

Out-of-Sample Equity Premium Prediction: Fundamental vs. Technical Analysis

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 CAFR
zhou@wustl.edu

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*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 was undertaken while Rapach and Zhou were Visiting Scholars at the Federal Reserve Bank of St. Louis. We thank seminar participants at the Cheung Kong Graduate School of Business, Federal Reserve Bank of St. Louis, Forecasting Financial Markets 2010 Conference, Fudan University, Singapore Management University 2010 Summer Finance Camp, Temple University, Third Annual Conference of The Society for Financial Econometrics, University of New South Wales, 2010 Midwest Econometrics Group Meetings, Hank Bessembinder, Henry Cao, Long Chen, Todd Clark, John Cochrane, Robert Engle, Bruce Grundy, Massimo Guidolin, Harrison Hong, Jennifer Huang, Michael McCracken, Adrian Pagan, Jesper Rangvid, and George Tauchen for helpful comments. The usual disclaimer applies. 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.

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Abstract

We compare the ability of economic fundamentals and technical trading rules to forecast the monthly U.S. equity premium using out-of-sample tests for 1960–2008. Both approaches provide statistically and economically significant out-of-sample forecasting gains, which are highly concentrated in U.S. business-cycle recessions. Nevertheless, fundamental and technical analysis capture different sources of equity premium fluctuations, and the two approaches appear largely complementary: technical rules detect the typical decline in the equity premium near cyclical peaks; economic fundamentals more readily pick up the typical rise in the equity premium near cyclical troughs. We also simulate data from two recent general equilibrium models—the Campbell and Cochrane (1999) habit-formation and Bansal and Yaron (2004) long-run risks models—that link rational equity premium predictability to macroeconomic shocks. Empirical p -values indicate that these models do not account for much of the out-of-sample forecasting gains evidenced by fundamental and, especially, technical analysis.

JEL classifications: C22, C53, E32, G11, G12, G17

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Researchers have long investigated two very different methods of predicting aggregate stock returns: fundamental and technical analysis. Fundamental analysis uses valuation ratios, interest rates, term and credit spreads, and related economic variables to forecast excess stock returns or, equivalently, the equity premium. In contrast, technical analysis studies past stock price behavior, often in conjunction with volume, to ascertain future price movements and thereby guide trading decisions.

Economic fundamentals are commonly analyzed using a predictive regression framework, in which the equity premium is regressed on a lagged potential predictor. Rozeff (1984), Fama and French (1988), and Campbell and Shiller (1988a, 1988b) employ this framework and present evidence that valuation ratios, such as the dividend yield, predict the U.S. equity premium. Similarly, Keim and Stambaugh (1986), Campbell (1987), Breen, Glosten, and Jagannathan (1989), and Fama and French (1989) find predictive ability for nominal interest rates and the default and term spreads, while Nelson (1976) and Fama and Schwert (1977) detect predictive capability for the inflation rate. More recent studies continue to support equity premium predictability using valuation ratios (Cochrane (2008), Pástor and Stambaugh (2009)), interest rates (Ang and Bekaert (2007)), and inflation (Campbell and Vuolteenaho (2004)). Other studies identify additional economic variables with predictive power, including corporate equity issuing activity (Baker and Wurgler (2000), Boudoukh, Michaely, Richardson, and Roberts (2007)), the consumption-wealth ratio (Lettau and Ludvigson (2001)), and volatility (Guo (2006)).

Technical analysis dates at least to 1700 and was popularized in the late nineteenth and early twentieth centuries by the “Dow Theory” of Charles Dow and William Peter Hamilton.¹ Numerous studies examine the profitability of technical trading rules in equity markets. Early studies, including Cowles (1933), Fama and Blume (1966), and Jensen and Benington (1970), report mixed results for a variety of popular technical indicators. More recently, Brock, Lakonishok, and LeBaron (1992) find that moving-average and trading-range-break rules have predictive power for the Dow Jones index for 1897–1986, and Lo, Mamaysky, and Wang (2000) find that several technical indicators based on automatic pattern recognition with kernel regressions have some practical value. Using White’s (2000) “reality check” bootstrap, Sullivan, Timmermann, and White (1999) confirm the results for 1897–1986 in Brock, Lakonishok, and LeBaron (1992), but they find little support for the profitability of trading rules for 1987–1996.²

¹Nison (1991) notes that Munehisa Homma reportedly made a fortune in eighteenth-century Japan using an early version of “candlestick” patterns to predict rice market prices using past prices. Schwager (1993, 1995) and Covel (2005) discuss how technical analysis is an important tool for many of today’s most successful traders.

²Park and Irwin (2007) provide a survey of the empirical literature on technical analysis. Zhu and Zhou (2009) and

The literatures on fundamental and technical analysis have evolved largely independently. In the present paper, we merge the two literatures by employing technical indicators in the same way that economic fundamentals are used to forecast the equity premium, thereby enabling us to address a number of interesting issues surrounding fundamental and technical approaches to predicting stock returns: Do the two approaches demonstrate comparable predictive power? Do economic fundamentals and technical indicators capture similar return predictability patterns in the data? Should the two approaches be viewed as substitutes or complements in asset-allocation decisions? Can rational fluctuations in the expected equity premium explain the predictive ability of either or both approaches? Our analysis of these issues has four basic components.

First, we compare equity premium forecasts based on economic fundamentals and technical trading rules in terms of the Campbell and Thompson (2008) out-of-sample R^2 statistic, R_{OS}^2 , which measures the reduction in mean square prediction error (MSPE) for a competing forecast relative to the historical average (random walk with drift) benchmark forecast. For assessing return predictability, Goyal and Welch (2008) show that out-of-sample criteria are important. We generate equity premium forecasts based on economic fundamentals in the usual manner via recursively estimated predictive regression models. Similarly, we transform the trading signals produced by technical rules into equity premium forecasts using a recursive predictive regression framework. This allows us to directly compare equity premium forecasts based on economic fundamentals and technical rules in terms of MSPE. We analyze the forecasting ability of a variety of economic fundamentals from the literature and popular moving-average (MA), momentum, and volume-based technical trading rules.

Second, we compare the economic value of equity premium forecasts based on fundamental and technical analysis from an asset-allocation perspective. Specifically, we calculate utility gains for a mean-variance investor who optimally allocates a portfolio between equities and risk-free Treasury bills using equity premium forecasts based on either economic fundamentals or technical rules relative to an investor who uses the historical average equity premium forecast. While numerous studies investigate the profitability of technical indicators, these studies are *ad hoc* in that they do no account for risk aversion in the asset-allocation decision. Analogous to Zhu and Zhou (2009), we address this drawback and compare the utility gains for a risk-averse investor who forecasts the equity premium using economic fundamentals to those of an identical investor who forecasts the equity premium with technical rules.

references therein provide some theoretical reasons why technical analysis can be profitable.

Third, to investigate links between out-of-sample return predictability and the real economy, we compute the R_{OS}^2 statistics and utility gains over both NBER-dated cyclical expansions and recessions, and we examine closely the behavior of the forecasts over the course of recessions. Insofar as predictability is linked to the real economy, we expect that there will be more predictability in the rapidly changing macroeconomic conditions of recessions (e.g., Henkel, Martin, and Nadari (2009)).

Fourth, we explore whether rational fluctuations in the expected equity risk premium can account for the out-of-sample forecasting gains evidenced by economic fundamentals and technical rules. Given our interest in measuring forecasting gains over different business-cycle phases, we generate simulated data using two leading general equilibrium models that imply rational equity premium predictability in response to macroeconomic shocks, namely, the Campbell and Cochrane (1999) habit-formation and Bansal and Yaron (2004) long-run risks models.

We find that monthly equity premium forecasts based on either economic fundamentals or technical rules produce economically significant R_{OS}^2 statistics and utility gains, but that the gains are highly concentrated in recessions. This is especially evident for the utility metric. For example, a mean-variance investor with a risk aversion coefficient of five would pay an annualized portfolio management fee of 1.82% to have access to the equity premium forecast based on the dividend yield relative to the historical average benchmark forecast for the entire 1960:01–2008:12 forecast evaluation period; during recessions, the same investor would pay a hefty annual fee of 13.02%. Similarly, an investor with the same preferences would pay a fee of 3.07% during the full forecast evaluation period and a very substantial fee of 14.97% during recessions for access to an equity premium forecast based on a monthly MA(1,12) technical rule rather than the historical average benchmark.

Although economic fundamentals and technical rules both forecast better than the benchmark during recessions, the two approaches exploit different patterns. Technical rules detect the typical fall in the equity premium near business-cycle peaks, while economic fundamentals correctly pick up the typical rise in the equity premium later in recessions near business-cycle troughs. These results may help to explain the simultaneously prominent roles for economic fundamentals in the academic literature and technical indicators among practitioners. Both approaches seem useful for predicting returns, neither approach clearly outperforms the other, and they appear to complement each other. Indeed, we show that pooling information from both the fundamental and technical approaches provides additional out-of-sample gains relative to using each approach in isolation.

Finally, empirical p -values generated using the habit-formation or long-run risks model indicate that these models cannot account for much of the out-of-sample forecasting gains evidenced by economic fundamentals and technical rules, particularly technical rules during recessions. It thus appears that economic fundamentals and, especially, technical rules capture something beyond the rational equity premium predictability implied by the habit-formation and long-run risks models. Behavioral models seem to offer some explanations. Hong and Stein (1999) and Hong, Lim, and Stein (2000) provide both theory and empirical evidence on the slow transmission of bad news in financial markets. Recessions are presumably associated with large adverse macroeconomic news shocks, which may take longer to be fully incorporated into stock prices. As a result, the market will exhibit stronger trending patterns during recessions, creating greater scope for trend-based technical rules to forecast equity prices. Consistent with this is the disposition effect—investors tend to hold losers too long and sell winners too early (Odean (1998)). During the early stages of recessions, there are more share price declines and hence more losers; this implies that the disposition effect is stronger in recessions, thereby reinforcing the stronger trend. In general, our results point to the importance in future research of developing and testing general equilibrium models capable of accounting for the predictive ability of both economic fundamentals and technical rules over the business cycle.

The remainder of the paper is organized as follows. Section I outlines the construction of equity premium forecasts based on economic fundamentals and technical trading rules, as well as the forecast evaluation criteria. Section II reports the out-of-sample test results. Section III examines the ability of the habit-formation and long-run risks models to account for the out-of-sample results. Section IV contains concluding remarks.

I. Econometric Methodology

This section describes the construction and evaluation of out-of-sample equity premium forecasts based on economic fundamentals and technical rules.

A. Forecast Construction

The conventional framework for analyzing equity premium predictability based on economic fundamentals is the following predictive regression model:

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

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

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

where $\hat{\alpha}_{i,t}$ and $\hat{\beta}_{i,t}$ are the ordinary least squares (OLS) estimates of α_i and β_i , respectively, in (1) computed by regressing $\{r_k\}_{k=2}^t$ on a constant and $\{x_{i,k}\}_{k=1}^{t-1}$. Dividing the total sample of T observations into q_1 in-sample and q_2 out-of-sample observations, where $T = q_1 + q_2$, we can calculate a series of out-of-sample equity premium forecasts based on $x_{i,t}$ over the last q_2 observations: $\{\hat{r}_{i,t+1}\}_{t=q_1}^{T-1}$.³ The historical average of the equity premium, $\bar{r}_{t+1} = (1/t)\sum_{k=1}^t r_k$, is a natural benchmark forecast corresponding to the random walk with drift model ($\beta_i = 0$ in (1)). Goyal and Welch (2008) show that \bar{r}_{t+1} is a stringent benchmark: predictive regression forecasts based on economic fundamentals frequently fail to outperform the historical average forecast in out-of-sample tests.

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

Rapach, Strauss, and Zhou (2010) analyze the gains from pooling N individual predictive regression forecasts. A pooled forecast takes the form,

$$\hat{r}_{p,t+1} = \sum_{i=1}^N \omega_{i,t} \hat{r}_{i,t+1}, \quad (3)$$

where $\{\omega_{i,t}\}_{i=1}^N$ are the *ex ante* combining weights and $\sum_{i=1}^N \omega_{i,t} = 1$. Rapach, Strauss, and Zhou (2010) show that a simple pooling scheme ($\omega_{i,t} = 1/N$ for all i, t) consistently outperforms the his-

³Observe that the forecasts are generated using a recursive (or expanding) window for estimating α_i and β_i in (1). Forecasts could also be generated using a rolling window (which drops earlier observations as additional observations become available) in recognition of potential structural instability. Pesaran and Timmermann (2007) and Clark and McCracken (2009), however, show that the optimal estimation window for a quadratic loss function can include pre-break data due to the familiar bias-efficiency tradeoff. We use recursive estimation windows in Section II, although we obtain similar results using rolling estimation windows of various sizes.

torical average benchmark forecast, despite the inconsistent performance of individual forecasts.⁴ In Section II, we generate $N = 14$ individual predictive regression forecasts of the monthly equity premium with Campbell and Thompson (2008) restrictions imposed, where each individual forecast is based on an economic fundamental from the literature. We also compute a pooled forecast as a simple average of these $N = 14$ individual predictive regression forecasts. While more elaborate pooling schemes are available, relatively simple schemes that hew more closely to equal weighting typically perform better than elaborate schemes when N is large (Timmermann (2006)).

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

$$S_t = \begin{cases} 1 & \text{if } MA_{s,t} \geq MA_{l,t} \\ 0 & \text{if } MA_{s,t} < MA_{l,t} \end{cases}, \quad (4)$$

where

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

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 rule with MA lengths s and l as $MA(s, l)$. Intuitively, the MA rule is designed to detect changes in stock price trends. For example, when prices have been recently falling, the short MA will tend to be lower than the long MA. If prices begin trending upward, then the short MA tends to increase faster than the long MA, eventually exceeding the long MA and generating a buy signal. In Section II, we analyze monthly MA rules with $s = 1$ and $l = 3, 6, 9, 12$.

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

$$S_t = \begin{cases} 1 & \text{if } P_t \geq P_{t-m} \\ 0 & \text{if } P_t < P_{t-m} \end{cases}. \quad (6)$$

Intuitively, a current stock price that is higher than its level m periods ago is interpreted as an indicator of “positive” momentum and thus relatively high expected excess returns for period $t + 1$,

⁴Rapach, Strauss, and Zhou (2010) show that simple averaging is a type of shrinkage forecast that stabilizes individual forecasts and thereby provides out-of-sample gains more consistently over time. Mamaysky, Spiegel, and Zhang (2007) pool predictions from an OLS model and the Kalman filter model of Mamaysky, Spiegel, and Zhang (2008) to significantly increase the number of mutual funds with predictable out-of-sample alphas. Timmermann (2008) pools forecasts from linear and nonlinear autoregressive models of monthly stock returns. Goyal and Welch (2008) find that simply including numerous predictors simultaneously in the same regression—the “kitchen sink” model—performs very poorly in out-of-sample equity premium forecasting. This is not surprising; it is well known that unrestricted, highly parameterized models often overfit the in-sample data and forecast poorly out-of-sample. Ludvigson and Ng (2007) pursue an alternative strategy by incorporating information from a very large number of macroeconomic and financial variables to predict stock returns and volatility using a dynamic factor model.

which generates a buy signal. We denote the momentum rule that compares P_t to P_{t-m} as $MOM(m)$, and we compute monthly signals for $m = 3, 6, 9, 12$ in Section II.

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

$$OBV_t = \sum_{k=1}^t VOL_k D_k, \quad (7)$$

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

$$S_t = \begin{cases} 1 & \text{if } MA_{s,t}^{OBV} \geq MA_{l,t}^{OBV} \\ 0 & \text{if } MA_{s,t}^{OBV} < MA_{l,t}^{OBV} \end{cases}, \quad (8)$$

where

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

Intuitively, relatively high recent volume together with recent price increases, say, indicate a strong positive market trend and generate a buy signal. In Section II, we compute monthly signals for $s = 1$ and $l = 3, 6, 9, 12$.

