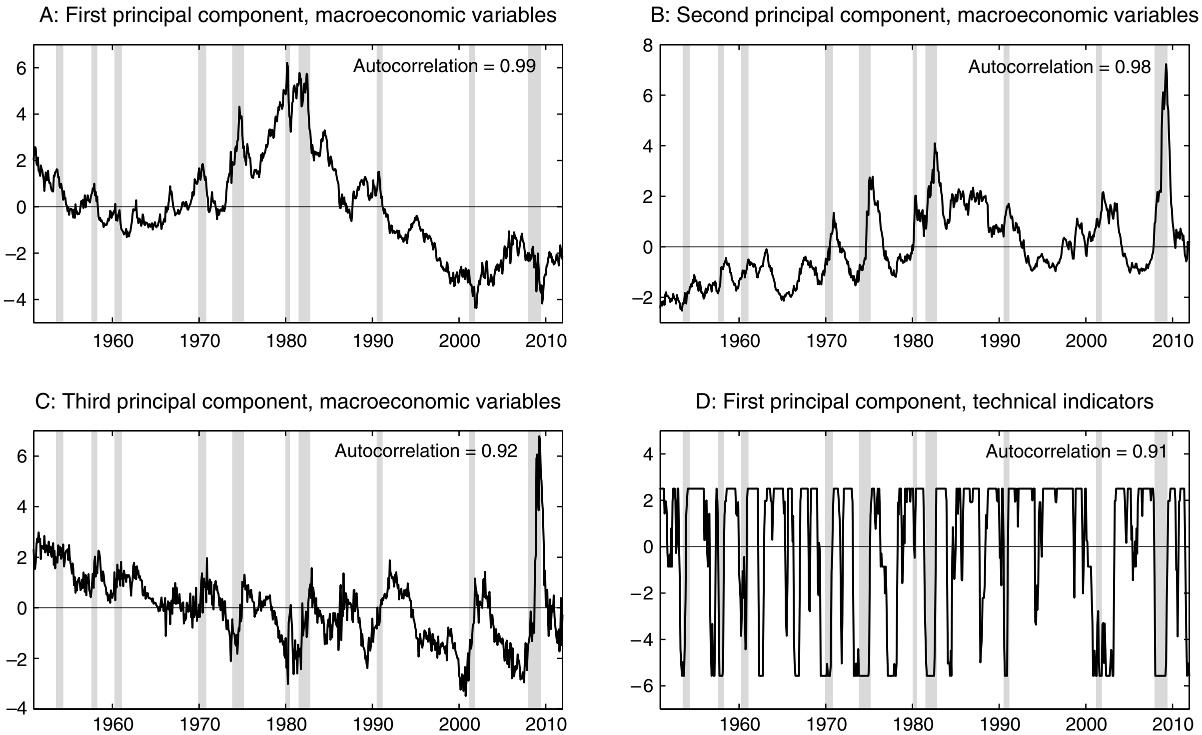
We again estimate (10) via OLS, compute heteroskedasticity-consistent t-statistics, and base inferences on wild bootstrapped p-values. The first five columns of panel B in Table 2 report estimation results for (10) with $K = 3$, the value selected by the adjusted R^2.[6] The coefficient estimate on the 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. The R^2_{EXP} and R^2_{REC} statistics indicate that equity risk premium predictability is more than twice as large for recessions compared to expansions.

To illustrate the economic content of the principal components, panels A–C of Figure 1 present the estimated principal components ($\{\hat{F}_{k,t}^{\text{ECON}}\}_{k=1}^{3}$), and the corresponding panels in Figure 2 display the estimated loadings for the individual macroeconomic variables on the principal components. Panel A of Figure 2 shows that the valuation ratios (DP, EY, EP, and BM) load heavily on $\hat{F}_{1,t}^{\text{ECON}}$; 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 $\hat{F}_{1,t}^{\text{ECON}}$ (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 $\hat{F}_{2,t}^{\text{ECON}}$; accordingly, $\hat{F}_{2,t}^{\text{ECON}}$ spikes during the global financial crisis in Figure 1, panel B, when stock

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

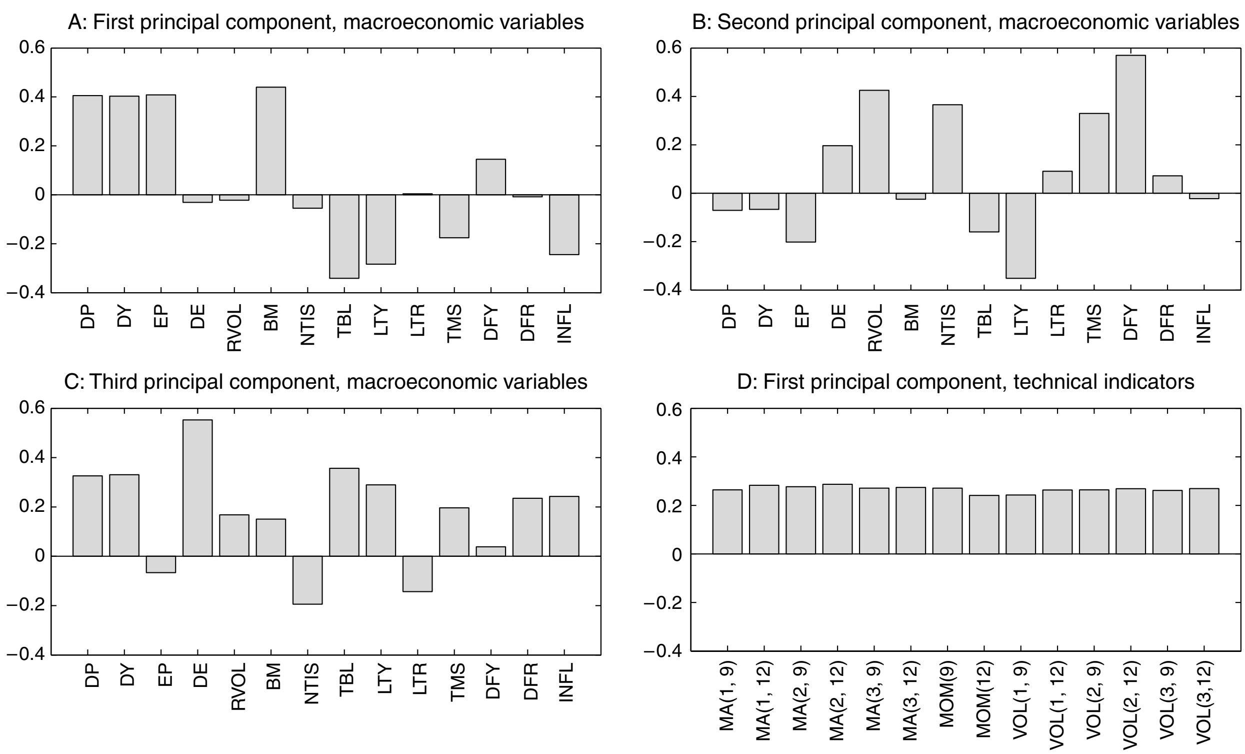
[6] The Akaike information criterion also selects $K = 3$. To keep the model reasonably parsimonious, we consider a maximum K value of three, given the 14 macroeconomic variables. Note that we account for the "estimated regressors" in (10) via the wild bootstrap procedure (as explained in the online appendix).

