Out-of-Sample Equity Premium Prediction: Economic Fundamentals vs. Moving-Average Rules

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Abstract

This paper analyzes the ability of both economic variables and moving-average 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 concentrated in U.S. business-cycle recessions. Nevertheless, economic variables and moving-average rules capture different sources of equity premium fluctuations: moving-average rules detect the decline in the average equity premium early in recessions, while economic variables more readily pick up the rise in the average equity premium later in recessions. When we simulate data with a habit-formation model characterized by time-varying return volatility and risk aversion relating to business-cycle fluctuations, we find that this model cannot fully account for the out-of-sample forecasting gains in the actual data evidenced by economic variables and moving-average rules.

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1. Introduction

Researchers have long investigated two very different methods of predicting aggregate stock returns: fundamental analysis and technical analysis. Fundamental analysis uses valuation ratios, interest rates, interest rate spreads, and related economic variables to forecast excess stock returns or, equivalently, the equity premium. In contrast, technical analysis studies past stock price behavior 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 equity premium. Similarly, Keim and Stambaugh (1986), Campbell (1987), Breen, Glosten and Jagannathan (1989), and Fama and French (1989) find that nominal interest rates and interest rate spreads, such as the default and term spreads, predict the equity premium, while Nelson (1976) and Fama and Schwert (1977) find predictive ability 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 issuing activity (Baker and Wurgler, 2000; Boudoukh, Michaely, Richardson, and Roberts, 2007), the consumption-wealth ratio (Lettau and Ludvigson, 2001), and volatility (Guo, 2006).\(^1\)

While the consensus appears to be that economic variables predict a significant component of the U.S. equity premium (Campbell, 2000), this vast literature relies predominantly on in-sample tests. Goyal and Welch (2008) recently argue strongly that economic fundamentals fail to consistently predict the equity premium in out-of-sample tests. Given the widespread view that out-of-sample tests are more demanding than in-sample tests, this failure casts doubt on the robustness of return predictability and limits its usefulness to investors in real time. In response, Campbell and Thompson (2008) show that imposing reasonable restrictions on equity premium forecasts

\(^1\)This is not meant to be an exhaustive list of studies; see, for example, Campbell (2000), Cochrane (2007), Goyal and Welch (2008), and Lettau and Ludvigson (2009) for surveys of the extensive literature on return predictability using economic variables.
improves the out-of-sample performance of a number of individual predictive regression models. Furthermore, Rapach, Strauss, and Zhou (2010a) find that combining individual predictive regression forecasts generates consistent out-of-sample gains, despite the inconsistent performance of individual forecasts. In addition to the conventional mean squared prediction error (MSPE) statistical metric, Campbell and Thompson (2008) and Rapach, Strauss, and Zhou (2010a) find substantial economic value for predictability in an asset-allocation problem. Overall, there appears to be significant out-of-sample evidence for return predictability using economic variables, at least when individual forecasts are restricted and/or used in combination.

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.² Despite its popularity, academic economists have traditionally been quite skeptical of the value of technical analysis (e.g., Malkiel, 2007), because its success would violate the intuitively attractive weak-form efficient market hypothesis, which holds that past prices—which are clearly known to traders—should not help traders earn abnormal risk-adjusted returns.


ply genetic programming—an automated procedure to search for *ex ante* “optimal” trading rules—to S&P 500 data for 1928–1995 but fail to identify rules that outperform a simple buy-and-hold strategy. Neely (2003) confirms Allen and Karjalainen’s (1999) results for risk-adjusted excess returns. In summary, a number of studies present evidence that technical indicators provide informative trading signals, although the performance of various indicators can vary over time.\(^3\)

The literatures on return predictability based on economic fundamentals and technical analysis have evolved largely independently of each other. Since both literatures report evidence of return predictability, this raises a number of intriguing questions: Does one approach clearly outperform the other? Do economic fundamentals and technical indicators capture similar return predictability patterns in the data? To what extent is the predictive power of each approach related to the real economy and business-cycle fluctuations? Should fundamental and technical approaches be viewed as substitutes or complements in asset-allocation decisions? In the present paper, we merge the two literatures in an attempt to answer these important questions. We do this by comparing the out-of-sample predictive ability of a host of popular economic fundamentals to that of a number of moving-average (MA) rules. MA rules are relatively transparent technical indicators that conveniently embody the trend investigation at the heart of technical analysis.

Our strategy for merging the two literatures has four key elements. First, we compare equity premium forecasts based on economic fundamentals and MA rules in terms of the Campbell and Thompson (2008) out-of-sample \(R^2\) statistic, which measures the reduction in MSPE for a competing forecasting model relative to the historical average (random walk with drift) benchmark forecast. Goyal and Welch (2008) show that the historical average forecast is a very stringent benchmark. Following Campbell and Thompson (2008) and Goyal and Welch (2008), we generate equity premium forecasts based on economic fundamentals using recursively estimated predictive regression models. While MA rules provide trading signals—rather than point forecasts *per se*—we transform the signals into point forecasts using a recursive regression framework. This allows us to directly compare equity premium forecasts based on economic variables and MA rules.

Second, we compare the economic value of equity premium forecasts based on either set of variables from an asset-allocation perspective. More specifically, we calculate utility gains in a simulated real-time setting for a mean-variance investor who optimally allocates a portfolio between equities and a risk-free Treasury bill using equity premium forecasts based on either eco-

\(^3\)Again, this is not meant to be an exhaustive list of studies; see Park and Irwin (2007) for a survey of the technical analysis literature for the equity and foreign exchange markets. Menkhoff and Taylor (2007) provide an extensive survey focusing on technical analysis in the foreign exchange market.
nomic variables or MA 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 the sense that the degree of risk aversion is not incorporated into the asset-allocation decision. Analogous to Zhu and Zhou (2009), we address this drawback in a utility framework by generating point forecasts based on MA rules that can be used for optimal portfolio allocation by a mean-variance investor. We compare the utility gains for a risk-averse investor who forecasts the equity premium using economic variables to the utility gains for an investor with the same degree of risk aversion who forecasts the equity premium with MA rules.

Third, to explore links between out-of-sample return predictability and the real economy, we compute out-of-sample $R^2$ statistics and utility gains for equity premium forecasts based on economic fundamentals and MA rules during both 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, as evidenced by Henkel, Martin, and Nadari (2009) and Rapach, Strauss, and Zhou (2010b), who show that equity premium predictability using economic variables is concentrated in cyclical downturns.

In our comparison study, we find that monthly equity premium forecasts based on both economic fundamentals and MA rules often outperform the historical average benchmark forecast according to the out-of-sample $R^2$ and utility metrics, but that the gains are concentrated during business-cycle recessions. 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 13.02%. Similarly, an investor with the same preferences would pay a fee of 3.43% during the full forecast evaluation period and 16.78% during recessions for access to an equity premium forecast based on an MA(1,12) rule rather than the historical average benchmark. Overall, our results connect equity premium predictability based on both economic fundamentals and technical indicators to business-cycle fluctuations.

Although both economic and technical variables forecast better during recessions, the two approaches exploit different patterns. MA rules generally detect the falling average equity premium early in recessions, while economic fundamentals correctly pick up the rising average equity premium later in recessions near business-cycle troughs. These results help to explain the simultane-
ously prominent roles for economic fundamentals in the academic literature and technical indicators among practitioners. Both approaches seem useful for predicting returns, and they appear to complement each other.

Our results also provide insight into the time-varying nature of the return predictability literature. Henkel, Martin, and Nadari (2009) observe that because equity premium predictability using economic fundamentals is concentrated in recessions, empirical findings will depend on the prevalence of such conditions in particular studies. Early predictability studies employing economic variables typically use samples ending in the early-to-mid 1980s. Relatively large parts of the samples in these studies will thus include the turbulent 1970s and the deep recession of the early 1980s. Later studies, such and Goyal and Welch (2008), use samples that cover much of the “Great Moderation” stretching from the mid 1980s to the early 21st century, which will dampen the evidence of predictability emanating from economic fundamentals. Empirical studies of technical analysis display similar time variation. For example, Brock, Lakonishok, and LeBaron (1992) find significant evidence for the profitability of technical rules for 1897–1986, a sample covering numerous severe recessions, including the Great Depression. While confirming their findings for 1897–1986, Sullivan, Timmermann, and White (1999) fail to find support for technical rules for 1987–1996, a sample that falls entirely within the Great Moderation and includes only a single recession, the relatively mild 1990–1991 recession. Given that both economic fundamentals and MA rules evince much stronger predictability during recessions, we expect that both literatures will find stronger support for predictability when incorporating more recent data from the “Great Recession” beginning in 2008, as our study portends.