The three types of trading rules we consider (MA, momentum, and volume) conveniently capture the trend-following idea at the center of technical analysis and are representative of the technical rules analyzed in the academic literature (e.g., Brock, Lakonishok, and LeBaron (1992), Sullivan, Timmermann, and White (1999)). To directly compare these trading rules to equity premium forecasts based on economic fundamentals, we transform the trading signals to point forecasts of the equity premium by replacing the economic fundamental $x_{i,t}$ in the predictive regression, (1), with S_t from (4), (6), or (8). We then generate out-of-sample equity premium forecasts using S_t as the explanatory variable in a manner analogous to the forecasts based on economic fundamentals described earlier, and we again compute a pooled forecast as a simple average of the individual forecasts generated from technical rules.

B. Forecast Evaluation

We consider two metrics for evaluating forecasts based on economic fundamentals and technical rules. The first is the Campbell and Thompson (2008) R_{OS}^2 statistic, which measures the

proportional reduction in MSPE for a competing model relative to the historical average forecast:

$$R_{OS}^2 = 1 - \frac{\sum_{k=1}^{q_2} (r_{q_1+k} - \hat{r}_{q_1+k})^2}{\sum_{k=1}^{q_2} (r_{q_1+k} - \bar{r}_{q_1+k})^2}, \quad (10)$$

where \hat{r}_{q_1+k} represents an equity premium forecast based on an economic fundamental or technical rule. Clearly, when $R_{OS}^2 > 0$, the competing forecast outperforms the historical average benchmark in terms of MSPE. We employ the Clark and West (2007) *MSPE-adjusted* statistic to test the null hypothesis that the competing and historical average forecasts have equal MSPE against the one-sided alternative hypothesis that the competing forecast has a lower MSPE, corresponding to $H_0 : R_{OS}^2 = 0$ against $H_A : R_{OS}^2 > 0$. Clark and West (2007) develop the *MSPE-adjusted* statistic by modifying the familiar Diebold and Mariano (1995) and West (1996) statistic so that it has a standard normal asymptotic distribution when comparing forecasts from nested models. Comparing the fundamental or technical forecasts with the historical average forecast entails comparing nested models, since setting $\beta_i = 0$ in (1) yields the random walk with drift model.⁵

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

In particular, we compute the average utility for a mean-variance investor with a risk aversion coefficient of five who monthly allocates between stocks and risk-free bills using an equity premium forecast based on an economic fundamental or technical rule. 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 excess returns.⁶ We then calculate the average utility for the

⁵While the Diebold and Mariano (1995) and West (1996) statistic has a standard normal asymptotic distribution when comparing forecasts from non-nested models, Clark and McCracken (2001) and McCracken (2007) show that it has a complicated non-standard distribution when comparing forecasts from nested models. The non-standard distribution can lead the Diebold and Mariano (1995) and West (1996) statistic to be severely undersized when comparing forecasts from nested models, thereby substantially reducing power.

⁶Again following Campbell and Thompson (2008), we constrain the equity weight in the portfolio to lie between 0% and 150%

same investor using the historical average forecast of the equity premium. The utility gain is the difference between the two average utilities. We multiply this difference by 1200, so that it can be interpreted as the annual percentage portfolio management fee that an investor would be willing to pay to have access to the fundamental or technical forecast relative to the historical average forecast.

II. Empirical Results

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

A. Data

Our monthly data span 1927:01–2008:12. The data are from Amit Goyal’s web page, which provides updated data from Goyal and Welch (2008).⁷ The aggregate market return is the continuously compounded return on the S&P 500 (including dividends), and the equity premium is the difference between the aggregate market return and the Treasury bill rate. The following 14 economic variables, which are well representative of the literature (Goyal and Welch (2008)), constitute the set of economic fundamentals used to predict the equity premium:

- *Dividend-price ratio (log)*, DP: log of dividends paid on the S&P 500 index minus the log of stock prices (S&P 500 index), where dividends are measured as a twelve-month moving sum.
- *Dividend yield (log)*, DY: log of dividends minus the log of lagged stock prices.
- *Earnings-price ratio (log)*, EP: log of earnings on the S&P 500 index minus the log of stock prices, where earnings are measured as a twelve-month moving sum.
- *Dividend-payout ratio (log)*, DE: log of dividends minus log of earnings.
- *Stock variance*, SVAR: monthly sum of squared daily returns on the S&P 500 index.
- *Book-to-market ratio*, BM: book-to-market value ratio for the Dow Jones Industrial Average.
- *Net equity expansion*, NTIS: ratio of twelve-month moving sum of net equity issues by NYSE-listed stocks to total end-of-year market capitalization of NYSE stocks.

⁷The data are available at <http://www.bus.emory.edu/AGoyal/Research.html>.

- *Treasury bill rate*, TBL: interest rate on a three-month Treasury bill (secondary market).
- *Long-term yield*, LTY: long-term government bond yield.
- *Long-term return*, LTR: return on long-term government bonds.
- *Term spread*, TMS: long-term yield minus the Treasury bill rate.
- *Default yield spread*, DFY: BAA- minus AAA-rated corporate bond yields.
- *Default return spread*, DFR: long-term corporate bond return minus the long-term government bond return.
- *Inflation*, INFL: calculated from the CPI (all urban consumers); we follow Goyal and Welch (2008) and use $x_{i,t-1}$ in (1) for inflation to account for the delay in CPI releases.

We use the S&P 500 index for P_t when computing the trading signals based on the MA and momentum rules in (4) and (6), respectively. In addition to the S&P 500 index, we use monthly volume data (beginning in 1940:01) from Google Finance to compute the trading signal in (8).⁸

B. R_{OS}^2 Statistics

Panel A of Table I reports R_{OS}^2 statistics for predictive regression forecasts based on economic fundamentals over the 1960:01–2008:12 forecast evaluation period. We use 1926:01–1959:12 as the initial in-sample period when forming the recursive out-of-sample forecasts. We assess the statistical significance of R_{OS}^2 using the Clark and West (2007) *MSPE-adjusted* statistic, as described in Section I. We compute R_{OS}^2 statistics separately for the full 1960:01–2008:12 forecast evaluation period, as well as NBER-dated expansions and recessions.⁹ The U.S. economy is in recession for 87 of the 588 months (15%) spanning 1960:01–2008:12.

According to the second column of Table I, Panel A, nine of the 14 individual economic fundamentals produce positive R_{OS}^2 statistics over the full 1960:01–2008:12 out-of-sample period, so that they outperform the historical average benchmark forecast in terms of MSPE. Six of the nine

⁸The volume data are available at <http://www.google.com/finance>. While daily data are frequently used to generate trading signals using technical indicators, we compute technical rules using monthly data to put the forecasts based on economic fundamentals and technical rules on a more equal footing. In ongoing research, we are investigating the use of daily data to generate monthly trading signals to study the more practical problem of maximizing portfolio performance using technical rules.

⁹NBER peak and trough dates that define the expansion and recession phases of the U.S. business cycle are available at <http://www.nber.org/cycles.html>.

positive R_{OS}^2 statistics for the individual fundamentals are significant at the 10% level or better. DP and DY have the highest R_{OS}^2 statistics, 0.73% and 0.71%, respectively, among the individual economic fundamentals. The fourth and sixth columns of Table I report R_{OS}^2 statistics separately for business-cycle expansions and recessions, respectively. Recessions markedly enhance the out-of-sample predictive ability of most economic fundamentals compared to the historical average. For example, the predictive ability of DP and DY is highly concentrated in recessions: the R_{OS}^2 statistics for DP (DY) are 0.15% and 2.15% (−0.26% and 3.09%) during expansions and recessions, respectively. The R_{OS}^2 statistics for DP, DY, LTR, and TMS are significant at the 5% level during recessions, despite the reduced number of available observations. Panel C of Table I also reports R_{OS}^2 statistics for the pooled economic fundamental forecast (POOL-ECON) based on (3) with $\omega_{i,t} = 1/N$ ($N = 14$). The R_{OS}^2 is 0.80% for the POOL-ECON forecast, which is significant at the 1% level and greater than the R_{OS}^2 for any of the individual fundamental forecasts. The POOL-ECON forecast also has an R_{OS}^2 that is higher during recessions than expansions (1.01% and 0.72%, respectively, both of which are significant at the 5% level).

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

Figure 2 provides time-series perspective on the out-of-sample predictive ability of economic fundamentals over the business cycle. The figure portrays the cumulative differences in square prediction errors between the historical average forecast and forecasts based on economic fun-

damentals.¹⁰ A segment of the curve that is higher (lower) at its end point relative to its initial point indicates that the fundamental forecast outperforms (underperforms) the historical average forecast in terms of MSPE over the period corresponding to the segment. The curves are predominantly positively sloped—sometimes quite steeply—during many recessions in Figure 2; outside of recessions, the curves are often flat or negatively sloped.

We turn next to the forecasting performance of the technical rules in Table I, Panel B. For the MA and momentum rules in (4) and (6), respectively, we again use data for 1928:01–1959:12 as the initial in-sample period to estimate the predictive regression model that transforms the trading signals to point forecasts. Data availability limits the starting date for the volume rules’ in-sample period to 1940:01. The second column of Table I, Panel B shows that seven of the twelve individual technical forecasts have positive R_{OS}^2 statistics, so that they outperform the historical average forecast according to the MSPE metric. Two of the seven positive R_{OS}^2 statistics are significant at conventional levels (MA(1,12) and MOM(9)). The R_{OS}^2 is also positive for the POOL-TECH forecast in Panel C, which is a simple average of the individual technical forecasts, but the statistic is not significant at conventional levels. The fourth and sixth columns of Panel B show even starker differences in forecasting performance across business-cycle phases for the technical forecasts in Panel B compared to the fundamental forecasts in Panel A. Eleven of the twelve individual technical forecasts exhibit negative R_{OS}^2 statistics during expansions, while all forecasts have positive R_{OS}^2 statistics during recessions; ten of these positive statistics are significant at conventional levels. Moreover, the R_{OS}^2 statistics for the technical forecasts are quite sizable during recessions, ranging from approximating 1.50%–3.00%. The POOL-TECH forecast also achieves a markedly higher R_{OS}^2 during recessions vis-à-vis expansions: 2.02% versus –0.52%, respectively, where the former is significant at the 5% level.

As shown in Figure 3, the technical forecasts almost always drop below the historical average forecast—often substantially so—throughout recessions. There are also expansionary episodes, especially for MA and volume (momentum) forecasts based on small l (m) values, where the technical forecasts frequently fall below the historical average forecast. The fourth column of Table I, Panel B indicates that these declines detract from the accuracy of the technical forecasts during expansions. The fifth and seventh columns of Panel B show that the average technical forecasts are uniformly lower during recessions than expansions; this is especially the case for MA and volume (momentum) forecasts based on large l (m) values, which offer the largest accuracy

¹⁰Goyal and Welch (2008) employ this device to assess the consistency of out-of-sample predictive ability.

gains, among the technical rules, during recessions.

Analogous to Figure 2, Figure 4 graphs the cumulative differences in square prediction errors between the historical average forecast and forecasts based on technical rules. The positive slopes of the curves during recessions in Figure 4 show that most of the technical forecasts consistently produce out-of-sample gains during these periods. But the curves are almost always flat or negatively sloped for the technical forecasts outside of recessions, so that out-of-sample gains are nearly limited to recessions. Taken together, the results in Table I and Figures 2 and 4 highlight the relevance of business-cycle fluctuations for equity premium predictability using either economic fundamentals or technical rules. Section III explores the ability of general equilibrium models that link equity premium predictability to macroeconomic shocks to account for these out-of-sample predictability patterns in the data.

Heretofore, we have generated equity premium forecasts separately using fundamental and technical analysis. Can employing economic fundamentals and technical rules in conjunction produce additional out of sample gains? We address this issue in the context of the POOL-ECON and POOL-TECH forecasts, which conveniently summarize information from the fundamental and technical approaches. Specifically, we form a pooled forecast as a convex combination of the POOL-ECON and POOL-TECH forecasts. We estimate the combining weights for these conceptually distinct forecasts by maximizing the R_{OS}^2 computed over a holdout out-of-sample period (Geweke and Amisano (2009)). The initial holdout out-of-sample period covers the first 15 years of the out-of-sample period (1960:01–1974:12), and the combining weights are computed using a rolling estimation window over the remainder of the forecast evaluation period. For the 1960:01–1974:12 period, we simply average the POOL-ECON and POOL-TECH forecasts. The bottom row of Table I, denoted POOL-ALL, reports the results. The POOL-ALL forecast delivers a higher R_{OS}^2 , 0.89% (which is significant at the 1% level), than any of the individual fundamental or technical forecasts, as well as the POOL-ECON and POOL-TECH forecasts, for the full 1960:01–2008:12 period. Not surprisingly, the POOL-ALL forecast produces a substantially higher R_{OS}^2 during recessions relative to expansions (2.40% and 0.27%, respectively, where the former is significant at the 1% level).

C. Reality Check

When considering a host of potential predictors, “data snooping” concerns naturally arise. Sullivan, Timmermann, and White (1999) use the White (2000) reality check to assess the importance

of data snooping when analyzing technical trading rules. We make two modifications to the White (2000) reality check for our framework. First, we use Hansen’s (2005) studentized version of White’s (2000) maximum statistic, which is potentially more powerful. Second, we generate a p -value for the Hansen (2005) statistic using a wild fixed-regressor bootstrap procedure. As Clark and McCracken (2010) emphasize, the asymptotic and finite-sample properties of the nonparametric bootstrap procedures in White (1999) and Hansen (2005) do not generally apply when comparing forecasts from multiple models that all nest the benchmark model, as in our application. Clark and McCracken (2010), however, show that a wild fixed-regressor bootstrap procedure delivers asymptotically valid critical values for the studentized maximum statistic when comparing nested forecasts. They also find that this bootstrap procedure has good finite-sample properties.

We use the studentized maximum statistic for a quadratic loss function (in accord with the R_{OS}^2 statistic) to test whether any of the 14 economic fundamental, twelve technical rule, and three pooled forecasts in Table I has lower expected loss than the historical average benchmark forecast.¹¹ For the 1960:01–2008:12 forecast evaluation period, the studentized maximum statistic is 2.46. Based on the wild fixed-regressor bootstrap (described in the appendix), the corresponding p -value is 1.00%, so that we reject the null hypothesis that none of the competing forecasts outperforms the historical average benchmark in terms of expected quadratic loss. Data snooping cannot readily explain the out-of-sample equity premium predictability in Table I.

D. Utility Gains

Table II reports average utility gains, in annualized percent, for a mean-variance investor with a risk aversion coefficient of five who allocates monthly across stocks and risk-free bills using fundamental (Panel A), technical (Panel B), or pooled (Panel C) forecasts of the equity premium relative to the historical average benchmark forecast. The results in Panel A indicate that forecasts based on economic fundamentals often produce sizable utility gains vis-à-vis the historical average benchmark. The utility gain is above 1% for six of the individual fundamentals (as well as POOL-ECON) in the second column, so that the investor would be willing to pay an annual management fee of a full percentage point or more to have access to forecasts based on economic fundamentals relative to the historical average forecast. Similar to Table I, the out-of-sample gains are typically concentrated in recessions. Consider, for example, DY, which generates the largest

¹¹Let $d_{h,t+1} = (r_{t+1} - \bar{r}_{t+1})^2 - (r_{t+1} - \hat{r}_{h,t+1})^2$, where $\hat{r}_{h,t+1}$ is an economic, technical, or pooled forecast indexed by h ($h = 1, \dots, H$), and $\bar{d}_h = q_2^{-1} \sum_{k=1}^{q_2} d_{h,q_1+k}$. The studentized maximum statistic for quadratic loss is then given by $\tau_{\max} = \max_{h=1, \dots, H} q_2^{1/2} \bar{d}_h \hat{S}_h^{-1/2}$, where $\hat{S}_h = q_2^{-1} \sum_{k=1}^{q_2} (d_{h,q_1+k} - \bar{d}_h)^2$.

utility gain (1.82%) for the full 1960:01–2008:12 forecast evaluation period. The utility gain is slightly negative (−0.17%) during expansions, while it is a very sizable 13.02% during recessions. DP, TBL, LTY, LTR, TMS, and DFR also provide utility gains above 5% during recessions. The POOL-ECON forecast provides more consistent gains across expansions (0.97%) and recessions (1.66%), although the gains are still more sizable during recessions.

