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THE SUM OF THE PARTS IS MORE THAN THE WHOLE

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ABSTRACT

We propose forecasting separately the three components of stock market returns: dividend yield, earnings growth, and price-earnings ratio growth. We obtain out-of-sample R-square coefficients (relative to the historical mean) of nearly 1.6% with monthly data and 16.7% with yearly data using the most common predictors suggested in the literature. This compares with typically negative R-squares obtained in a similar experiment by Goyal and Welch (2008). An investor who timed the market with our approach would have had a certainty equivalent gain of as much as 2.3% per year and a Sharpe ratio 77% higher relative to the historical mean. We conclude that there is substantial predictability in equity returns and that it would have been possible to time the market in real time.

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Prediction is very difficult, especially about the future. — Niels Bohr

1. Introduction

There is a long literature on forecasting stock market returns. Predictive variables that have been proposed include price multiples, macro variables, corporate actions, and measures of risk. Dow (1920), Campbell (1987), Fama and French (1988), Hodrick (1992), Ang and Bekaert (2007), Cochrane (2008), and many others use the dividend yield; Campbell and Shiller (1988) and Lamont (1998) use the earnings-price ratio; and Kothari and Shanken (1997) and Pontiff and Schall (1998) use the book-to-market ratio. Fama and Schwert (1977), Campbell (1987), Breen, Glosten, and Jagannathan (1989), Ang and Bekaert (2007) use the short-term interest rate; Nelson (1976), Fama and Schwert (1977), Campbell and Vuolteenaho (2004) use inflation; Campbell (1987) and Fama and French (1988) use the term and default yield spreads; and Lettau and Ludvigson (2001) use the consumption-wealth ratio. Baker and Wurgler (2000) and Boudoukh, Michaely, Richardson, and Roberts (2007)) use corporate issuing activity. French, Schwert, and Stambaugh (1987), Ghysels, Santa-Clara, and Valkanov (2005), and Guo (2006) use stock market volatility and Goyal and Santa-Clara (2003) use idiosyncratic volatility. All these studies find evidence in favor of return predictability *in sample*.[1]

These findings, however, have been questioned by several authors on the grounds that the persistence of the forecasting variables and the correlation of their innovations with returns might bias the regression coefficients and affect t-statistics (Nelson and Kim (1993), Cavanagh, Elliott, and Stock (1995), Stambaugh (1999), Lewellen (2004), Torous, Valkanov, and Yan (2004)). A further problem is the possibility of data mining (Foster, Smith, and Whaley (1997), Ferson, Sarkissian, and Simin (2003)) illustrated by a long list of spurious predictive variables that regularly show up in the press, including hem lines, football results, and butter production in Bangladesh. The predictability of stock market returns is therefore still an open question.

In an important recent paper, Goyal and Welch (2008) examine the out-of-sample performance of a long list of predictors. They compare forecasts of returns at time $t+1$ from a predictive regression estimated using data up to time t with forecasts based on the historical mean in the same period. They find that the historical mean actually has a better out-of-sample performance than the traditional predictive regressions of stock returns. They conclude that "these models would not have helped an investor with access to available information to profitably time the market." (See also Bossaerts and Hillion (1999).) Several authors have argued that this is not evidence against predictability per se but only evidence

[1] Several authors consider the implications of return predictability for portfolio choice: Brennan, Lagnado, and Schwartz (1997), Balduzzi and Lynch (1999), Brandt (1999), Campbell and Viceira (1999), Barberis (2000), Brandt and Santa-Clara (2006), among others.

of the difficulty in exploiting predictability with trading strategies (Inoue and Kilian (2004), Cochrane (2008)). But the Goyal and Welch (2008) challenge remains largely unanswered.

In this paper, we offer an alternative method to predict stock market returns — *the sum-of-the-parts method*. We decompose the stock market return into three components — the dividend yield, the earnings growth rate, and the growth rate in the price-earnings ratio — and forecast each of these components separately. We forecast the dividend yield using the currently observed dividend yield. The earnings growth rate is forecasted with its twenty-year moving average. We use two alternatives to predict the growth rate in the price-earnings ratio. In the first alternative, we use predictive regressions for the growth rate in the price-earnings ratio. In the second alternative, we regress the price-earnings ratio on macro variables and calculate the growth rate that would take the currently observed ratio to the fitted value. In both cases we use shrinkage to improve the robustness of the predictions. (Parenthetically, we also show that shrinkage also improves significantly the out-of-sample performance of traditional predictive regressions.)

We apply the sum-of-the-parts method to the same data as Goyal and Welch (2008) for the 1927-2007 period.[2] The performance of our approach clearly beats both the historical mean and the traditional predictive regressions. We obtain out-of-sample R-squares (relative to the historical mean) that range from 0.68% to 1.55% with monthly data and from 4.65% to 16.72% with yearly data (and non-overlapping observations). This contrasts with out-of-sample R-squares ranging from -1.78% to 0.69% (monthly) and from -17.57% to 7.54% (yearly) obtained on the same data set with the predictive regression approach used by Goyal and Welch (2008). The results are robust in subsamples.

The economic gains from a trading strategy that uses the sum-of-the-parts method are substantial. The certainty equivalent gains of applying the sum-of-the-parts method (relative to a trading strategy based on the historical mean) are always positive and more than 2% per year for some of the predictive variables. Sharpe ratios are always larger (more than 75% in some cases) than the Sharpe ratio of a strategy based on the historical mean. In contrast, trading strategies based on predictive regressions would have generated significant economic losses. We conclude that there is substantial predictability in equity returns and that it would have been possible to time the market in real time.

The papers closest to ours is Campbell and Thompson (2008). They show that imposing restrictions on the signs of the coefficients of the predictive regressions modestly improves out-of-sample performance in both statistical and economic terms. More importantly, they suggest an alternative decomposition of expected stock returns based on the Gordon growth model coupled with the assumption that earnings growth is financed from retained earnings. In our framework, this corresponds to assuming that the price-earnings multiple growth is expected to be zero and forecasting the earnings growth rate with the product of the return on equity and the plowback ratio (both estimated with long-term averages). The out-of-sample R-square obtained in our sample period with the Campbell and Thompson (2008)

[2] The sample period in Goyal and Welch (2008) is 1927-2004. We obtain in general slightly better out-of-sample performance using the 1927-2004 period.

method is 0.54% with monthly frequency and 3.24% with yearly frequency. Our out-of-sample forecasting results are substantially better than those in Campbell and Thompson (2008) for two reasons: our forecast of earnings growth works better and our forecast of the price-earnings multiple growth has incremental explanatory power.

The remainder of the paper is organized as follows. Section 2 describes the methodology. Section 3 describes the data and presents the results. Section 4 concludes.

2. Methodology

In this section we first describe the traditional predictive regression methodology to forecast stock market returns. We then describe a simple decomposition of stock returns and how we forecast each of the components of stock returns.

2.1. Forecasting Returns with Predictive Regressions

The traditional *predictive regression* methodology regresses stock returns on lagged predictors:[3]

$$r_{t+1} = \alpha + \beta x_t + \epsilon_{t+1}. \tag{1}$$

In this study, we generate out-of-sample forecasts of the stock market return using a sequence of expanding windows. Specifically, we take a subsample of the first s observations $t = 1, ..., s$ of the entire sample of T observations and estimate regression (1). We then use the estimated coefficients (denoted with hats) together with the value of the predictive variable at time s to predict the return at time $s + 1$:

$$E_s(r_{s+1}) = \hat{\alpha} + \hat{\beta} x_s, \tag{2}$$

where $E_s(\cdot)$ is the expectation operator conditional on the information available at time s.[4] We follow this process for $s = s_0, ..., T - 1$, thereby generating a sequence of out-of-sample return forecasts $E_s(r_{s+1})$. To start the procedure, we require an initial sample of size s_0 (20 years in the empirical application). This process simulates what a forecaster could have done in real time.

We evaluate the performance of the forecasting exercise with an out-of-sample R-square similar to the one proposed by Goyal and Welch (2008).[5] This measure compares the pre-

[3] Alternatives to predictive regressions based on Bayesian methods, latent variables, analyst forecasts, and surveys have been suggested by several authors, including Welch (2000), Claus and Thomas (2001), Brandt and Kang (2004), Pastor and Stambaugh (2008), and Binsbergen and Koijen (2008).

[4] To be more rigorous the estimated coefficients of the regression should be indexed by s, $\widehat{\alpha}_s$ and $\widehat{\beta}_s$, as they change with the expanding sample. We suppress the subscript for simplicity.

[5] See Diebold and Mariano (1995) and Clark and McCracken (2001) for alternative criteria to evaluate out-of-sample performance.

dictive ability of the regression with the historical sample mean (which implicitly assumes that expected returns are constant):

$$R^2 = 1 - \frac{MSE_R}{MSE_M}. \tag{3}$$

MSE_R is the mean squared error of the out-of-sample predictions from the model:

$$MSE_R = \frac{1}{T - s_0} \sum_{s=s_0}^{T-1} \left(r_{s+1} - E_s\left(r_{s+1}\right)\right)^2, \tag{4}$$

and MSE_M is the mean squared error of the historical sample mean:

$$MSE_M = \frac{1}{T - s_0} \sum_{s=s_0}^{T-1} \left(r_{s+1} - \overline{r}_s\right)^2, \tag{5}$$

where $\overline{r}_s$ is the historical mean of stock market returns up to time s.[6] The out-of-sample R-square will take negative values when the historical sample mean predicts returns better than the model. Goyal and Welch (2008) offer evidence (that we replicate below) that predictive regressions using most variables proposed in the literature have poor out-of-sample performance.

The fitted value from a regression is a noisy estimate of the conditional expectation of the left-hand side variable. This noise arises from the sampling error inherent in estimating model parameters using a finite (and often quite limited) sample. Since a regression tries to minimize squared errors, it tends to overfit in sample. That is, the regression coefficients are calculated to minimize the sum of squared errors that arise both from the fundamental relation between the variables and from the sampling noise in the data. Needless to say, the second component is unlikely to hold robustly out of sample. Ashley (2006) shows that the unbiased forecast is no longer squared-error optimal in this setting. Instead, the minimum-MSE forecast is shown to be a shrinkage of the unbiased forecast toward zero. This process squares nicely with a prior of no predictability in returns.