Figure 1 **Principal Components Extracted from 14 Macroeconomic Variables and 14 Technical Indicators, December 1950 to December 2011**



Notes. Panels A–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. Vertical bars depict NBER-dated recessions.

Figure 2 **Loadings on Principal Components Extracted from 14 Macroeconomic Variables and 14 Technical Indicators, December 1950 to December 2011**



Notes. Panels A–C depict loadings for 14 individual macroeconomic variables on the first three principal components, respectively, extracted from the 14 macroeconomic variables. Panel D depicts loadings for 14 technical indicators on the first principal component extracted from the 14 technical indicators.

market volatility and credit spreads increased dramatically. Panel C of Figure 2 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. The third principal component, $\hat{F}^{\text{ECON}}_{3,t}$, 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 equity risk premium than $\hat{F}^{\text{ECON}}_{1,t}$ and $\hat{F}^{\text{ECON}}_{2,t}$. Furthermore, $\hat{F}^{\text{ECON}}_{3,t}$ is 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 countercyclical tendencies in panels A–C of Figure 1. 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 (10) with $\hat{F}^{\text{TECH}}_{t}$ replacing $\hat{F}^{\text{ECON}}_{t}$ (PC-TECH model):

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

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 five columns of panel B in Table 2 report estimation results for (11) with $K = 1$ (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 equity risk premium. Similarly to panel A, the last two columns of panel B indicate that return predictability based on technical indicators is substantially higher for recessions vis-à-vis expansions.

The last panels in Figures 1 and 2 show $\hat{F}^{\text{TECH}}_{1,t}$ and the estimated loadings for the technical indicators, 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, whereas 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):

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

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 $z_t = (x'_t, S'_t)'$, the $2N$-vector of 14 macroeconomic variables and 14 technical indicators. Panel C of Table 2 reveals that the coefficient estimates on $\hat{F}^{\text{ALL}}_{1,t}$, $\hat{F}^{\text{ALL}}_{3,t}$, and $\hat{F}^{\text{ALL}}_{4,t}$ are significant in the PC-ALL model at the 5%, 10%, and 1% levels, respectively.[7] 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.[8] This indicates that the macroeconomic variables and technical predictors essentially contain complementary information. Continuing the pattern, the fourth and fifth columns of panel C show that equity risk premium predictability is much stronger in the PC-ALL model for recessions compared to expansions.[9]

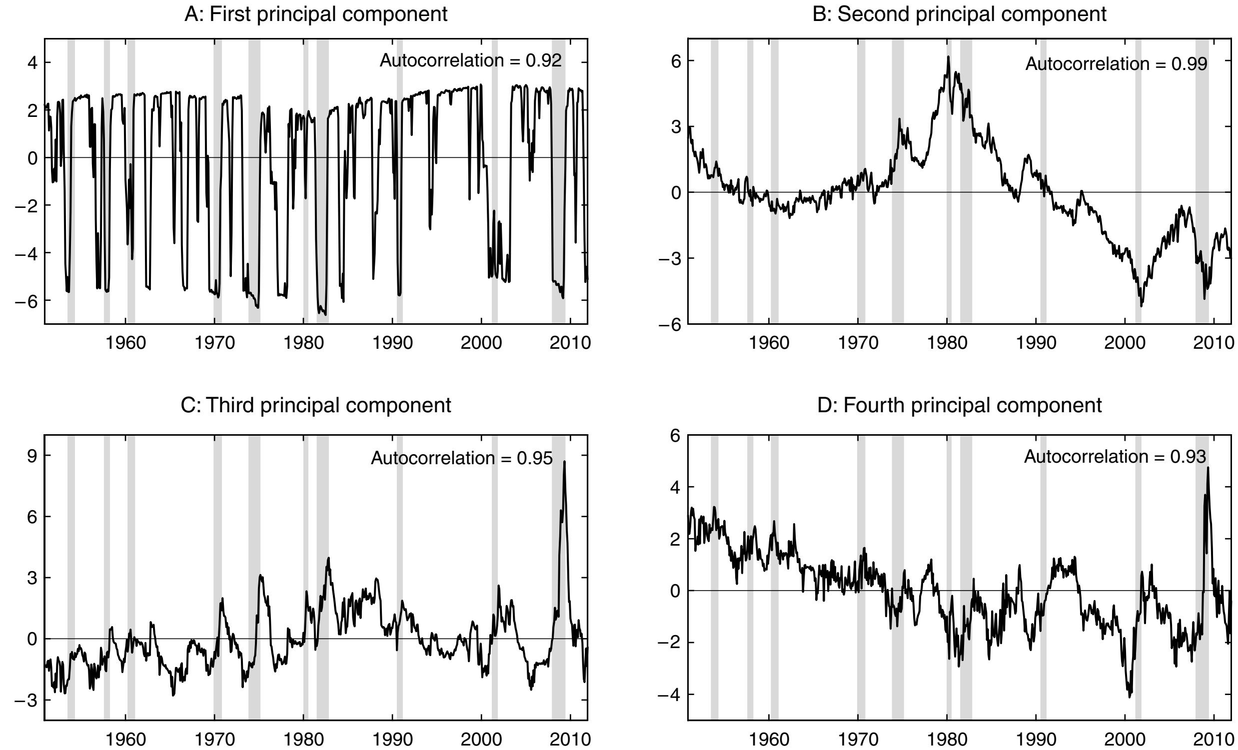
The $\{\hat{F}^{\text{ALL}}_{k,t}\}_{k=1}^{4}$ estimates and corresponding loading estimates, shown in Figures 3 and 4, respectively, reflect the complementarity of the macroeconomic variables and technical indicators; that is, the principal components extracted from the entire set of predictors are often very similar to those extracted separately from the set of macroeconomic variables or technical indicators. Panel A of Figure 4 shows that the 14 technical indicators load nearly uniformly on the first principal component, whereas the macroeconomic variables are relatively insensitive to this factor, so that $\hat{F}^{\text{ALL}}_{1,t}$ is closely related to $\hat{F}^{\text{TECH}}_{1,t}$. Panel A of Figure 3 confirms this relationship because $\hat{F}^{\text{ALL}}_{1,t}$ behaves very similarly to $\hat{F}^{\text{TECH}}_{1,t}$ in Figure 1, panel D. Panels B–D of Figures 3 and 4 demonstrate that $\hat{F}^{\text{ALL}}_{2,t}$, $\hat{F}^{\text{ALL}}_{3,t}$, and $\hat{F}^{\text{ALL}}_{4,t}$ closely correspond to $\hat{F}^{\text{ECON}}_{1,t}$, $\hat{F}^{\text{ECON}}_{2,t}$, and $\hat{F}^{\text{ECON}}_{3,t}$, respectively. The same macroeconomic variables that load heavily on $\hat{F}^{\text{ECON}}_{1,t}$, $\hat{F}^{\text{ECON}}_{2,t}$, and $\hat{F}^{\text{ECON}}_{3,t}$ in panels A–C of Figure 2 also load heavily on $\hat{F}^{\text{ALL}}_{2,t}$, $\hat{F}^{\text{ALL}}_{3,t}$, and $\hat{F}^{\text{ALL}}_{4,t}$ in

[7] The K value of four is selected by the adjusted R^2. We consider a maximum K 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.