Figure 5 portrays the equity portfolio weights computed based on fundamental and historical average forecasts. Because the investor uses the same volatility forecast for all of the portfolio allocations, only the equity premium forecasts produce differences in the equity weights. Figure 5 shows that the equity weight computed using the historical average forecast is procyclical, which, given that the historical average forecast of the equity premium is relatively smooth, primarily reflects changes in expected volatility: the rolling-window estimate of volatility tends to be countercyclical, leading to a procyclical equity weight for the risk-averse investor.¹² The equity weights based on economic fundamentals often deviate substantially from the equity weight based on the historical average, with a tendency for the weights computed using economic fundamentals to lie below the historical average weight during expansions and move closer to or above the historical average weight during recessions. Panel A of Table II indicates that these deviations create significant utility gains for our mean-variance investor, especially during recessions.

All but one of the utility gains based on the technical forecasts are positive in the second column of Table II, Panel B for the full 1960:01–2008:12 out-of-sample period. Eight of the individual technical forecasts (as well as POOL-TECH) provide utility gains above 1%, with the MA(1,12) forecast generating the largest gain (3.07%). Comparing the fourth and sixth columns, the utility gains are substantially higher during recessions than during expansions. The MA(1,12) forecast provides a leading example: during expansions, the utility gain is 0.97%, while it jumps to 14.97% during recessions. In all, eight of the individual technical forecasts and the POOL-TECH forecast produce utility gains above 10% during recessions. The fifth and seventh columns reveal that the average equity weight is lower during recessions than expansions for all of the TECH forecasts. The differences between the average equity weights across business-cycle phases are especially sizable for MA and volume (momentum) forecasts based on large l (m) values, and these l and m values generate the largest gains during recessions.

Figure 6 further illustrates that technical forecast weights tend to decrease during recessions,

¹²French, Schwert, and Stambaugh (1987), Schwert (1989, 1990), Whitelaw (1994), Harvey (2001), Ludvigson and Ng (2007), Lundblad (2007), and Lettau and Ludvigson (2009), among others, also find evidence of countercyclical expected volatility using alternative volatility estimators.

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

Overall, Table II shows that equity premium forecasts based on both economic fundamentals and technical rules usually generate sizable utility gains, especially during recessions, highlighting the economic significance of equity premium predictability using either approach. Comparing Panels A and B of Table II, technical forecasts typically provide larger utility gains than economic forecasts over the full 1960:01–2008:12 forecast evaluation period and during recessions. Nevertheless, the best-performing economic variable in Table II, DY, generates utility gains reasonably comparable to those of the best-performing technical forecasts.

To again explore potential benefits to using economic fundamentals and technical rules in conjunction, the bottom row of Table II reports utility gains for the POOL-ALL forecast. The POOL-ALL forecast generates a utility gain of 1.97% for the full 1960:01–2008:12 out-of-sample period. This is greater than the gain for each of the individual fundamental forecasts, as well as the POOL-ECON forecast, so that employing economic fundamentals and technical rules in conjunction for the purpose of asset allocation offers gains relative to using economic fundamentals alone. The POOL-ALL forecast generates a utility gain greater than that of eight of the twelve individual technical forecasts and the POOL-TECH forecast. While certain individual technical forecasts produce larger utility gains than the POOL-ALL forecast, it will likely prove difficult to identify these particular technical rules *a priori*, so that the POOL-ALL forecast provides a practical advantage over using technical rules in isolation.

E. A Closer Look at Forecast Behavior Near Cyclical Peaks and Troughs

Tables I and II and Figures 1–6 present somewhat of a puzzle. For equity premium forecasts based on both economic fundamentals and technical rules, out-of-sample gains are typically concentrated in business-cycle recessions. However, equity premium forecasts based on economic fundamentals often increase during recessions, while forecasts based on technical rules are usually substantially lower during recessions than expansions. Despite the apparent differences in the behavior of the two types of forecasts during recessions, the out-of-sample gains are concentrated in cyclical downturns for both approaches. Why?

We investigate this issue by examining the behavior of the actual equity premium and the

fundamental and technical forecasts around business-cycle peaks and troughs, which define the beginnings and ends of recessions, respectively. We first estimate the following regression model around business-cycle peaks:

$$r_t - \bar{r}_t = a_P + \sum_{k=-2}^4 b_{P,k} I_{k,t}^P + e_{P,t}, \quad (11)$$

where $I_{k,t}^P$ is an indicator variable that takes a value of unity k months after an NBER-dated business-cycle peak and zero otherwise. The estimated $b_{P,k}$ coefficients measure the incremental change in the average difference between the realized equity premium and historical average forecast k months after a cyclical peak. We then estimate a corresponding model that replaces r_t with \hat{r}_t , where \hat{r}_t signifies a fundamental or technical forecast of the equity premium:

$$\hat{r}_t - \bar{r}_t = a_P + \sum_{k=-2}^4 b_{P,k} I_{k,t}^P + e_{P,t}. \quad (12)$$

The slope coefficients describe the incremental change in the average difference between a fundamental or technical forecast relative to the historical average forecast k periods after a cyclical peak. Similarly, we measure the incremental change in the average behavior of the realized equity premium and the fundamental and technical forecasts around business-cycle troughs:

$$r_t - \bar{r} = a_T + \sum_{k=-4}^2 b_{T,k} I_{k,t}^T + e_{T,t}, \quad (13)$$

$$\hat{r}_t - \bar{r}_t = a_T + \sum_{k=-4}^2 b_{T,k} I_{k,t}^T + e_{T,t}, \quad (14)$$

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

The first panel of Figure 7 graphs OLS slope coefficient estimates (in percent) and 90% confidence bands for (11), and the remaining panels depict corresponding estimates for (12) based on the economic fundamentals. The first panel shows that the actual equity premium tends to move significantly below the historical average forecast one month before through two months after a business-cycle peak. The remaining panels in Figure 7 indicate that most economic fundamentals fail to pick up this decline in the equity premium early in recessions. Only the LTR, TMS, and INFL forecasts fall significantly below the historical average forecast for any of the months early in recessions when the equity premium itself is lower than average. The TMS forecast does the best job of matching the lower-than-average actual equity premium for the month before through two months after a peak. However, the TMS forecast is also significantly lower than the historical average forecast two months before and three and four months after a peak, unlike the actual equity

premium. The LTR forecast is significantly below the historical average during the two months after a peak, matching the actual equity premium, but it fails to track the actual equity premium prior to a peak. Although the confidence bands signal a significant decrease in the INFL forecast in the immediate months after a peak, the magnitude of the decline is small. Overall, Figure 7 suggests that equity premium forecasts based on economic fundamentals are not particularly adept at detecting the typical decline in the equity premium near cyclical peaks. Only the LTR and TMS forecasts exhibit sizable decreases near peaks; this variation presumably contributes to the forecasting gains for these variables in Tables I and II.

How do the equity premium forecasts based on technical rules behave near cyclical peaks? The first panel of Figure 8 again shows estimates for (11), while the other panels graph estimates for (12) for the technical forecasts. Figure 8 reveals that MA and volume (momentum) forecasts based on l (m) values of 6–12 (9–12) and the POOL-TECH and POOL-ALL forecasts move substantially below the historical average forecast in the months immediately following a cyclical peak, in accord with the behavior of the actual equity premium. Given that the actual equity premium moves substantially below average in the month before and month of a business-cycle peak, it is not surprising that technical forecasts are nearly all lower than the historical average in the first two months after a peak, since the technical forecasts are based on signals that recognize trends in equity prices. This trend-following behavior early in recessions apparently helps to generate the sizable out-of-sample gains during recessions for the MA and volume (momentum) forecasts based on large l (m) values in Tables I and II. The technical forecasts in Figure 8 tend to remain well below the historical average for too long after a peak, however.

Figures 9 and 10 depict estimates of the slope coefficients in (13) and (14) for the fundamental and technical forecasts, respectively. The first panel in each figure shows that the actual equity premium moves significantly above the historical average forecast in the fourth through second months before a cyclical trough, so that the equity premium is higher than usual in the late stages of recessions. Figure 9 indicates that many of the fundamental forecasts, particularly those based on valuation ratios (DP, DY, EP, and BM) and LTR, are also significantly higher than the historical average forecast in the fourth through second months before a trough. TMS, DFY, and POOL-ECON are also significantly above the historical average in the later stages of recessions, although by less than the previously mentioned fundamentals. The ability of many of the fundamental forecasts to match the higher-than-average equity premium late in recessions helps to account for the sizable out-of-sample gains during recessions for the fundamental forecasts in Tables I and II.

Figure 10 shows that the technical forecasts typically start low but rise quickly late in recessions, in contrast to the pattern in the actual equity premium. Only the MA(1,3) and MA(1,6) forecasts are above the historical average forecast in the second and third months prior to a business-cycle trough. The out-of-sample gains for the technical forecasts during recessions in Tables I and II thus occur despite the relatively poor performance of technical forecasts late in recessions. While the trend-following technical forecasts detect the decrease in the actual equity premium early in recessions (see Figure 8), they are less adept at recognizing the unusually high actual equity premium late in recessions. Note that the POOL-ALL forecast is significantly above the historical average forecast late in recessions, although the increase is small.

In summary, Figures 7–10 paint the following nuanced picture with respect to the sizable out-of-sample gains during recessions in Tables I and II. Economic fundamentals typically fail to detect the decline in the actual equity premium early in recessions, but generally do detect the increase in the actual equity premium late in recessions. Technical rules exhibit the opposite pattern: they pick up the decline in the actual premium early in recessions but fail to match the unusually high premium late in recessions. Although fundamental and technical forecasts both generate substantial out-of-sample gains during recessions, they capture different aspects of equity premium fluctuations during cyclical downturns. Together with the performance of the POOL-ALL forecast, this suggests that fundamental and technical analysis provide complementary approaches to out-of-sample equity premium predictability.

III. Accounting for Out-of-Sample Predictability

We next explore whether the well-known Campbell and Cochrane (1999) habit-formation model or Bansal and Yaron (2004) long-run risks model could produce the out-of-sample forecasting gains in Section II. These models link time-varying equilibrium expected returns to macroeconomic shocks. This makes them natural benchmarks in our context, since the out-of-sample gains in Section II vary systematically over the business cycle.

To examine whether these models can explain the predictive ability of economic fundamentals and technical rules, we simulate data from the habit-formation or long-run risks model, apply the out-of-sample tests from Section II to the simulated data, and compare the degree of predictability in the simulated and actual data. If the habit-formation or long-run risks model could produce the equity premium predictability in Section II through rational expected equity premium fluctuations, then empirical p -values computed from the simulated data for the R_{OS}^2 statistics and utility gains

in Tables I and II should be “large.”¹³

A. Habit-Formation Model

We briefly describe the habit-formation model; see Campbell and Cochrane (1999) and Wachter (2005) for details. The representative agent’s preferences over consumption (C_t) and an external (or exogenous) habit (X_t) give rise to the first-order Euler condition,

$$E_t(M_{t+1}R_{j,t+1}) = 1, \quad (15)$$

where $R_{j,t+1}$ is the gross return on asset j ,

$$M_{t+1} \equiv \delta \left(\frac{S_{t+1} C_{t+1}}{S_t C_t} \right)^{-\gamma} \quad (16)$$

is the intertemporal marginal rate of substitution (or stochastic discount factor), $\delta > 0$ ($\gamma > 0$) is the time-preference (utility-curvature) parameter, and S_t is surplus consumption,

$$S_t \equiv \frac{C_t - X_t}{C_t}, \quad (17)$$

which is related to the local curvature of the utility function (or risk aversion): $\eta_t \equiv \gamma/S_t$. Intuitively, a “small” S_t represents a “bad” state in which consumption is near habit. As S_t decreases and η_t increases, the representative investor becomes more risk averse.

The log of surplus consumption obeys the following heteroskedastic, autoregressive process:

$$s_{t+1} = (1 - \phi)\bar{s} + \phi s_t + \lambda(s_t)[\Delta c_{t+1} - E_t(\Delta c_{t+1})], \quad (18)$$

where $s_t \equiv \log(S_t)$, \bar{s} is the unconditional mean of s_t , ϕ is the persistence parameter for s_t , $\lambda(s_t)$ describes the sensitivity of log surplus consumption to consumption growth shocks, and $c_t \equiv \log(C_t)$. The sensitivity function is given by

$$\lambda(s_t) = (1/\bar{S})\sqrt{1 - 2(s_t - \bar{s})} - 1, \quad (19)$$

where $\bar{S} = \sigma_v \sqrt{\gamma/(1 - \phi)}$ and $\bar{s} = \log(\bar{S})$.¹⁴ The log of consumption follows a random walk with drift:

$$\Delta c_{t+1} = g + v_{t+1}, \quad (20)$$

¹³This approach is similar in spirit to Brock, Lakonishok, and LeBaron (1992), who calculate empirical p -values to examine whether GARCH processes can explain the profitability of technical strategies. Fama (1991) emphasizes that this type of exercise is a test of the joint null of market efficiency and a particular model of equilibrium expected returns, so that either the failure of market efficiency or an inadequate model of equilibrium expected returns could lead to a rejection of the joint null.

¹⁴Campbell and Cochrane (1999) select this specification so that the risk-free real interest rate is constant. They observe that the behavior of excess returns is not sensitive to this assumption. To ensure that (19) is positive, they also assume that $s_t < s_{\max}$, where $s_{\max} = \bar{s} + (1/2)(1 - \bar{S}^2)$.

where $\Delta c_{t+1} = c_{t+1} - c_t$ and $v_{t+1} \sim \text{i.i.d. } N(0, \sigma_v^2)$.

The aggregate stock market represents a claim to the future consumption stream. Let $R_{t+1} = (P_{t+1} + D_{t+1})/P_t$ denote the gross aggregate stock market return, where P_t is the stock price (excluding dividends) and D_t is the dividend. In this endowment economy, $C_t = D_t$ in equilibrium, so that P_t/C_t also represents the price-dividend ratio, P_t/D_t .¹⁵ Using $P_t/C_t = P_t/D_t$, $R_{j,t+1} = R_{t+1}$, and rewriting (15), we have

$$E_t \left[M_{t+1} \left(\frac{P_{t+1}}{D_{t+1}}(s_{t+1}) + 1 \right) \frac{C_{t+1}}{C_t} \right] = \frac{P_t}{D_t}(s_t), \quad (21)$$

where P_t/D_t is a function of s_t , the only state variable for the economy. A closed-form solution is not available for P_t/D_t ; we use the Wachter (2005) series method to numerically approximate this pricing function.¹⁶ Observe that P_t/D_t is monotonically increasing in s_t . Intuitively, a lower s_t value implies that consumption is closer to habit, making the representative investor more risk averse, so that lower stock prices (higher expected returns) are required for the investor to willingly hold risky stocks.