We apply a simple shrinkage approach to the predictive regression suggested by Connor (1997).[7] We transform the estimated coefficients of equation (2) by:

$$\beta^* = \frac{s}{s+i}\hat{\beta}, \tag{6}$$

$$\alpha^* = \overline{r}_s - \beta^* \overline{x}_s, \tag{7}$$

[6] Goyal and Welch (2008) include a degree-of-freedom adjustment in their R-squared measure which we do not use. The purpose of adjusting a measure of goodness of fit for the degrees of freedom is to penalize in-sample overfit which would likely decrease out-of-sample performance. Since the measure we use is already fully out of sample, there is no need for such adjustment. In any case, for the sample sizes and the number of explanatory variables used in this study, the degree-of-freedom adjustment would be minimal.

[7] Interestingly, shrinkage has been widely used in finance for portfolio optimization problems but not for return forecasting. See Brandt (2004) and the references therein for portfolio optimization applications of shrinkage.

where $\overline{x}_s$ is the historical mean of the predictor up to time s. In this way, the slope coefficient is shrunk towards zero and the intercept changes to preserve the unconditional mean return. The shrinkage intensity i can be intuitively thought of as the weight given to the prior of no predictability. It is measured in units of time periods. Thus, if i is set equal to the number of data periods in the data set s, the slope coefficient is shrunk by half. Connor (1997) shows that it is optimal to choose $i = 1/\rho$, where ρ is the expectation of a function of the regression R-square:

$$\rho = E\left(\frac{R^2}{1-R^2}\right) \approx E(R^2). \tag{8}$$

This is the expected explanatory power of the model. We use $i = 100$ with annual data and $i = 1,200$ with monthly data. This corresponds to giving a weight of 100 years of data to the prior of no predictability. Alternatively, we can interpret this as an expected R-square of approximately 1% for predictive regressions with annual data and less than 0.1% with monthly data which seems reasonable in light of the extant literature. This means that if we run the predictive regression with 30 years of data, the slope coefficient is shrunk to 23% $(= 30/(100 + 30))$ of its estimated magnitude.

Finally, we use these coefficients to forecast the stock market return r as:

$$E_s\left(r_{s+1}\right) = \alpha^* + \beta^* x_s. \tag{9}$$

2.2. Return Components

We decompose the total return of the stock market index into dividend yield and capital gains:

$$1 + R_{t+1} = 1 + CG_{t+1} + DY_{t+1} = \frac{P_{t+1}}{P_t} + \frac{D_{t+1}}{P_t}, \tag{10}$$

where R_{t+1} is the return obtained from time t to time $t+1$; CG_{t+1} is the capital gain; DY_{t+1} is the dividend yield; P_{t+1} is the stock price at time $t+1$; and D_{t+1} is the dividend paid during the return period.[8]

The capital gain component can be written as follows:

$$\begin{aligned} 1 + CG_{t+1} &= \frac{P_{t+1}}{P_t} \\ &= \frac{P_{t+1}/E_{t+1}}{P_t/E_t}\frac{E_{t+1}}{E_t} \\ &= \frac{M_{t+1}}{M_t}\frac{E_{t+1}}{E_t} \\ &= (1 + GM_{t+1})(1 + GE_{t+1}), \end{aligned} \tag{11}$$

[8] Fama and French (1998), Arnott and Bernstein (2002), and Ibbotson and Chen (2003) offer alternative decompositions of returns.

where E_{t+1} denotes earnings per share at time $t+1$; M_{t+1} is the price-earnings ratio; GM_{t+1} is the price-earnings ratio growth rate; and GE_{t+1} is the earnings growth. In this decomposition we use earnings and the price-earnings ratio but could alternatively use any other price multiple such as the price-dividend ratio or the price-to-book ratio. Under these alternatives, we should replace the growth in earnings by the growth rate of the denominator in the multiple.

The dividend yield can in turn be decomposed as follows:

$$\begin{aligned} DY_{t+1} &= \frac{D_{t+1}}{P_t} \\ &= \frac{D_{t+1}}{P_{t+1}}\frac{P_{t+1}}{P_t} \\ &= DP_{t+1}(1+GM_{t+1})(1+GE_{t+1}), \end{aligned} \tag{12}$$

where DP_{t+1} is the dividend-price ratio (which is distinct from the dividend yield in the timing of the dividend relative to the price).

Replacing the capital gain and the dividend yield in equation (10), we can write the total return as the product of the dividend-price ratio and the growth rates of the price-earnings ratio and of earnings:

$$\begin{aligned} 1+R_{t+1} &= (1+GM_{t+1})(1+GE_{t+1}) + DP_{t+1}(1+GM_{t+1})(1+GE_{t+1}) \\ &= (1+GM_{t+1})(1+GE_{t+1})(1+DP_{t+1}). \end{aligned} \tag{13}$$

Finally, we can make this expression additive by taking logs:

$$\begin{aligned} r_{t+1} &= \log(1+R_{t+1}) \\ &= gm_{t+1} + ge_{t+1} + dp_{t+1}, \end{aligned} \tag{14}$$

where lower case variables denote log rates. Thus, log returns can be written as the sum of the log dividend-price ratio, the growth in earnings, and the growth in the price-earnings ratio.

2.3. The Sum-of-the-Parts Method

As an alternative to the predictive regressions, we propose forecasting separately the components of the stock market return from expression (14):

$$E_s\left(r_{s+1}\right) = E_s\left(gm_{s+1}\right) + E_s\left(ge_{s+1}\right) + E_s\left(dp_{s+1}\right). \tag{15}$$

We estimate the expected earnings growth $E_s\left(ge_{s+1}\right)$ using a 20-year moving average of the growth in earnings per share up to time t. This is consistent with the view that earnings growth is nearly unforecastable (Campbell and Shiller (1988), Fama and French

(2002), Cochrane (2008)). The expected dividend-price ratio $E_s(dp_{s+1})$ is estimated with the current dividend-price ratio dp_s. This implicitly assumes that the dividend-price ratio follows a random walk as Campbell (2008) proposes. We use two alternative methods to forecast the growth in the price-earnings ratio.

In the first approach, we run a traditional predictive regression — *multiple growth regression* — with the multiple growth gm (instead of the stock market return r) as the dependent variable:

$$gm_{t+1} = \alpha + \beta x_t + \epsilon_{t+1}, \tag{16}$$

to obtain a forecast of the price-multiple growth. We generate out-of-sample forecasts of the multiple growth using a sequence of expanding windows. We again apply shrinkage to the estimated coefficients as explained above. We then add the expected earnings growth and expected dividend-price ratio to obtain the stock market return forecast.

The second approach — *multiple reversion* — assumes that the price multiple reverts to its expectation conditional on the state of the economy. We first run a time series regression of the valuation ratio $m_t = \log M_t = \log(P_t/E_t)$ on the explanatory variable x_t:

$$m_t = a + bx_t + u_t. \tag{17}$$

Note that this is a contemporaneous regression since both sides of the equation are known at the same time. The fitted value of the regression gives us the multiple that historically prevailed, on average, during economic periods characterized by the same level of the explanatory variable x. The expected value of the multiple at time s is:

$$E_s(m_s) = \hat{a} + \hat{b}x_s. \tag{18}$$

If the observed multiple m_s is above this expectation, we anticipate a negative growth for the multiple and vice versa. For example, suppose that the current price-earnings ratio is 10 and the regression indicates that the expected value of the multiple is 12 given the current value of the explanatory variable. We would expect a return from this component of 20%. The estimated regression residual gives an estimate of the expected growth in the price multiple:

$$\begin{aligned} -\hat{u}_s &= E_s(m_s) - m_s \\ &= E_s(gm_{s+1}). \end{aligned} \tag{19}$$

In practice, the reversion of the multiple to its expectation is quite slow, and does not take place in a single period. To take this into account, we run a second regression of the realized multiple growth on the expected multiple growth using the estimated residuals from regression equation (18):

$$gm_{t+1} = c + d\widehat{u}_t + v_t. \tag{20}$$

We again apply shrinkage to the estimated coefficients as follows:

$$d^* = \frac{s}{s+i}\widehat{d}, \quad (21)$$

$$c^* = -d^*\overline{gm}_s, \quad (22)$$

where $\overline{gm}_s$ is the sample mean of the price multiple growth up to time s. This assumes that the unconditional expectation of the multiple growth is equal to zero. That is, with no information about the state of the economy, we do not expect the multiple to change. Finally, we use these coefficients to forecast gm as:

$$E_s\left(gm_{s+1}\right) = c^* + d^*\widehat{u}_s. \quad (23)$$

We generate out-of-sample forecasts of the multiple growth using a sequence of expanding windows.

3. Empirical Analysis

3.1. Data

We use the data set constructed by Goyal and Welch (2008).[9] We use monthly data to predict the monthly stock market return and annual data (non-overlapping) to predict the annual stock market return.[10] The market return is proxied by the S&P 500 index continuously compounded return including dividends. The sample period is from December 1927 to December 2007 (or 1927 to 2007 with annual data). Table 1 presents summary statistics of sock market return (r) and its components (gm, ge, and dp) at monthly and yearly frequency. The mean monthly stock market return is 9.48% (annualized) and the standard deviation (annualized) is 19.23% over the whole sample period. Figure 1 plots the monthly cumulative realized components of stock market return over time.

The predictors of stock returns x are:

Stock variance (SVAR): sum of squared daily stock market returns on S&P 500.

Default return spread (DFR): difference between long-term corporate bond and long-term bond returns.

Long-term yield (LTY): long-term government bond yield.

[9] The data are drawn from Goyal's website: http://www.bus.emory.edu/AGoyal. See Goyal and Welch (2008) for a complete description of the variables and their sources.