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

[9] We tested for structural breaks in all of the predictive regression models using the Elliott and Müller (2006) $\widehat{qLL}$ statistic, which is asymptotically efficient for a broad range of persistent breaking processes and has good size and power properties in the presence of heteroskedasticity. Overall, there is little evidence of structural instability in the predictive regressions. The complete results are reported in the online appendix.

Figure 3 Principal Components Extracted from 14 Macroeconomic Variables and 14 Technical Indicators Taken Together, December 1950 to December 2011



Notes. Panels A–D depict the first four principal components, respectively, extracted from 14 macroeconomic variables and 14 technical indicators taken together. Vertical bars depict NBER-dated recessions.

panels B–D of Figure 4, whereas the technical indicators respond relatively weakly to the latter three factors.[10] Furthermore, $\hat{F}_{2,t}^{\mathrm{ALL}}$, $\hat{F}_{3,t}^{\mathrm{ALL}}$, and $\hat{F}_{4,t}^{\mathrm{ALL}}$ in panels B–D of Figure 3 behave similarly to the factors in panels A–C of Figure 1. The coefficient estimates on $\hat{F}_{2,t}^{\mathrm{ALL}}$ and $\hat{F}_{4,t}^{\mathrm{ALL}}$ in panel C of Table 2 are similar to those on $\hat{F}_{1,t}^{\mathrm{ECON}}$ and $\hat{F}_{3,t}^{\mathrm{ECON}}$, respectively, in panel B.

The PC-ALL model estimation results thus imply that the macroeconomic variables and technical indicators provide almost completely 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 $\hat{F}_{1,t}^{\mathrm{ALL}}$, $\hat{F}_{3,t}^{\mathrm{ALL}}$, and $\hat{F}_{4,t}^{\mathrm{ALL}}$ in the PC-ALL model demonstrate that macroeconomic variables and technical indicators both provide useful information for predicting the equity risk premium.

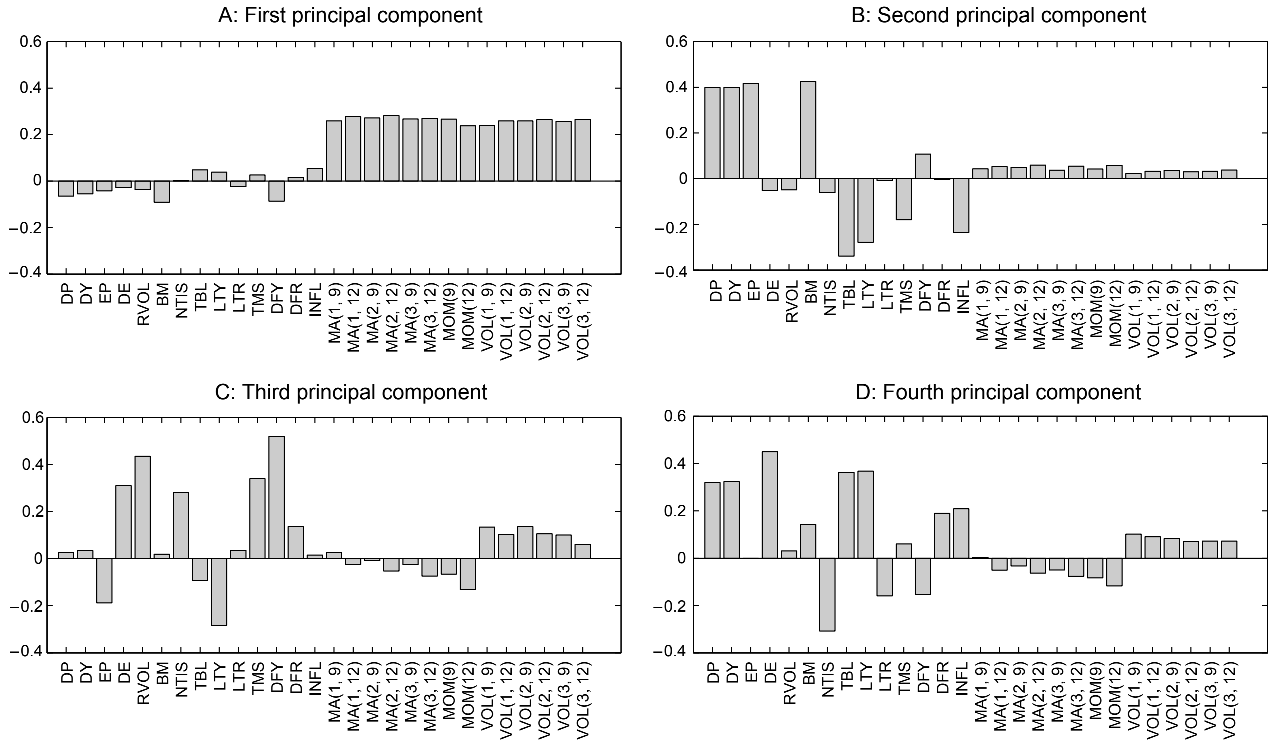
Figure 5 further illustrates the complementary roles of macroeconomic variables and technical indicators. The figure shows in-sample forecasts of the equity risk premium for the PC-ECON, PC-TECH, and PC-ALL models, which represent in-sample estimates of the expected equity risk premium. The expected equity risk premium for the PC-ECON model in panel A of Figure 5 displays a relatively smooth countercyclical pattern, in line with the estimated factors in panels A–C of Figure 1. The countercyclical movements in the expected equity risk premium for the PC-TECH model in panel B of Figure 5 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, but it rises to higher levels around cyclical troughs relative to panel B. The complementary information in macroeconomic variables and technical indicators thus accentuates the countercyclical fluctuations in the PC-ALL model's expected equity risk premium.