With assumed values for δ , γ , ϕ , g , and σ_v , we can simulate consumption, dividend, stock price, and equity premium data using the habit-formation model. When simulating data, we use the parameter values (reported in the notes to Table III) from Campbell and Cochrane (1999). They select these parameter values to match certain moments of U.S. postwar data and show that the habit-formation model reproduces key features of the data, including the “high” average equity premium and “low” risk-free rate. The habit-formation model generates two of the economic fundamentals considered in Section II, DP and DY, which happen to produce the largest out-of-sample gains among the economic fundamentals in Tables I and II.¹⁷ With respect to the technical forecasts, the simulated price data allow us to compute trading signals based on the MA and momentum rules (but not the volume-based rules).

We compute empirical p -values for the R_{OS}^2 statistics and average utility gains corresponding to the DP, DY, MA, and momentum forecasts in Tables I and II via the following steps:

1. Use the habit-formation model to generate a pseudo sample of 984 observations for consumption, dividends, stock prices, and the equity premium. This pseudo sample has the same length as the original sample (1927:01–2008:12).

¹⁵Campbell and Cochrane (1999) also consider a model where consumption and dividends are imperfectly correlated and find that stock returns behave very similarly to the $C_t = D_t$ case.

¹⁶Wachter (2005) finds that the series method provides a better approximation than the fixed-point method used by Campbell and Cochrane (1999).

¹⁷Wachter (2006) extends the habit-formation model by including multiple bonds to investigate term-structure implications of habit formation.

2. For the pseudo sample, construct pseudo out-of-sample equity premium forecasts based on DP, DY, MA(1, l), and MOM(m) ($l, m = 3, 6, 9, 12$), as well as the historical average, for the last 588 observations, matching the length of the forecast evaluation period in the original sample (1960:01–2008:12).
3. Compute R_{OS}^2 statistics and average utility gains for the pseudo DP, DY, MA, and momentum forecasts. In addition to computing R_{OS}^2 statistics and utility gains for the full forecast evaluation period of the pseudo sample, we compute these statistics for business-cycle expansions and contractions.¹⁸ For the simulated consumption data, we identify business-cycle peaks and troughs that define expansions and recessions using the Harding and Pagan (2002) modified Bry and Boschan (1971, BB) algorithm, which provides a good approximation to the NBER business-cycle dating methodology.¹⁹
4. Repeat steps 1–3 1,000 times, generating empirical distributions for the R_{OS}^2 statistics and average utility gains for the DP, DY, MA, and momentum forecasts for the full forecast evaluation period, expansions, and recessions.
5. For each statistic, the empirical p -value is the proportion of simulated statistics greater than the corresponding statistic in Table I or II computed using the original data.

The second through fourth columns of Table III report empirical p -values for the R_{OS}^2 statistics in Table I based on the habit-formation model. The empirical p -values in Table III, Panel A do not signal significance at conventional levels, so that the habit-formation model’s rational expected equity premium fluctuations can account for the out-of-sample predictive ability of DP and DY, as measured by R_{OS}^2 , in the actual data. In the habit-formation model, s_t declines—and risk aversion increases—over the course of a recession, thereby elevating the expected equity premium over recessions. This is consistent with the behavior of DP and DY near cyclical troughs in Figure 9, so that this mechanism appears capable of explaining the predictive power of DP and DY captured by R_{OS}^2 in the actual data. While the habit-formation model can account for the DP and DY R_{OS}^2 statistics in the actual data, a number of the empirical p -values in the second through fourth columns of Table III, Panel B indicate significance at conventional levels for the MA and momentum R_{OS}^2

¹⁸The process in (20) represents the evolution of the real economy in the habit-formation model. It is well known that such a process can generate business-cycle-like patterns, with peaks and troughs corresponding to similar turning points identified by the NBER.

¹⁹We implement the modified BB algorithm using James Engel’s MATLAB code downloaded from <http://www.ncer.edu.au/data/>.

statistics over the full out-of-sample period and recessions. Rational expected equity premium fluctuations from the habit-formation model thus cannot account for the predictive power of MA and momentum rules, as measured by R_{OS}^2 , in the actual data.

The eighth through tenth columns of Table III report empirical p -values generated from the habit-formation model corresponding to the average utility gains in Table II. The empirical p -values in Table III, Panel A point to significant utility gains for DP and DY over the full forecast evaluation period (p -values of 4.50% and 1.40%, respectively) and for DY during recessions (p -value of 8.70%). In interpreting these gains, keep in mind that the habit-formation model generates time variation in the expected equity premium in response to time-varying risk aversion on the part of the representative investor. When computing average utility gains, however, we consider an investor with a constant risk aversion coefficient of five. Our non-representative investor with constant risk aversion can thus exploit the Campbell and Cochrane (1999) representative investor's time-varying risk aversion by holding more stocks during periods when the equilibrium expected market return is elevated due to the representative investor's low habit/high risk aversion.²⁰ From this perspective, the significant empirical p -values represent significant utility gains beyond those exploitable by a non-representative investor resulting from time-varying risk aversion on the part of the representative investor. The empirical p -values in the eighth through tenth columns of Table III, Panel B reveal significant utility gains at the 1% level over the full out-of-sample period and recessions for MA and momentum forecasts based on $l, m = 6, 9, 12$. In summary, Table III indicates that the habit-formation model cannot fully account for the out-of-sample forecasting gains offered by economic fundamentals and, especially, technical rules.

B. Long-Run Risks Model

Turning to the long-run risks model, we again briefly describe the model; Bansal and Yaron (2004) and Bansal, Kiku, and Yaron (2009) provide the details. The representative agent has Epstein and Zin (1989) and Weil (1989) recursive preferences, so that the intertemporal marginal rate of substitution in (15) becomes

$$M_{t+1} \equiv \delta^\theta (C_{t+1}/C_t)^{-\theta/\psi} R_{c,t+1}^{-(1-\theta)} R_{j,t+1}, \quad (22)$$

where γ is the risk-aversion parameter, ψ is the intertemporal elasticity of substitution, $\theta \equiv (1 - \gamma)/[1 - (1/\psi)]$, and $R_{c,t+1}$ is the gross return on an asset that pays aggregate consumption as its

²⁰This brings to mind the well-known Warren Buffett quote: "We simply attempt to be fearful when others are greedy and to be greedy only when others are fearful."

dividend each period. The following processes govern consumption and the dividend paid on the market portfolio:

$$\Delta c_{t+1} = \mu_c + x_t + \sigma_t \eta_{t+1}, \quad (23)$$

$$x_{t+1} = \rho x_t + \varphi_e \sigma_t e_{t+1}, \quad (24)$$

$$\sigma_{t+1}^2 = \bar{\sigma}^2 + \nu(\sigma_t^2 - \bar{\sigma}^2) + \sigma_w w_{t+1}, \quad (25)$$

$$\Delta d_{t+1} = \mu_d + \phi x_t + \pi \sigma_t \eta_{t+1} + \varphi_d \sigma_t u_{t+1}, \quad (26)$$

where $d_t \equiv \log(D_t)$; D_t is the dividend paid on the market portfolio; and η_{t+1} , e_{t+1} , w_{t+1} , and u_{t+1} are contemporaneously uncorrelated i.i.d. $N(0, 1)$ shocks. The variable x_{t+1} is the predictable component of consumption growth, while σ_{t+1}^2 represents time-varying consumption risk. Bansal, Kiku, and Yaron (2009) add the $\pi \sigma_t^2 \eta_{t+1}$ term in (26) to the original Bansal and Yaron (2004) specification to allow for an additional source of aggregate market risk. Bansal and Yaron (2004) show that σ_t^2 generates variability in the expected equity premium.

We follow Bansal, Kiku, and Yaron (2009) in analytically approximating the solution to the long-run risks model. The familiar Campbell and Shiller (1988a) log-linear approximation measures the return on the aggregate market portfolio:

$$r_{m,t+1} = \kappa_{0,m} + \kappa_{1,m} z_{m,t+1} - z_{m,t} + \Delta d_{t+1}, \quad (27)$$

where $z_{m,t} = \log(P_t/D_t)$ and $\kappa_{0,m}$ and $\kappa_{1,m}$ are log-linearization constants that are computed as part of the model solution based on the steady-state value of $z_{m,t}$. The relevant state variables are x_t and σ_t^2 , so that the solution for $z_{m,t}$ takes the form,

$$z_{m,t} = A_{0,m} + A_{1,m} x_t + A_{2,m} \sigma_t^2, \quad (28)$$

where $A_{0,m}$, $A_{1,m}$, and $A_{2,m}$ are functions of the preference and technology parameters (see (12) in the appendix to Bansal, Kiku, and Yaron (2009) for the exact expressions). Armed with (23)–(26) and (28), we can simulate consumption, dividend, stock price, and equity premium data using the long-run risks model and preference and technology parameter values from Table I in Bansal, Kiku, and Yaron (2009). These parameter values (reported in the notes to Table III) are calibrated from particular moments in U.S. data and enable the long-run risks model to account for the U.S. equity premium and risk-free rate puzzles. We generate empirical p -values based on the long-run risks model in a manner analogous to the procedure described for the habit-formation model.

Empirical p -values corresponding to the R_{OS}^2 statistics in Table I based on the long-run risks model are given in the fifth through seventh columns of Table III. Panel A of Table III indicates

that the long-run risks model cannot account for the out-of-sample predictive ability of DP and DY, as measured by R_{OS}^2 , for the full out-of-sample period and recessions, with empirical p -values of 2.60% and 1.60% (3.00% and 6.90%) for DP (DY) during the full period and recessions, respectively. Furthermore, Table III, Panel B demonstrates that the long-run risks model fails to explain the predictive ability of a number of the technical rules as captured by R_{OS}^2 , particularly during recessions, where five of the empirical p -values in the seventh column are close to or less than 1%. The empirical p -values in the final three columns of Table III clearly show that the long-run risks model also cannot account for the out-of-sample equity premium predictability revealed by the average utility gains in Table II: a number of the empirical p -values are very near or equal to 0% for both economic fundamentals and technical rules during the full forecast evaluation period and recessions.

Overall, Table III points to the inability of the habit-formation and long-run risk models to explain much of the out-of-sample equity premium predictability in the actual data. While the habit-formation model accounts for the predictive ability of DP and DY, as measured by R_{OS}^2 , it cannot account for the predictive power indicated by R_{OS}^2 for MA and momentum rules for the full out-of-sample period and recessions. Moreover, the habit-formation model cannot explain the average utility gains produced by economic fundamentals and technical rules during the full forecast evaluation period and recessions. The long-run risks model generally fails to explain the predictive ability of either economic fundamentals or technical rules, particularly during recessions.

IV. Conclusion

Fundamental and technical analysis are conceptually quite different methods of predicting aggregate stock returns. Researchers have long studied both approaches, but the two literatures have evolved largely independently; there has been little attempt to directly compare fundamental analysis with technical analysis. This paper fills this gap by comparing monthly out-of-sample forecasts of the U.S. equity premium for 1960–2008 generated with well-known economic fundamentals and popular trend-following technical rules. We analyze equity premium forecasts using two out-of-sample metrics: (i) the Campbell and Thompson (2008) R_{OS}^2 statistic and (ii) the average utility gain for a mean-variance investor who optimally reallocates a monthly portfolio between equities and risk-free Treasury bills using equity premium forecasts based on either economic fundamentals or technical rules relative to the historical average benchmark forecast.

Both economic fundamentals and technical rules produce economically and statistically signif-

icant out-of-sample forecasting gains; moreover, these gains are highly concentrated in business-cycle recessions. While both approaches perform disproportionately well during recessions, a careful analysis of their performance during cyclical downturns reveals that they exploit very different patterns: technical rules recognize the typical drop in the equity premium near business-cycle peaks; economic fundamentals identify the typical increase in the equity premium near business-cycle troughs. Thus, we find that fundamental and technical analysis both significantly forecast returns and represent complementary approaches. Furthermore, we show that pooling information from both economic fundamentals and technical rules can produce additional out-of-sample forecasting gains.

We also simulate data from the Campbell and Cochrane (1999) habit-formation and Bansal and Yaron (2004) long-run risks models—two leading frameworks linking macroeconomic shocks to rational time variation in the expected equity premium—to study whether these models can explain the out-of-sample forecasting ability of economic fundamentals and technical rules. Empirical p -values generated under the habit-formation and long-run risk models indicate that these models fail to account for much of the forecasting gains in the actual data. We cannot, of course, exclude the possibility that other models with a rational time-varying expected equity premium may better explain the predictability in the data; see, for example, Bekaert, Engstrom, and Xing (2009) and Bollerslev, Tauchen, and Zhou (2009), who extend the habit-formation and/or long-run risks models along various dimensions. Behavioral influences also potentially play a key role in explaining equity premium predictability over the business cycle. We deem the identification of theoretical models capable of explaining the out-of-sample predictive ability of economic fundamentals and technical rules in the data an especially important area for future research.

Appendix: Wild Fixed-Regressor Bootstrap

This appendix outlines the wild fixed-regressor bootstrap used to calculate the p -value for the Hansen (2005) studentized maximum statistic in our reality check. We first estimate the constant expected equity premium (random walk with drift) model, corresponding to the null of no predictability: $\bar{r} = \sum_{t=1}^T r_t$. We next estimate an unrestricted model that includes all of the potential predictors as regressors using OLS; denote the OLS residuals from this model as $\{\hat{u}_t\}_{t=1}^T$. We then generate a pseudo sample of equity premium observations under the null of no predictability as $r_{t,b} = \bar{r} + v_{t,b}\hat{u}_t$ for $t = 1, \dots, T$, where $v_{t,b}$ is a draw from an i.i.d. $N(0, 1)$ process. Generating residual draws in this manner allows for conditional heteroskedasticity and makes this a “wild” bootstrap. Denote the pseudo sample of equity premium observations as $\{r_{t,b}\}_{t=1}^T$. We compute fundamental, technical, and pooled forecasts for the last q_2 simulated equity premium observations using $\{r_t^b\}_{t=1}^T$ in conjunction with the economic fundamentals and technical trading signals from the original sample. Using fundamentals and signals from the original sample makes this a “fixed-regressor” bootstrap. Based on $\{r_{t,b}\}_{t=q_1+1}^T$ and the simulated forecasts, we compute the studentized maximum statistic for the pseudo sample, $\tau_{\max,b}$. Generating $B = 1,000$ pseudo samples in this manner yields an empirical distribution of studentized maximum statistics, $\{\tau_{\max,b}\}_{b=1}^B$. The bootstrapped p -value is given by $B^{-1} \sum_{b=1}^B I_b$, where $I_b = 1$ for $\tau_{\max,b} \geq \tau_{\max}$ and zero otherwise and τ_{\max} is the studentized maximum statistic from the original sample (see footnote 11).