[10] Goyal and Welch (2008) forecast the equity premium, i.e., the stock market return minus the short-term riskless interest rate. We obtain qualitatively similar results when we apply our approach to the equity premium.

Long-term return (LTR): long-term government bond return.

Inflation (INFL): growth in the Consumer Price Index with a 1-month lag.

Term spread (TMS): difference between the long-term government bond yield and the T-bill.

Treasury bill rate (TBL): 3-month Treasury bill rate.

Default yield spread (DFY): difference between BAA and AAA-rated corporate bond yields.

Net equity expansion (NTIS): ratio of 12-month moving sums of net issues by NYSE listed stocks to NYSE market capitalization.

Return on equity (ROE): ratio of 12-month moving sums of earnings to book value of equity for the S&P 500.

Dividend payout ratio (DE): difference between the log of dividends (12-month moving sums of dividends paid on S&P 500) and the log of earnings (12-month moving sums of earnings on S&P 500).

Earnings price ratio (EP): difference between the log of earnings (12-month moving sums of earnings on S&P 500) and the log of prices (S&P 500 index price).

Smooth earnings price ratio (SEP): 10-year moving average of earnings price ratio.

Dividend price ratio (DP): difference between the log of dividends (12-month moving sums of dividends paid on S&P 500) and the log of prices (S&P 500 index price).

Dividend yield (DY): difference between the log of dividends (12-month moving sums of dividends paid on S&P 500) and the log of lagged prices (S&P 500 index price).

Book-to-market (BM): ratio of book value to market value for the Dow Jones Industrial Average.

We use the same variables to forecast the multiple growth gm in the multiple growth regression approach, with the exception of the predictors that depend on the stock index price (EP, SEP, DP, DY, and BM).

3.2. Base Case

In this section we perform an out-of-sample forecasting exercise along the lines of Goyal and Welch (2008). Table 2 report the results for the whole sample period from December 1927 to December 2007 for monthly frequency (1927 to 2007 for annual frequency). The forecast period starts 20 years after the beginning of the sample, i.e., in January 1948 (1948 for annual frequency) and ends in December 2007 (2007 for annual frequency). Panel A reports results for monthly return forecasts and Panel B reports results for annual return forecasts. Each row of the table considers a different forecasting variable, which is identified in the first and second columns.

The third column of the table reports the in-sample R-square of the full-sample regression. In panel A, it is clear that most of the variables have modest predictive power for monthly stock returns over the long sample period considered here. The most successful variable is net equity expansion with an R-square of 1.07%. All other variables have in-sample R-squares below 1%.

The remaining columns evaluate the out-of-sample performance of the alternative forecasts using the out-sample R-square relative to the historical mean. The fourth column reports the out-of-sample R-squares from the traditional predictive regression approach as in Goyal and Welch (2008). The fifth column reports the out-of-sample R-squares from the predictive regression with shrinkage. The sixth and seventh columns present out-of-sample R-squares of forecasting separately the components of the stock market return (the sum-of-the-parts method). In the sixth column we use the multiple growth regression approach, while in the seventh column we forecast the price-earning ratio growth using the multiple reversion approach.

Several conclusions stand out from panel A for monthly return forecasts. First, consistent with Goyal and Welch (2008), the traditional predictive regression out-of-sample R-squares are in general negative ranging from -1.78% to -0.05%. The only exception is the net equity expansion variable that presents an out-of-sample R-square of 0.69%.

Second, shrinkage improves the out-of-sample performance of most predictors. There are now 8 variables with positive R-squares out of 16 variables. The R-squares, however, are still modest, with a maximum of 0.53%.

Third, there is a very significant improvement in the out-of-sample forecasting performance when we model separately the components of the stock market return. A considerable part of the improvement comes from the dividend yield and earnings growth components alone. We present in the last row of each panel, the out-of-sample R-square of using only the dividend yield and earnings growth components to forecast stock market returns (i.e., ignoring the multiple growth component). We obtain an out-of-sample R-square of 1.32%, which is much better than the performance of the traditional predictive regressions. Furthermore, we obtain positive out-of-sample R-squares for every variable. The R-squares from the multiple growth regression (and the dividend-price and earnings growth forecasts) range from 0.76% (dividend yield) to 1.55% (net equity expansion). Several variables present a good performance with R-squares above 1.3%, such as the term spread, inflation, T-bill rate, and the default yield spread.

Finally, there is similar good performance when we forecast the price-earnings growth using the multiple reversion approach. We present R-squares for only those variables that do not depend on the stock index price.[11] The last column shows that 3 (out 11 variables) have

[11] We do not use EP, SEP, DP, DY, and BM in the multiple reversion approach since running a contem-

higher R-squares than in the multiple growth regression approach. The R-square coefficients of the multiple reversion approach range from 0.68% to 1.40%. The last figure in the last column gives the R-square of just using the historical mean of the price-earnings growth as a forecast of this component (and separately forecasting dividend-price and earnings growth). We obtain a remarkable R-square of 1.35%.

Figure 2 shows the realized price-earnings ratio and the fitted value from regression equation (17) of the price earnings on three different explanatory variables: SVAR, TMS, and TBL. It is remarkable how little of the time variation of the price-earnings ratio is captured by these explanatory variables. It seems that the changes in the market multiple over time have little to do with the state of the economy. Importantly for our approach, we see that the realized multiple reverts to the fitted value. Note that this is not automatically guaranteed since the forecasted price-earnings ratio is not the fitted value of a regression estimated ex post but is constructed from a series of regressions estimated with data up to each point in time. However, the reversion is quite slow and at times takes almost 10 years. The second regression (20) captures this speed of adjustment. The expected return coming from multiple reversion varies substantially over time and takes both positive and negative values.

Figure 3 shows the different components of the expected stock market return for the same three predictive variables. We see substantial time variation of expected stock market returns over time, from zero (actually slightly negative) around the year 2000 to almost 1.5% per month in the 1950s and the 1970s. All three components of expected returns show time variation. The dividend-price ratio and expected earnings growth display low-frequency movements, each of the order of 0.2% to 0.3% per month. The expected multiple changes more with values between -0.3% and 0.3% per month at times.

Figure 4 compares the expected return from the sum-of-the-parts method (with multiple reversion) with traditional predictive regressions for the same three predictors and with the historical mean. We see that there are large differences between the three forecasts. The expected returns using predictive regressions change drastically depending on the predictor used whereas there is very little change in the sum-of-the-parts method estimates.

Figure 5 shows cumulative out-of-sample R-squares for both the sum-of-parts method and predictive regressions. The sum-of-parts method dominates over most of the sample with good fit, although there has been a drop in predictability over time.

We now turn to the annual stock market return forecasts results in panel B of Table 2. We use non-overlapping returns to avoid the concerns with the measurement of R-squares with overlapping returns pointed out by Valkanov (2003) and Boudoukh, Richardson, and Whitelaw (2008). Our findings for monthly return forecasts are also valid for annual return forecasts: forecasting separately the components of stock market returns delivers out-of-sample R-squares significantly higher than traditional predictive regressions. The improvement is even more striking at the annual frequency. Additionally, with annual return fore-

poraneous regression of the price-earnings ratio on other multiples does not make sense.

casts, the multiple reversion approach presents the best performance (relative to the multiple growth regression) in a significant number of cases. This finding is not entirely surprising as the speed of the multiple mean reversion is quite low.

The traditional predictive regression R-squares are in general negative at the annual frequency (13 out of 16 variables) consistent with Goyal and Welch (2008). The R-squares range from -17.57% to 7.54%. Using shrinkage with the traditional prediction regression gives eleven variables with positive R-squares. Forecasting separately the components of stock market returns dramatically improves the performance. We obtain an R-square of 13.43% (last row in table) when we use only the dividends and earnings growth components to forecast stock market returns. When we add the forecast of the price-earnings growth from a predictive regression, we obtain an even higher R-square for some variables: 14.31% (earnings price) and 14.40% (default return spread). When we alternatively add the forecast of the price-earnings growth from the multiple reversion approach, the R-squares reach values of 16.72% (long-term bond return) and 15.04% (term spread).

It is instructive to compare our results with Campbell and Thompson (2008). We can describe their method using our equation (15) with $E_t(gm_{t+1}) = 0$ and $E_t(ge_{t+1}) = [1 - E_t(D_{t+1}/E_{t+1})]\, E_t(ROE_{t+1})$. The last component assumes that earnings growth corresponds to retained earnings times the return on equity and implicitly assumes that there are no external financing flows and that the marginal investment opportunities earn the same as the average return on equity. Campbell and Thompson (2008) use historical averages to forecast the payout ratio and the return on equity. We implement their method in our sample and the out-of-sample R-square is 0.54% with monthly frequency and 3.24% with yearly frequency.[12] Our method using only the dividend yield and earnings growth components gives significantly higher R-squares: 1.32% with monthly frequency and 13.43% with yearly frequency. When we include the multiple growth component, the R-squares are even higher as shown in Table 2.

An alternative forecast of earnings is obtained from analyst estimates drawn from I/B/E/S and aggregated across all S&P 500 stocks. We use this forecast to calculate both the price earnings ratio and the earnings growth. Panel A of Table 3 reports the results for the sample period from January 1982 (when I/B/E/S data starts) to December 2007 with monthly frequency. In this exercise we begin forecasts 5 years after the sample start, rather than 20 years as we did before, due to the shorter sample. Panel B replicates the analysis of Table 2 for the same sample period for comparison. We find that analyst forecasts work quite well with out-of-sample R-squares between 1.67% and 3.09%. However, using our previous approach works even better in this sample period, with out-of-sample R-squares between 2.81% and 4.66%.

[12] Campbell and Thompson (2008) use a longer sample period from 1891 to 2005 (with forecasts begining in 1927) and obtain out-of-sample R-squares of 0.63% with monthly frequency and 4.35% with yearly frequency. We thank John Campbell for letting us use the data and programs used in their study for this comparison.