Finally, we explore whether rational fluctuations in the expected equity risk premium can account for the out-of-sample forecasting gains demonstrated by economic variables and MA rules. Specifically, we simulate data from the Campbell and Cochrane (1999) habit-formation model that generates time-varying conditional return volatility and risk aversion relating to business-cycle fluctuations. If the economic variables and technical indicators exploit only rational fluctuations of the type produced by this model, the simulated data should show comparable forecastability to the real data. This is not the case, however, as empirical $p$-values indicate that the out-of-sample gains typically remain significantly greater than those in the simulated data.

The remainder of the paper is organized as follows. Section 2 outlines the construction of point forecasts of the equity premium based on economic fundamentals and MA rules, as well as the forecast evaluation criteria. Section 3 reports empirical results for the forecast comparisons.
Section 4 examines the ability of a habit-formation model to account for the out-of-sample results. Section 5 contains concluding remarks.

2. Econometric Methodology

This section outlines the construction and evaluation of out-of-sample equity premium point forecasts based on both economic variables and MA rules.

2.1. Construction of Point Forecasts

The conventional framework for analyzing return predictability based on economic variables is the following predictive regression model:

\[ r_{t+1} = \alpha + \beta x_{i,t} + \epsilon_{t+1}, \]  

where \( r_{t+1} \) is the return on a broad stock market index in excess of the risk-free rate from time \( t \) to \( t+1 \), \( x_{i,t} \) is a predictor, and \( \epsilon_{t+1} \) is a disturbance term. To generate out-of-sample forecasts based on (1), we first divide the total sample of \( T \) observations into \( m \) in-sample and \( q \) out-of-sample observations, where \( T = m + q \). The initial out-of-sample equity premium forecast for period \( m+1 \) using the economic variable \( x_{i,t} \) is given by

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

where \( \hat{\alpha}_{i,m} \) and \( \hat{\beta}_{i,m} \) are the ordinary least squares (OLS) estimates of \( \alpha \) and \( \beta \), respectively, in (1) computed by regressing \( \{ r_{t} \}_{t=2}^{m} \) on a constant and \( \{ x_{i,t} \}_{t=1}^{m-1} \). The subsequent forecast for period \( m+2 \) is given by

\[ \hat{r}_{i,m+2} = \hat{\alpha}_{i,m+1} + \hat{\beta}_{i,m+1} x_{i,m+1}, \]

where \( \hat{\alpha}_{i,m+1} \) and \( \hat{\beta}_{i,m+1} \) are the OLS estimates calculated by regressing \( \{ r_{t} \}_{t=2}^{m+1} \) on a constant and \( \{ x_{i,t} \}_{t=1}^{m} \). We proceed in this manner through the end of the available out-of-sample period, producing a set of \( q \) out-of-sample equity premium forecasts based on \( x_{i,t}, \{ \hat{r}_{i,t+1} \}_{t=m}^{T-1} \). This procedure simulates a real-time forecasting exercise.\(^4\) Observe that the forecasts are generated using a recursive (or expanding) estimation window. Forecasts could also be generated using a rolling window.

\(^4\)This is apart from data availability and revisions, of course. Data availability and revisions are typically not an issue for the economic variables considered in the literature. For the monthly data that we employ in Section 3, the inflation rate is the only economic variable not available at the end of the month. Following Goyal and Welch (2008), we thus replace \( x_{i,t} \) with \( x_{i,t-1} \) for the inflation rate in the predictive regression model given by (1).
which drops earlier observations as additional observations become available. Rolling samples are sometimes justified by appealing to structural instability. Pesaran and Timmermann (2007) and Clark and McCracken (2009), however, show that it can be optimal to include pre-break data when estimating a forecasting model for a quadratic loss function, due to the familiar bias-efficiency tradeoff.  

The historical average equity premium forecast, $\bar{r}_{t+1} = (1/t) \sum_{j=1}^{t} r_j$, is a natural benchmark corresponding to the random walk with drift model. In their influential study, Goyal and Welch (2008) show that $\bar{r}_{t+1}$ is a stringent benchmark. More specifically, they find that forecasts from individual predictive regression models based on numerous economic variables from the literature are unable to consistently outperform the historical average forecast.

Campbell and Thompson (2008) find that restrictions help individual predictive regression forecasts to more consistently outperform the historical average forecast of the equity premium. For example, theory often indicates the expected sign of $\beta_i$ in (1), so that we set $\beta_i = 0$ when forming a forecast if the estimated slope coefficient does not have the expected sign. Campbell and Thompson (2008) also 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.

Rapach, Strauss, and Zhou (2010a) analyze combinations of $N$ individual predictive regression forecasts. A combination forecast takes the form,

$$\hat{r}_{c,t+1} = \sum_{i=1}^{N} \omega_i \hat{r}_{i,t+1},$$

(4)

where $\{\omega_i\}_{i=1}^{N}$ are the ex ante combining weights and $\sum_{i=1}^{N} \omega_i = 1$. Rapach, Strauss, and Zhou (2010a) show that a simple averaging scheme ($\omega_i = 1/N$ for all $i$) consistently outperforms the historical average benchmark forecast, despite the inability of individual predictive regression forecasts to do so. In Section 3, we generate individual predictive regression forecasts with Campbell

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5We use recursive estimation windows in Section 3, although we obtain similar results using rolling estimation windows of various sizes.

6Rapach, Strauss, and Zhou (2010a) show that simple averaging is a type of shrinkage forecast that stabilizes individual predictive regression forecasts and thereby helps to provide out-of-sample gains more consistently over time. Forecast combination is also used successfully by Mamaysky, Spiegel, and Zhang (2007), who find that combining predictions from an OLS model and the Kalman filter model of Mamaysky, Spiegel, and Zhang (2008) significantly increases the number of mutual funds with predictable out-of-sample alphas. Timmermann (2008) combines forecasts from linear and nonlinear models of monthly stock returns. Another method for incorporating information from numerous predictors is to include them simultaneously in a multiple regression model—a general or “kitchen sink” model. Goyal and Welch (2008) and Rapach, Strauss, and Zhou (2010a) find, however, that this approach performs very poorly in out-of-sample equity premium forecasting. This is not surprising, given the well-known result that unrestricted, highly parameterized models often entail in-sample overfitting that translates into poor out-of-sample forecasting performance. Ludvigson and Ng (2007) pursue an alternative strategy by incorporating information from
and Thompson (2008) restrictions imposed and compute a combination forecast as a simple average of the individual predictive regression forecasts.

Technical indicators, such as MA rules, generate a trading signal (e.g., buy/sell), rather than a point forecast per se. Consider an MA rule that, in its simplest form, provides a buy or sell signal \( S_{t+1} = 1 \) or \( S_{t+1} = 0 \), respectively, by comparing two moving averages:

\[
S_{t+1} = \begin{cases} 
1 & \text{if } MA_{s,t} \geq MA_{l,t} \\
0 & \text{if } MA_{s,t} < MA_{l,t}
\end{cases}
\]  

(5)

where

\[
MA_{j,t} = \left( \frac{1}{j} \right) \sum_{i=0}^{j-1} P_{t-i} \text{ for } j = s, l,
\]  

(6)

\( P_t \) is the level of a stock price index, \( s \) (\( l \)) is the size of the short (long) MA \( (s < l) \), and \( S_{t+1} = 1 \) \( (S_{t+1} = 0) \) signals positive (negative) expected excess returns.

We denote the MA rule with MA sizes \( s \) 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 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.

To directly compare MA rules to economic variables with statistical and economic metrics, we use MA trading signals to generate point forecasts of the equity premium in a regression framework.\(^7\) Consider the following regression model:

\[
r_t = \alpha^{s,l} + \beta^{s,l} S^{s,l}_t + \epsilon^{s,l}_t,
\]  

where \( S^{s,l}_t \) is the trading signal generated by MA\((s,l)\) based on information through period \( t-1 \). The next forecast for period \( m+2 \) is given by

\[
\hat{r}^{s,l}_{m+2} = \hat{\alpha}^{s,l}_{m+1} + \hat{\beta}^{s,l}_{m+1} S^{s,l}_{m+2},
\]  

(9)

where \( \hat{\alpha}^{s,l}_{m+1} \) and \( \hat{\beta}^{s,l}_{m+1} \) are the OLS estimates calculated by regressing \( \{r_t\}_{t=1}^{m+1} \) on a constant and \( \{S^{s,l}_t\}_{t=1}^{m+1} \). Proceeding through the remainder of the out-of-sample period produces \( q \) out-of-sample equity premium forecasts based on \( S^{s,l}_t, \{\hat{r}^{s,l}_t\}_{t=m-1}^{T-1} \).