2.3. Behavior of Expected Equity Risk Premium Around Cyclical Peaks and Troughs

The following regressions provide further insight into the behavior of the expected equity risk premium

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

Figure 4 **Loadings on Principal Components Extracted from 14 Macroeconomic Variables and 14 Technical Indicators Taken Together, December 1950 to December 2011**



Note. Panels A–D depict loadings for 14 macroeconomic variables and 14 technical indicators on the first four principal components, respectively, extracted from the 14 macroeconomic variables and 14 technical indicators taken together.

around business-cycle peaks and troughs:

$$r_t = a_{\mathrm{A}} + \sum_{m=4}^{-2} b^{\mathrm{P}}_{\mathrm{A},m} I^{\mathrm{P}}_{t-m} + \sum_{m=4}^{-2} b^{\mathrm{T}}_{\mathrm{A},m} I^{\mathrm{T}}_{t-m} + u_{\mathrm{A},t}, \tag{13}$$

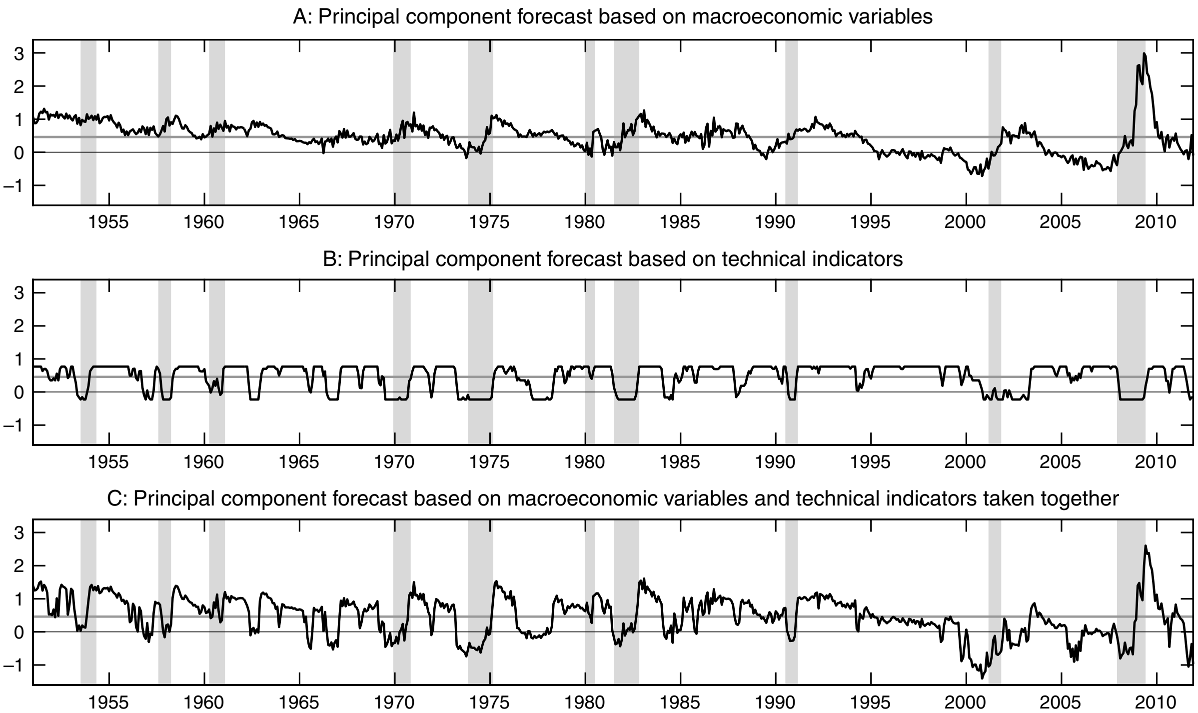
$$\hat{r}_t = a_{\mathrm{FC}} + \sum_{m=4}^{-2} b^{\mathrm{P}}_{\mathrm{FC},m} I^{\mathrm{P}}_{t-m} + \sum_{m=4}^{-2} b^{\mathrm{T}}_{\mathrm{FC},m} I^{\mathrm{T}}_{t-m} + u_{\mathrm{FC},t}, \tag{14}$$

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 (13) measures the average change in the actual equity risk premium m months from a cyclical peak (trough), whereas 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 four months before and two months after a peak or trough.

Figure 6 presents OLS estimates of the slope coefficients in (13) and (14), 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 the increase is not significant. 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 large during and after a trough,

Figure 5 **In-Sample Log Equity Risk Premium Forecasts Based on 14 Macroeconomic Variables and 14 Technical Indicators, January 1951 to December 2011**



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.

again helping the PC-ALL model to better match the rise in the actual equity risk premium around 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, whereas 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 produce an expected equity risk premium that better tracks the substantial countercyclical fluctuations in the equity risk premium.

2.4. Sentiment and Conditional Asset Pricing

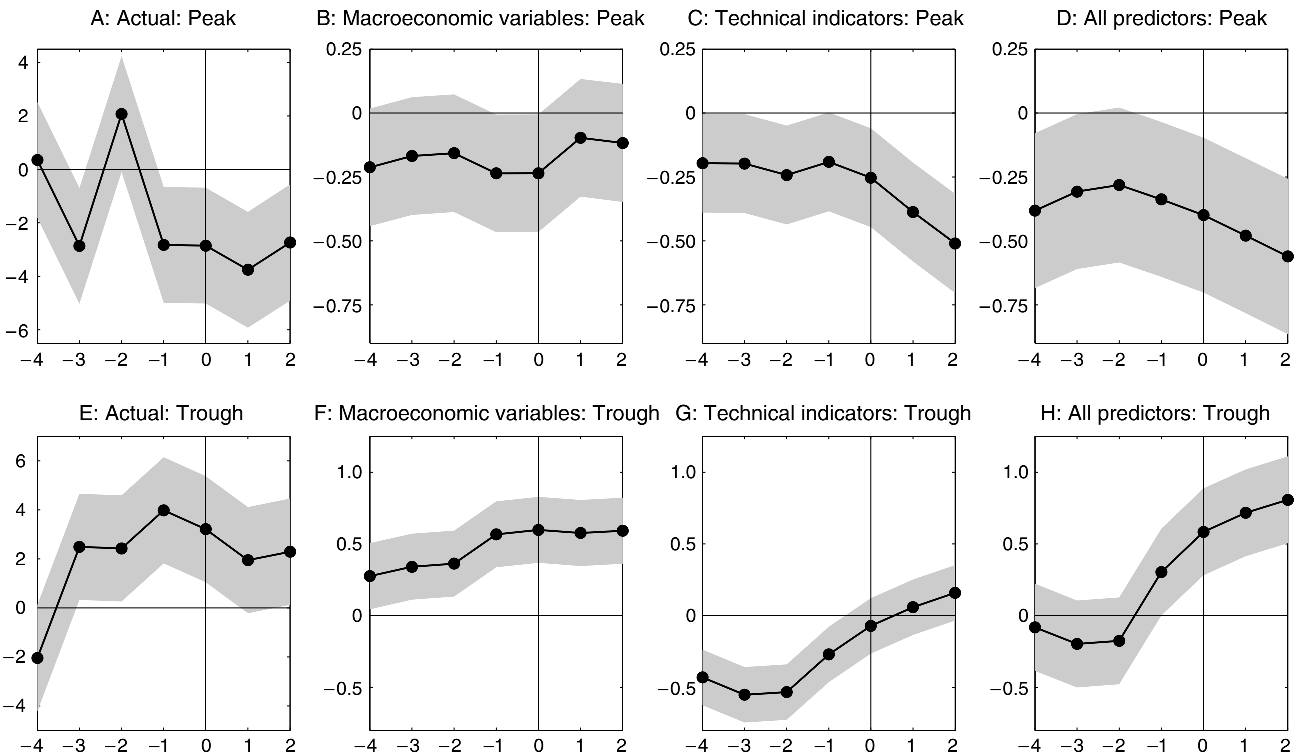
Sections 2.1 and 2.2 show that technical indicators predict the equity risk premium. To further establish that technical indicators contain meaningful economic information, we ask two questions.[11] First, do technical indicators forecast changes in investor sentiment, which are known to be correlated with stock returns? Second, do technical indicators have significant effects in a conditional asset pricing model? Positive answers to these questions provide further evidence of the economic relevance of technical indicators.