References

- Ang, Andrew, and Geert Bekaert, 2007, Return predictability: is it there? *Review of Financial Studies* 20, 651–707.
- Baker, Malcolm, and Jeffrey Wurgler, 2000, The equity share in new issues and aggregate stock returns, *Journal of Finance* 55, 2219–2257.
- Bansal, Ravi, Dana Kiku, and Amir Yaron, 2009, An empirical evaluation of the long-run risk model for asset prices, manuscript, Duke University.
- Bansal, Ravi, and Amir Yaron, 2004, Risks for the long run: A potential resolution of asset pricing puzzles, *Journal of Finance* 59, 1481–1590.
- Bekaert, Geert, Eric Engstrom, and Yuhang Xing, 2009, Risk, uncertainty, and asset prices, *Journal of Financial Economics* 91, 59–82.
- Bollerslev, Tim, George Tauchen, and Hao Zhou, 2009, Expected stock returns and variance risk premia, *Review of Financial Studies* 22, 4463–4492.
- Boudoukh, Jacob, Roni Michaely, Matthew P. Richardson, and Michael R. Roberts, 2007, On the importance of measuring payout yield: Implications for empirical asset pricing, *Journal of Finance* 62, 877–915.
- Breen, William, Lawrence R. Glosten, and Ravi Jagannathan, 1989, Economic significance of predictable variations in stock index returns, *Journal of Finance* 64, 1177–1189.
- Bry, Gerhard, and Charlotte Boschan, 1971, *Cyclical Analysis of Time Series: Selected Procedures and Computer Programs* (NBER, New York).
- Brock, William, Josef Lakonishok, and Blake LeBaron, 1992, Simple technical trading rules and the stochastic properties of stock returns, *Journal of Finance* 47, 1731–1764.
- Campbell, John Y., 1987, Stock returns and the term structure, *Journal of Financial Economics* 18, 373–399.
- Campbell, John Y., and John H. Cochrane, 1999, By force of habit: A consumption-based explanation of aggregate stock market behavior, *Journal of Political Economy* 107, 205–251.
- Campbell, John Y., and Robert J. Shiller, 1988a, The dividend-price ratio and expectations of future dividends and discount factors, *Review of Financial Studies* 1, 195–228.
- Campbell, John Y., and Robert J. Shiller, 1988b, Stock prices, earnings, and expected dividends, *Journal of Finance* 43, 661–676.
- Campbell, John Y., and Samuel B. Thompson, 2008, Predicting excess stock returns out of sample: Can anything beat the historical average? *Review of Financial Studies* 21, 1509–1531.

- Campbell, John Y., and Tuomo Vuolteenaho, 2004, Inflation illusion and stock prices, *American Economic Review* 94, 19–23.
- Clark, Todd E., and Michael W. McCracken, 2001, Tests of equal forecast accuracy and encompassing for nested models, *Journal of Econometrics* 105, 85–110.
- Clark, Todd E., and Michael W. McCracken, 2009, Improving forecast accuracy by combining recursive and rolling forecasts, *International Economic Review* 50, 363–395.
- Clark, Todd E., and Michael W. McCracken, 2010, Reality checks and nested forecast model comparisons, manuscript, Federal Reserve Bank of Kansas City.
- Clark, Todd E., and Kenneth D. West, 2007, Approximately normal tests for equal predictive accuracy in nested models, *Journal of Econometrics* 138, 291–311.
- Cochrane, John H., 2008, The dog that did not bark: A defense of return predictability, *Review of Financial Studies* 21, 1533–1575.
- Covel, Michael W., 2005, *Trend Following: How Great Traders Make Millions in Up or Down Markets* (Prentice-Hall, New York).
- Cowles, Alfred, 1933, Can stock market forecasters forecast? *Econometrica* 1, 309–324.
- Diebold, Francis X., and Robert S. Mariano, 1995, Comparing predictive accuracy, *Journal of Business and Economic Statistics* 13, 253–263.
- Epstein, Lawrence, and Stanley Zin, 1989, Substitution, risk aversion and the temporal behavior of consumption and asset returns: A theoretical framework, *Econometrica* 57, 937–969.
- Fama, Eugene F., 1991, Efficient capital markets: II, *Journal of Finance* 46, 1575–1617.
- Fama, Eugene F., and Marshall E. Blume. 1966. Filter rules and stock market trading, *Journal of Business* 39, 226–41.
- Fama, Eugene F., and Kenneth R. French, 1988, Dividend yields and expected stock returns, *Journal of Financial Economics* 22, 3–25.
- Fama, Eugene F., and Kenneth R. French, 1989, Business conditions and expected returns on stocks and bonds, *Journal of Financial Economics* 25, 23–49.
- Fama, Eugene F., and G. William Schwert, 1977, Asset returns and inflation, *Journal of Financial Economics* 5, 115–146.
- Person, Wayne E., and Campbell R. Harvey, 1991, The variation of equity risk premiums, *Journal of Political Economy* 99, 385–415.
- French, Kenneth R., G. William Schwert, and Robert F. Stambaugh, 1987, Expected stock returns and volatility, *Journal of Financial Economics* 19, 3–29.

- Geweke, John, and Gianni Amisano, 2009, Optimal prediction pools, European Central Bank Working Paper No. 1017.
- Goyal, Amit, and Ivo Welch, 2008, A comprehensive look at the empirical performance of equity premium prediction, *Review of Financial Studies* 21, 1455–1508.
- Granville, Joseph, 1963, *Granville's New Key to Stock Market Profits* (Prentice Hall, Englewood Cliffs, N.J.).
- Guo, Hui, 2006, On the out-of-sample predictability of stock market returns, *Journal of Business* 79, 645–670.
- Hansen, Peter R., 2005, A test for superior predictive ability, *Journal of Business and Economic Statistics* 23, 365–380.
- Harding, Don, and Adrian Pagan, 2002, Dissecting the cycle: A methodological investigation, *Journal of Monetary Economics* 49, 365–381.
- Harvey, Campbell R., 2001, The specification of conditional expectations, *Journal of Empirical Finance* 8, 573–637.
- Henkel, Sam James, J. Spencer Martin, and Frederico Nadari, 2009, Time-varying short-horizon predictability, *Journal of Financial Economics*, forthcoming.
- Hong, Harrison, and Jeremy C. Stein, 1999, A unified theory of underreaction, momentum trading and overreaction in asset markets, *Journal of Finance* 54, 2143–2184.
- Hong, Harrison, Terence Lim, and Jeremy C. Stein, 2000, Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies, *Journal of Finance* 55, 265–295.
- Jensen, Michel C., and George A. Benington, 1970, Random walks and technical theories: Some additional evidence, *Journal of Finance* 25, 469–482.
- Kandel, Shmuel, and Robert F. Stambaugh, 1996, On the predictability of stock returns: An asset allocation perspective, *Journal of Finance* 51, 385–424.
- Keim, Donald B., and Robert F. Stambaugh, 1986, Predicting returns in the stock and bond markets, *Journal of Financial Economics* 17, 357–390.
- Lettau, Martin, and Sydney C. Ludvigson, 2001, Consumption, aggregate wealth, and expected stock returns, *Journal of Finance* 56, 815–849.
- Lettau, Martin, and Sydney C. Ludvigson, 2009, Measuring and modeling variation in the risk-return tradeoff, in Yacine Aït-Sahalia and Lars P. Hansen, eds., *Handbook of Financial Econometrics* (Elsevier, Amsterdam).
- Lo, Andrew W., Harry Mamaysky, and Jiang Wang, 2000, Foundations of technical analysis: Com-

- putational algorithms, statistical inference, and empirical implementation, *Journal of Finance* 55, 1705–1065.
- Ludvigson, Sydney C., and Serena Ng, 2007, The empirical risk-return relation: A factor analysis approach, *Journal of Financial Economics* 83, 171–222.
- Lundblad, Christian, 2007, The risk return tradeoff in the long run: 1836–2003, *Journal of Financial Economics* 85, 123–150.
- Mamaysky, Harry, Matthew Spiegel, and Hong Zhang, 2007, Improved forecasting of mutual fund alphas and betas, *Review of Finance* 11, 359–400.
- Mamaysky, Harry, Matthew Spiegel, and Hong Zhang, 2008, Estimating the dynamics of mutual fund alphas and betas, *Review of Financial Studies* 21, 233–264.
- Marquering, Wessel, and Marno Verbeek, 2004, The economic value of predicting stock index returns and volatility, *Journal of Financial and Quantitative Analysis* 39, 407–429.
- McCracken, Michael W., 2007, Asymptotics for out of sample tests of Granger causality, *Journal of Econometrics* 140, 719–752.
- Nelson, Charles R., 1976, Inflation and the rates of return on common stock, *Journal of Finance* 31, 471–483.
- Nison, Steve, 1991, *Japanese Candlestick Charting Techniques: A Contemporary Guide to the Ancient Investment Techniques of the Far East* (Simon & Schuster, New York).
- Odean, Terrance, 1998, Are investors reluctant to realize their losses? *Journal of Finance* 53, 1775–1798.
- Park, Cheol-Ho, and Scott H. Irwin, 2007, What do we know about the profitability of technical analysis? *Journal of Economic Surveys* 21, 786–826.
- Pástor, Ľuboš, and Robert F. Stambaugh, 2009, Predictive systems: Living with imperfect predictors, *Journal of Finance* 64, 1583–1628.
- Pesaran, M. Hashem, and Allan Timmermann, 2007, Selection of estimation window in the presence of breaks, *Journal of Econometrics* 137, 134–161.
- Rapach, David E., Jack K. Strauss, and Guofu Zhou, 2010, Out-of-sample equity premium prediction: Combination forecasts and links to the real economy, *Review of Financial Studies* 23, 821–862.
- Rozeff, Michael S., 1984, Dividend yields are equity risk premiums, *Journal of Portfolio Management* 11, 68–75.
- Schwager, Jack D., 1993, *Market Wizards: Interviews with Top Traders* (Harper-Collins, New

- York).
- Schwager, Jack D., 1995, *The New Market Wizards: Conversations with America's Top Traders* (Wiley, New York).
- Schwert, G. William, 1989, Why does stock market volatility change over time? *Journal of Finance* 44, 1115–1153.
- Schwert, G. William, 1990, Stock volatility and the crash of '87, *Review of Financial Studies* 3, 77–102.
- Sullivan, Ryan, Allan Timmermann, and Halbert White, 1999, Data-snooping, technical trading rule performance, and the bootstrap, *Journal of Finance* 54, 1647–1691.
- Timmermann, Allan, 2006, Forecast combinations, in Graham Elliott, Clive W.J. Granger, and Allan Timmermann, eds., *Handbook of Economic Forecasting* (Elsevier, Amsterdam).
- Timmermann, Allan, 2008, Elusive return predictability, *International Journal of Forecasting* 24, 1–18.
- Wachter, Jessica A., 2005, Solving models with external habit, *Finance Research Letters* 2, 210–226.
- Wachter, Jessica A., 2006, A consumption-based model of the term structure of interest rates, *Journal of Financial Economics* 79, 365–399.
- Weil, Philippe, 1989, The equity premium puzzle and the risk-free rate puzzle, *Journal of Monetary Economics* 24, 401–421.
- West, Kenneth D., 1996, Asymptotic inference about predictive ability, *Econometrica* 64, 1067–1084.
- White, Halbert, 2000, A reality check for data snooping, *Econometrica* 68, 1097–1126.
- Whitelaw, Robert F., 1994, Time variations and covariations in the expectation and volatility of stock market returns, *Journal of Finance* 49, 515–541.
- Xu, Yexiao, 2004, Small levels of predictability and large economic gains, *Journal of Empirical Finance* 11, 247–275.
- Zhu, Yingzi, and Guofu Zhou, 2009, Technical analysis: An asset allocation perspective on the use of moving averages, *Journal of Financial Economics* 92, 519–544.

Table I
Out-of-sample equity premium forecasting results, 1960:01–2008:12

R_{OS}^2 is the Campbell and Thompson (2008) out-of-sample R^2 statistic, which measures the percent reduction in mean square prediction error (MSPE) for the forecast given in the first column relative to the historical average benchmark forecast. POOL-ECON (POOL-TECH) is a pooled forecast based on the individual fundamental (technical) forecasts in Panel A (Panel B); POOL-ALL is a pooled forecast based on the individual fundamental and technical forecasts. The R_{OS}^2 statistics and average forecasts are computed for the entire 1960:01–2008:12 forecast evaluation period (second and third columns) and separately for NBER-dated business-cycle expansions (fourth and fifth columns) and recessions (sixth and seventh columns). Average forecast is the average predicted equity premium during the indicated period. Statistical significance of R_{OS}^2 is assessed with the Clark and West (2007) *MSPE-adjusted* statistic corresponding to the null hypothesis of equal MSPE against the alternative hypothesis that the forecast indicated in the first column has a lower MSPE than the historical average benchmark forecast; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Predictor	Overall		Expansion		Recession	
	R_{OS}^2 (%)	Average forecast (%)	R_{OS}^2 (%)	Average forecast (%)	R_{OS}^2 (%)	Average forecast (%)
Panel A: Fundamental forecasts						
DP	0.73***	0.25	0.15**	0.21	2.15**	0.52
DY	0.71***	0.22	-0.26	0.17	3.09**	0.48
EP	-0.19	0.49	-0.15	0.44	-0.28	0.78
DE	-0.76	0.79	-0.80	0.80	-0.65	0.75
SVAR	-0.56	0.67	-0.60	0.67	-0.48	0.68
BM	-1.64	0.50	-1.57	0.41	-1.79	1.02
NTIS	-1.75	0.98	-0.34	0.96	-5.20	1.11
TBL	0.31*	0.38	0.11*	0.40	0.80	0.28
LTY	0.42**	0.30	0.25**	0.32	0.85	0.21
LTR	0.33*	0.77	-0.88	0.76	3.30***	0.83
TMS	0.14	0.81	-0.62	0.84	2.00**	0.65
DFY	0.39*	0.64	0.33*	0.62	0.55	0.78
DFR	0.22	0.71	0.04	0.71	0.65	0.67
INFL	0.18	0.64	0.20	0.67	0.14	0.50
Panel B: Technical forecasts						
MA(1,3)	-0.58	0.69	-1.09	0.70	0.67	0.61
MA(1,6)	-0.68	0.70	-2.16	0.76	2.94**	0.34
MA(1,9)	0.08	0.69	-0.98	0.74	2.68**	0.38
MA(1,12)	0.78**	0.71	0.04	0.78	2.59**	0.33
MOM(3)	-0.12	0.69	-0.25	0.69	0.20	0.66
MOM(6)	0.18	0.69	-0.48	0.74	1.79**	0.43
MOM(9)	0.18*	0.73	-0.57	0.81	2.02*	0.23
MOM(12)	0.26	0.71	-0.26	0.77	1.53*	0.41
VOL(1,3)	-0.38	0.66	-1.07	0.68	1.31*	0.57
VOL(1,6)	-0.29	0.66	-1.02	0.68	1.50*	0.52
VOL(1,9)	0.14	0.67	-0.78	0.71	2.40**	0.42
VOL(1,12)	0.42	0.65	-0.55	0.71	2.82**	0.32
Panel C: Pooled forecasts						
POOL-ECON	0.80***	0.58	0.72**	0.57	1.01**	0.66
POOL-TECH	0.22	0.69	-0.52	0.73	2.02**	0.44
POOL-ALL	0.89***	0.63	0.27	0.63	2.40***	0.59

Table II
Asset-allocation results, 1960:01–2008:12

Average utility gain (Δ) is the portfolio management fee (in annualized percent return) that an investor with mean-variance preferences and risk aversion coefficient of five would be willing to pay to have access to the forecast given in the first column relative to the historical average benchmark forecast. POOL-ECON (POOL-TECH) is a pooled forecast based on the individual fundamental (technical) forecasts in Panel A (Panel B); POOL-ALL is a pooled forecast based on the individual fundamental and technical forecasts. The utility gains and average equity weights are computed for the entire 1960:01–2008:12 forecast evaluation period (second and third columns) and separately for NBER-dated business-cycle expansions (fourth and fifth columns) and recessions (sixth and seventh columns). Average equity weight is the average value during the indicated period.