\(^7\)Gencay (1998) uses a similar approach to map daily trading signals to point forecasts of the Dow Jones index.
2.2. Forecast Evaluation

We consider two metrics for evaluating forecasts. The first is the Campbell and Thompson (2008) out-of-sample $R^2$ statistic, $R^2_{OS}$, which measures the proportional reduction in MSPE for a competing model relative to the historical average forecast. It is similar to the familiar in-sample $R^2$ statistic and is given by
\[ R^2_{OS} = 1 - \frac{\sum_{k=1}^{q} (r_{m+k} - \hat{r}_{m+k})^2}{\sum_{k=1}^{q} (r_{m+k} - \bar{r}_{m+k})^2}, \]  
(10)
where $\hat{r}_{m+k}$ represents an equity premium forecast based on an economic variable or MA rule. Clearly, when $R^2_{OS} > 0$, 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 alternative hypothesis that the competing forecast has a lower MSPE, which corresponds to $H_0 : R^2_{OS} = 0$ against $H_A : R^2_{OS} > 0$. Clark and West (2007) produce 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 economic or MA forecasts with the historical average forecast clearly entails comparing nested models, since setting $\beta_i = 0$ in (1) or $\beta_s, l = 0$ in (7) yields the random walk with drift model.\(^8\) The MSPE-adjusted statistic is straightforwardly calculated by first defining
\[ f_{t+1} = (r_{t+1} - \bar{r}_{t+1})^2 - [(r_{t+1} - \hat{r}_{t+1})^2 - (\bar{r}_{t+1} - \hat{r}_{t+1})^2], \]  
(11)
and then regressing $\{f_{s+1}\}_{s=m}^{T-1}$ on a constant. The MSPE-adjusted statistic is the $t$-statistic corresponding to the constant, and a $p$-value for a one-sided (upper-tail) test is based on the standard normal distribution. Monte Carlo simulations show that the MSPE-adjusted statistic performs well in finite samples.

Although $R^2_{OS}$ statistics are typically small for equity premium forecasts, since aggregate excess returns contain a large unpredictable component, a relatively small $R^2_{OS}$ statistic can still signal economically important gains for an investor (Kandel and Stambaugh, 1996; Xu, 2004; Campbell and Thompson, 2008). From an asset-allocation perspective, however, the $R^2_{OS}$ alone does not

\(^8\)While the Diebold and Mariano (1995) and West (1996) statistic has a standard normal asymptotic distribution when comparing forecasts from non-nested models, Clark and McCracken (2001) and McCracken (2007) show that it has a complicated non-standard distribution when comparing forecasts from nested models. The non-standard distribution can lead the Diebold and Mariano (1995) and West (1996) statistic to be severely undersized when comparing forecasts from nested models, thereby substantially reducing power.
explicitly account for the risk borne by an investor. To address this drawback, we follow Marquering and Verbeek (2004), Campbell and Thompson (2008), Goyal and Welch (2008), Wachter and Warusawitharana (2009), and Rapach, Strauss, and Zhou (2010a) and compute realized utility gains for a mean-variance investor on a simulated real-time basis. As discussed in Section 1, this procedure addresses the failure of many existing studies of technical trading rules to incorporate the degree of risk aversion into the asset-allocation decision.

We consider a mean-variance investor who allocates between stocks and risk-free bills using an equity premium forecast based on an economic variable or MA rule. At the end of period $t$, the investor allocates

$$w_{jt} = \frac{1}{\gamma} \frac{\hat{r}_{jt+1}}{\hat{\sigma}^2_{jt+1}}$$

(12)
of her portfolio to stocks during period $t+1$, where $\gamma$ is the coefficient of risk aversion, $\hat{r}_{jt+1}$ is an equity premium forecast formed at time $t$ based on an economic variable or MA rule indexed by $j$, and $\hat{\sigma}^2_{jt+1}$ is a forecast of stock return variance. Following Campbell and Thompson (2008), we assume that the investor uses a five-year moving window of past monthly returns to estimate the variance.\(^9\) Over the out-of-sample period, the investor who uses forecast $j$ realizes an average utility level of

$$\hat{\nu}_j = \hat{\mu}_j - 0.5 \gamma \hat{\sigma}^2_j,$$

(13)

where $\hat{\mu}_j$ and $\hat{\sigma}^2_j$ are the sample mean and variance, respectively, for the portfolio formed using the sequence of $\hat{r}_{jt+1}$ forecasts. We compare (13) to the average utility for the same investor when she instead uses the historical average, $\bar{r}_{t+1}$, to forecast the equity premium. At the end of period $t$, she allocates

$$w_{0,t} = \frac{1}{\gamma} \frac{\bar{r}_{t+1}}{\hat{\sigma}^2_{t+1}}$$

(14)
to stocks during period $t+1$ and realizes an average utility of

$$\hat{\nu}_0 = \hat{\mu}_0 - 0.5 \gamma \hat{\sigma}^2_0$$

(15)
during the out-of-sample period, where $\hat{\mu}_0$ and $\hat{\sigma}^2_0$ are the sample mean and variance, respectively, for the portfolio formed using the sequence of historical average forecasts. The utility gain accruing to the $\hat{r}_{jt+1}$ forecast vis-à-vis the $\bar{r}_{t+1}$ forecast is given by the difference between (13) and (15). We multiply this difference by 1200, so that it can be interpreted as the annual percentage portfolio

\(^9\)Again following Campbell and Thompson (2008), we constrain the equity weight in the portfolio to lie between 0% and 150% (inclusive), so that $w_{jt} = 0$ ($w_{jt} = 1.5$) if $w_{jt} < 0$ ($w_{jt} > 1.5$). We impose the same constraint on $w_{0,t}$ below.
management fee that an investor would be willing to pay to have access to the \( \hat{r}_{jt+1} \) forecast relative to the historical average forecast. In Section 3, we use \( \gamma = 5 \); results are qualitatively similar for other \( \gamma \) values.

3. Empirical Results

This section describes the data and reports the out-of-sample test results for \( R^2_{OS} \) statistics and utility gains.

3.1. Data

Our monthly data span 1927:01–2008:12. All data are from Amit Goyal’s web page, which provides updated data from Goyal and Welch (2008).\(^{10}\) 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. As in Goyal and Welch (2008), we use the following 14 economic variables to generate predictive regression forecasts using the recursive procedure described in Section 2.1:

- *Dividend-price ratio (log)*, DP: difference between the log of dividends paid on the S&P 500 index and the log of stock prices (S&P 500 index), where dividends are measured using a one-year 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 using a one-year moving sum.
- *Dividend-payout ratio (log)*, DE: log of dividends minus the log of earnings.
- *Net equity expansion*, NTIS: ratio of twelve-month moving sums of net issues by NYSE-listed stocks to total end-of-year market capitalization of NYSE stocks.

\(^{10}\)The data are available at http://www.bus.emory.edu/AGoyal/Research.html.
• **Treasury bill rate**, TBL: interest rate on a 3-month Treasury bill (secondary market).


• **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 MA rule-based forecasts described in Section 2.1.\(^{11}\)

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

Panel A of Table 1 reports $R^{2}_{OS}$ statistics for predictive regression forecasts based on economic variables 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. Table 1, Panel A also reports the $R^{2}_{OS}$ for a combination of the individual predictive regression forecasts (COMBINE-ECON) based on (4) with $\omega_i = 1/N$ ($N = 14$). We assess the statistical significance of $R^{2}_{OS}$ using the Clark and West (2007) \textit{MSPE-adjusted} statistic, as described in Section 2.2. In addition to the full 1960:01–2008:12 forecast evaluation period, we compute $R^{2}_{OS}$ statistics separately for NBER-dated business-cycle expansions and recessions.\(^{12}\) 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 1, Panel A, nine of the 14 individual economic variables have positive $R^{2}_{OS}$ statistics, so that they outperform the historical average benchmark forecast in terms of MSPE. Six of the nine positive $R^{2}_{OS}$ statistics for the individual economic

\(^{11}\)While daily data are frequently used to generate trading signals using technical indicators, we compute MA rules using monthly data to put the forecasts based on economic variables and MA 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 MA rules.