Positive answers to these questions also allay data-mining concerns, which are relevant for stock return predictability (e.g., Ferson et al. 2003). In particular, exploring the economic relevance of technical indicators along additional dimensions reduces the likelihood that the significant predictive ability of technical indicators is a spurious result of excessively searching among meaningless predictors. Our out-of-sample tests in §3, including a modified version of the White (2000) reality check, also address data-mining concerns.

We answer the first question using the monthly sentiment-changes index from Baker and Wurgler (2007). This index (ΔSENT) is the first principal component extracted from changes in six sentiment proxies from Baker and Wurgler (2006): trading volume (measured by NYSE turnover), dividend premium (average market-to-book ratios of dividend paying and nonpaying firms), closed-end fund discount, initial public offering (IPO) number, IPO first-day returns, and equity share of total equity and debt issues by all corporations. We use an updated ΔSENT series for

[11] We thank the anonymous referees for suggesting these two interesting ideas.

Figure 6 **Average Behavior of the Log Equity Risk Premium and Forecasts Around Business-Cycle Peaks and Troughs, January 1951 to December 2011**



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.

August 1965 to December 2010.[12] Baker and Wurgler (2007) point out that aggregate market returns and changes in sentiment will be positively correlated if the average stock is affected by sentiment. In support of this notion, they report that the contemporaneous correlation between a capitalization-weighted market return index and ΔSENT is a sizable and statistically significant 0.32 for January 1966 to December 2005; the correlation between the equity risk premium and ΔSENT is also a sizable and statistically significant 0.28 for the updated August 1965 to December 2010 sample.

Because the equity risk premium and ΔSENT are sizably contemporaneously correlated, if an equity risk premium predictor also predicts ΔSENT, this suggests that the variable's ability to predict the equity risk premium stems in part from its ability to predict changes in sentiment. We investigate this idea using the same predictive regression framework as before, with r_{t+1} replaced by $\Delta\mathrm{SENT}_{t+1}$ in (1), (8), (10), (11), and (12).[13] Taken individually or together, the macroeconomic variables display no significant predictive ability for ΔSENT in the predictive regressions. In sharp contrast to the macroeconomic variables, the technical indicators evince significant predictive ability for ΔSENT both individually and as a group: 12 of the 14 individual indicators display significant predictive ability in the bivariate predictive regressions (with 10 of the R^2 statistics above 0.5%), and the first principal component extracted from the 14 technical indicators is a significant predictor of ΔSENT at the 1% level (with an R^2 of 0.96%). In addition, the first principal component extracted from the 14 macroeconomic variables and 14 technical indicators taken together, which is heavily influenced by the technical indicators and essentially unaffected by the macroeconomic variables, exhibits significant predictive ability. The R^2 statistics computed separately for expansions and recessions indicate that the predictive ability of technical indicators is concentrated during recessions, following the pattern for the technical indicators in Table 2. In sum, the differential information useful for predicting the equity risk premium found in technical indicators appears to relate in part to changes in investor sentiment, particularly during recessions.[14]

[12] The updated series is available from Jeffrey Wurgler's homepage at http://people.stern.nyu.edu/jwurgler/.

[13] For brevity, we summarize the results. The complete results are reported in the online appendix.

[14] Of course, these results alone do not establish whether the changes in sentiment themselves reflect a rational time-varying equity risk

Turning to the second question, in the spirit of Ferson and Harvey (1999), we estimate a conditional version of the Fama and French (1993) three-factor model:

$$R_{i,t+1} - R_{f,t+1} = \alpha_{i,t} + \beta_{i,t}^{\mathrm{MKT}}\mathrm{MKT}_{t+1} + \beta_{i,t}^{\mathrm{SMB}}\mathrm{SMB}_{t+1} + \beta_{i,t}^{\mathrm{HML}}\mathrm{HML}_{t+1} + \varepsilon_{i,t+1}, \tag{15}$$

where $R_{i,t+1}$ is the (simple) return on portfolio i, R_f is the risk-free return, MKT is the excess market return, SMB (HML) is the size (value) premium, and

$$\alpha_{i,t} = \alpha_{i,0} + \sum_{k=1}^{4} \alpha_{i,k}\hat{F}_{k,t}^{\mathrm{ALL}}, \tag{16}$$

$$\beta_{i,t}^{j} = \beta_{i,0}^{j} + \sum_{k=1}^{4} \beta_{i,k}^{j}\hat{F}_{k,t}^{\mathrm{ALL}} \quad \text{for } j = \mathrm{MKT},\ \mathrm{SMB},\ \mathrm{HML}. \tag{17}$$

Equation (15) is a conditional asset pricing model in that it permits time variation in both "alpha" via (16) and the factor exposures via (17). We estimate (15) for 10 momentum-sorted portfolios, as well as the "up-minus-down" (UMD) zero-investment momentum portfolio, using data from Kenneth French's Data Library.[15] Momentum portfolios present challenges for the unconditional Fama–French three-factor model (e.g., Fama and French 1996, Carhart 1997), and we examine whether the information in lagged macroeconomic variables and technical indicators, as captured by $\hat{F}_{k,t}^{\mathrm{ALL}}$ $(j = 1, \ldots, 4)$, enters significantly into a conditional version of the model.

For each of the 11 momentum portfolios, we first test the joint null hypothesis,

$$\alpha_{i,1} = \beta_{i,1}^{\mathrm{MKT}} = \beta_{i,1}^{\mathrm{SMB}} = \beta_{i,1}^{\mathrm{HML}} = 0. \tag{18}$$

Because $\hat{F}_{1,t}^{\mathrm{ALL}}$ corresponds closely to the technical indicators, (18) essentially tests the significance of the technical indicators as a group in the conditional asset pricing model. Using heteroskedasticity-robust χ^2-statistics, we reject the restrictions in (18) for 10 of the 11 momentum portfolios.[16] Technical indicators thus significantly explain returns in the conditional asset pricing model given by (15) for nearly all portfolios, which provides additional evidence that technical indicators represent genuine economic information.