3.3. Subperiods

We have examined so far the out-of-sample performance of the alternative approaches to forecast stock market returns using the full-sample period from December 1927 to December 2007. Goyal and Welch (2008) find that predictive regressions have a particularly poor performance in the last decades. In this section, we repeat the performance analysis using two subsamples that divide the full-sample period in halves: from December 1927 to December 1976 and from December 1956 to December 2007. As in the previous analysis, forecasts begin 20 years after the subsample start, i.e., January 1948 in the first subsample and January 1977 in the second subsample. Table 4 presents the results. Panels A.1 and A.2 present the results using monthly returns and Panels B.1 and B.2 using annual returns (non-overlapping).

The out-of-sample performance of the alternative approaches is better in the first subsample (that includes the Great Depression and World War II) than in the second subsample (that includes the oil shock of the 1970s and the internet bubble of the end of the 20th Century). Consistent with Goyal and Welch (2008), there is a decline over time in the out-of-sample performance meaning that the variables are not outperforming the historical mean as significantly as in the earlier years of the sample. We find that the sum-of-the-parts method dominates the traditional predictive regressions in both subsamples.

Using monthly data, the out-of-sample R-squares of the traditional predictive regression are in general negative, ranging from -2.20% to 0.37% in the first subperiod and from -2.09% to 0.53% in the second subperiod. Net equity expansion has the best performance in both subperiods.

In both subperiods, there is a very significant improvement in the out-of-sample forecasting performance when we model separately the components of the stock market return. As before, a considerable part of the improvement comes from the dividend yield and earnings growth components alone: out-of-sample R-square of 1.80% in the first subperiod and 0.98% in the second subperiod. This is much better than the performance of the traditional predictive regressions. The maximum R-squares using the multiple growth regression are 2.29% in the first subperiod and 1.44% in the second subperiod.

There is similar performance when we forecast the price-earnings growth using the multiple reversion approach. The maximum R-squares are roughly 2% (9 out of 11 variables in the first subperiod) and 1% (in the second subperiod).

At the annual frequency, we find that most variables have worse performance in the most recent subperiod, but the sum-of-the-parts method dominates the traditional predictive regressions in both subsamples. Using annual data, the out-of-sample R-squares of the traditional predictive regressions are in general negative in both subperiods. In contrast, forecasting separately the components of stock market returns delivers positive out-of-sample R-squares in both subperiods. As before, a considerable part of the improvement comes from the dividend yield and earnings growth components alone. We obtain out-of-sample R-squares of 14.66% in the first subperiod and 12.10% in the second subperiod. The maximum

R-squares using the multiple growth regression are more than 20% in the first subperiod and 15% in the second subperiod. This is much better than the performance of the traditional predictive regressions.

Overall, the result that the sum-of-the-parts method beats the predictive regression (and the historical mean) to forecast stock market returns is robust in subsamples.

3.4. Trading Strategies

To assess the economic importance of the different approaches to forecast returns, we run out-of-sample trading strategies. Each period, we use the various estimates of expected returns to calculate the Markowitz optimal weight on the stock market:

$$w_s = \frac{E_s(r_{s+1}) - rf_{s+1}}{\gamma \sigma_s^2} \tag{24}$$

where rf_{s+1} denotes the risk-free return from time s to $s+1$ (which is known at time s); γ is the risk-aversion coefficient that we assume to be 2; and σ_s^2 is the variance of the stock market returns that we estimate using all the available data up to each forecasting period.[13] The only thing that varies across portfolio policies are the estimates of the expected returns from predictive regressions and the sum-of-the-parts method. Note that these portfolio policies could have been implemented in real time with data available at the time of the decision.[14]

We then calculate the portfolio return at the end of each period as:

$$rp_{s+1} = w_s r_{s+1} + (1 - w_s) rf_{s+1}. \tag{25}$$

We iterate this process until the end of the sample T, thereby obtaining a time series of returns for each trading strategy.

To evaluate the performance of the strategies, we calculate their certainty equivalent return:

$$ce = \overline{rp} - \frac{\gamma}{2}\sigma^2(rp). \tag{26}$$

where $\overline{rp}$ is the sample mean portfolio return and $\sigma^2(rp)$ is the sample variance portfolio return. This is the risk-free return that a mean-variance investor with risk-aversion γ (= 2) would consider equivalent to investing in the strategy. The certainty equivalent can also be interpreted as the fee that the investor would be willing to pay to exploit the information in each forecast model. We also calculate the Sharpe ratio (annualized) for each strategy.

[13] Given the average stock market excess return and variance, a mean-variance investor with risk-aversion coefficient of 2 would allocate the entire wealth to the stock market. This is therefore consistent with equilibrium with this representative investor. We obtain qualitatively similar results using other values for the risk-aversion coefficient.

[14] In unreported results, we obtain in general slightly better certainty equivalents and Shape ratio gains if we impose portfolio constraints preventing investors from shorting stocks ($w_s \geq 0\%$) and taking more than 50% of leverage ($w_s \leq 150\%$).

Table 5 reports the certainty equivalent gains (in percentage) relative to investing based on the historical mean forecast. Using the historical mean, the certainty equivalents are 7.4% and 6.4% per year at the monthly and annual frequency. Using traditional predictive regressions leads to losses relative to the historical mean in most cases. Applying shrinkage to the traditional predictive regression slightly improves the performance of the trading strategies. The sum-of-the-parts method always leads to economic gains in both the multiple growth regression and multiple reversion approaches. In fact, using only the dividend yield and earnings growth components we obtain an economic gain of 1.79% per year. The largest gains in the multiple growth regression and multiple reversion approaches are 2.33% and 1.72% per year. We obtain similar economic gains using annual (and non-overlapping) returns.

Table 6 reports the gains in Sharpe ratio (annualized) relative to investing with the historical mean. Using the historical mean, the Sharpe ratios are 0.45% and 0.30% at the monthly and annual frequency. We find once again that using the traditional predictive regressions leads to losses relative to the historical mean in most cases. Applying shrinkage to the traditional predictive regression significantly improves the performance of the trading strategies. Most important, the sum-of-the-parts method always leads to Sharpe ratio gains in both the multiple growth regression and multiple reversion alternatives. In fact, using only the dividend yield and earnings growth components, we obtain a Sharpe ratio gain of 67%. The maximum gains in the multiple growth regression and multiple reversion approaches are 73% and 53%. We obtain similar Sharpe ratio gains using annual (and non-overlapping) returns.

Finally, our gains in terms of certainty equivalent and Sharpe ratio are higher than the gains obtained using the Campbell and Thompson (2008) approach in our sample: 1.5% gain in certainty equivalent and 27% gain in Sharpe ratio.

4. Conclusion

We abandon predictive regressions of total stock returns in favor of separately forecasting the capital gains and dividend yield components of market returns — the sum-of-the-parts method. We apply our method to forecast stock markets returns out-of-sample in the 1927-2007 period. Our method leads to statistically and economically significant gains for investors. These findings contrast with Goyal and Welch (2008) and revive the long literature on market predictability. The out-of-sample performance of the sum-of-the-parts method is better than the performance of the historical mean and of predictive regressions. Predictive regressions perform poorly because estimated parameters are unstable over time as shown by Campbell and Thompson (2008). Most of the gains in performance in our method comes from combining a steady-state forecast for earnings growth with the market's current valuation. We get a further improvement in predictive power from the multiple growth forecast.

Our results have important consequences for corporate finance and investments. Our forecasts of the equity premium can be used for cost-of-capital calculations in project and firm valuation. The results presented suggest that discount rates and corporate decisions should be more closely dependent on market conditions. In the investments world, we show that there are important gains from timing the market. Of course, to the extent that we are capturing excessive predictability rather than risk premia, the very success of our analysis will eventually destroy its usefulness. Once a sufficiently large number of investors follow our approach to predict returns, they will impact market prices and again make returns unpredictable.

References

Ang, Andrew, and Geert Bekaert, 2007, Stock return predictability: Is it there?, *Review of Financial Studies* 20, 651–707.

Arnott, Robert, and Peter Bernstein, 2002, What risk premium is normal?, *Financial Analyst Journal* 58, 64–85.

Ashley, Richard, 2006, Beyond optimal forecasting, working paper, Virginia Tech.

Baker, Malcolm, and Jeffrey Wurgler, 2000, The equity share in new issues and aggregate stock returns, *Journal of Finance* 55, 2219–2257.

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

Barberis, Nicholas, 2000, Investing for the long run when returns are predictable, *Journal of Finance* 55, 225–264.

Binsbergen, Jules Van, and Ralph Koijen, 2008, Predictive regressions: A present-value approach, working paper, Duke University.

Bossaerts, Peter, and Pierre Hillion, 1999, Implementing statistical criteria to select return forecasting models: What do we learn?, *Review of Financial Studies* 12, 405–428.

Boudoukh, Jacob, Roni Michaely, Matthew Richardson, and Michael Roberts, 2007, On the importance of measuring payout yield: Implications for empirical asset pricing, *Journal of Finance* 62, 877–915.

Boudoukh, Jacob, Matthew Richardson, and Robert Whitelaw, 2008, The myth of long-horizon predictability, *Review of Financial Studies* 21, 1577–1605.

Brandt, Michael, 1999, Estimating portfolio and consumption choice: A conditional euler equations approach, *Journal of Finance* 54, 1609–1646.

Brandt, Michael, 2004, Portfolio choice problems, in Y. Ait-Sahalia and L.P. Hansen, (eds.) *Handbook of Financial Econometrics*, forthcoming (Elsevier Science, Amsterdam).

Brandt, Michael, and Qiang Kang, 2004, On the relationship between the conditional mean and volatility of stock returns: A latent VAR approach, *Journal of Financial Economics* 72, 217–257.

Brandt, Michael, and Pedro Santa-Clara, 2006, Dynamic portfolio selection by augmenting the asset space, *Journal of Finance* 61, 2187–2217.

Breen, William, Lawrence Glosten, and Ravi Jagannathan, 1989, Economic significance of predictable variations in stock index returns, *Journal of Finance* 64, 1177–1189.

Brennan, Michael, Ronald Lagnado, and Eduardo Schwartz, 1997, Strategic asset allocation, *Journal of Economics Dynamics and Control* 21, 1377–1403.