\(^{12}\)NBER peak and trough dates that define the expansion and recession phases of the U.S. business cycle are available at http://www.nber.org/cycles.html.
variables are significant at the 10% level or better. DP and DY have the highest $R^2_{OS}$ statistics, 0.73% and 0.71%, respectively, among the individual economic variables. The $R^2_{OS}$ is 0.80% for the COMBINE-ECON forecast, which is significant at the 1% level and greater than the $R^2_{OS}$ for any of the individual predictive regression forecasts, similar to results reported in Rapach, Strauss, and Zhou (2010a) for quarterly U.S. excess returns.

The last four columns of Table 1, Panel A report results separately for business-cycle expansions and recessions. Recessions markedly enhance the out-of-sample predictive ability of most economic variables compared to the historical average. For example, the predictive ability of DP and DY—which have the largest $R^2_{OS}$ statistics among the individual economic variables over the full 1960:01–2008:12 forecast evaluation period—is highly concentrated in recessions: the $R^2_{OS}$ statistics for DP (DY) are 0.15% and 2.15% (−0.26% and 3.09%) during expansions and recessions, respectively. The $R^2_{OS}$ statistics for DP, DY, LTR, and TMS are significant at the 5% level during recessions, despite the reduced number of available observations. The COMBINE-ECON forecast also has an $R^2_{OS}$ that is higher during recessions than expansions (1.01% and 0.72%, respectively, both of which are significant at the 5% level). The enhanced predictive ability of economic variables during cyclical downturns in Table 1, Panel A complements recent findings in Henkel, Martin, and Nadari (2009) and Rapach, Strauss, and Zhou (2010b) and strongly ties out-of-sample equity premium predictability to business-cycle fluctuations.

To learn how equity premium forecasts vary over the business cycle, Figure 1 graphs the individual predictive regression forecasts and COMBINE-ECON forecast, along with the historical average benchmark. The vertical lines in the figure delineate NBER-dated business-cycle peaks and troughs (in succession). 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, the early 1980s, and the most recent recessions. While averaging across individual forecasts produces a smoother forecast, the COMBINE-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 1, Panel A show that the average forecast value is higher
during recessions than expansions for a number of economic variables, especially DP and DY.

We turn next to the forecasting performance of the MA rules. Panel B of Table 1 reports \( R^2_{OS} \) statistics for point forecasts based on MA(s, l) rules. Because the choices of s and l are somewhat arbitrary, we consider s = 1, 2 and l = 3, 6, 9, 12, 15, 18, 21, 24, providing us with 16 individual MA rule-based forecasts. The COMBINE-MA forecast in Panel B is a simple average of the 16 individual MA forecasts. In addition to the full 1960:01–2008:12 forecast evaluation period, we again report results separately for NBER-dated expansions and recessions.

The second column of Table 1, Panel B shows that twelve of the 16 individual MA forecasts have positive \( R^2_{OS} \) statistics, so that they outperform the historical average forecast according to the MSPE metric. Seven of the twelve positive \( R^2_{OS} \) statistics are significant at conventional levels. The \( R^2_{OS} \) is also positive for COMBINE-MA and significant at the 10% level. The MA(2,12) forecast has the highest \( R^2_{OS} \) (1.08%) in Panel B. As seen in the fourth and sixth columns of Panel B, the results in the second column mask important differences in predictive ability during different phases of the business cycle. As with the economic forecasts in Panel A, the predictive ability of the MA rules varies markedly over the business cycle: with the exception of the MA(1,24) forecast, all of the \( R^2_{OS} \) statistics are substantially higher during recessions than expansions. The \( R^2_{OS} \) statistics during recessions are especially large for l values of 6–15 months, ranging from 1.45%–3.05%, all of which are significant at the 5% level.\(^{13}\)

Figure 2 depicts the MA forecasts, where NBER-dated peaks and troughs are again delineated by vertical lines. Figure 2 shows that the MA forecasts often drop well below the historical average forecast early in and throughout recessions. There are also expansionary episodes, especially for MA forecasts based on small s values, where the MA forecasts frequently fall well below the historical average forecast. The fourth column of Table 1, Panel B indicates that these declines detract from the accuracy of the MA forecasts during expansions. The fifth and seventh columns of Panel B show that the average equity premium forecast is lower during recessions than expansions for nearly all of the MA forecasts. MA forecasts with l values of 6–15 months offer the largest

\(^{13}\)The consideration of 32 economic and MA forecasts in Table 1 raises data-snooping concerns. The White (2000) reality check and its more powerful variant developed by Hansen (2005) are the state-of-the-art data-snooping tests. Unfortunately for our purposes, strictly speaking, the White-Hansen tests are not valid for comparing nested models. Similar to the situation analyzed by Clark and McCracken (2001) and McCracken (2007) for the Diebold and Mariano (1995) and West (1996) statistic (see footnote 8), the Hansen-White tests are potentially severely undersized when comparing nested model forecasts. Nevertheless, to get some sense of the relevance of data snooping in Table 1, we compute bootstrapped \( p \)-values for the Hansen (2005) \( SPA_c \) and \( SPA_p \) statistics to test for significant differences in MSPE relative to the historical average benchmark when considering all 32 competing forecasts. The \( p \)-values are relatively small, 0.16 and 0.17, respectively; given that the tests are likely to be undersized, these \( p \)-values suggest that the results in Table 1 are not simply an artifact of data snooping.
accuracy gains during recessions and display the greatest differences in average forecast values across expansions and recessions.

Overall, Table 1 and Figures 1–2 indicate that forecasts based on economic variables and MA forecasts with moderate $l$ values predict the U.S. equity premium out of sample, especially during recessions. The $R^2_{OS}$ statistics are similar in size for the best-performing economic variables and MA rules during recessions, so that there is not strong evidence for preferring economic forecasts over MA forecasts or vice versa according to the $R^2_{OS}$ statistics. Table 1 and Figures 1–2, however, point to an interesting difference in the behavior of the two types of forecasts during recessions. Many of the forecasts based on economic variables move substantially above the historical average forecast over the course of recessions, while MA forecasts are typically well below the historical average forecast throughout recessions. This difference in behavior is curious, because both types of forecasts display greater out-of-sample predictive ability during recessions. We explain this puzzle in Section 3.4, after measuring utility gains accruing to the two types of forecasts.

### 3.3. Utility Gains

Table 2 reports average utility gains, in annualized percent, for a mean-variance investor with $\gamma = 5$ who allocates across stocks and a risk-free bill using equity premium forecasts based on economic variables (Panel A) or MA rules (Panel B) relative to the historical average benchmark forecast. The results in Panel A indicate that forecasts based on economic variables often produce sizable utility gains vis-à-vis the historical average benchmark. The utility gain is above 1% for six of the individual economic variables (as well as COMBINE-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 variables relative to the historical average forecast. Similar to Table 1, the out-of-sample gains are typically concentrated in recessions. Consider, for example, DY, which generates the largest 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 substantial $13.02\%$ during recessions. DP, TBL, LTY, LTR, TMS, and DFR also provide utility gains above 5% during recessions. The COMBINE-ECON forecast provides more consistent gains across expansions (0.97%) and recessions (1.66%), although the gains are still more sizable during recessions.

Figure 3 portrays the equity portfolio weights computed using predictive regression, COMBINE-ECON, and historical average forecasts. Recall that the investor uses the same volatility forecast
for all of the portfolio allocations, so that the equity weights only differ because of differences in the equity premium forecast. Figure 3 shows that the equity weight computed using the historical average forecast is procyclical. Given that the historical average forecast of the equity premium is relatively smooth, this primarily reflects changes in expected volatility: the rolling-window estimate of volatility tends to be countercyclical, leading to a procyclical equity weight using (14). The equity weights based on economic variables often deviate substantially from the equity weight based on the historical average, with a tendency for the weights computed using economic variables to lie below the historical average weight during expansions and to move closer to or above the historical average weight during recessions. Panel A of Table 2 indicates that these deviations translate into significant utility gains, especially during recessions.

Panel B of Table 2 reports average utility gains for MA forecasts relative to the historical average benchmark. All of the utility gains are positive in the second column for the full 1960:01–2008:12 forecast evaluation period. The MA forecasts based on \( l \) values of 12 and 15 months have average utility gains near or above above 3%, with the MA(2,12) forecast generating the largest gain (3.43%). Comparing the fourth and sixth columns, the utility gains are markedly higher during recessions vis-à-vis expansions. The MA(2,12) forecast provides a leading example. During expansions, the utility gain is only 1.07%, while it jumps to 16.78% during recessions. The fifth and seventh columns reveal that the average equity weight is lower during recessions than expansions for all MA forecasts. The differences between the average equity weights across business-cycle phases are especially sizable for MA forecasts with moderate \( l \) values of 9–18 months, and these \( l \) values generate the largest gains during recessions.