We next test the joint null hypothesis,

$$\alpha_{i,k} = \beta_{i,k}^{\mathrm{MKT}} = \beta_{i,k}^{\mathrm{SMB}} = \beta_{i,k}^{\mathrm{HML}} = 0 \quad \text{for } k = 2, 3, 4. \tag{19}$$

Because $\hat{F}_{2,t}^{\mathrm{ALL}}$, $\hat{F}_{3,t}^{\mathrm{ALL}}$, and $\hat{F}_{4,t}^{\mathrm{ALL}}$ correspond closely to the macroeconomic variables, (19) tests the significance of the macroeconomic variables as a group. We reject the restrictions in (19) for all 11 momentum portfolios; like technical indicators, macroeconomic variables significantly explain portfolio returns in the conditional asset pricing model. We also test the null,

$$\alpha_{i,k} = \beta_{i,k}^{\mathrm{MKT}} = \beta_{i,k}^{\mathrm{SMB}} = \beta_{i,k}^{\mathrm{HML}} = 0 \quad \text{for } k = 1, 2, 3, 4, \tag{20}$$

which tests the significance of the technical indicators and macroeconomic variables taken together. We also reject the restrictions in (20) for all 11 portfolios. In accord with our predictive regression results, we thus find that macroeconomic variables and technical indicators both enter significantly in the conditional Fama–French three-factor model.[17]

3. Out-of-Sample Analysis

As a robustness check, 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

$$\hat{r}_{t+1} = \hat{\alpha}_{t,i} + \hat{\beta}_{t,i}x_{i,t}, \tag{21}$$

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 December 1950 to December 1965 as the initial estimation period, so that the forecast evaluation period spans from January 1966 to December 2011 (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.[18]

The out-of-sample forecast based on an individual technical indicator in (8) is given by

$$\hat{r}_{t+1} = \hat{\alpha}_{t,i} + \hat{\beta}_{t,i}S_{i,t}, \tag{22}$$

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

premium or irrational fluctuations in investor sentiment (or both). Determining the sources of the changes in investor sentiment requires a full-fledged model of equilibrium returns, which is beyond the scope of the present paper.

[15] The data are available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[16] The complete set of χ^2-statistics is reported in the online appendix.

[17] We also estimated a conditional version of the Fama–French three-factor model that does not permit time variation in the alphas, so that $\alpha_{i,t} = \alpha_{i,0}$ in (16). The qualitative results are unchanged for tests of relevant versions of (18), (19), and (20).

[18] 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.

out-of-sample forecasts based on principal components, as in (10), (11), and (12):

$$\hat{r}^{j}_{t+1} = \hat{\alpha}_t + \sum_{k=1}^{K} \hat{\beta}_{t,k} \hat{F}^{j}_{1:t,k,t} \quad \text{for } j = \text{ECON, TECH, or ALL}, \qquad (23)$$

where $\hat{F}^{j}_{1:t,k,t}$ 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 $\{\hat{F}^{j}_{1:t,k,s}\}_{s=1}^{t-1}$ ($k = 1, \ldots, K$).[19]

We compare the forecasts given by (21), (22), and (23) to the historical average forecast:

$$\hat{r}^{\text{HA}}_{t+1} = (1/t) \sum_{s=1}^{t} r_s. \qquad (24)$$

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 (24) is a very stringent out-of-sample benchmark: predictive regression forecasts based on individual macroeconomic variables typically fail to outperform the historical average.

We analyze forecasts in terms of the Campbell and Thompson (2008) out-of-sample R^2 (R^2_{OS}) and Clark and West (2007) *MSFE-adjusted* statistics. The R^2_{OS} statistic measures the proportional reduction in mean squared forecast error (MSFE) for the predictive regression forecast relative to the historical average. A positive value thus indicates that the predictive regression forecast outperforms the historical average in terms of MSFE, whereas a negative value signals the opposite. Like their in-sample counterparts, monthly R^2_{OS} statistics appear small at first glance because of the inherently large unpredictable component in stock returns; nevertheless, a monthly R^2_{OS} statistic near 0.5% is economically significant (Campbell and Thompson 2008). The *MSFE-adjusted* statistic 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 (corresponding to H_0: $R^2_{OS} \leq 0$ against H_A: $R^2_{OS} > 0$).[20]

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 is interesting to note that the *MSFE-adjusted* statistics indicate that the MSFEs for TBL, LTY, and TMS are significantly less than that of 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 West 2007, McCracken 2007).[21] Reminiscent of Goyal and Welch (2003, 2008), individual macroeconomic variables display limited out-of-sample predictive ability in Table 3, panel A. Similarly to the in-sample results in Table 2, a number of macroeconomic variables—including DP, DY, TBL, LTR, and TMS—predict the equity risk premium better during recessions than expansions on an out-of-sample basis.

Overall, individual technical indicators appear to perform as well as, or better than, individual macroeconomic variables in terms of MSFE. All of the R^2_{OS} statistics are positive in the eleventh 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 0.70%, and the MSFEs for six of the technical indicators are significantly less than the historical average MSFE based on the *MSFE-adjusted* statistics. Again matching the in-sample results, the out-of-sample predictive ability of technical indicators is uniformly stronger for recessions relative to expansions.

To get a sense of potential bias-efficiency trade-offs in the forecasts, Table 3 also reports the Theil (1971) MSFE decomposition into the squared forecast bias and a remainder term. The remainder term depends, among other things, on the forecast volatility, and limiting forecast volatility helps to reduce the remainder term

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

[20] 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, because the predictive regression model reduces to the constant expected equity risk premium model under the null hypothesis.

[21] 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 does 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.