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

Campbell, John, 2008, Estimating the equity premium, *Canadian Economic Review* 41, 1–21.

Campbell, John, and Robert Shiller, 1988, Stock prices, earnings, and expected dividends, *Journal of Finance* 43, 661–676.

Campbell, John, and Samuel Thompson, 2008, Predicting the equity premium out of sample: Can anything beat the historical average?, *Review of Financial Studies* 21, 1509–1531.

Campbell, John, and Luis Viceira, 1999, Consumption and portfolio decisions when expected returns are time varying, *Quarterly Journal of Economics* 114, 433–495.

Campbell, John, and Tuomo Vuolteenaho, 2004, Inflation illusion and stock prices, *American Economic Review* 94, 19–23.

Cavanagh, Christopher, Graham Elliott, and James Stock, 1995, Inference in models with nearly integrated regressors, *Econometric Theory* 11, 1131–1147.

Clark, Todd, and Michael McCracken, 2001, Test of equal forecast accuracy and encompassing for nested models, *Journal of Econometrics* 105, 85–110.

Claus, James, and Jacob Thomas, 2001, Equity premia as low as three percent? evidence from analysts' earnings forecasts for domestic and international stock markets, *Journal of Finance* 56, 1629–1666.

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

Connor, Gregory, 1997, Sensible return forecasting for portfolio management, *Financial Analyst Journal* 53, 44–51.

Diebold, Francis, and Roberto Mariano, 1995, Comparing predictice accuracy, *Journal of Business and Economic Statistics* 13, 253–263.

Dow, Charles, 1920, Scientific stock speculation, the Magazine of Wall Street.

Fama, Eugene, and Kenneth French, 1988, Dividend yields and expected stock returns, *Journal of Financial Economics* 22, 3–25.

Fama, Eugene, and Kenneth French, 1998, Value versus growth: The international evidence, *Journal of Finance* 53, 1975–1999.

Fama, Eugene, and Kenneth French, 2002, The equity premium, *Journal of Finance* 57, 637–659.

Fama, Eugene, and G. William Schwert, 1977, Asset returns and inflation, *Journal of Financial Economics* 5, 155–146.

Ferson, Wayne, Sergei Sarkissian, and Timothy Simin, 2003, Spurious regressions in financial economics, *Journal of Finance* 58, 1393–1413.

Foster, F. Douglas, Tom Smith, and Robert Whaley, 1997, Assessing goodness-of-fit of asset pricing models: The distribution of the maximal R^2, *Journal of Finance* 52, 591–607.

French, Kenneth, G. William Schwert, and Robert Stambaugh, 1987, Expected stock returns and volatility, *Journal of Financial Economics* 19, 3–30.

Ghysels, Eric, Pedro Santa-Clara, and Rossen Valkanov, 2005, There is a risk-return trade-off after all, *Journal of Financial Economics* 76, 509–548.

Goyal, Amit, and Pedro Santa-Clara, 2003, Idiosyncratic risk matters!, *Journal of Finance* 58, 975–1007.

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

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

Hodrick, Robert, 1992, Dividend yields and expected stock returns: Alternative procedures for inference and measurement, *Review of Financial Studies* 5, 357–386.

Ibbotson, Roger, and Peng Chen, 2003, Long-run stock returns: Participating in the real economy, *Financial Analyst Journal* 59, 88–98.

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

Kothari, S. P., and Jay Shanken, 1997, Book-to-market, dividend yield, and expected market returns: A time-series analysis, *Journal of Financial Economics* 44, 169–203.

Lamont, Owen, 1998, Earnings and expected returns, *Journal of Finance* 53, 1563–1587.

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

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

Nelson, Charles, 1976, Inflation and rates of return on common stocks, *Journal of Finance* 31, 471–483.

Nelson, Charles, and Myung Kim, 1993, Predictable stock returns: The role of small sample bias, *Journal of Finance* 48, 641–661.

Pastor, Lubos, and Robert Stambaugh, 2008, Predictive systems: Living with imperfect predictors, *Journal of Finance,* forthcoming.

Pontiff, Jeffrey, and Lawrence Schall, 1998, Book-to-market ratios as predictors of market returns, *Journal of Financial Economics* 49, 141–160.

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

Torous, Walter, Rossen Valkanov, and Shu Yan, 2004, On predicting returns with nearly integrated explanatory variables, *Journal of Business* 77, 937–966.

Valkanov, Rossen, 2003, Long-horizon regressions: Theoretical results and applications, *Journal of Financial Economics* 68, 201–232.

Welch, Ivo, 2000, Views of financial economists on the equity premium and other issues, *Journal of Business* 73, 501–537.

Table 1
Summary Statistics

This table reports summary statistics of the realized components of stocks market returns. *gm* is the growth in the price-earnings ratio. *ge* is the growth in earnings. *dp* is the dividend-price ratio. *r* is the stock market return. The sample period is from December 1927 to December 2007.

	Mean	Median	Sdt Dev	Min	Max	Skew	Kurt	AR(1)
Panel A: Univariate Statistics								
Panel A.1: Monthly frequency (December 1927 - December 2007)								
gm	0.03	0.14	5.95	-30.41	36.71	0.05	9.74	0.16
ge	0.42	0.65	2.23	-9.52	15.12	-0.23	8.19	0.88
dp	0.33	0.31	0.14	0.09	1.27	1.15	6.84	0.98
rm	0.79	1.26	5.55	-33.88	34.82	-0.43	11.19	0.08
Panel A.2: Annual frequency (1927 - 2007)								
gm	0.44	-1.44	26.33	-62.26	78.83	0.27	3.12	-0.17
ge	5.09	9.64	21.49	-70.56	56.90	-1.02	5.42	0.17
dp	3.90	3.60	1.64	1.13	9.62	0.75	3.99	0.79
rm	9.69	13.51	19.42	-60.97	43.60	-0.97	4.50	0.09
Panel B: Correlations								
Panel B.1: Monthly frequency (December 1927 - December 2007)								
	gm	*ge*	*dp*	*rm*				
gm	1							
ge	-0.35	1						
dp	-0.07	-0.20	1					
rm	0.93	0.02	-0.13	1				
Panel B.2: Annual frequency (1927 - 2007)								
	gm	*ge*	*dp*	*rm*				
gm	1							
ge	-0.66	1						
dp	-0.21	-0.16	1					
rm	0.60	0.19	-0.38	1				

Table 2
Forecasts of Stock Market Returns

This table presents in-sample and out-of-sample R-square (in percentage) for stock market returns forecasts at the monthly and annual (non-overlapping) frequency. The in-sample R-square is estimated over the full sample period. The out-of-sample R-square compares the forecast error versus the forecast error of the historical mean. The sample period is from December 1927 to December 2007. Forecasts begin 20 years after the sample start.

Variable	Description	In-sample R-square	Out-of-Sample R-square			
			Predictive regression	Predictive regression (shrinkage)	$gm + ge + dp$ with gm regression (shrinkage)	$gm + ge + dp$ with multiple reversion (shrinkage)
Panel A: Monthly returns			**Sample: December 1927 - December 2007**			
SVAR	Stock variance	0.05	-0.10	-0.02	0.91	1.29
DFR	Default return spread	0.08	-0.35	-0.05	1.27	1.35
LTY	Long term bond yield	0.02	-1.19	-0.09	1.22	0.68
LTR	Long term bond return	0.17	-0.98	-0.05	1.24	1.35
INFL	Inflation	0.04	-0.07	-0.02	1.37	1.32
TMS	Term spread	0.08	-0.05	0.04	1.50	1.40
TBL	T-bill rate	0.00	-0.59	-0.10	1.31	1.07
DFY	Default yield spread	0.03	-0.21	-0.03	1.32	1.33
NTIS	Net equity expansion	1.07	0.69	0.50	1.55	1.29
ROE	Return on equity	0.07	-0.05	0.03	1.20	1.01
DE	Dividend payout	0.34	-0.63	0.11	1.20	0.99
EP	Earnings price	0.76	-0.51	0.53	1.35	
SEP	Smooth earning price	0.74	-1.25	0.02	0.94	
DP	Dividend price	0.15	-0.18	0.04	0.89	
DY	Dividend yield	0.23	-0.58	0.07	0.76	
BM	Book-to-market	0.58	-1.78	-0.06	0.68	
Constant						1.35
$ge + dp$					1.32	
Panel B: Annual returns			**Sample: 1927 - 2007**			
SVAR	Stock variance	0.34	-0.15	0.00	12.74	13.31
DFR	Default return spread	1.95	1.64	0.99	14.40	13.71
LTY	Long term bond yield	0.71	-8.31	-0.85	10.92	4.65
LTR	Long term bond return	2.29	-2.94	2.65	12.62	16.72
INFL	Inflation	1.39	-1.04	0.53	12.91	13.93
TMS	Term spread	0.80	-7.23	-1.20	11.28	15.04
TBL	T-bill rate	0.13	-11.69	-2.09	11.51	10.88
DFY	Default yield spread	0.03	-1.13	-0.31	12.57	13.56
NTIS	Net equity expansion	12.29	1.06	2.30	13.31	14.01
ROE	Return on equity	0.02	-10.79	-2.40	13.66	9.68
DE	Dividend payout	1.58	-0.17	0.47	12.60	9.87
EP	Earnings price	5.69	7.54	4.56	14.31	
SEP	Smooth earning price	8.27	-17.57	2.47	11.07	
DP	Dividend price	1.63	-1.01	0.28	8.99	
DY	Dividend yield	2.31	-17.21	1.45	12.51	
BM	Book-to-market	5.76	-8.80	0.82	10.20	
Constant						14.40
$ge + dp$					13.43	

Table 3
Forecasts of Stock Market Returns: Analysts Earnings Forecasts

This table presents in-sample and out-of-sample R-square (in percentage) for stock market returns forecasts at the monthly (non-overlapping) frequency. The in-sample R-square is estimated over the full sample period. The out-of-sample R-square compares the forecast error versus the forecast error of the historical mean. Panel A uses analyst earnings forecasts to calculate *gm* and *ge*. Panel B uses actual earnings to calculate *ge* and *gm*. The sample period is from January 1982 to December 2007. Forecasts begin 5 years after the sample start.