Figure 4 further illustrates the tendency for equity weights computed using MA forecasts to decrease during recessions, with equity weights based on MA forecasts typically 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, the declines in equity weights using MA forecasts during recessions results from declines in the MA equity premium forecasts during recessions; see Section 3.2 and Figure 2.

In summary, Table 2 shows that equity premium forecasts based on both economic variables and MA rules usually generate sizable utility gains, especially during recessions, highlighting the economic significance of equity premium predictability using either approach. Comparing Panels

\[ \text{French, Schwert, and Stambaugh (1987), Schwert (1989, 1990), Whitelaw (1994), Harvey (2001), Ludvigson and Ng (2007), Lundblad (2007), and Lettau and Ludvigson (2009), among others, also find evidence of countercyclical expected volatility using alternative volatility estimators.} \]
A and B of Table 2, MA 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 2, DP, generates utility gains that are reasonably comparable to those of the best-performing MA forecasts. Table 2 also shows that MA forecasts produce substantially lower equity weights on average during recessions relative to expansions, while forecasts based on valuation ratios, such as DP and DY, allocate a larger portfolio share to equity on average during recessions compared to expansions.

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

Tables 1–2 and Figures 1–4 present somewhat of a puzzle. For equity premium forecasts based on both economic variables and MA rules, out-of-sample gains are typically concentrated in business-cycle recessions. However, equity premium forecasts based on economic variables often increase during recessions, while forecasts based on MA 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 equity premium and the economic and MA 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:

\[ r_t - \bar{r}_t = a_0^P + \sum_{k=-2}^{4} b_{0,k}^P I_{k,t}^P + e_{0,t}^P, \]  

(16)

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 \( b_{0,k}^P \) 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 \( \hat{r}_{j,t} \), where \( \hat{r}_{j,t} \) signifies an economic or MA forecast of the equity premium:

\[ \hat{r}_{j,t} - \bar{r}_t = a_j^P + \sum_{k=-2}^{4} b_{j,k}^P I_{k,t}^P + e_{j,t}^P. \]  

(17)

The slope coefficients describe the incremental change in the average difference between an economic or MA 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 pre-
mium and the economic and MA forecasts around business-cycle troughs:

\[ r_t - \bar{r} = a_0^T + \sum_{k=-4}^2 b_{0,k} I_{k,t}^T + e_{0,t}, \]  

(18)  

\[ \hat{r}_{j,t} - \bar{r}_t = a_j^T + \sum_{k=-4}^2 b_{j,k} I_{k,t}^T + e_{j,t}, \]  

(19)

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 5 graphs OLS slope coefficient estimates (in percent) and 90% confidence bands for (16), and the remaining panels depict corresponding estimates for (17) based on the economic forecasts. The first panel shows that the average equity premium moves significantly below the historical average forecast one month before through two months after a business-cycle peak. In other words, the equity premium declines the month before a recession begins and stays low for three more months.

The remaining panels in Figure 5 indicate that most economic forecasts fail to pick up this decline in the equity premium early in recessions. Only the LTR, TMS, and INFL forecasts decline significantly on average for any of the months early in recessions when the average 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 average two months before and three and four months after a peak, unlike the actual equity premium. The LTR forecast is significantly below 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 significantly lower-than-average INFL forecast in the immediate months after a peak, the magnitude of the decline is small. Overall, Figure 5 suggests that equity premium forecasts based on economic variables are not particularly adept at detecting the decline in the average 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 1 and 2.

How do the equity premium forecasts based on MA rules behave near cyclical peaks? The first panel of Figure 6 again shows estimates for (16), while the other panels graph estimates for (17) for the MA forecasts. Figure 6 reveals that MA forecasts with \( l \) values of 6–18 months move substantially below average in the months immediately following a cyclical peak. For example, the MA(2,12) forecast is significantly below average in the months immediately after a peak, in accord with the behavior of the actual equity premium. Given that the actual equity premium moves below average substantially in the month before and month of a business-cycle peak, it is not surprising
that the MA forecasts generally are lower than average in the first two months after a peak, since
the MA forecasts are based on signals that recognize a downward trend in equity prices. This
trend-following behavior early in recessions apparently helps to generate the sizable out-of-sample
gains during recessions for MA forecasts with moderate $l$ values, especially MA(2,12), in Tables 1
and 2. The MA forecasts in Figure 6 tend to remain well below the historical average for too long
after a peak, however.

Figures 7 and 8 depict estimates of (18) and (19) for the economic and MA forecasts, respect-
ively. The first panel in each figure shows that the actual equity premium moves significantly
above average 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 7 indicates that many of the
economic forecasts, particularly those based on valuation ratios (DP, DY, EP, and BM) and LTR, are
also significantly higher than average in the fourth through second months before a trough. TMS,
DFY, and COMBINE-ECON are also significantly above average in the later stages of recessions,
although by less than the previously mentioned economic variables. The ability of many of the
economic 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 economic forecasts in Tables
1 and 2.

Figure 8 shows that the MA forecasts generally start low but rise quickly late in recessions, in
contrast to the pattern in the actual equity premium. Only a few of the MA forecasts–for example,
MA(1,3), MA(1,6), and MA(1,9)–are above average in the second and third months prior to a
business-cycle trough. The out-of-sample gains for the MA forecasts during recessions in Tables
1 and 2 thus occur despite the relatively poor performance of MA forecasts late in recessions.
While the trend-following MA forecasts detect the decrease in the actual equity premium early
in recessions (see Figure 6), they are less adept at recognizing the unusually high actual equity
premium late in recessions.

Figures 5–8 paint the following nuanced picture with respect to the sizable out-of-sample gains
in Tables 1 and 2. Economic variables typically fail to detect the average decline in the actual
equity premium early in recessions, while they generally detect the average increase in the actual
equity premium late in recessions. MA 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 economic and MA forecasts both generate substantial out-of-sample gains
during recessions, they capture different aspects of equity premium fluctuations during cyclical
downturns and thus can be viewed as complements with respect to out-of-sample equity premium predictability. This suggests that one should rely primarily on MA (economic) forecasts near cyclical peaks (troughs). Of course, it is notoriously difficult to forecast business-cycle turning points in real time, making it challenging to exploit the complementarity of the economic and MA forecasts in practice.\textsuperscript{15}

4. Simulated Data From a Habit-Formation Model

We next explore whether the out-of-sample forecasting gains in Section 3 are consistent with rational fluctuations in the expected equity premium. As emphasized by Fama (1991), this type of exercise always involves a test of the joint null hypothesis of market efficiency and a particular model of equilibrium expected returns. A rejection of the joint null thus does not necessarily constitute evidence against market efficiency \textit{per se}, since the rejection could be due to an inadequate model of equilibrium expected returns. With this important caveat in mind, we test whether the out-of-sample gains are consistent with the well-known Campbell and Cochrane (1999, CC) habit-formation model. The CC model links time-varying equilibrium expected returns to business-cycle fluctuations. This makes it a natural benchmark for our purposes, given that the out-of-sample gains in Section 3 vary over the business cycle.\textsuperscript{16}

We outline the basic structure of the CC model; see CC and Wachter (2005) for details. The representative investor’s utility is defined over consumption, \( C_t \), and external habit, \( X_t \), according to

\[
E_t \sum_{t=0}^{\infty} \delta^t \left( \frac{(C_t - X_t)^{1-\gamma}}{1-\gamma} \right), \tag{20}
\]

where \( \delta > 0 \) (\( \gamma > 0 \)) is the time-preference (utility-curvature) parameter. A key variable in the CC model is surplus consumption,

\[
S_t = \frac{C_t - X_t}{C_t}, \tag{21}
\]

\textsuperscript{15}While beyond the scope of the present paper, which focuses on the nature of economic and MA forecasts, in ongoing research we are investigating the more practical problem of improving portfolio performance by exploiting economic and MA forecast complementarity (also see footnote 11). More specifically, we use a model for forecasting turning points (e.g., Chauvet and Senyuz, 2009) to provide information on the extent to which we rely on economic or MA forecasts for a portfolio-allocation problem. Observe that we considered simple combinations of economic and MA forecasts. This approach, however, did not improve significantly on the economic or MA forecasts individually, so that combining did not generate a forecast synergy in this instance. It appears that the relatively poor performance of economic (MA) forecasts early (late) in recessions largely offset any gains to combining economic and MA forecasts during recessions.