Table 3 Out-of-Sample Forecasting Results, January 1966 to December 2011

Macroeconomic variables								Technical indicators							
Predictor	MSFE	R^2_{OS} (%)	*MSFE-adjusted*	R^2_{OS}, EXP (%)	R^2_{OS}, REC (%)	$(\bar{\hat{e}})^2$	Rem. term	Predictor	MSFE	R^2_{OS} (%)	*MSFE-adjusted*	R^2_{OS}, EXP (%)	R^2_{OS}, REC (%)	$(\bar{\hat{e}})^2$	Rem. term
HA	20.23					0.07	20.16								
Panel A: Bivariate predictive regression forecasts															
DP	20.23	−0.02	1.27	−0.79	1.55	0.00	20.23	MA(1, 9)	20.18	0.24	0.98	−0.81	2.39	0.05	20.13
DY	20.22	0.05	1.41*	−1.08	2.39	0.00	20.22	MA(1, 12)	20.10	0.63	1.52*	−0.66	3.30	0.05	20.05
EP	20.35	−0.58	0.02	−0.29	−1.18	0.02	20.32	MA(2, 9)	20.16	0.32	1.16	−0.75	2.54	0.05	20.11
DE	20.39	−0.78	0.73	−1.59	0.89	0.00	20.39	MA(2, 12)	20.07	0.78	1.69**	−0.56	3.53	0.05	20.02
RVOL	20.19	0.19	1.59*	0.02	0.53	0.13	20.06	MA(3, 9)	20.15	0.41	1.41*	−0.82	2.94	0.05	20.09
BM	20.48	−1.23	−1.27	−0.22	−3.31	0.08	20.40	MA(3, 12)	20.21	0.08	0.63	−0.46	1.19	0.06	20.16
NTIS	20.43	−0.97	0.38	−0.21	−2.54	0.17	20.26	MOM(9)	20.21	0.11	0.61	−0.49	1.34	0.06	20.15
TBL	20.46	−1.12	2.04**	−2.35	1.42	0.08	20.38	MOM(12)	20.20	0.15	0.69	−0.45	1.39	0.06	20.14
LTY	20.42	−0.95	1.56*	−1.88	0.98	0.09	20.33	VOL(1, 9)	20.15	0.40	1.25	−0.67	2.61	0.06	20.09
LTR	20.17	0.29	2.00**	−1.95	4.90	0.10	20.07	VOL(1, 12)	20.07	0.80	1.76**	−0.24	2.94	0.05	20.02
TMS	20.43	−0.99	2.08**	−3.44	4.06	0.23	20.20	VOL(2, 9)	20.14	0.44	1.36*	−0.01	1.37	0.07	20.07
DFY	20.36	−0.64	−0.34	−0.55	−0.83	0.13	20.23	VOL(2, 12)	20.16	0.33	1.12	0.16	0.68	0.06	20.10
DFR	20.32	−0.46	0.05	0.33	−2.06	0.06	20.26	VOL(3, 9)	20.23	0.01	0.46	−0.41	0.89	0.06	20.17
INFL	20.32	−0.45	0.32	−0.08	−1.21	0.02	20.30	VOL(3, 12)	20.09	0.71	1.68**	0.13	1.90	0.05	20.04
Panel B: Principal component predictive regression forecasts															
PC-ECON	20.40	−0.86	2.58***	−3.95	5.51	0.02	20.38	PC-TECH	20.10	0.65	1.46*	−0.42	2.84	0.05	20.04
Panel C: Principal component predictive regression forecasts, all predictors taken together															
PC-ALL	19.87	1.79	3.28***	−2.80	11.24	0.04	19.83								

Notes. The historical average (HA) forecast is given by

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

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 (ninth) 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

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

where $\hat{F}^{j}_{1:t,k,t}$ 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 $\{\hat{F}^{j}_{1:t,s,k}\}_{s=1}^{t-1}$ ($k = 1, \ldots, K$). We select K via the adjusted R^2 based on data through t. MSFE is the mean squared forecast error. R^2_{OS} measures the proportional reduction in MSFE for the competing forecast given in the first or ninth 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. The R^2_{OS} statistics are also reported separately for NBER-dated expansions (EXP) and recessions (REC). The $(\bar{\hat{e}})^2$ term and Rem. term are the squared forecast bias and remainder term, respectively, for the Theil (1971) MSFE decomposition.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively; 0.00 indicates less than 0.005 in absolute value.

(Rapach et al. 2010).[22] The squared bias (remainder term) 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. The remainder terms for these five variables, however, 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, ranging from 0.13 to 0.23. Among these variables, only RVOL has a smaller remainder term (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 remainder terms 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 indicators are generally

[22] The Theil (1971) MSFE decomposition is given by $(\bar{\hat{r}} - \bar{r})^2 + (\sigma_{\hat{r}} - \rho\sigma_r)^2 + (1-\rho^2)\sigma_r^2$, where $\bar{r}$ ($\bar{\hat{r}}$) is the mean of the actual (forecasted) value, σ_r ($\sigma_{\hat{r}}$) is the standard deviation of the actual (forecasted) value, and ρ is the correlation coefficient between the actual and forecasted values. The remainder term is given by $(\sigma_{\hat{r}} - \rho\sigma_r)^2 + (1-\rho^2)\sigma_r^2$.

both less biased and more efficient than 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.[23] 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 does the historical average. The remainder term for the PC-ECON forecast, however, substantially exceeds that of the historical average; in contrast, the remainder term for the PC-TECH forecast is well below that of the historical average. Both the PC-ECON and PC-TECH forecasts manifest much stronger out-of-sample predictive ability in recessions than in expansions.

We next compare the information content of the PC-ECON and PC-TECH forecasts using encompassing tests. Harvey et al. (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 forecast (both at the 1% level; the complete results are omitted for brevity). 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 remainder term for the PC-ALL forecast are both below the respective values for the historical average; indeed, the remainder term for the PC-ALL forecast is well below that of any of the other forecasts. The out-of-sample results in Table 3 thus confirm the in-sample results in §2: macroeconomic variables and technical indicators capture different types of information relevant for forecasting the equity risk premium.[24] The R^2_{OS} for the PC-ALL forecast is a very sizable 11.24% for recessions, whereas it is −2.80% for expansions, so that the out-of-sample predictive power of the macroeconomic variables and technical indicators taken together is highly concentrated in recessions.

To control for data mining—which becomes a concern when considering many predictors—we use the Clark and McCracken (2012) modified version of the White (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 minimum MSFE of all the 28 bivariate predictive regression forecasts and three principal component predictive regression forecasts in Table 3. 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, so that data mining cannot readily explain the significant out-of-sample predictive power of the PC-ALL forecast.[25]

4. Asset Allocation Exercise

As a final exercise, we 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 an investor with mean-variance preferences who monthly 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 risk aversion into the asset allocation decision.

[23] See Footnote 21 for the intuition behind this seemingly strange result.

[24] The PC-ALL forecast also has a lower MSFE than the constant 0.5% equity risk premium benchmark forecast used by Simin (2008). Rapach et al. (2010) show that a combination forecast of the equity risk premium based on individual predictive regressions with macroeconomic variables delivers consistent out-of-sample gains. 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.

[25] Ferson et al. (2003) demonstrate that size distortions related to the Stambaugh bias can exacerbate data-mining 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 the issues raised by Ferson et al. (2003) do not appear of great concern for our out-of-sample analysis.