Variable	Description	In-sample R-square	Out-of-Sample R-square			
			Predictive regression	Predictive regression (shrinkage)	$gm + ge + dp$ with gm regression (shrinkage)	$gm + ge + dp$ with multiple reversion (shrinkage)
Panel A: Analysts forecasts			**Sample: January 1982 - December 2007**			
SVAR	Stock variance	0.88	-2.97	-0.17	2.26	2.11
DFR	Default return spread	0.60	-2.20	-0.14	2.20	2.19
LTY	Long term bond yield	0.26	-0.67	-0.02	2.25	3.09
LTR	Long term bond return	0.26	-0.45	-0.01	2.26	2.17
INFL	Inflation	0.04	-0.76	-0.06	2.22	2.12
TMS	Term spread	0.01	-2.00	-0.15	2.15	2.06
TBL	T-bill rate	0.29	-1.18	-0.03	2.19	2.59
DFY	Default yield spread	0.51	-0.49	0.04	2.12	2.31
NTIS	Net equity expansion	0.66	-1.23	0.06	2.01	2.36
ROE	Return on equity	0.02	-1.84	-0.10	1.97	2.22
DE	Dividend payout	0.02	-1.79	-0.12	2.26	1.67
EP	Earnings price	2.68	1.78	0.56	2.39	
SEP	Smooth earning price	1.25	-0.22	0.19	2.13	
DP	Dividend price	1.74	0.00	0.29	2.08	
DY	Dividend yield	1.74	-0.23	0.28	2.07	
BM	Book-to-market	1.02	0.14	0.14	2.16	
Constant						2.17
$ge + dp$				2.32		
Panel B: Actuals			**Sample: January 1982 - December 2007**			
SVAR	Stock variance	0.88	-2.97	-0.17	2.81	3.58
DFR	Default return spread	0.60	-2.20	-0.14	3.51	3.62
LTY	Long term bond yield	0.26	-0.67	-0.02	3.52	4.66
LTR	Long term bond return	0.26	-0.45	-0.01	3.60	3.58
INFL	Inflation	0.04	-0.76	-0.06	3.54	3.61
TMS	Term spread	0.01	-2.00	-0.15	3.22	3.58
TBL	T-bill rate	0.29	-1.18	-0.03	3.37	4.23
DFY	Default yield spread	0.51	-0.49	0.04	3.34	3.51
NTIS	Net equity expansion	0.66	-1.23	0.06	2.97	3.64
ROE	Return on equity	0.02	-1.84	-0.10	3.17	3.54
DE	Dividend payout	0.02	-1.79	-0.12	3.59	3.11
EP	Earnings price	2.68	1.78	0.56	3.61	
SEP	Smooth earning price	1.25	-0.22	0.19	3.39	
DP	Dividend price	1.74	0.00	0.29	3.29	
DY	Dividend yield	1.74	-0.23	0.28	3.25	
BM	Book-to-market	1.02	0.14	0.14	3.39	
Constant						3.61
$ge + dp$				3.62		

Table 4
Forecasts of Stock Market Returns: Subsamples

This table presents in-sample and out-of-sample R-square (in percentage) for stock market returns forecasts at the monthly and annual (non-overlapping) frequency. The in-sample R-square is estimated over the full sample period. The out-of-sample R-square compares the forecast error versus the forecast error of the historical mean. The sample period is from December 1927 to December 2007. The subsamples divide the data in halfs. Forecasts begin 20 years after the sample start.

Variable	Description	In-sample R-square	Out-of-Sample R-square			
			Predictive regression	Predictive regression (shrinkage)	$gm + ge + dp$ with gm regression (shrinkage)	$gm + ge + dp$ with multiple reversion (shrinkage)
Panel A.1: Monthly returns			**Sample: December 1927 - December 1976**			
SVAR	Stock variance	0.00	-0.18	-0.04	1.64	2.12
DFR	Default return spread	0.01	-1.04	-0.22	1.57	2.09
LTY	Long term bond yield	0.11	-1.72	0.04	1.61	0.89
LTR	Long term bond return	0.12	-2.20	-0.34	1.42	2.16
INFL	Inflation	0.13	0.21	0.08	2.19	2.23
TMS	Term spread	0.12	0.24	0.10	2.06	2.18
TBL	T-bill rate	0.17	-0.15	0.09	1.90	1.64
DFY	Default yield spread	0.01	-0.53	-0.09	1.80	2.11
NTIS	Net equity expansion	1.08	0.37	0.16	1.85	2.12
ROE	Return on equity	0.01	-0.17	-0.03	1.74	2.25
DE	Dividend payout	0.47	-1.09	0.02	1.73	2.16
EP	Earnings price	1.07	-0.40	0.65	2.15	
SEP	Smooth earning price	1.83	-1.45	0.11	2.06	
DP	Dividend price	0.24	0.29	0.20	2.26	
DY	Dividend yield	0.47	-0.07	0.33	2.29	
BM	Book-to-market	1.62	0.04	0.39	2.28	
Constant						2.14
$ge + dp$				1.80		
Panel B.1: Annual returns			**Sample: 1927 - 1976**			
SVAR	Stock variance	0.19	-0.76	-0.21	13.93	21.26
DFR	Default return spread	2.34	4.52	1.66	14.82	20.47
LTY	Long term bond yield	0.70	-10.95	-0.82	9.62	8.35
LTR	Long term bond return	6.82	9.64	5.10	13.44	24.79
INFL	Inflation	1.49	-0.99	0.72	13.77	21.89
TMS	Term spread	1.91	-6.66	-0.68	12.80	21.57
TBL	T-bill rate	1.59	-12.14	-1.43	11.66	17.12
DFY	Default yield spread	0.05	-1.64	-0.43	14.56	22.06
NTIS	Net equity expansion	14.91	0.65	0.31	14.59	21.73
ROE	Return on equity	0.91	-12.62	-1.93	14.73	22.98
DE	Dividend payout	1.30	-0.23	-0.12	13.09	21.44
EP	Earnings price	6.74	14.14	4.71	21.77	21.76
SEP	Smooth earning price	22.44	-10.42	5.91	23.21	17.53
DP	Dividend price	2.93	4.48	1.82	21.02	19.30
DY	Dividend yield	5.28	-17.74	4.34	18.16	16.49
BM	Book-to-market	14.73	8.30	4.41	19.87	21.72
Constant						21.76
ge+dp				14.66		

Table 4: continued

Variable	Description	In-sample R-square	Out-of-Sample R-square: Predictive regression	Predictive regression (shrinkage)	$gm+ge+dp$ with gm regression (shrinkage)	$gm+ge+dp$ with multiple reversion (shrinkage)
Panel A.2: Monthly returns			**Sample: December 1956 - December 2007**			
SVAR	Stock variance	0.36	-0.99	-0.22	0.00	1.07
DFR	Default return spread	0.14	-0.02	0.00	1.00	0.87
LTY	Long term bond yield	0.05	-0.74	-0.11	0.93	0.87
LTR	Long term bond return	0.74	-0.67	0.19	1.17	0.86
INFL	Inflation	0.03	-0.78	-0.13	0.88	0.98
TMS	Term spread	0.46	-1.63	-0.01	1.10	0.90
TBL	T-bill rate	0.02	-2.09	-0.26	0.85	1.09
DFY	Default yield spread	1.02	-0.14	0.25	1.01	0.61
NTIS	Net equity expansion	0.85	0.53	0.58	1.44	0.80
ROE	Return on equity	0.12	-0.88	-0.09	0.62	0.79
DE	Dividend payout	0.00	-1.07	-0.17	0.74	-0.22
EP	Earnings price	0.61	0.30	0.19	0.87	
SEP	Smooth earning price	0.58	-0.53	0.11	0.62	
DP	Dividend price	0.56	-1.01	0.08	0.32	
DY	Dividend yield	0.61	-1.31	0.08	0.23	
BM	Book-to-market	0.17	-0.73	-0.08	0.57	
Constant						0.86
$ge+dp$				0.98		
Panel B.2: Annual returns			**Sample: 1956 - 2007**			
SVAR	Stock variance	0.71	-25.88	-1.32	10.83	7.28
DFR	Default return spread	3.15	-5.65	-0.58	13.56	11.51
LTY	Long term bond yield	2.37	-3.39	-0.09	11.55	7.37
LTR	Long term bond return	3.26	-21.50	-0.15	12.35	10.09
INFL	Inflation	2.24	-10.39	-0.80	9.64	11.64
TMS	Term spread	1.27	-15.70	-2.04	9.92	10.75
TBL	T-bill rate	0.51	-17.57	-2.53	9.24	8.81
DFY	Default yield spread	5.71	-14.77	-0.22	8.83	9.38
NTIS	Net equity expansion	2.53	1.53	3.30	10.76	8.08
ROE	Return on equity	0.45	-9.68	0.43	15.32	5.13
DE	Dividend payout	0.14	-9.82	-1.79	11.35	-7.56
EP	Earnings price	8.42	1.82	3.49	9.83	
SEP	Smooth earning price	7.11	-12.50	1.39	5.85	
DP	Dividend price	6.97	-26.89	0.62	0.01	
DY	Dividend yield	5.69	-15.74	0.52	6.60	
BM	Book-to-market	3.04	-11.16	-0.50	6.33	
Constant						9.74
$ge+dp$				12.10		

Table 5
Trading Strategies: Certainty Equivalent Gains

This table presents out-of-sample portfolio choice results at the monthly and annual (non-overlapping) frequency. The numbers are the certainty equivalent gains (in percentage) relative to the historical mean. The utility function is $E(R_p) - (\gamma/2)Var(R_p)$ with a risk-aversion coefficient of $\gamma = 2$. All numbers are annualized (monthly certainty equivalents gains are multiplied by 12). The sample period is from December 1927 to December 2007. Forecasts begin 20 years after the sample start.