\textsuperscript{16}This exercise is in the spirit of Brock, Lakonishok, and LeBaron (1992), who examine whether the profitability of technical strategies can be explained by GARCH processes.
which is related to the local curvature of the utility function (or risk aversion) via $\eta_t = \gamma / S_t$. Intuitively, a “small” $S_t$ represents a “bad” state in which consumption is near habit. As $S_t$ decreases and $\eta_t$ increases, the representative investor becomes more risk averse.

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

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

where $s_t = \log(S_t)$, $\bar{s}$ is the unconditional mean of $s_t$, $\phi$ is the persistence parameter for $s_t$, $\lambda (s_t)$ is a sensitivity function, and $c_t = \log(C_t)$. The sensitivity function is given by

$$\lambda (s_t) = \left(1 / \bar{S}_t\right) \sqrt{1 - 2(s_t - \bar{s})} - 1,$$

where $\bar{S} = \sigma_v \sqrt{1 / (1 - \phi)}$ and $\bar{s} = \log(\bar{S})$.\(^{17}\) The log-level of consumption follows a random walk with drift:

$$\Delta c_{t+1} = g + \nu_{t+1},$$

where $\nu_{t+1} \sim \text{i.i.d.} N(0, \sigma_v^2)$.

The aggregate stock market represents a claim to the future consumption stream. The individual investor treats habit as exogenous (external habit), so that the intertemporal marginal rate of substitution (or stochastic discount factor) is given by

$$M_{t+1} = \delta \left(S_{t+1} / S_t \right) C_{t+1} / C_t)^{-\gamma}.$$

According to the first-order Euler condition,

$$E_t(M_{t+1} R_{t+1}) = 1,$$

where $R_{t+1} = (P_{t+1} + C_{t+1}) / P_t$ is the gross aggregate stock market return and $P_t$ is the stock price (excluding dividends). In this endowment economy, $C_t = D_t$ in equilibrium, so that $P_t / C_t$ also represents the price-dividend ratio, $P_t / D_t$.\(^{18}\) Using $P_t / C_t = P_t / D_t$ and rewriting (26), we have

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

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

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\(^{17}\)CC 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 (23) is positive, they also assume that $s_t < s_{\text{max}}$, where $s_{\text{max}} = \bar{s} + (1/2)(1 - \bar{S}^2)$.

\(^{18}\)CC 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.
this pricing function. 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. Since $s_t$ falls during recessions, the CC model generates a rising expected equity premium near cyclical troughs.

With assumed values for $\delta$, $\gamma$, $\phi$, $g$, and $\sigma_v$, we can simulate consumption, dividend, stock price, and equity premium data using the CC model. While the CC model is a general-equilibrium model, its streamlined structure only allows us to simulate observations for two of the economic variables considered in Section 3, DP and DY. Fortunately, it is these two variables that generate the largest out-of-sample gains among the economic forecasts in Tables 1 and 2. With respect to the MA forecasts, we focus on the MA(1,12) and MA(2,12) rules for brevity. These are two of the best-performing MA forecasts in Tables 1 and 2.

We generate empirical $p$-values for the $R^2_{OS}$ statistics and utility gains corresponding to the DP, DY, MA(1,12), and MA(2,12) forecasts in Tables 1 and 2 via the following steps:

1. Use the CC 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).

2. For the pseudo sample, construct pseudo equity premium forecasts based on DP, DY, MA(1,12), and MA(2,12) for the last 588 observations, matching the length of the forecast evaluation period in the original sample (1960:01–2008:12).

3. Compute $R^2_{OS}$ statistics and utility gains for the pseudo DP, DY, MA(1,12), and MA(2,12) forecasts. In addition to computing $R^2_{OS}$ statistics and utility gains for the full forecast evaluation period of the pseudo sample, we compute these statistics for business-cycle expansions and contractions. The random walk with drift process (24) represents the evolution of the real economy in the CC 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. For the simulated consumption data, we identify business-cycle peaks and troughs that define expansions and recessions using the Harding and Pagan (2002) BB algorithm.

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19 Wachter (2005) finds that the series method provides a better approximation than the fixed-point method used by CC.

20 Wachter (2006) extends the CC model by including multiple bonds to investigate term-structure implications of habit formation.
which provides a good approximation to the NBER business-cycle dating methodology.\textsuperscript{21}

4. Repeat steps 1–3 200 times, generating empirical distributions for the $R_{OS}^2$ statistics and utility gains for the DP, DY, MA(1,12), and MA(2,12) forecasts for the full forecast evaluation period and during expansions and recessions.

5. For each statistic, the empirical $p$-value is the proportion of simulated statistics greater than the corresponding statistic in Table 1 or 2 computed using the original data.

Table 3 reproduces the $R_{OS}^2$ statistics and utility gains from Tables 1 and 2 for the DP, DY, MA(1,12), MA(2,12) forecasts and reports the corresponding empirical $p$-values (in percent) based on the CC habit-formation model. We use the same parameter values (reported in the notes to Table 3) as those used by CC in their simulations. CC select these parameter values to match certain moments of U.S. postwar data.

Panel A of Table 3 reports results for forecasts based on DP and DY. The empirical $p$-values corresponding to the $R_{OS}^2$ statistics for the full forecast evaluation period are above 50\% for both DP and DY. The out-of-sample predictive ability evidenced by these economic variables as measured by $R_{OS}^2$ is thus largely attributable to the rational fluctuations in the expected equity premium generated by the CC model. The empirical $p$-values are both above 90\% during expansions for these variables. While they are substantially lower during recessions—17.5\% for both DP and DY—they are still not significant at conventional levels. Overall, the CC model appears capable of accounting for the predictive ability of DP and DY as indicated by the $R_{OS}^2$ statistics.

The empirical $p$-values for the utility gains in Table 3, Panel A point to significant gains for DP and DY over the full forecast evaluation period ($p$-values of 3\% and 2\%, respectively) and for DY during recessions ($p$-value of 7\%). In interpreting these gains, keep in mind that the CC model generates time variation in the equity premium in response to time-varying risk aversion on the part of the representative investor. When computing 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 representative investor’s time-varying risk aversion by, for example, holding more stocks during periods when the equilibrium expected market return is elevated due to the representative investor’s low habit and correspondingly high degree of risk aversion.\textsuperscript{22}

\textsuperscript{21}We implement the BB algorithm using James Engel’s MATLAB code downloaded from http://www.ncer.edu.au/data/.

\textsuperscript{22}This brings to mind a well-known Warren Buffet quote: “We simply attempt to be fearful when others are greedy and to be greedy only when others are fearful.”
this perspective, the significant empirical \( p \)-values in Panel A 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.

Empirical \( p \)-values for the MA(1,12) and MA(2,12) forecasts are reported in Table 3, Panel B. \( R^2_{OS} \) is significant for both MA forecasts at the 1% level for the full forecast evaluation period. The \( p \)-values for the \( R^2_{OS} \) statistics are well above 10% for both forecasts during expansions, while \( R^2_{OS} \) is significant at the 5% and 1% levels for the MA(1,12) and MA(2,12) forecasts, respectively, during recessions—despite the reduced number of observations. The \( p \)-values for the utility gains in Panel B reveal significant gains at the 1% level for both forecasts for the full forecast evaluation period and during recessions, as well as significant gains at the 5% level during expansions.

Overall, Table 3 indicates that the CC habit-formation model cannot fully account for the out-of-sample forecasting gains offered by either the economic variables or, especially, the MA rules. The fact that we still find significant forecasting gains according to empirical \( p \)-values generated from the CC model, which links rational fluctuations in expected returns to business-cycle fluctuations, suggests a degree of equity mispricing, perhaps relating to challenges in forecasting future cash flows in environments, such as recessions, with rapidly changing macroeconomic fundamentals. Of course, as emphasized above, the significant results in Table 3 could be due to an inadequate model of equilibrium expected returns. Whether alternative models that link time-varying equilibrium expected returns to business-cycle fluctuations can explain the significant forecasting gains evidenced by economic and MA forecasts is a fruitful area for future research.

5. Conclusion

Fundamental and technical analysis are very different methods of predicting aggregate stock returns. While fundamental analysis relies on economic variables that are used in predictive regressions, technical analysis uses functions of past price history to guide trading decisions. Researchers have long studied both methods, but the two literatures have evolved independently; there has been little attempt to directly compare fundamental and technical methods.