At the end of month t, the investor optimally allocates the following share of the portfolio to equities during month $t+1$:

$$w_t = \left(\frac{1}{\gamma}\right)\left(\frac{\hat{r}_{t+1}}{\hat{\sigma}^2_{t+1}}\right), \tag{25}$$

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

$$R_{p,\,t+1} = w_t r_{t+1} + R_{f,\,t+1}. \tag{26}$$

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 constrain w_t to lie between 0 and 1.5.[26]

The CER for the portfolio is

$$\mathrm{CER}_p = \hat{\mu}_p - \tfrac{1}{2}\gamma\hat{\sigma}^2_p, \tag{27}$$

where $\hat{\mu}_p$ and $\hat{\sigma}^2_p$ 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 (21), (22), or (23) and the CER for an investor who uses the historical average forecast given by (24). We multiply this difference by 1,200, 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 ninth columns of panel A in Table 4 present CER gains for an investor with a relative risk coefficient of five who relies on the bivariate predictive regression forecast given by (21) or (22), respectively, instead of the historical average forecast; for the historical average forecast, the table reports the CER level. Table 4 also reports additional portfolio performance measures. The monthly Sharpe ratio in the fifth and twelfth columns is the mean portfolio return in excess of the risk-free rate divided by the standard deviation of the excess portfolio return. The sixth and thirteenth columns report average monthly turnover, where monthly turnover is the percentage of wealth traded each month. 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 forecast). The seventh and final 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% for January 1966 to December 2011. The CER gains are positive for 9 of the 14 macroeconomic variables in the second column of Table 4, panel A, with TBL, LTY, LTR, and TMS providing gains of more than 100 basis points. In accord with the R^2_{OS} statistics in Table 3, the CER gains are substantially larger for recessions vis-à-vis expansions for many of the macroeconomic variables. Eight of the macroeconomic predictors produce higher monthly 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 six columns of panel A in Table 4 reveal that portfolios based on technical indicators generally outperform those based on macroeconomic variables. The CER gains in the ninth column are positive for all of the technical indicators, reaching a maximum of 317 basis points. Again in accord with the R^2_{OS} statistics, the CER gains are uniformly larger during recessions relative to expansions, and the gains for recessions are greater than 1,000 basis points for 10 of the 14 individual technical indicators. 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 (23). PC-ECON delivers a sizable CER gain of 224 basis points in the second column of panel B, and its monthly Sharpe ratio of 0.10 is twice that of the historical average. The CER gain for PC-ECON is much larger for recessions (1,269 basis points) compared to expansions (9 basis points). 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 ninth column of panel B, 25 basis points more than PC-ECON, and a monthly Sharpe ratio of 0.10, matching that

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

Table 4 Portfolio Performance Measures, January 1966 to December 2011

Macroeconomic variables							Technical indicators						
Predictor	Δ (ann.) (%)	Δ (ann.), EXP (%)	Δ (ann.), REC (%)	Sharpe ratio	Relative average turnover	Δ (ann.), cost = 50 bps (%)	Predictor	Δ (ann.) (%)	Δ (ann.), EXP (%)	Δ (ann.), EXP (%)	Sharpe ratio	Relative average turnover	Δ (ann.), cost = 50 bps (%)
HA	3.54			0.05	2.09%	3.40							
Panel A: Bivariate predictive regression forecasts													
DP	−0.26	−0.98	2.94	0.03	2.17	−0.38	MA(1, 9)	1.69	−0.51	12.69	0.08	4.40	1.22
DY	0.27	−1.13	6.89	0.04	3.05	0.02	MA(1, 12)	2.91	−0.27	18.91	0.11	3.94	2.51
EP	0.42	−0.01	2.43	0.05	1.72	0.34	MA(2, 9)	2.08	−0.49	14.08	0.09	4.48	1.63
DE	−0.19	−1.26	4.99	0.04	2.17	−0.34	MA(2, 12)	3.17	−0.07	19.17	0.12	3.62	2.82
RVOL	−0.52	−0.11	−2.97	0.08	4.20	−0.90	MA(3, 9)	2.54	−0.37	17.54	0.11	4.60	2.08
BM	−1.26	−0.16	−6.69	0.03	2.52	−1.45	MA(3, 12)	1.40	−0.39	10.40	0.08	2.69	1.18
NTIS	0.15	0.65	−2.30	0.08	3.52	−0.18	MOM(9)	1.38	−0.41	10.38	0.07	2.58	1.16
TBL	1.62	0.76	5.81	0.08	1.52	1.56	MOM(12)	1.32	−0.40	9.32	0.07	2.19	1.16
LTY	1.65	0.48	7.40	0.07	1.03	1.65	VOL(1, 9)	1.61	−0.72	13.61	0.08	5.21	1.05
LTR	1.07	−0.63	9.17	0.09	23.94	−1.87	VOL(1, 12)	2.63	−0.26	17.63	0.11	4.59	2.25
TMS	1.88	0.42	8.95	0.12	4.45	1.44	VOL(2, 9)	1.48	−0.07	9.48	0.08	2.94	1.23
DFY	−0.82	−0.19	−4.01	0.05	2.70	−1.03	VOL(2, 12)	1.32	0.10	7.32	0.08	2.40	1.13
DFR	0.26	0.66	−1.68	0.06	10.16	−0.91	VOL(3, 9)	0.71	−0.42	6.71	0.06	2.52	0.52
INFL	0.38	0.03	2.13	0.06	7.77	−0.49	VOL(3, 12)	2.22	−0.05	13.22	0.10	2.80	1.99
Panel B: Principal component predictive regression forecasts													
PC-ECON	2.24	0.09	12.69	0.10	6.73	1.51	PC-TECH	2.49	−0.29	16.37	0.10	3.58	2.15
Panel C: Principal component predictive regression forecasts, all predictors taken together													
PC-ALL	4.94	0.70	26.21	0.16	7.51	4.12							

Notes. This table reports portfolio performance measures for an investor with mean-variance preferences and relative risk-aversion coefficient of five who monthly allocates between equities and risk-free bills using either an historical average (HA) 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 (eighth) 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). The Δ statistic 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; Δ statistics are also reported separately for NBER-dated expansions (EXP) and recessions (REC). 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. The Δ, cost = 50 bps statistic is the CER gain assuming a proportional transactions cost of 50 basis points per transaction.

of PC-ECON. PC-TECH provides substantially larger CER gains for recessions (1,637 basis points) relative to expansions (−29 basis points). 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 panel C of Table 4 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 monthly Sharpe ratio, 0.16, and the highest net-of-transactions-costs CER gain, 412 basis points, of all the portfolios. The CER gain accruing to PC-ALL reaches a very sizable 2,621 basis points for recessions compared to 70 basis points for expansions, again in line with the R^2_{OS} statistics in Table 3. The asset allocation exercise demonstrates the substantial economic value of combining information from macroeconomic variables and technical indicators.

5. Conclusion

We utilize technical indicators to directly forecast the equity risk premium and compare their performance with that of macroeconomic variables. Our results show that technical indicators exhibit statistically and economically significant in-sample and out-of-sample predictive 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 offers sizable utility gains to investors by better tracking the substantial countercyclical fluctuations in the equity risk premium.

Although numerous theories explain why technical indicators may work (as reviewed in the introduction), little is known about their ability to explain key stylized facts concerning stock market returns, such as the equity risk premium puzzle (i.e., the average equity risk premium appears too large in light of conventional risk considerations). In contrast, more traditional asset pricing models, such as the habit model of Campbell and Cochrane (1999) and long-run risks model of Bansal and Yaron (2004), can explain important stylized facts, but they leave no role for technical analysis. Given the growing empirical evidence supporting the predictive power of technical indicators, which is in line with the behavior of many practitioners, it appears important to bridge the gap between theoretical models of technical analysis and more traditional asset pricing models. Exploring the connections between these two types of models holds the promise of significantly improving our understanding of the economic forces that drive the equity risk premium and cross-section of expected asset returns.

Supplemental Material

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