Variable	Description	Predictive regression	Predictive regression (shrinkage)	$gm + ge + dp$ with gm regression (shrinkage)	$gm + ge + dp$ with multiple reversion (shrinkage)
Panel A: Monthly returns		**Sample: December 1927 - December 2007**			
SVAR	Stock variance	-0.04	0.00	0.97	1.59
DFR	Default return spread	-0.26	-0.04	1.75	1.71
LTY	Long term bond yield	-1.56	-0.29	1.76	1.25
LTR	Long term bond return	-0.25	0.10	1.92	1.69
INFL	Inflation	-0.07	-0.02	1.86	1.66
TMS	Term spread	0.41	0.18	2.13	1.72
TBL	T-bill rate	-0.86	-0.18	1.75	1.38
DFY	Default yield spread	-0.19	-0.05	1.53	1.64
NTIS	Net equity expansion	2.14	0.94	2.33	1.60
ROE	Return on equity	0.28	0.17	1.69	1.17
DE	Dividend payout	1.40	0.57	1.56	0.93
EP	Earnings price	0.20	0.35	1.69	
SEP	Smooth earning price	-1.15	-0.41	0.73	
DP	Dividend price	-0.84	-0.26	0.62	
DY	Dividend yield	-1.21	-0.33	0.45	
BM	Book-to-market	-2.58	-0.52	0.49	
Constant					1.69
$ge + dp$			1.79		
Panel B: Annual returns		**Sample: 1927 - 2007**			
SVAR	Stock variance	0.12	0.04	1.66	1.48
DFR	Default return spread	0.48	0.20	2.07	1.58
LTY	Long term bond yield	-1.05	-0.19	1.75	0.71
LTR	Long term bond return	1.48	0.66	1.88	2.00
INFL	Inflation	-0.08	0.08	1.73	1.45
TMS	Term spread	-0.58	-0.08	1.52	1.75
TBL	T-bill rate	-1.48	-0.31	1.69	1.16
DFY	Default yield spread	-0.01	-0.01	1.58	1.50
NTIS	Net equity expansion	1.25	0.54	1.89	1.61
ROE	Return on equity	-1.09	-0.28	2.04	0.90
DE	Dividend payout	0.60	0.24	1.91	0.76
EP	Earnings price	0.58	0.34	1.66	
SEP	Smooth earning price	-1.39	-0.14	0.88	
DP	Dividend price	-0.71	-0.22	0.54	
DY	Dividend yield	-2.04	-0.16	1.41	
BM	Book-to-market	-1.53	-0.27	0.97	
Constant					1.67
$ge + dp$			1.82		

Table 6
Trading Strategies: Sharpe Ratio Gains

This table presents out-of-sample portfolio choice results at the monthly and annual (non-overlapping) frequency. The numbers are the the percentage gain in Sharpe ratio relative to the historical mean. All numbers are annualized. The sample period is from December 1927 to December 2007. Forecasts begin 20 years after the sample start.

Variable	Description	Predictive regression	Predictive regression (shrinkage)	$gm + ge + dp$ with gm regression (shrinkage)	$gm + ge + dp$ with multiple reversion (shrinkage)
Panel A: Monthly returns		**Sample: December 1927 - December 2007**			
SVAR	Stock variance	-0.20	0.56	26.41	46.19
DFR	Default return spread	-12.79	-2.05	65.19	51.54
LTY	Long term bond yield	-54.56	-13.87	63.17	19.34
LTR	Long term bond return	-26.10	-3.34	51.13	51.39
INFL	Inflation	-8.80	-2.30	67.51	41.05
TMS	Term spread	-10.98	-3.46	60.93	51.02
TBL	T-bill rate	-38.84	-9.64	70.69	36.13
DFY	Default yield spread	-3.83	-0.17	72.98	50.59
NTIS	Net equity expansion	9.86	12.96	61.61	52.84
ROE	Return on equity	-12.51	-4.09	59.96	24.94
DE	Dividend payout	-5.38	-0.25	69.27	29.85
EP	Earnings price	-18.92	66.87	51.34	
SEP	Smooth earning price	-45.76	26.91	26.45	
DP	Dividend price	23.48	18.54	29.94	
DY	Dividend yield	-27.50	31.93	15.58	
BM	Book-to-market	-73.89	9.55	2.73	
Constant					51.56
$ge + dp$			67.44		
Panel B: Annual returns			**Sample: 1927 - 2007**		
SVAR	Stock variance	2.43	1.25	72.28	33.85
DFR	Default return spread	10.08	7.41	74.89	35.19
LTY	Long term bond yield	-45.83	-9.37	59.93	1.40
LTR	Long term bond return	24.21	20.22	72.92	47.29
INFL	Inflation	2.86	4.86	68.31	28.45
TMS	Term spread	-30.44	-7.44	58.80	43.26
TBL	T-bill rate	-61.57	-13.26	59.60	18.67
DFY	Default yield spread	-4.70	-1.67	76.46	34.71
NTIS	Net equity expansion	15.98	13.26	69.44	36.82
ROE	Return on equity	-48.08	-13.43	52.26	11.53
DE	Dividend payout	1.18	1.11	67.54	13.55
EP	Earnings price	15.45	49.53	38.70	
SEP	Smooth earning price	-47.01	21.86	20.24	
DP	Dividend price	-5.07	7.76	14.40	
DY	Dividend yield	-65.96	22.03	63.43	
BM	Book-to-market	-59.50	9.84	30.08	
Constant					40.02
$ge + dp$			71.46		

Figure 1. Cumulative Realized Stock Market Components

These figures show monthly cumulative realized price-earnings ratio growth (gm), earnings growth (ge), dividend price (dp), and stock market return (r).

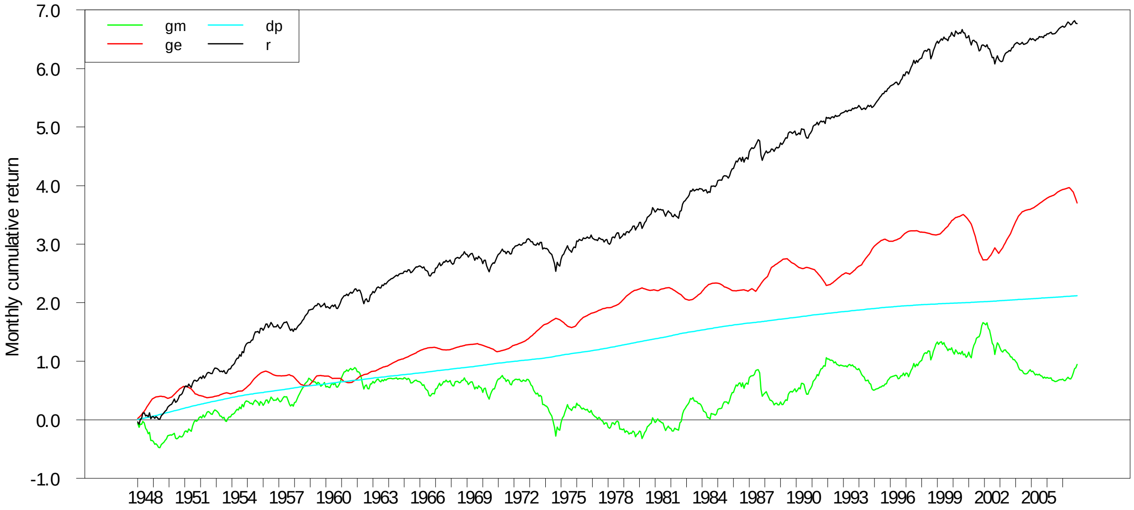

Figure 2. Realized and Forecasted Price Earnings Ratio

These figures show monthly realized and forecasted price-earnings ratio from the multiple reversion method using alternative predictors.