This paper fills that gap by comparing monthly, out-of-sample forecasts of the U.S. equity premium for 1960–2008 generated with well-known economic variables and popular trend-following technical methods (i.e., MA rules). We compare the methods with two metrics: the Campbell and Thompson (2008) out-of-sample \( R^2 \) statistic and utility gains in a simulated real-time setting for
a mean-variance investor who optimally reallocates a monthly portfolio between equities and a risk-free Treasury bill using equity premium forecasts.

We find evidence that both approaches produce out-of-sample forecasting gains that would be of significant value to a mean-variance investor. While both approaches perform disproportionately well during recessions, a careful analysis of their performance during cyclical downturns reveals that they exploit very different patterns. MA rules usually recognize sooner the drop in the average equity premium that occurs early in recessions, while economic variables tend to identify the increase in the average equity premium prior to business-cycle troughs. Thus, fundamental and technical approaches are complementary. This might explain the continued use of both by practitioners and academics. While each approach has significant economic value, there is clearly the possibility for dynamically combining these complementary forecasts into a superior trading rule. Future research will investigate this issue.

We simulate data from the Campbell and Cochrane (1999) habit-formation model to study whether this model’s rationally evolving expected equity premium can explain the forecasting ability of economic variables and MA rules. Even though the habit-formation model connects fluctuations in the expected equity premium to business-cycle fluctuations, simulated data from the model cannot fully account for the forecasting gains in the actual data. Exploring whether alternative models of time-varying equilibrium expected returns linked to business-cycle fluctuations can explain these forecasting gains is yet another important area for future research.
References


Clark, T.E. and M.W. McCracken. 2001. Tests of Equal Forecast Accuracy and Encompassing for


Table 1  
Out-of-sample equity premium forecasting results, 1960:01–2008:12 forecast evaluation period

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Overall $R^2_{OS}$ (%)</th>
<th>Average Expansion $R^2_{OS}$ (%)</th>
<th>Average Recession $R^2_{OS}$ (%)</th>
<th>Overall Average forecast (%)</th>
<th>Expansion Average forecast (%)</th>
<th>Recession Average forecast (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>A. Economic variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DP</td>
<td>0.73***</td>
<td>0.25</td>
<td>0.15**</td>
<td>0.21</td>
<td>2.15**</td>
<td>0.52</td>
</tr>
<tr>
<td>DY</td>
<td>0.71***</td>
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<td>−0.26</td>
<td>0.17</td>
<td>3.09**</td>
<td>0.48</td>
</tr>
<tr>
<td>EP</td>
<td>−0.19</td>
<td>0.49</td>
<td>−0.15</td>
<td>0.44</td>
<td>−0.28</td>
<td>0.78</td>
</tr>
<tr>
<td>DE</td>
<td>−0.76</td>
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<td>−0.80</td>
<td>0.80</td>
<td>−0.65</td>
<td>0.75</td>
</tr>
<tr>
<td>SVAR</td>
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<td>−0.60</td>
<td>0.67</td>
<td>−0.48</td>
<td>0.68</td>
</tr>
<tr>
<td>BM</td>
<td>−1.64</td>
<td>0.50</td>
<td>−1.57</td>
<td>0.41</td>
<td>−1.79</td>
<td>1.02</td>
</tr>
<tr>
<td>NTIS</td>
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<td>−0.34</td>
<td>0.96</td>
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<td>1.11</td>
</tr>
<tr>
<td>TBL</td>
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<td>0.11*</td>
<td>0.40</td>
<td>0.80</td>
<td>0.28</td>
</tr>
<tr>
<td>LTY</td>
<td>0.42**</td>
<td>0.30</td>
<td>0.25**</td>
<td>0.32</td>
<td>0.85</td>
<td>0.21</td>
</tr>
<tr>
<td>LTR</td>
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<td>0.76</td>
<td>3.30***</td>
<td>0.83</td>
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<tr>
<td>TMS</td>
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<td>−0.62</td>
<td>0.84</td>
<td>2.00**</td>
<td>0.65</td>
</tr>
<tr>
<td>DFY</td>
<td>0.39*</td>
<td>0.64</td>
<td>0.33*</td>
<td>0.62</td>
<td>0.55</td>
<td>0.78</td>
</tr>
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<td>DFR</td>
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<td>0.04</td>
<td>0.71</td>
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<tr>
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<td>0.20</td>
<td>0.67</td>
<td>0.14</td>
<td>0.50</td>
</tr>
<tr>
<td>COMBINE-ECON</td>
<td>0.80***</td>
<td>0.58</td>
<td>0.72**</td>
<td>0.57</td>
<td>1.01**</td>
<td>0.66</td>
</tr>
<tr>
<td><strong>B. Moving-average rules</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MA(1,3)</td>
<td>−0.58</td>
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<td>−1.19</td>
<td>0.67</td>
<td>0.92</td>
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<td>MA(1,6)</td>
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<td>0.73</td>
<td>2.94**</td>
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</tr>
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<td>0.19</td>
<td>0.74</td>
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<td>0.32</td>
</tr>
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<td>0.07</td>
<td>0.78</td>
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<td>0.27</td>
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<tr>
<td>MA(1,18)</td>
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<td>0.69</td>
<td>0.01</td>
<td>0.76</td>
<td>1.91*</td>
<td>0.32</td>
</tr>
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<td>MA(1,21)</td>
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<td>0.14</td>
<td>0.66</td>
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</tr>
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<td>0.68</td>
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<tr>
<td>MA(2,3)</td>
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<td>MA(2,6)</td>
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<td>0.69</td>
<td>1.45**</td>
<td>0.50</td>
</tr>
<tr>
<td>MA(2,9)</td>
<td>0.56*</td>
<td>0.66</td>
<td>−0.29</td>
<td>0.72</td>
<td>2.63**</td>
<td>0.36</td>
</tr>
<tr>
<td>MA(2,12)</td>
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<td>0.28</td>
<td>0.75</td>
<td>3.05**</td>
<td>0.30</td>
</tr>
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<td>−0.10</td>
<td>0.76</td>
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<td>0.71</td>
<td>1.06</td>
<td>0.44</td>
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<td>COMBINE-MA</td>
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<td>−0.11</td>
<td>0.70</td>
<td>1.78**</td>
<td>0.44</td>
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</table>

Notes: $R^2_{OS}$ is the Campbell and Thompson (2008) out-of-sample $R^2$ statistic, which measures the percent reduction in mean square prediction error for the forecast indicated in the first column relative to the historical average benchmark forecast. COMBINE-ECON (COMBINE-MA) is a combination forecast based on the individual economic-variable (moving-average) forecasts in Panel A (Panel B). Statistical significance of $R^2_{OS}$ is assessed with the Clark and West (2007) MSPE-adjusted statistic corresponding to the null hypothesis of equal mean square prediction error against the alternative hypothesis that the forecast indicated in the first column has a lower mean square prediction error than the historical average benchmark forecast; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The $R^2_{OS}$ statistics and average forecasts are computed for the entire 1960:01–2008:12 forecast evaluation period [columns (2)–(3)] and separately for NBER-dated business-cycle expansions [columns (4)–(5)] and recessions [columns (6)–(7)]. Average forecast is the average value during the evaluation period.
Table 2  
Asset-allocation results, 1960:01–2008:12 forecast evaluation period