Predictor	Overall		Expansion		Recession	
	Δ (ann. %)	Average equity weight	Δ (ann. %)	Average equity weight	Δ (ann. %)	Average equity weight
Panel A: Fundamental forecasts						
DP	1.44	0.28	0.12	0.22	8.76	0.62
DY	1.82	0.22	-0.17	0.17	13.02	0.55
EP	1.23	0.53	0.76	0.48	3.71	0.81
DE	-0.53	0.98	-0.27	0.98	-1.98	0.96
SVAR	-0.31	0.88	-0.25	0.88	-0.66	0.88
BM	-0.40	0.48	-0.94	0.41	2.37	0.87
NTIS	-0.49	1.06	0.47	1.05	-5.97	1.12
TBL	1.65	0.53	0.71	0.55	6.92	0.40
LTY	1.63	0.42	0.82	0.44	6.22	0.30
LTR	0.68	0.94	-0.56	0.94	7.50	0.95
TMS	1.21	0.97	0.12	1.00	7.27	0.79
DFY	0.43	0.82	0.20	0.80	1.61	0.96
DFR	0.92	0.91	0.09	0.92	5.60	0.85
INFL	0.68	0.85	0.22	0.87	3.33	0.68
Panel B: Technical forecasts						
MA(1,3)	0.19	0.86	-0.34	0.88	3.18	0.78
MA(1,6)	1.68	0.80	-0.48	0.87	13.90	0.43
MA(1,9)	2.06	0.84	0.05	0.90	13.39	0.48
MA(1,12)	3.07	0.86	0.97	0.94	14.97	0.40
MOM(3)	-0.07	0.89	-0.22	0.89	0.81	0.86
MOM(6)	1.73	0.87	0.27	0.92	10.05	0.56
MOM(9)	3.01	0.84	1.00	0.94	14.47	0.27
MOM(12)	1.93	0.88	0.48	0.95	10.23	0.53
VOL(1,3)	0.62	0.86	-0.31	0.88	5.81	0.75
VOL(1,6)	0.78	0.85	-0.34	0.88	7.11	0.69
VOL(1,9)	1.66	0.85	-0.37	0.90	13.17	0.55
VOL(1,12)	2.50	0.84	-0.07	0.91	17.10	0.44
Panel C: Pooled forecasts						
POOL-ECON	1.08	0.76	0.97	0.74	1.66	0.85
POOL-TECH	1.61	0.87	0.12	0.92	10.06	0.58
POOL-ALL	1.97	0.81	0.63	0.83	9.50	0.75

Table III
Empirical p -values (in percent) based on simulated data
from habit-formation and long-run risks models

The table reports empirical p -values computed from 1,000 pseudo samples generated using either the Campbell and Cochrane (1999) habit-formation or Bansal and Yaron (2004) long-run risks model. The empirical p -values are the percent of simulated R_{OS}^2 statistics and average utility gains greater than the corresponding values from Tables I and II. The habit-formation model uses the following parameter values: $\delta = 0.89^{1/12}$, $\gamma = 2$, $\phi = 0.86^{1/12}$, $g = 0.0189/12$, $\sigma_v = 0.0150/\sqrt{12}$. The long-run risks model uses the following parameter values: $\delta = 0.9989$, $\gamma = 10$, $\psi = 1.5$, $\mu_c = 0.0015$, $\rho = 0.975$, $\varphi_e = 0.038$, $\bar{\sigma} = 0.0072$, $\nu = 0.999$, $\sigma_w = 0.0000028$, $\mu_d = 0.0015$, $\phi = 2.5$, $\varphi_d = 5.96$, $\pi = 2.6$. ALL, EXP, and REC refer to R_{OS}^2 statistics and average utility gains computing for the full sample, expansions, and recessions, respectively.

Predictor	R_{OS}^2						Average utility gain					
	Habit-formation model			Long-run risks model			Habit-formation model			Long-run risks model		
	ALL	EXP	REC	ALL	EXP	REC	ALL	EXP	REC	ALL	EXP	REC
Panel A: Economic forecasts												
DP	52.20	92.00	19.20	2.60	34.90	1.60	4.50	62.00	13.40	0.00	24.90	0.00
DY	50.60	93.10	18.80	3.00	50.30	6.90	1.40	64.30	8.70	0.00	33.30	0.10
Panel B: Technical forecasts												
MA(1,3)	94.20	97.60	19.20	94.10	97.50	7.00	13.20	72.10	9.00	10.40	72.70	0.60
MA(1,6)	95.70	99.90	1.30	95.70	99.80	0.20	0.40	84.70	0.00	0.00	83.80	0.00
MA(1,9)	10.70	97.50	2.80	12.90	97.60	0.10	0.00	18.50	0.00	0.00	20.60	0.00
MA(1,12)	0.30	17.80	3.20	0.20	20.80	0.20	0.00	0.60	0.20	0.00	0.90	0.00
MOM(3)	36.20	61.30	37.30	39.60	66.10	22.60	38.20	58.70	35.80	31.30	57.70	11.40
MOM(6)	7.80	86.50	5.50	8.20	87.70	0.90	0.10	6.30	0.50	0.00	8.30	0.00
MOM(9)	6.80	90.30	6.00	8.30	91.70	1.30	0.00	0.40	0.20	0.00	1.30	0.00
MOM(12)	3.70	57.70	10.90	4.00	65.40	2.40	0.10	2.40	0.60	0.00	3.10	0.10

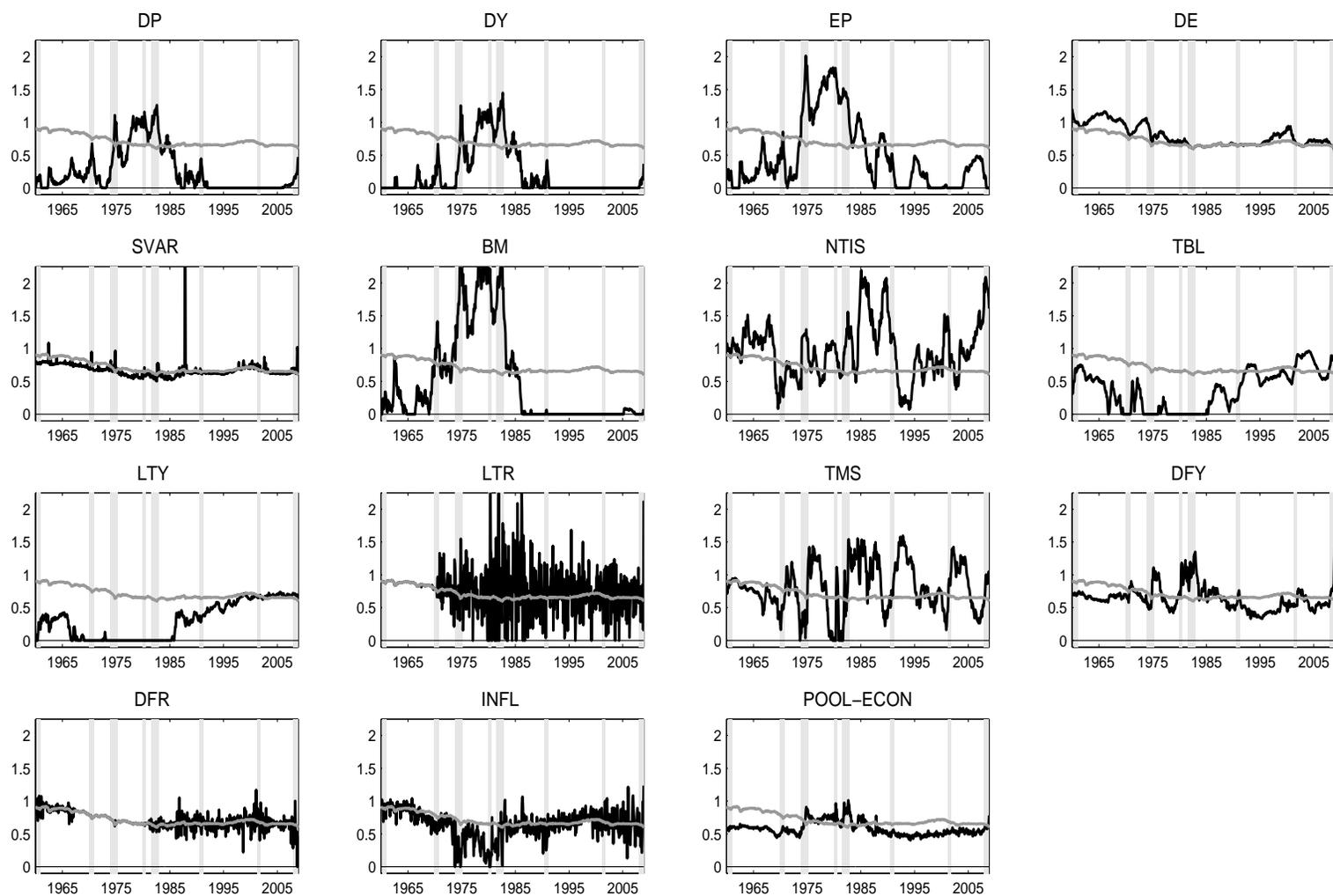


Figure 1. Out-of-sample equity premium forecasts based on economic fundamentals, 1960:01–2008:12. Black and gray lines delineate equity premium forecasts (in percent) based on the economic fundamental given in the panel heading and the historical average, respectively. POOL-ECON is a pooled forecast based on the individual fundamental forecasts. Vertical bars depict NBER-dated business-cycle recessions.

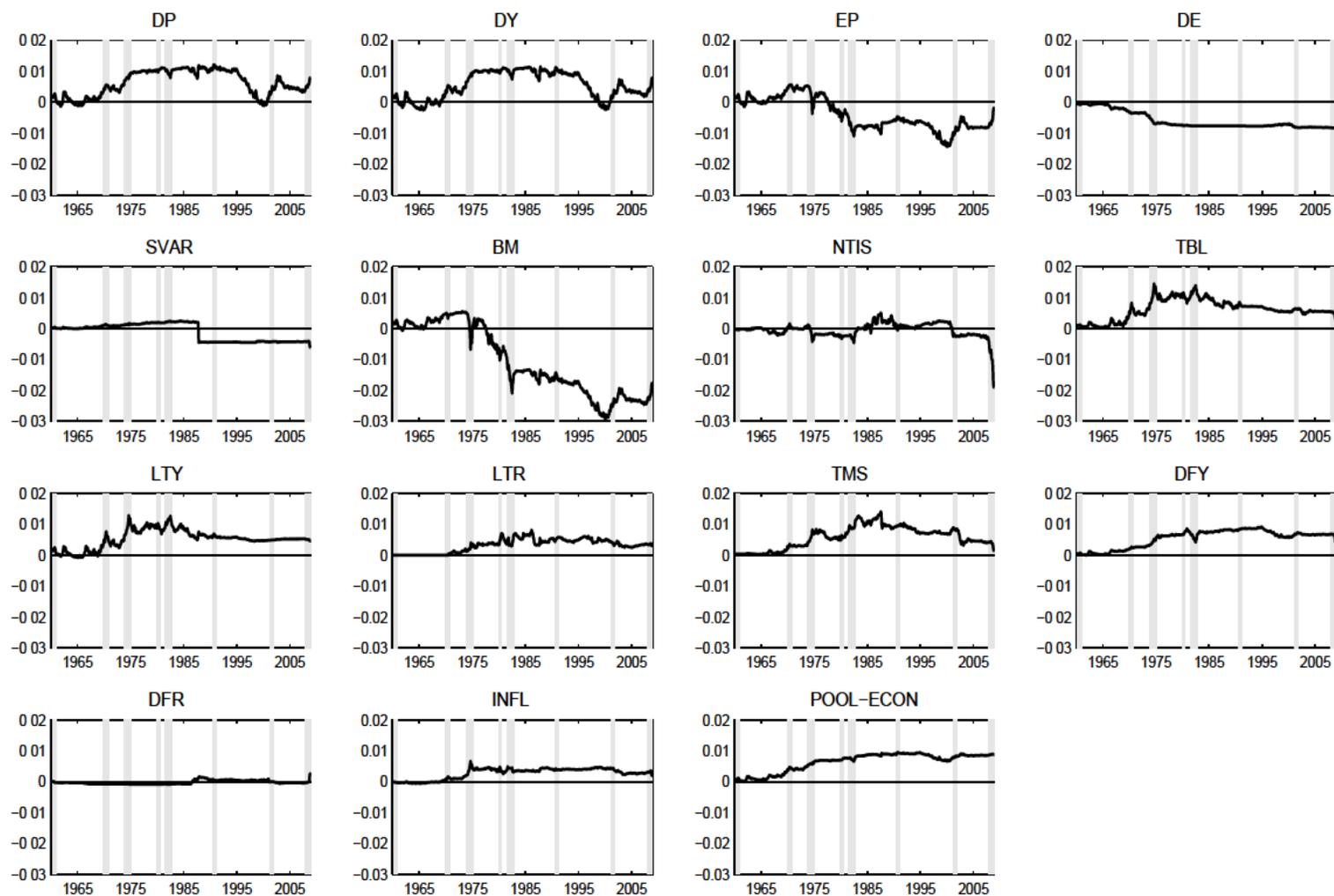


Figure 2. Cumulative square prediction error differences, out-of-sample equity premium forecasts based on the historical average and economic fundamentals, 1960:01–2008:12. The figure depicts cumulative differences between the mean square prediction errors for the historical average equity premium forecast and the equity premium forecast based on the economic fundamental indicated in the panel heading. POOL-ECON is a pooled forecast based on the individual fundamental forecasts. Vertical bars depict NBER-dated business-cycle recessions.

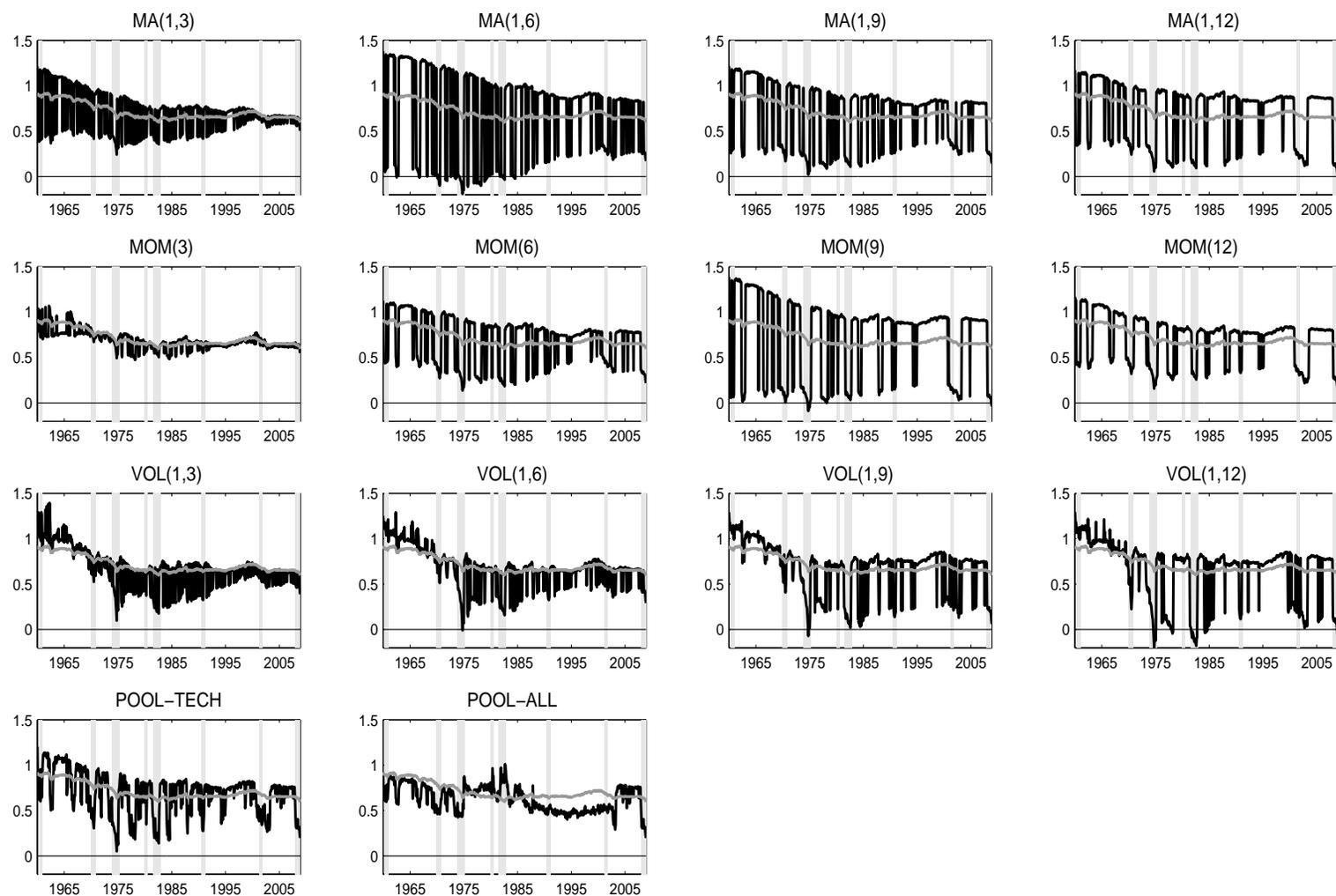


Figure 3. Out-of-sample equity premium forecasts based on technical rules, 1960:01–2008:12. Black and gray lines delineate equity premium forecasts (in percent) based on the technical rule given in the panel heading and the historical average, respectively. POOL-TECH is a pooled forecast based on the individual technical forecasts. POOL-ALL is a pooled forecast based on the individual fundamental and technical forecasts. Vertical bars depict NBER-dated business-cycle recessions.