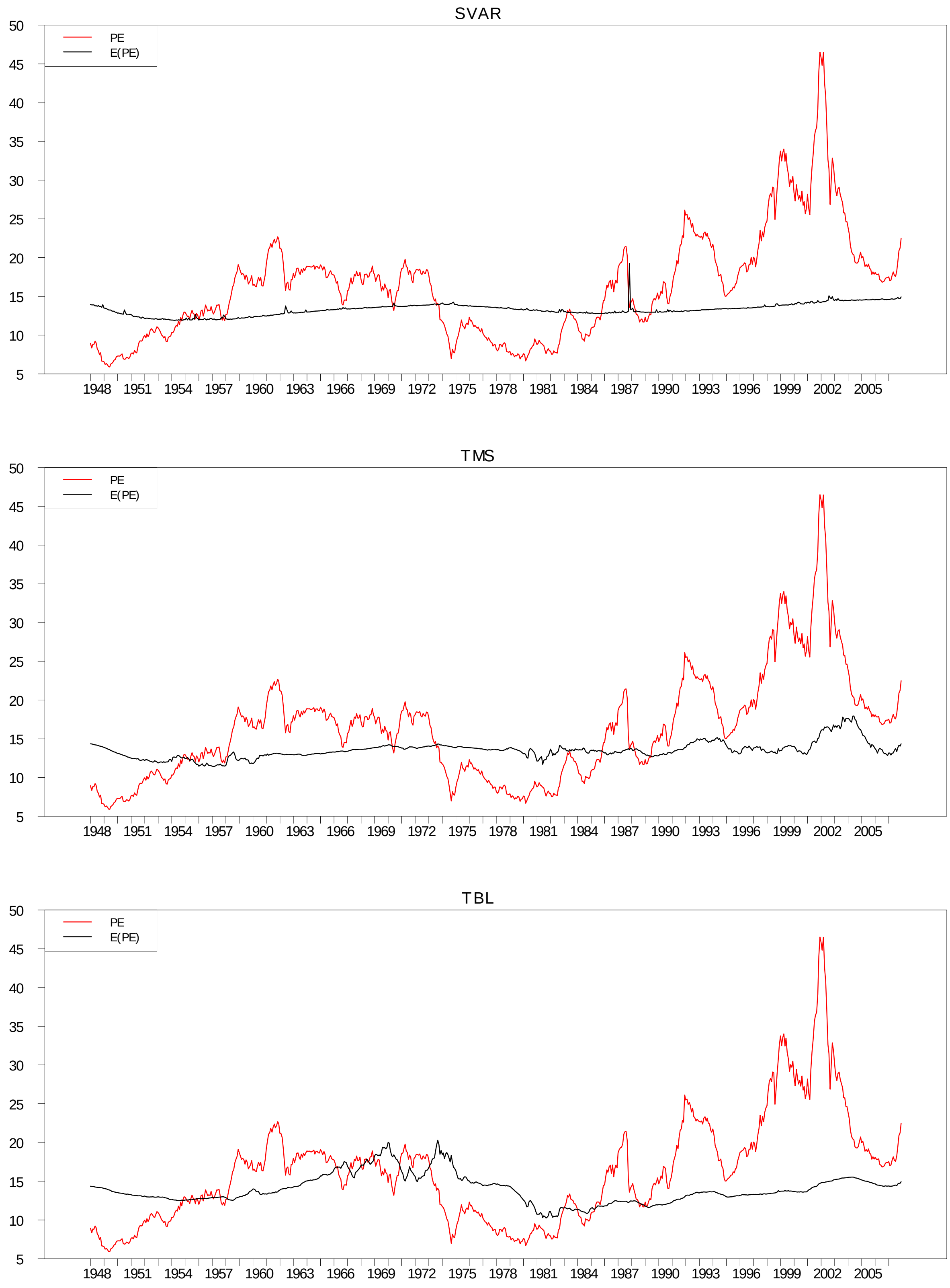

Figure 3. Forecasts of Stock Market Return Components

These figures show monthly forecasts of price-earnings ratio growth (gm), earnings growth (ge), dividend price (dp) and market return ($gm + ge + dp$) from the sum-of-the-parts method with multiple reversion using alternative predictors.

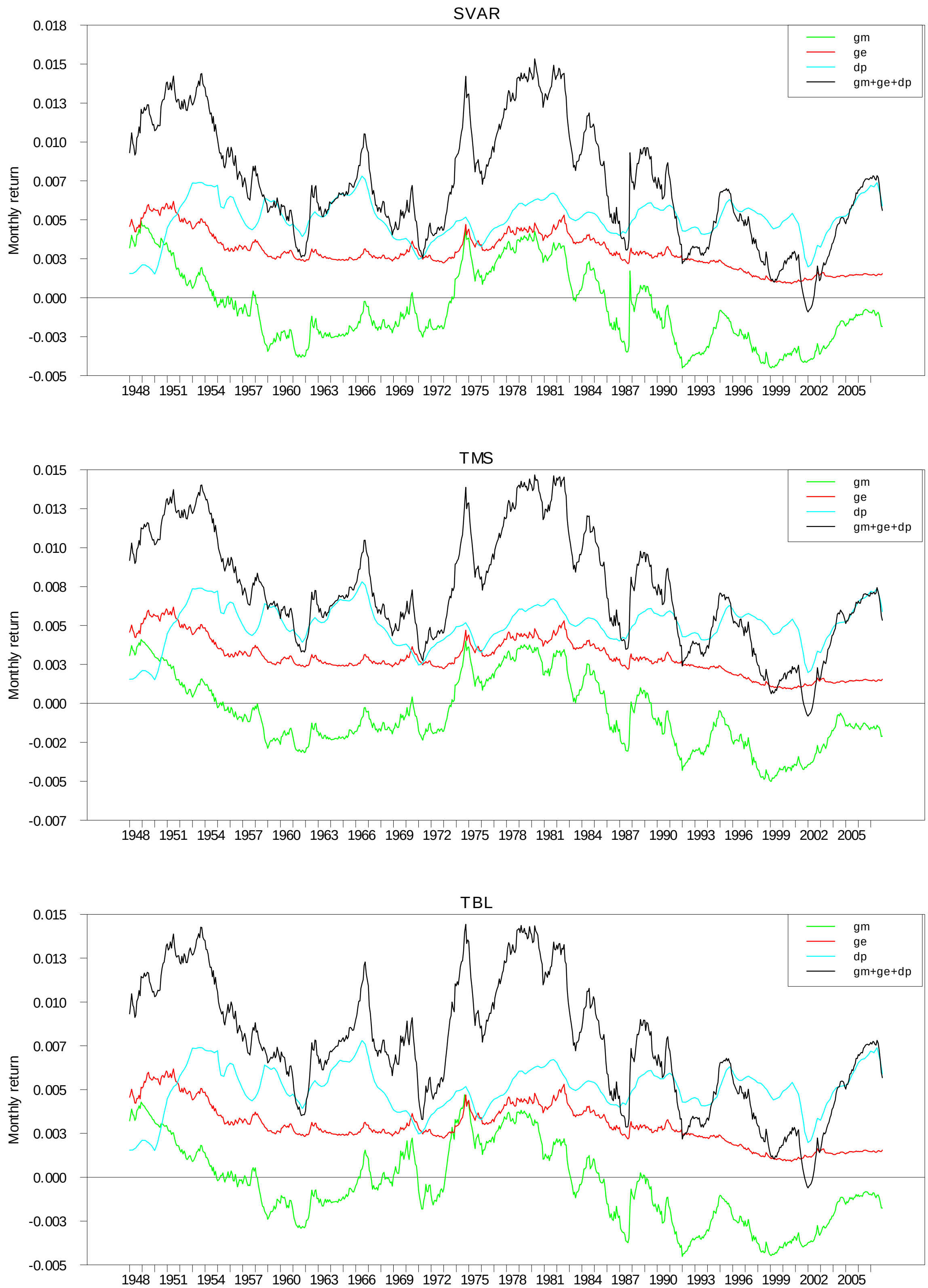

Figure 4. Forecasts of Stock Market Returns

These figures show monthly forecasts of market return from the predictive regression and sum-of-the-parts method with multiple reversion ($gm + ge + dp$) using alternative predictors.

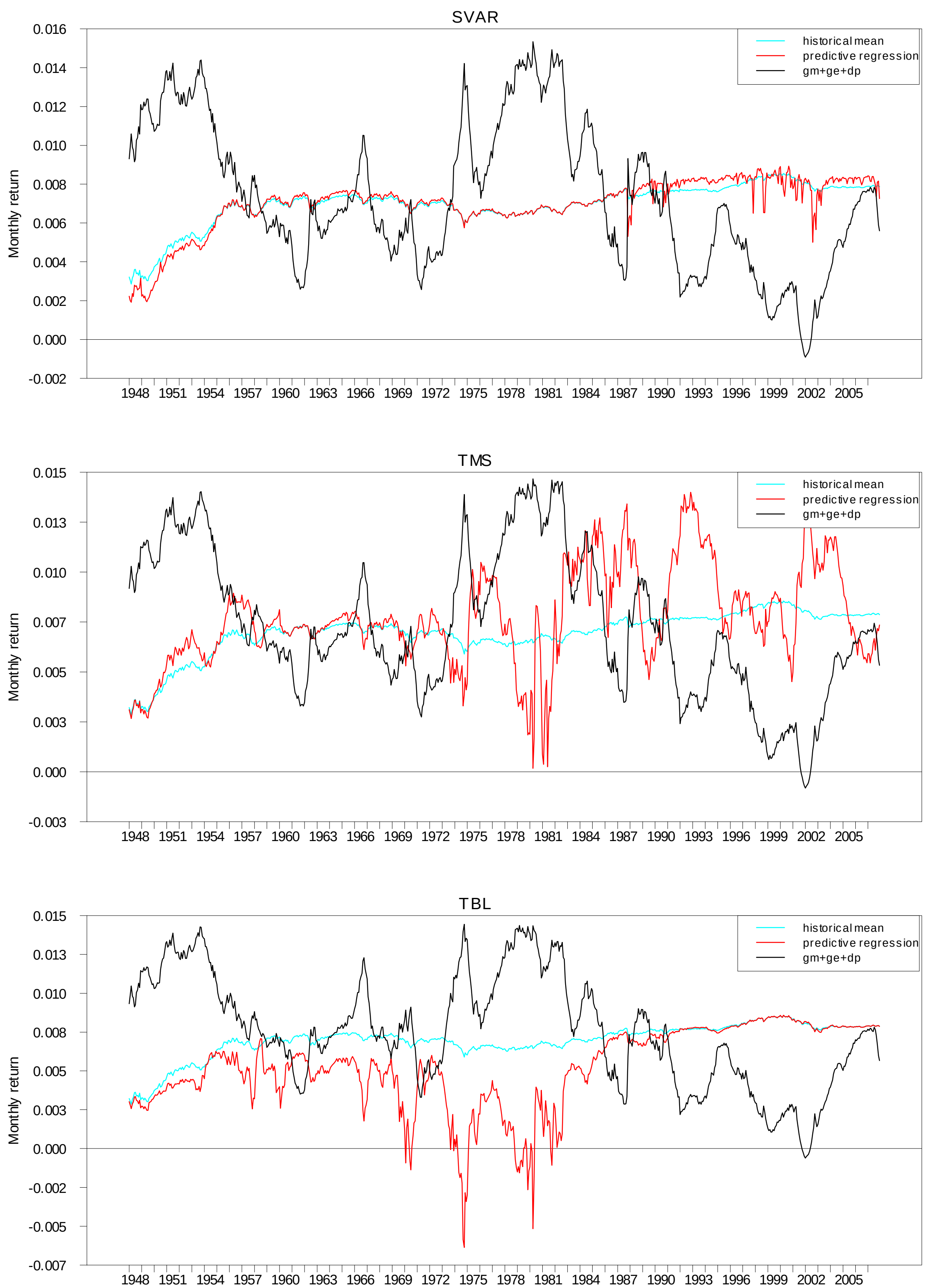

Figure 5. Cumulative R-square versus Historical Mean

These figures show out-of-sample cumulative R-square up to each month from the predictive regression and sum-of-the-parts method with multiple reversion ($gm + ge + dp$) using alternative predictors relative to the historical mean.