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Overall</th>
<th>Expansion</th>
<th>Recession</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Δ (annual %)</td>
<td>Average equity weight</td>
<td>Δ (annual %)</td>
</tr>
<tr>
<td>DP</td>
<td>1.44</td>
<td>0.28</td>
<td>0.12</td>
</tr>
<tr>
<td>DY</td>
<td>1.82</td>
<td>0.22</td>
<td>−0.17</td>
</tr>
<tr>
<td>EP</td>
<td>1.23</td>
<td>0.53</td>
<td>0.76</td>
</tr>
<tr>
<td>DE</td>
<td>−0.53</td>
<td>0.98</td>
<td>−0.27</td>
</tr>
<tr>
<td>SVAR</td>
<td>−0.31</td>
<td>0.88</td>
<td>−0.25</td>
</tr>
<tr>
<td>BM</td>
<td>−0.40</td>
<td>0.48</td>
<td>−0.94</td>
</tr>
<tr>
<td>NTIS</td>
<td>−0.49</td>
<td>1.06</td>
<td>0.47</td>
</tr>
<tr>
<td>TBL</td>
<td>1.65</td>
<td>0.53</td>
<td>0.71</td>
</tr>
<tr>
<td>LTY</td>
<td>1.63</td>
<td>0.42</td>
<td>0.82</td>
</tr>
<tr>
<td>LTR</td>
<td>0.68</td>
<td>0.94</td>
<td>−0.56</td>
</tr>
<tr>
<td>TMS</td>
<td>1.21</td>
<td>0.97</td>
<td>0.12</td>
</tr>
<tr>
<td>DFY</td>
<td>0.43</td>
<td>0.82</td>
<td>0.20</td>
</tr>
<tr>
<td>DFR</td>
<td>0.92</td>
<td>0.91</td>
<td>0.09</td>
</tr>
<tr>
<td>INFL</td>
<td>0.68</td>
<td>0.85</td>
<td>0.22</td>
</tr>
<tr>
<td>COMBINE-ECON</td>
<td>1.08</td>
<td>0.76</td>
<td>0.97</td>
</tr>
<tr>
<td>MA(1,3)</td>
<td>0.28</td>
<td>0.82</td>
<td>−0.44</td>
</tr>
<tr>
<td>MA(1,6)</td>
<td>1.79</td>
<td>0.78</td>
<td>−0.36</td>
</tr>
<tr>
<td>MA(1,9)</td>
<td>2.11</td>
<td>0.82</td>
<td>0.12</td>
</tr>
<tr>
<td>MA(1,12)</td>
<td>3.07</td>
<td>0.84</td>
<td>0.96</td>
</tr>
<tr>
<td>MA(1,15)</td>
<td>3.24</td>
<td>0.85</td>
<td>1.10</td>
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<td>MA(1,18)</td>
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<td>0.86</td>
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<td>0.01</td>
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<td>MA(2,3)</td>
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<td>−0.09</td>
</tr>
<tr>
<td>MA(2,6)</td>
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<td>−0.08</td>
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<td>0.83</td>
<td>0.32</td>
</tr>
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<td>MA(2,12)</td>
<td>3.43</td>
<td>0.84</td>
<td>1.07</td>
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<td>MA(2,15)</td>
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<td>0.84</td>
<td>0.86</td>
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<td>MA(2,18)</td>
<td>1.53</td>
<td>0.85</td>
<td>0.36</td>
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<td>MA(2,21)</td>
<td>0.94</td>
<td>0.85</td>
<td>0.09</td>
</tr>
<tr>
<td>MA(2,24)</td>
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<td>0.83</td>
<td>−0.13</td>
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<tr>
<td>COMBINE-MA</td>
<td>1.78</td>
<td>0.85</td>
<td>0.45</td>
</tr>
</tbody>
</table>

Notes: Average utility gain (Δ) is the portfolio management fee (in annualized percent return) that an investor with mean-variance preferences and risk aversion coefficient of five would be willing to pay to have access to the forecasting model given in the first column relative to the historical average benchmark forecasting model. COMBINE-ECON (COMBINE-MA) is a combination forecast based on the individual economic-variable (moving-average) forecasts in Panel A (Panel B). The utility gains and average equity weights are computed for the entire 1960:01–2008:12 forecast evaluation period [columns (2)–(3)] and separately for NBER-dated business-cycle expansions [columns (4)–(5)] and recessions [columns (6)–(7)]. Average equity weight is the average value during the evaluation period.
Table 3
Empirical \( p \)-values (in percent) based on simulated data from the Campbell and Cochrane (1999) habit-formation model

<table>
<thead>
<tr>
<th>Predictor</th>
<th>( R^2_{\text{OS}} ) (%)</th>
<th>( \Delta ) (annual %)</th>
<th>( R^2_{\text{OS}} ) (%)</th>
<th>( \Delta ) (annual %)</th>
<th>( R^2_{\text{OS}} ) (%)</th>
<th>( \Delta ) (annual %)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall</td>
<td>( \Delta )</td>
<td>( \Delta )</td>
<td>( \Delta )</td>
<td>( \Delta )</td>
<td>( \Delta )</td>
<td>( \Delta )</td>
</tr>
<tr>
<td>A. Economic variables</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DP</td>
<td>0.73 [53.50] 1.44 [3.00] 0.15 [90.50] 0.12 [58.50] 2.15 [17.50] 8.76 [12.50]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DY</td>
<td>0.71 [59.50] 1.82 [2.00] -0.26 [94.00] -0.17 [63.00] 3.09 [17.50] 13.02 [7.00]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>B. Moving-average rules</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MA(1,12)</td>
<td>0.88 [0.50] 3.07 [0.00] 0.68 [33.50] 0.96 [3.50] 2.57 [4.00] 15.03 [0.00]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MA(2,12)</td>
<td>1.08 [1.00] 3.43 [0.00] 0.68 [25.00] 1.07 [3.50] 3.05 [1.00] 16.78 [0.00]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: The table reproduces the \( R^2_{\text{OS}} \) statistics from Table 1 and utility gains from Table 2 for equity premium forecasts based on DP, DY, MA(1,12), and MA(2,12). Brackets report empirical \( p \)-values computed from 200 pseudo samples generated using the Campbell and Cochrane (1999) habit-formation model and the following parameter values: \( \delta = 0.89^{1/12}, \gamma = 2, \phi = 0.86^{1/12}, g = 0.0189/12, \sigma = 0.0150/\sqrt{12} \). The empirical \( p \)-values are the percent of simulated \( R^2_{\text{OS}} \) statistics and utility gains greater than the corresponding reproduced values from Tables 1 and 2.
Figure 1. Out-of-sample equity premium forecasts based on economic variables, 1960:01–2008:12. Black and blue lines delineate forecasts (in percent) based on the economic variable indicated in the panel heading and the historical average forecast, respectively. COMBINE-ECON is a combination forecast based on the individual economic-variable forecasts. Vertical red lines show NBER-dated business-cycle peaks and troughs (in succession).
Figure 2. Out-of-sample equity premium forecasts based on moving-average rules, 1960:01–2008:12. Black and blue lines delineate forecasts (in percent) based on the moving-average rule indicated in the panel heading and the historical average forecast, respectively. COMBINE-MA is a combination forecast based on the individual moving-average forecasts. Vertical red lines show NBER-dated business-cycle peaks and troughs (in succession).
Figure 3. Equity portfolio weights computed using equity premium forecasts based on economic variables, 1960:01–2008:12. Black (blue) lines delineate the equity portfolio weight for an investor with mean-variance preferences and risk aversion coefficient of five who uses an equity premium forecast based on the economic variable indicated in the panel heading (historical average). COMBINE-ECON is a combination forecast based on the individual economic-variable forecasts. Vertical red lines show NBER-dated business-cycle peaks and troughs (in succession).
Figure 4. Equity portfolio weights computed using equity premium forecasts based on moving-average rules, 1960:01–2008:12. Black (blue) lines delineate the equity portfolio weight for an investor with mean-variance preferences and risk aversion coefficient of five who uses an equity premium forecast based on the moving-average rule indicated in the panel heading (historical average). COMBINE-MA is a combination forecast based on the individual moving-average forecasts. Vertical red lines show NBER-dated business-cycle peaks and troughs (in succession).
Figure 5. Average actual equity premium and equity premium forecasts based on economic variables 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 an economic variable and the historical average equity premium forecast two months before through four months after a business-cycle peak. COMBINE-ECON is a combination forecast based on the individual economic-variable forecasts. All forecasts are measured in percent. Circles indicate point estimates and the outer solid lines delineate 90% confidence bands.
Figure 6. Average actual equity premium and equity premium forecasts based on moving-average 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 a moving-average rule and the historical average equity premium forecast two months before through four months after a business-cycle peak. COMBINE-MA is a combination forecast based on the individual moving-average forecasts. All forecasts are measured in percent. Circles indicate point estimates and the outer solid lines delineate 90% confidence bands.
Figure 7. Average actual equity premium and equity premium forecasts based on economic variables 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 an economic variable and the historical average equity premium forecast four months before through two months after a business-cycle trough. COMBINE-ECON is a combination forecast based on the individual economic-variable forecasts. All forecasts are measured in percent. Circles indicate point estimates and the outer solid lines delineate 90% confidence bands.
Figure 8. Average actual equity premium and equity premium forecasts based on moving-average 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 a moving-average rule and the historical average equity premium forecast four months before through two months after a business-cycle trough. COMBINE-MA is a combination forecast based on the individual moving-average forecasts. All forecasts are measured in percent. Circles indicate point estimates and the outer solid lines delineate 90% confidence bands.