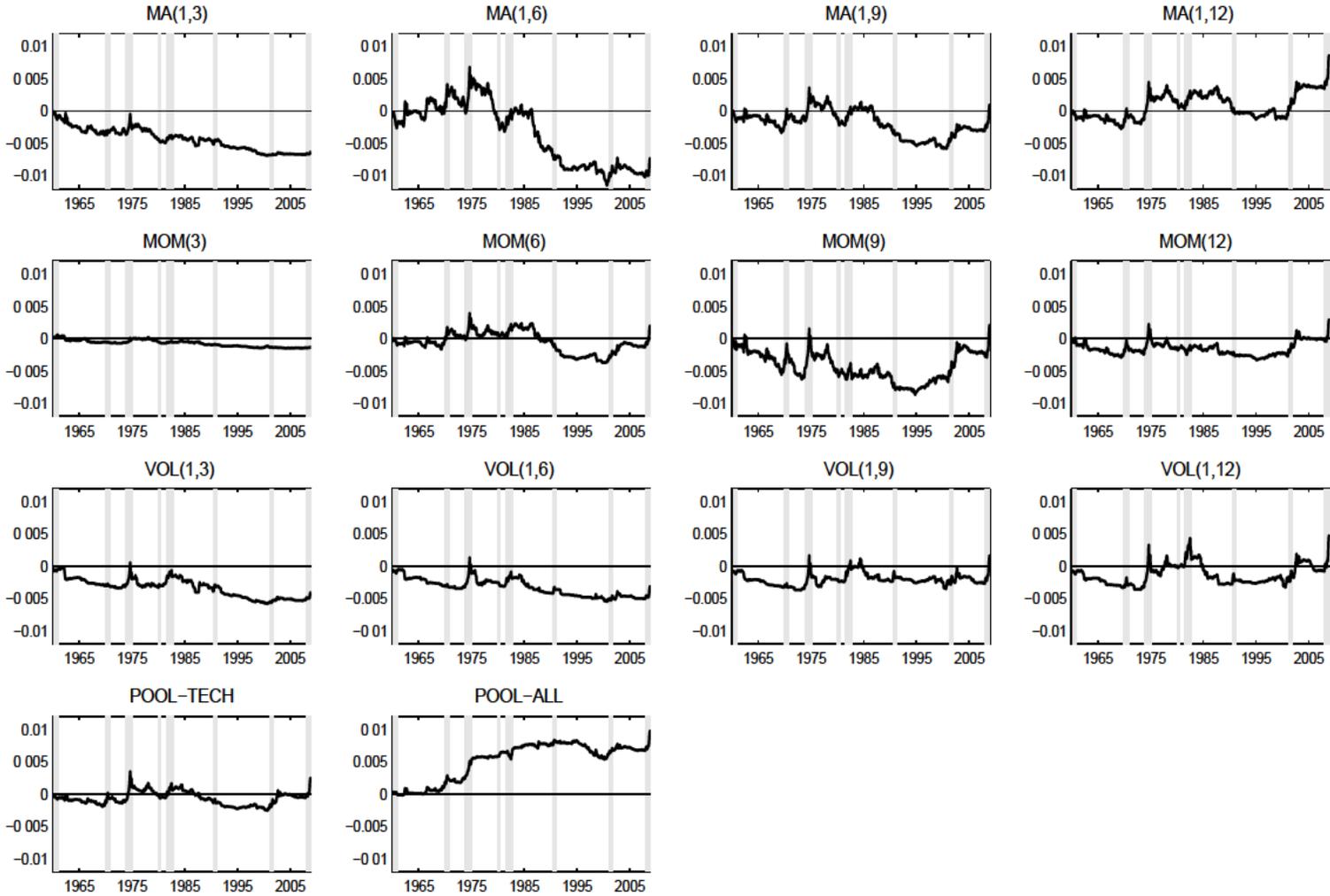


Figure 4. Cumulative square prediction error differences, out-of-sample equity premium forecasts based on the historical average and technical rules, 1960:01–2008:12. The figure depicts cumulative differences between the mean square prediction errors for the historical average equity premium forecast and the equity premium forecast based on the technical rule indicated in the panel heading. POOL-TECH is a pooled forecast based on the individual technical forecasts. POOL-ALL is a pooled forecast based on the individual fundamental and technical forecasts. Vertical bars depict NBER-dated business-cycle recessions.

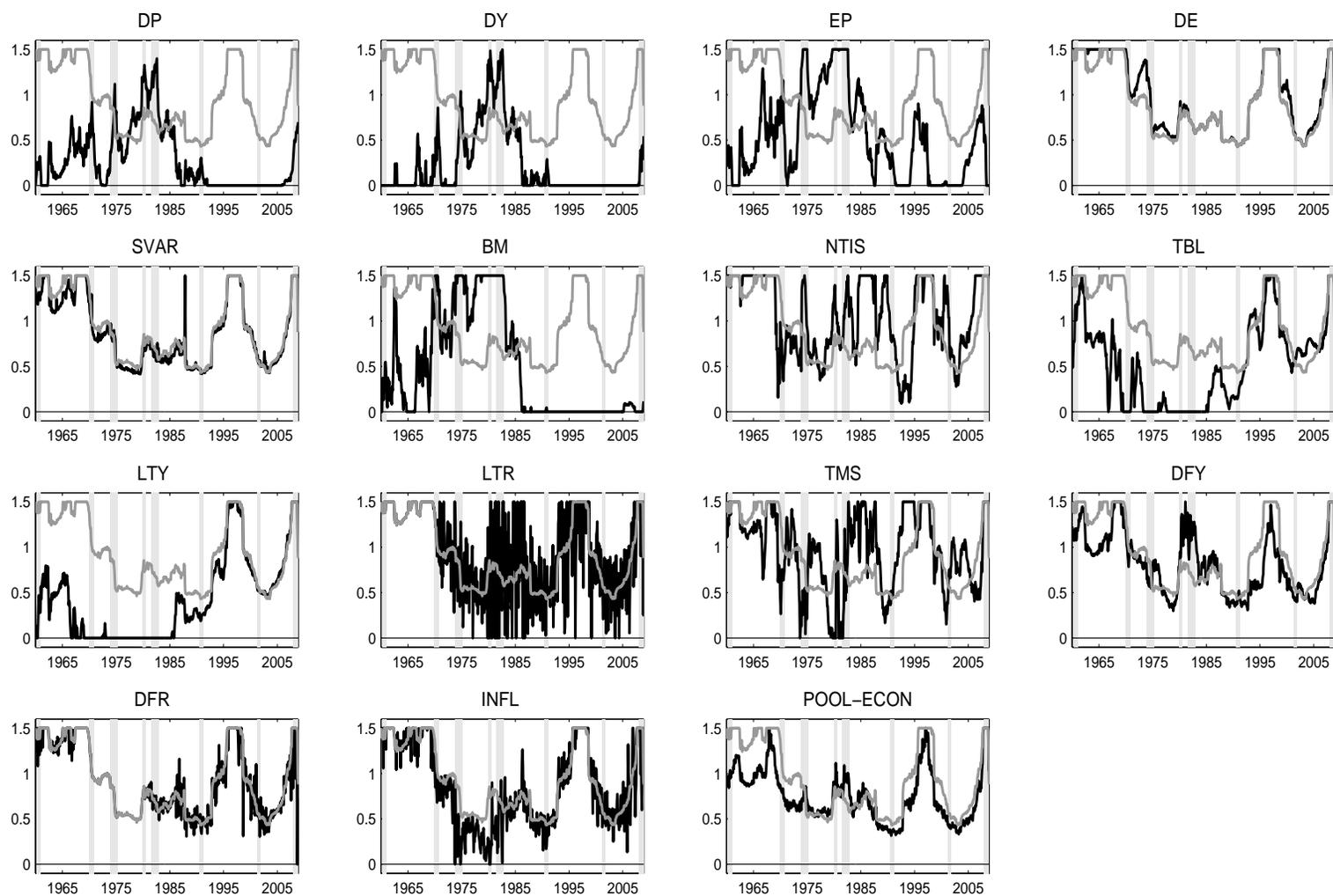


Figure 5. Equity portfolio weights computed using equity premium forecasts based on economic fundamentals, 1960:01–2008:12. Black (gray) lines delineate equity portfolio weights for an investor with mean-variance preferences and risk aversion coefficient of five who uses an equity premium forecast based on the economic fundamental given in the panel heading (historical average forecast). POOL-ECON is a pooled forecast based on the individual fundamental forecasts. Vertical bars depict NBER-dated business-cycle recessions.

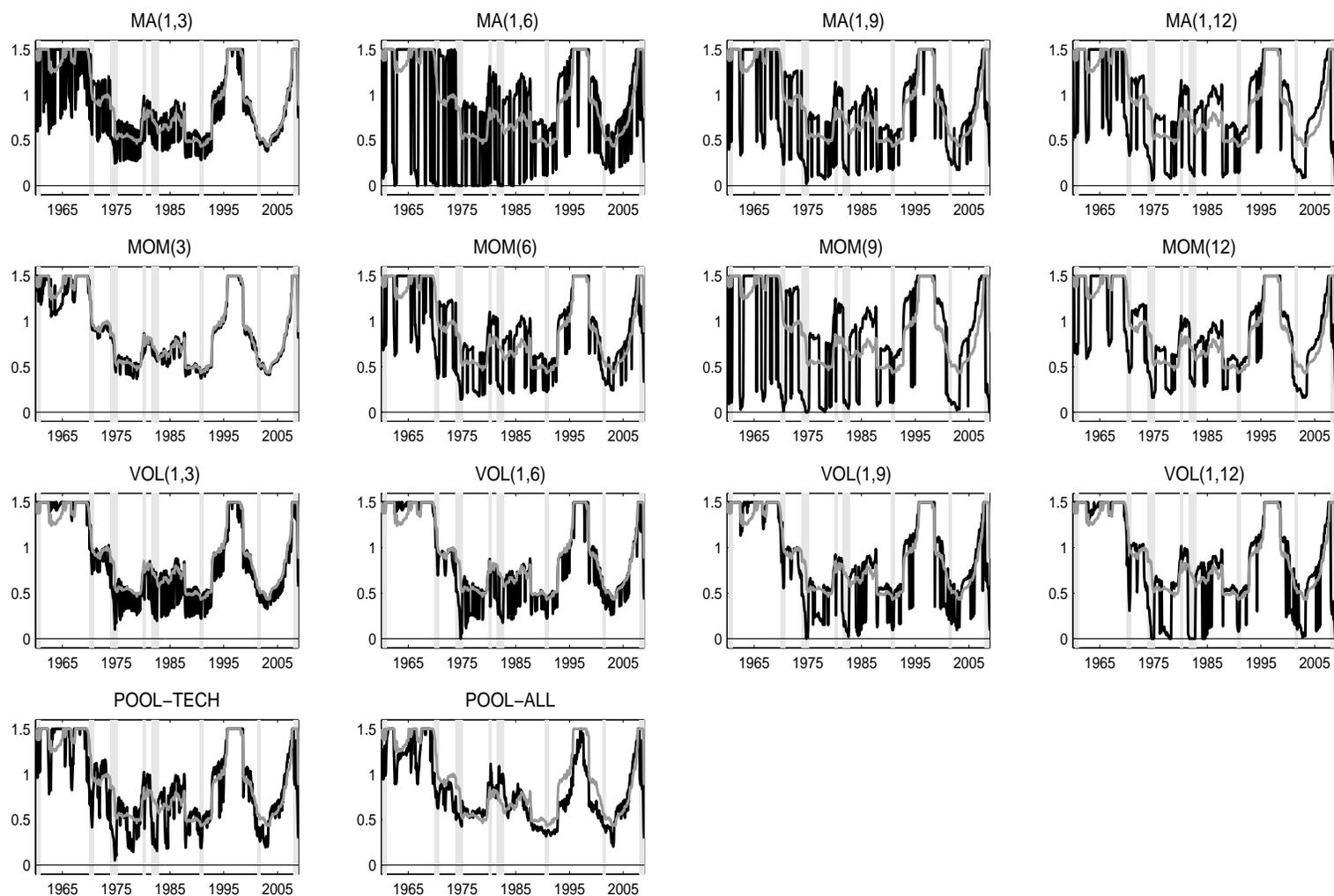


Figure 6. Equity portfolio weights computed using equity premium forecasts based on technical rules, 1960:01–2008:12. Black (gray) lines delineate equity portfolio weights for an investor with mean-variance preferences and risk aversion coefficient of five who uses an equity premium forecast based on the technical rule given in the panel heading (historical average forecast). POOL-TECH is a pooled forecast based on the individual technical forecasts. POOL-ALL is a pooled forecast based on the individual fundamental and technical forecasts. Vertical bars depict NBER-dated business-cycle recessions.

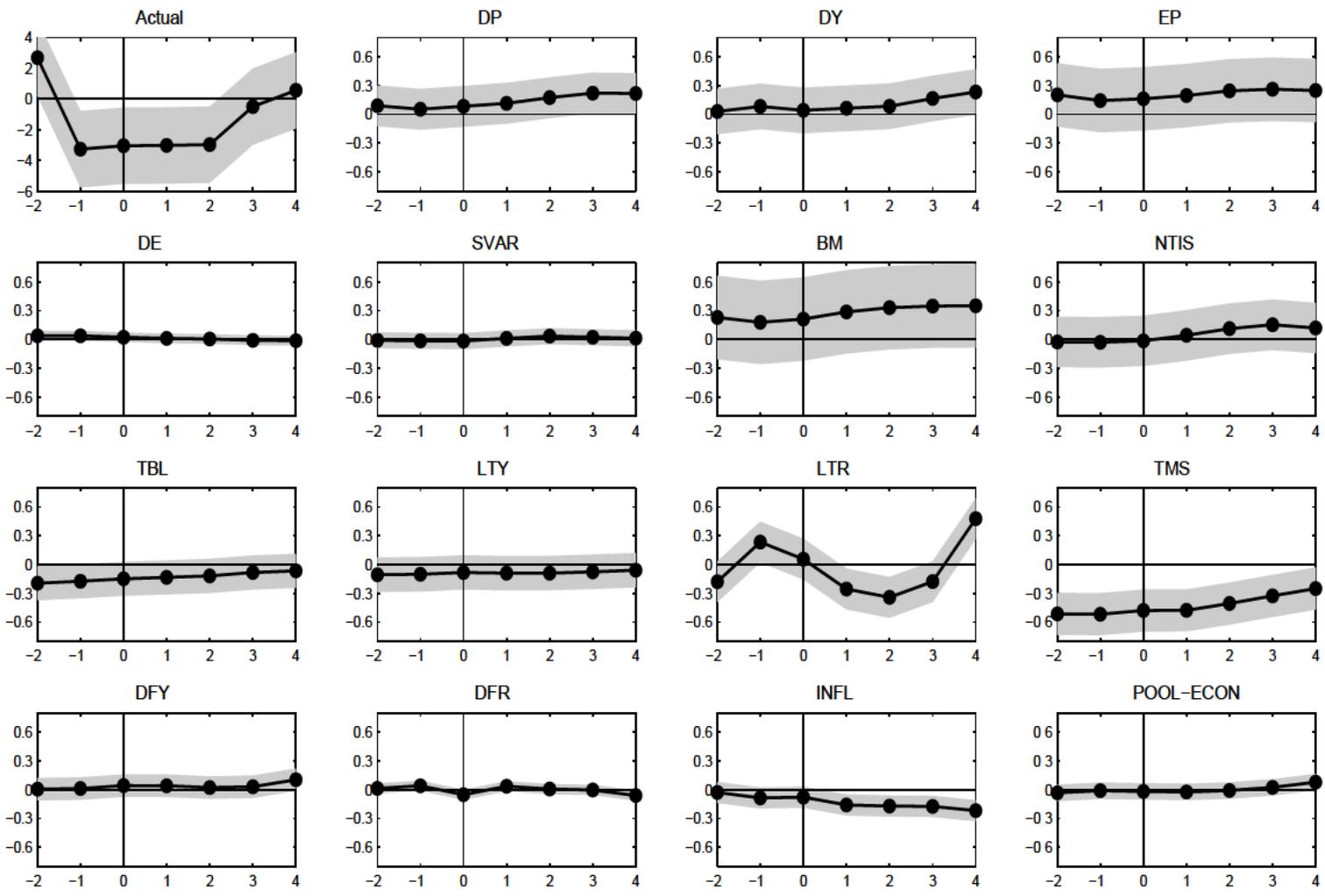


Figure 7. Actual equity premium and equity premium forecasts based on economic fundamentals near a U.S. business-cycle peak. The panels show the incremental change in the average difference between the actual equity premium or equity premium forecast based on the economic fundamental given in the panel heading and the historical average equity premium forecast two months before through four months after a business-cycle peak. POOL-ECON is a pooled forecast based on the individual fundamental forecasts. All forecasts are measured in percent. Circles indicate point estimates and shaded areas depict 90% confidence bands.

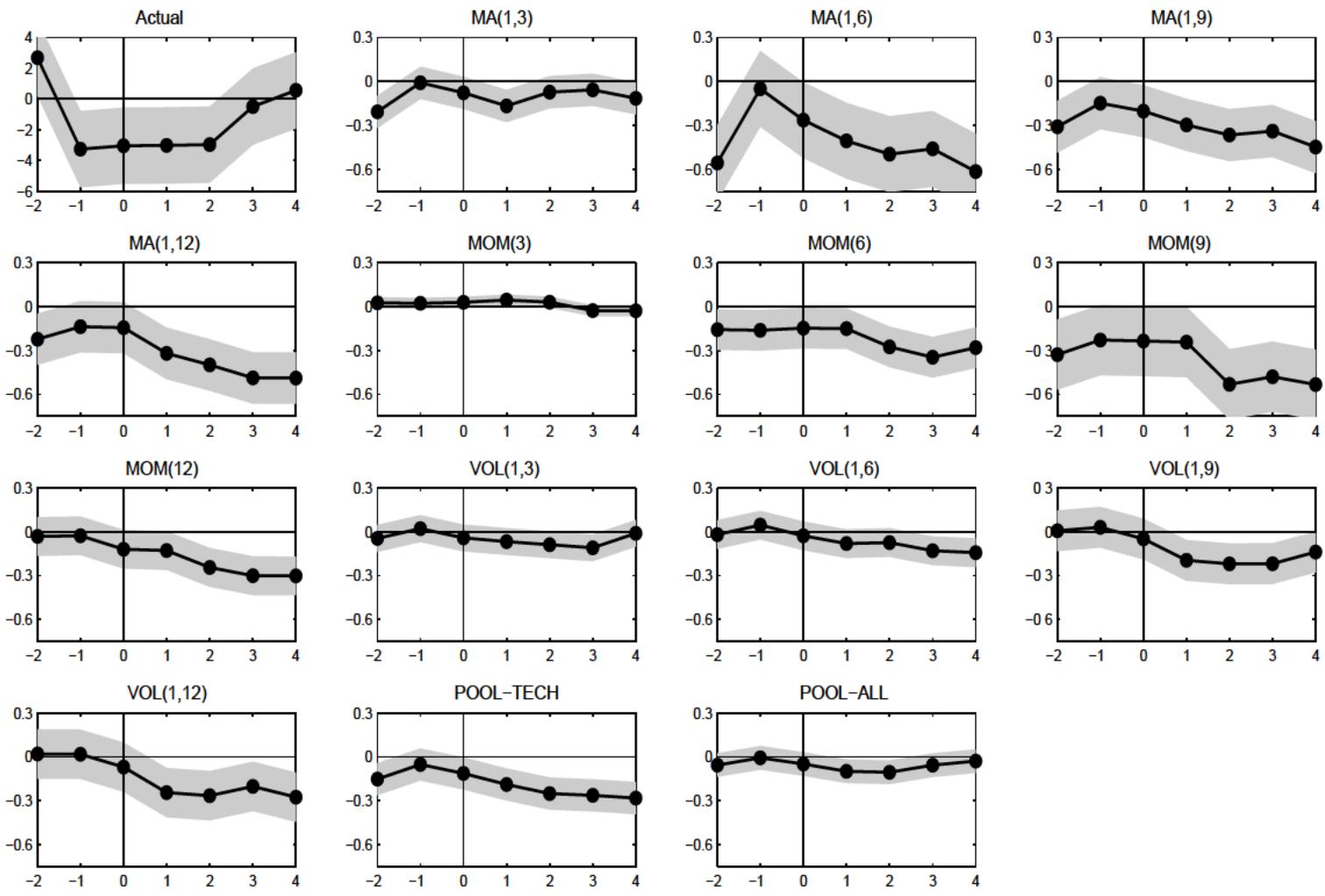


Figure 8. Actual equity premium and equity premium forecasts based on technical rules near a U.S. business-cycle peak. The panels show the incremental change in the average difference between the actual equity premium or equity premium forecast based on the technical rule given in the panel heading and the historical average equity premium forecast two months before through four months after a business-cycle peak. POOL-TECH is a pooled forecast based on the individual technical forecasts. POOL-ALL is a pooled forecast based on the individual fundamental and technical forecasts. All forecasts are measured in percent. Circles indicate point estimates and shaded areas depict 90% confidence bands.

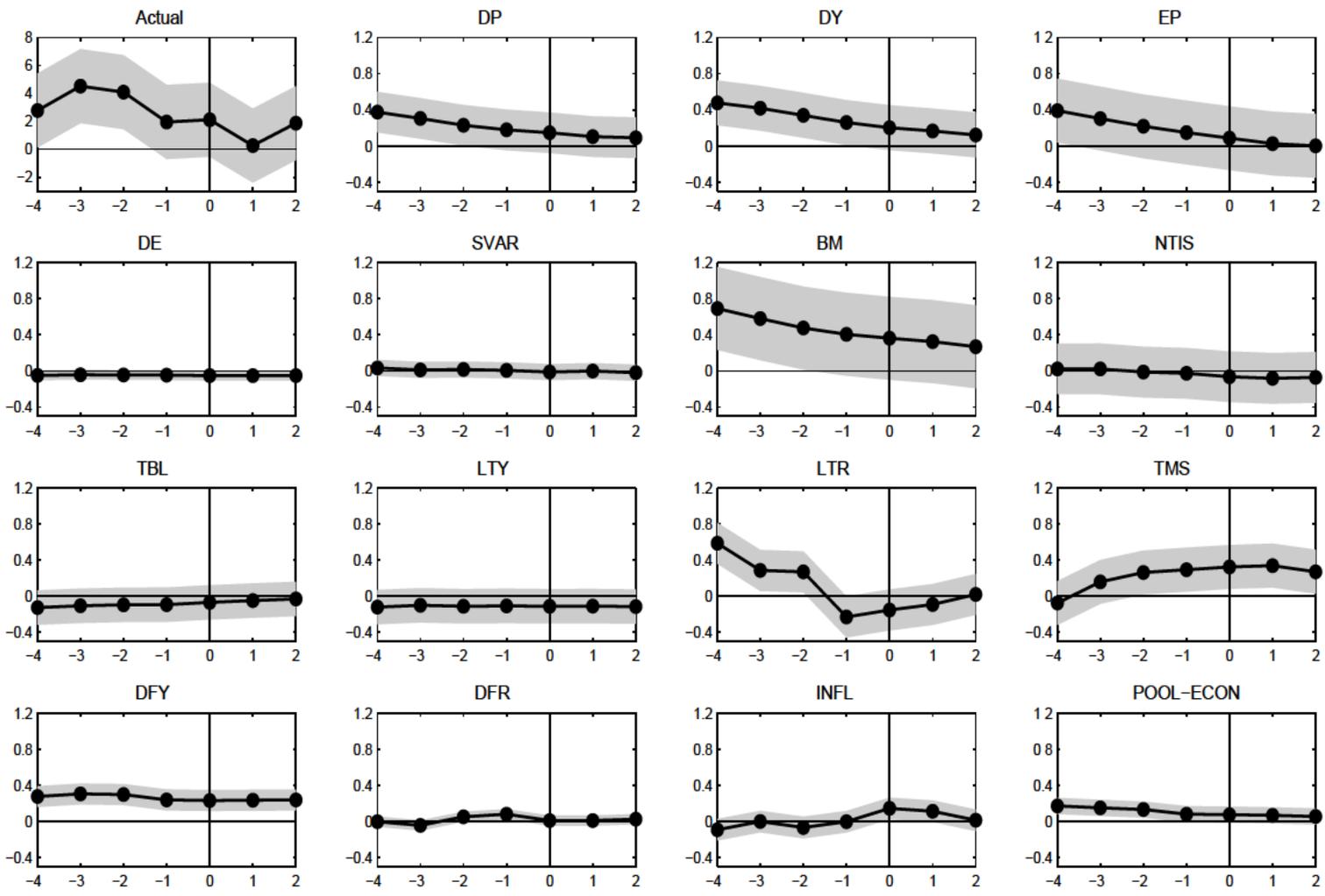


Figure 9. Actual equity premium and equity premium forecasts based on economic fundamentals near a U.S. business-cycle trough. The panels show the incremental change in the average difference between the actual equity premium or equity premium forecast based on the economic fundamental given in the panel heading and the historical average equity premium forecast four months before through two months after a business-cycle trough. POOL-ECON is a pooled forecast based on the individual fundamental forecasts. All forecasts are measured in percent. Circles indicate point estimates and shaded areas depict 90% confidence bands.

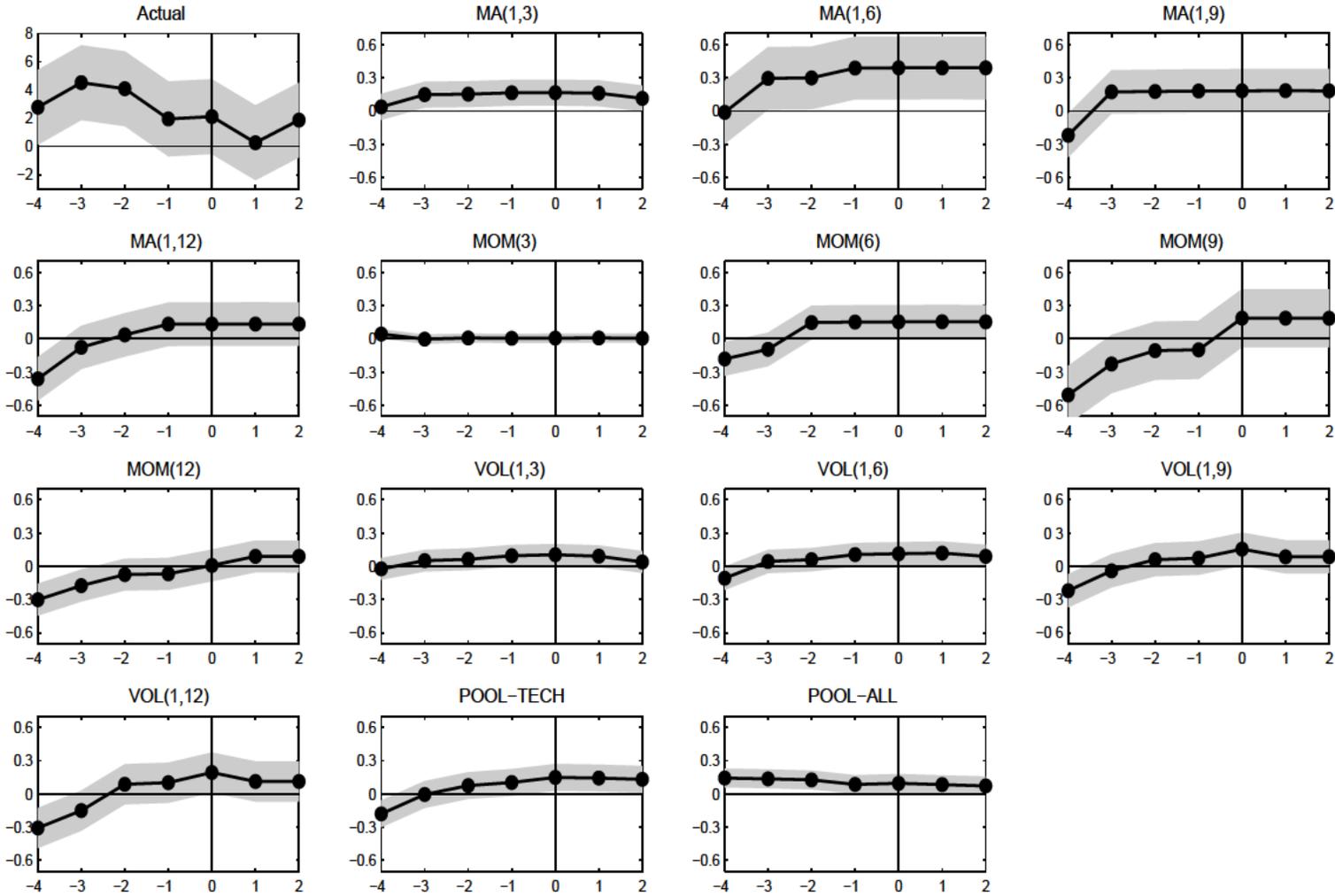


Figure 10. Actual equity premium and equity premium forecasts based on technical rules near a U.S. business-cycle trough. The panels show the incremental change in the average difference between the actual equity premium or equity premium forecast based on the technical rule given in the panel heading and the historical average equity premium forecast four months before through two months after a business-cycle trough. POOL-TECH is a pooled forecast based on the individual technical forecasts. POOL-ALL is a pooled forecast based on the individual fundamental and technical forecasts. All forecasts are measured in percent. Circles indicate point estimates and shaded areas depict 90% confidence bands.